

# Agent 2004 Conference Proceedings



## Conference on **Social Dynamics: Interaction, Reflexivity and Emergence**

October 7–9, 2004

co-sponsored by  
**Argonne National Laboratory**  
**The University of Chicago**

in association with  
*North American Association for Computational Social and Organizational Science*

edited by  
*Charles M. Macal, David Sallach, and Michael J. North*



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**Agent**  
**2004**

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## FOREWORD

We are pleased to publish the proceedings of the Agent 2004 conference, co-sponsored by Argonne National Laboratory and The University of Chicago. This proceedings is the fifth in a series; each of the documents in this series provides a window into the rapidly advancing subfield of social agent simulation.

The Agent 2004 conference, like previous Agent conferences, was organized around three topical areas: (1) methods, toolkits, and techniques; (2) computational social theory; and (3) simulation applications. The first theme emphasizes the way in which substantive social science modeling and computational modeling must co-evolve in order to progress. The second stresses the theoretical and conceptual advances that, given computational breakthroughs, can be explored and assessed. The third theme focuses on the fact that in order for these advances to ultimately contribute to society, they must support the understanding of application domains or the assessment of policy alternatives. These three topical areas, which summarize recurring priorities within this emergent subfield, are now also Special Interest Groups within the North American Association for Computational Social and Organizational Science (NAACSOS), the professional organization with which Agent 2004 staff coordinated.

One way to assess the progression of the subfield is to consider the diversity of topics and application areas it covers. At Agent 2004, methodological topics included generative models, ontological design, life-cycle methods, data farming, and GIS. Theoretical topics included balance theory, intimate interaction, prototype inference and microinteraction, ethnic preferences and segregation, technological trajectories, and threshold models of collective behavior. Application areas included archeology, land use, logistics, supply networks, national security, open-source software development, and the prospects for a hydrogen transportation infrastructure. While none of the lists are exhaustive, each is sufficient to show that as the subfield of computational social science addresses new domains, novel insights into the modeling process are gained, and vice versa.

We hope you enjoy the richness of the proceedings as much as we benefited from the depth of the conference. We also hope that the work reported here inspires you to undertake original investigations, the results of which can be shared with our research community at future Agent conferences.

Charles Macal, Director  
Michael North, Deputy Director  
David Sallach, Associate Director

Center for Complex Adaptive Agent Systems Simulation (CAS<sup>2</sup>)  
Decision and Information Sciences Division  
Argonne National Laboratory



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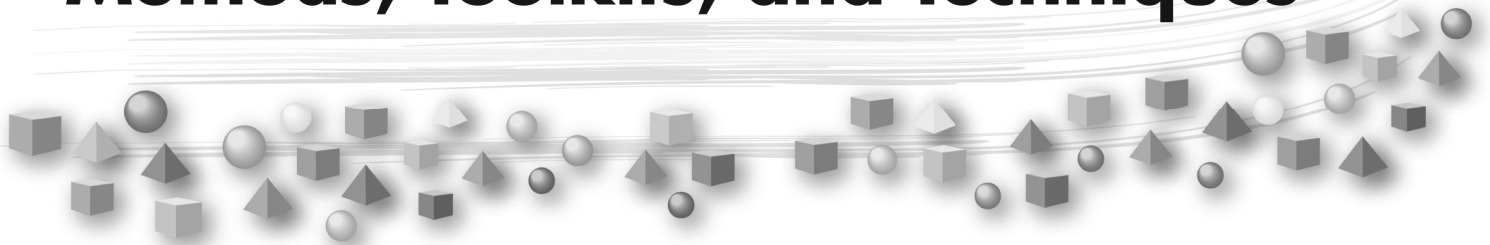
## **ORGANIZING COMMITTEE**

Charles Macal, Argonne National Laboratory  
Michael North, Argonne National Laboratory  
David Sallach, Argonne National Laboratory and The University of Chicago  
Thomas Wolsko, Argonne National Laboratory



Thursday, October 7, 2004

# **Methods, Toolkits, and Techniques**

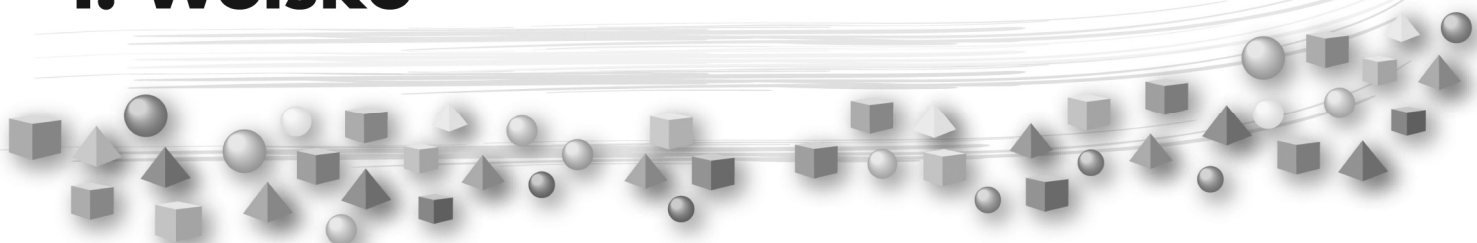






Welcome

**T. Wolsko**





## WELCOME

T. WOLSKO, Argonne National Laboratory

I'd like to welcome you to the Agent 2004 conference. As most of you are aware, this conference is the fifth in a series of meetings that began in 1999. A conference followed the next year in 2000. The 2001 conference was skipped because of some conflicts with other conferences, and the conferences have proceeded annually since then. We have the proceedings of the previous conferences available here on CDs. One CD has the proceedings from 1999, 2000, and 2002; the other contains last year's proceedings.

The purpose of these conferences is to advance the state of the computational social sciences and to integrate the social sciences with the decision sciences and something that is traditionally known as the management sciences. Those of you in the operations/research area are familiar with the traditional school of modeling simulation that emerged from that scientific area. This conference will bring together a different group of people to talk about the topic of agent-based theories and simulations.

This fifth agent conference is one of a group of conferences held annually around the country. Most of you are probably aware of the CASOS Conference held at Carnegie Mellon University, usually in July. UCLA holds the Arrowhead Conference, generally around May. The University of Michigan is now holding a conference as well. Of course everyone is aware of SwarmFest, which has been held annually for about a decade. The Swarm seems to "swarm" in different locations each year.

As you're well aware, this conference is organized into a three-day program. This is the first time we've used three days for the full conference setting. Last year, we held simultaneous sessions, and that didn't work well for most of those who attended. We had complaints from people who missed sessions and papers because of scheduling, so we decided to extend this year's conference by one day. As a result, we now have a program designed to present the papers in a serial sequence rather than in a parallel manner.

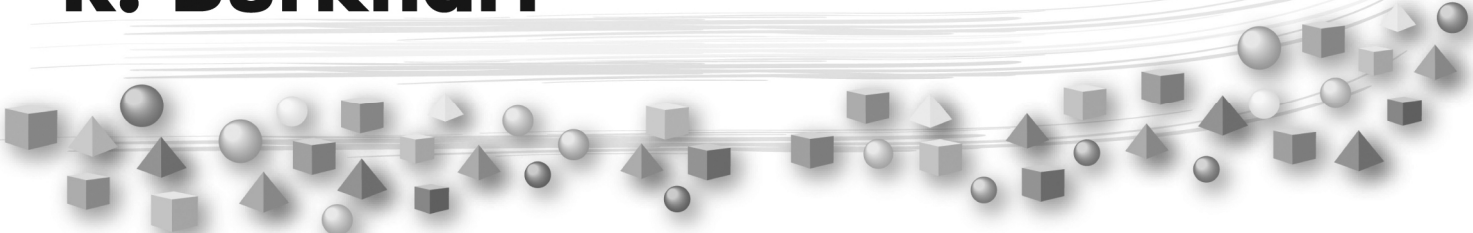
Today, we'll focus on toolkits. Tomorrow we'll look at computational social theory, and Saturday is application day. We'll talk about how we're taking some of the theories and toolkits to look at real-world problems in order to understand how our very complex world works and maybe even to predict how it might work in the future.

In addition to the content of the papers themselves, one of the more important things about this conference is the discussion that is inspired by these papers. I invite you to ask penetrating questions, offer insightful comments, share your experiences with toolkits or your ideas on theories, and help to create an atmosphere that will help this field move along and grow. It's a fairly new science — it is just emerging — but it seems to have been gaining momentum in the last couple of years. This is a conference to get your energy going and perhaps foster your creativity. With that, I welcome you to Agent 2004; have a great time at the conference.



Invited Speaker

# R. Burkhart





## Standardizing an Agent Life-cycle Model

Agent 2004

October 7, 2004

Roger Burkhart  
Deere & Company  
burkhartrgerm@johndeere.com



## Summary of Talk

This talk explored a range of topics that could contribute to standardized approaches for modeling agent systems. A basic theme was that agent systems need to piggyback on more general frameworks for both modeling and execution. Multi-level systems engineering is a particular field of industrial application that shares many needs for modeling complex systems. Agent systems, however, can be made more expressive by building a process of internal development into the individual life cycle of each agent. Each such agent would include within it an architecture of building blocks and internal structure, using the same concepts that could be shared with many other domains.

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## State of agent-based modeling

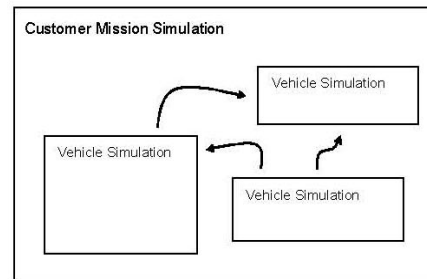
- Future of agent-based modeling is assured
  - Major progress in acceptance as mainstream technique in diverse scientific disciplines
  - Becoming recognized as an essential method to explore and understand behavior in complex systems
  - Frameworks to implement real-time agent systems much less mature
- Remaining challenges
  - Broaden familiarity and reliance as a tool of understanding
  - Engineering artificial agent systems that can be deployed and scaled as working parts of real-time computing networks

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## Engineering use of agent models



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## Multi-level Systems Engineering

- Simulation-based design and optimization of working elements based on field scenarios
- Analysis for robustness, efficiency, adaptability, reusability, ...
- Hierarchically nested based on level of interest
  - External customer processes
  - Products and missions
  - Design & internal operations
- Multiple scales in time & space
  - Design time
  - "Inventory" of available resources and capabilities
  - Reconfiguration & deployment
  - Real-time operation

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## ABM applications

- Theoretical analysis & understanding of complex systems
- Training & "flight simulators"
- Business applications
  - Organization behavior / business process modeling / E-commerce & B2B collaboration
  - Real-time optimization and response
    - Logistics & scheduling
    - Autonomic maintenance and control
    - Supply chain management
  - Networks & computing infrastructure
- ...

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## Roles of computing in organizations

- Collaboration
  - Automation
  - Analysis
- 
- Hybrids of human and computer capability

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## Working roles of models

- Collaboration using shared access to complex models
- Capture and communication of static content to be stored, exchanged, and interpreted semantically
- Query, reduction, and inference to analyze or predict system characteristics or actual history
- Simulation to generate representative forms of system behavior and test conditions that produce them
- Model-based systems in which an endogenous model helps control a larger physical or organizational system
- Agents utilizing endogenous models in their local contexts to predict and adapt to their environment, including each other
- Understanding (and augmenting or extending) cognition and intelligence

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## Stretching the range of modeling

- Integrate databases, programming, and complex systems modeling
- Feeding real-world data and integrating external program logic is a key part of many agent system models
- Real-time operation and scaling in size and time is key to many practical uses
- Need to broaden investment and use of modeling tools beyond those the CAS research community can do on its own

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## Potential roles of standardization

- Co-existence of agent models in a larger world of modeling, programming, and applications
- Accelerate the growth and use of agent-based models by piggybacking on larger trends
- Provide standardized concepts, reusable patterns and structures, and working platforms for agent systems
- Link agent models to commercial and applied roles that can drive development and support for robust, industrial-grade platforms

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## Trends in modeling

- Growing move to "model-driven development" to abstract the function and content of systems from the machinery of programming
- Deployment and sharing of function and content across ever-wider scales
  - Web services turning the net into a real-time agent platform
  - REST vs. RPC debate raising issue of explicit representation and identity vs. opaque operations
- Move towards formal logic to define content and provide neutral language for system description
  - Semantic web and web vocabularies/ontologies
  - Fully axiomatized ontologies

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## Process Specification Language

Sample definitions of PSL-Core:  
 (occurrence\_of ?occ ?a)  
 (= ?t (beginof ?x))

... the activity denoted by the term (paint House1 Paintcan1) is an instance of the class of Painting activities:  
 (Painting (paint House1 Paintcan1))

There may be multiple distinct occurrences of this instance:  
 (occurrence\_of Occ1 (paint House1 Paintcan1))  
 (occurrence\_of Occ2 (paint House1 Paintcan1))  
 (= (beginof Occ1) 1100)  
 (= (endof Occ1) 1200)  
 (= (beginof Occ2) 1500)  
 (= (endof Occ2) 1800)

[www.nist.gov/psl](http://www.nist.gov/psl)

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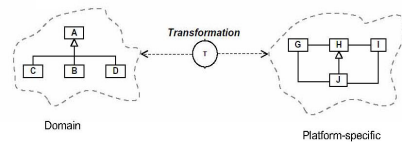
## Use of models in development

- Use of Unified Modeling Language (UML) to provide various views of a system across its development life-cycle
  - Object Management Group (OMG) initiative for Model-Driven Architecture (MDA)
  - Integration of UML into vendor life-cycle development tools, including Microsoft Visual Studio Team Edition
- Fragmenting of programming into plug-in procedures within larger, language-neutral environments
- Generative and transformation methods to generate code from models, either generic or domain-specific
- Model-driven approaches are key to targeting new generations of distributed and parallel execution platforms

## OMG Query/Views/Transformations

- Transformation of “metamodels” using declarative, pattern-based rules
- Like XML transformations but on abstract metamodels including UML-derived metaobject structures
- Transformation of system models from platform-independent to platform-dependent forms, to implement in different target environments
- Key element of Model-Driven Architecture (MDA) initiative
  - Models and model transformations instead of program code

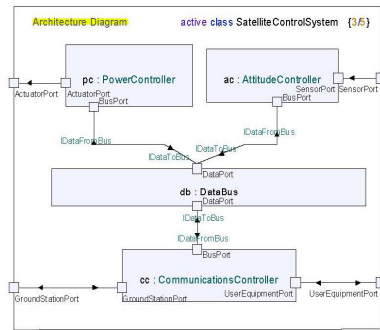
## Model-to-Model Transformation



## Generative Frameworks

- Czarnecki & Eisenecker, *Generative Software Frameworks: Methods, Tools, and Applications*, Addison Wesley 2000
  - Feature analysis by “domain”
  - Component selection & configuration
  - Code-generation frameworks to deal with complex & cross-cutting concerns

## UML 2.0 Composite Structure Example



## UML for Systems Engineering

- Joint initiative of International Council on Systems Engineering (INCOSE) and OMG Systems Engineering special-interest group
- Provide computer-interpretable representation of products throughout their development lifecycle
  - “Product” = “Engineered System”
  - Facilitate communication/collaboration
    - across engineering disciplines
    - across development tasks and responsibilities
- Support systems engineering processes

## Systems Engineering Processes

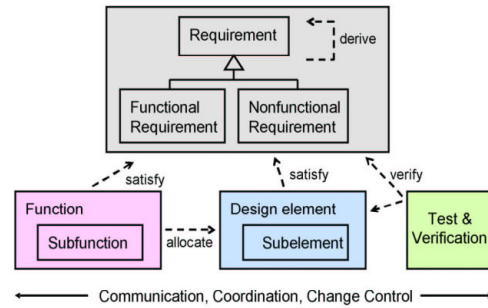
- Requirements capture, allocation, traceability
- Conceptual design synthesis
- Optimization and tradeoff analysis
- Virtual validation and verification
- Integration of specialized disciplines
- Transition to downstream processes
  - Detailed design definition
  - Manufacturing & lifetime support

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## Systems Engineering Life Cycle



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## SysML Partners



- Informal partnership of modeling tool users, vendors, etc.
  - organized in May 2003 to respond to UML for Systems Engineering RFP
- Charter
  - The SysML Partners are collaborating to define a modeling language for systems engineering applications, called Systems Modeling Language™ (SysML™). SysML will customize the Unified Modeling Language (UML) to support the specification, analysis, design, verification and validation of complex systems that may include hardware, software, data, personnel, procedures, and facilities.

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## From Product Structure to Product Architecture

- Beyond a simple tree of parts or bill of material
- Relations between parts that integrate them into a functioning whole
- Capture all the enabling elements of a “system”
- Many additional kinds of specification and knowledge to be managed at the level of a system
  - Interfaces
  - Functions
  - Modes
  - Patterns
  - ...

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## SysML Assemblies

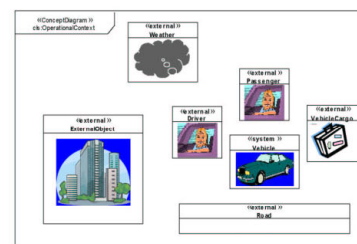
- Built on UML 2 Composite Structure Diagrams originally defined for specification of real-time software components
- «assembly» stereotype provides a common root for user-defined or domain-specific hierarchies of system component types
  - Hardware
  - Software
  - Data
  - Procedure
  - Facility
  - Person
- Assemblies provide the backbone of the “system hierarchy” or “system of systems” architecture which drives the systems engineering process

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## Operational Context

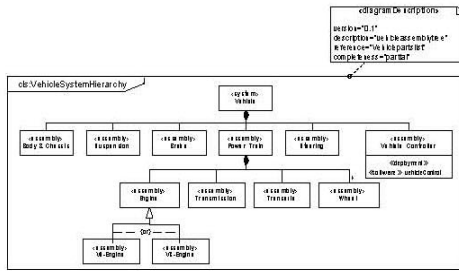


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## Product Structure Tree



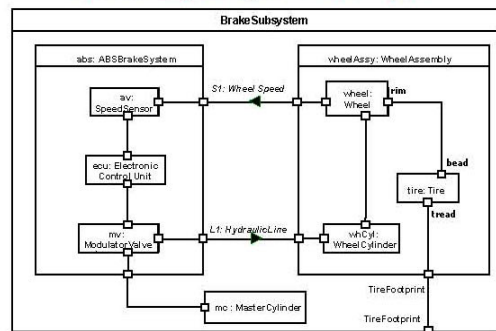
## Structure Modeling Foundation

- Assemblies are UML structured classes
  - Classes extended with an ability to hold ports, parts, and internal connectors
- “Assembly” captures a module at any level in the system hierarchy.
  - Can represent external systems, a system of interest, logical, physical, hardware, software, etc.
  - Assemblies provide both black-box view (without internal structure) and white-box view (showing internal parts and connectors)

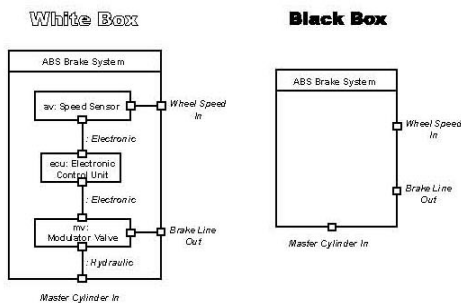
## Parts, Ports, Connectors

- Parts are properties that are enclosed by assemblies and typed by classes
  - “Part” is defined as internal to assembly vs. ordinary properties that reference other systems/objects
- Ports are parts that provide interaction points
  - notationally represented as a rectangle on the boundary of a part (same as UML 2, but with option to show name inside)
- Connectors bind one part to another
  - can connect parts with or without ports
  - typed by associations
  - structural features of the enclosing class

## Assembly Diagram - Example



## White vs. Black Box Views



## Concepts of Structure

- SysML “Assembly” defines abstractions of pure structure
  - Fundamental abstractions of whole-part dependence, roles, and connections
  - Reuse of standard components in larger whole
- Builds on class modeling foundations
  - Patterns and multiplicity of part occurrences
  - Built-in support for constraints and rules

### Selected Class of Application

- Engineering block diagram models with hybrid continuous/discrete behavior
  - Widely used with commercial tools across many engineering disciplines (Matlab/Simulink, LabView, etc.)
  - Examples can highlight added expressibility of SysML
    - Structural variation
    - Specialization/generalization
    - ...
  - Includes full detail for simulation/execution
    - Tangible verification with completeness check
    - Export to many other tools and mathematical solvers

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### Modelica Diagram Examples

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### Modelica Language

```

model circuit
  Resistor R1(R=10);
  Capacitor C(C=0.01);
  Resistor R2(R=100);
  Inductor L(L=0.1);
  Vsource AC AC;
  Ground G;
equation
  connect (AC.p, R1.p); // Capacitor
  connect (R1.n, C.p);
  connect (C.n, AC.n);
  connect (R1.p, R2.p); // Inductor
  connect (R2.n, L.p);
  connect (L.n, C.n);
  connect (AC.n, G.p); // Ground
end circuit;
            
```

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### Ptolemy II System

- Free package from U.C. Berkeley EECS Department
- Support for multiple "Models of Computation"
- Built on generic abstract syntax for "actor-oriented design" with hierarchical actors, ports, channels

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### Equivalent Schematic

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### SysML Test Example

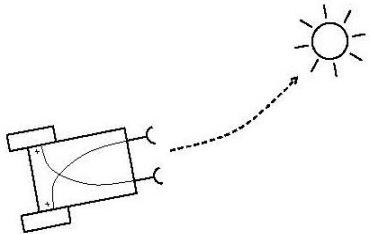
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### System structure models for agents

- "Systems thinking" is a hallmark of both agent systems and "system of systems" engineering
- Properties and functions at emergent levels is a persistent, common theme
  - Many new engineering applications are increasingly recognized as complex adaptive systems
  - Optimization criteria force attention to global vs. local levels
- Binding of components into system roles is a fundamental abstraction for a "chemistry of composition" by which larger scale systems (including multi-level agents) are built
  - Original goals for Swarm
  - Architecture for large-scale reuse
  - Agent life-cycle model for building the structure of an agent (and its behavior) over its lifetime

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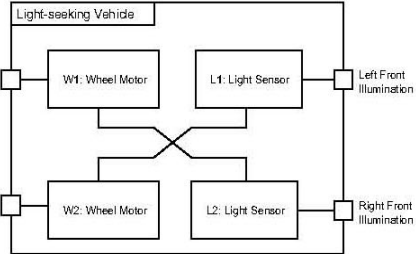
### Machine Structure Example



Bratlenberg Vehicle 2a  
(from Vehicles: Experiments in Synthetic Psychology, Valentino Bratlenberg, 1994)

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### Assembly Diagram



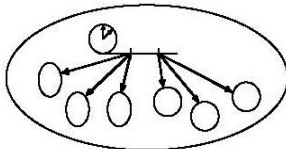
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### Swarm design goals

- Conceptual framework for agent models
- Programming support for building agent simulations
- Experimenter support for running simulations
- Nucleus for a community of agent modelers

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### Original Swarm Structure

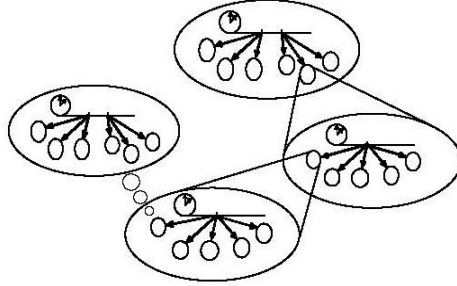


A swarm is:

- A collection of objects
- A schedule of actions over those agents

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### Hierarchical and Reflective Swarms



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## Swarm conceptual framework

- Agents as objects
- Agent behavior driven by schedules against objects (discrete-event actions)
- Composing behavior by mixing and merging multiple schedules with randomization and partial orders
- Swarms (collections of objects and activity) to express emergent levels

## Extension for agent life cycles

A swarm is:

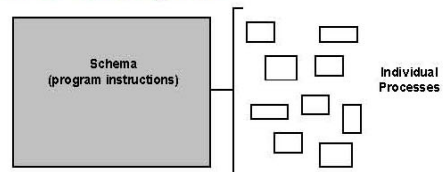
- A collection of objects
  - A schedule of actions over those agents
- ⇒ A schema that controls the development and behavior of the swarm over its entire lifetime

## Self-constructing swarms

- Starting from an initial, minimal structure and internal schema, let the swarm itself control the creation of all internal structure and the behavior it enables
- Similar to a process of biological development
- Initial schema serves as a shared "genetic code" that enables agents to share blueprints for component construction and binding, including transfers across independent lifetimes

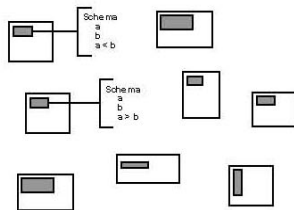
## Self-sufficient individuals

Traditional Programs

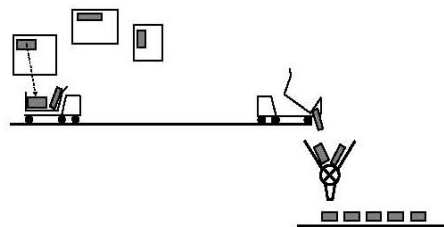


## Self-sufficient individuals

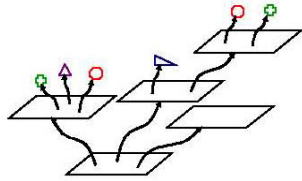
Diverse Population:



## Explicit schema for cultural recombination

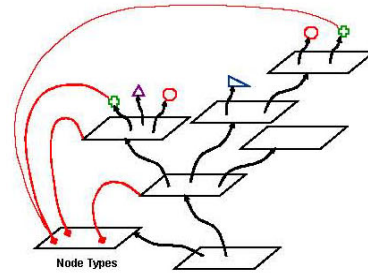


## Tree-structured substrate



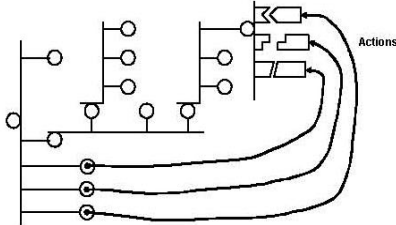
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## Type tagging (markup) of all nodes



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## Internal behavior nodes



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## High-level design

- Virtual structure built out of abstract objects (abstract graph with two directed arc types: node owner and node type)
- Fully connected structure that can grow as large or small as necessary to hold the complexity of diverse individuals
- Growth and behavior over the lifetime of the structure controlled by internal parts of the same structure, as enforced by a hidden virtual machine
- Definitions that control behavior published in an externally accessible form to extract, analyze, take apart, and put back together from existing individuals to any other

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## Types of schema declarations

- Elaboration of node types that may appear
- Restriction of behavior to external or internal access
- Immutability of structure once built
- Representation of complex state using attributes and relationships (including entire additional networks of internal references)
- Generation of distributed and concurrent behavior using the activity model of Swarm
- Selective erasure of memory
- Cessation of activity on entry to final state

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## Logical aspects of the schema

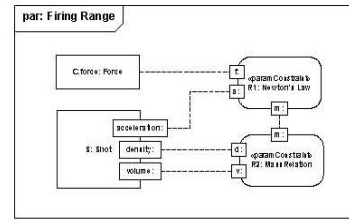
- Internal procedures on an explicit representation of "self" reduces the formulas of predicate logic to an easily understood operational form on an extremely well-defined and tractable universe
- The domain of these logical assertions is the finite history of the individual as it has developed to its current state, all of which is connected and accessible from a single root node
- All externally relevant features of the environment (including other individuals) must be represented by structures within self that capture only their potential significance or accessibility relative to self
- "Self" is ultimately all that cognitive processing can apprehend; all else is by implication from what appears in its behavior traces (operational assumption)
- Logic is processing that reviews the contents of real or generated behavior traces

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### From a schema-driven structure to a constraint-based programming framework

- Explicit representation of behavior and execution history enables purely declarative approach to actions and their results
- Constraints can be represented as role-binding structures using the same compositional syntax as the structures they constrain
- Library of functions can provide a complete functional programming framework
- A starting point for “creative exploration” of programming concepts and primitives as in the Mozart/Oz kernel-language approach

### SysML constraint example



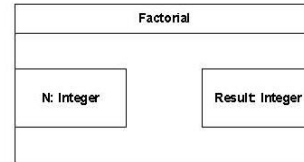
### Functional programming example

Standard tutorial example, in Oz syntax

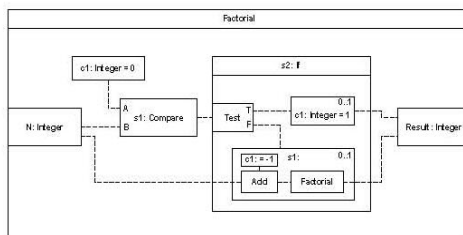
```

declare
fun {Fact N}
  if N==0 then 1 else N*{Fact N-1} end
end
    
```

### Black-box view of function



### White-box view of function



### Conclusions

- Abstract role-binding structures can serve as kernel-level representation for declarative programs
  - For now, this can serve as an important validation of the role-binding abstract syntax, to assure it provides a sufficiently general foundation for structure models
- Declarative programs can serve as elements of an internal schema for self-constructing swarms
- A life cycle of schema-driven development can serve as a general model of agents that grow, develop, and evolve



**DISCUSSION:****METHODS, TOOLKITS, AND TECHNIQUES****(Invited Speaker, Thursday, October 7, 2004, 9:15 to 10:15 a.m.)**Chair and Discussant: *Kathy Lee Simunich, Argonne National Laboratory***Standardizing an Agent Life-cycle Model**

**Kathy Lee Simunich:** Good morning. I'm Kathy Simunich from Argonne National Laboratory. I would like to introduce our keynote speaker, Roger Burkhart, who is a technical staff member at John Deere & Company in Moline, Illinois. He was one of the original members of the Swarm team and has been working in agent-based modeling for many years. His keynote talk is titled, "Standardizing an Agent Life-cycle Model." Roger has promised to leave about five minutes at the end of his presentation for questions and discussion.

**Roger Burkhart:** I think that toolkit developers are a special breed, so this is a very self-selected group. We've had very important and productive discussions at each of the preceding agent conferences, with a pre-conference workshop of agent toolkit developers. So I'm pleased to see a lot of the same people here. I think this is a good time to look at basic directions for where we're headed in agent modeling and agent toolkits.

At the agent developers' meeting at Agent 2002 in the pre-conference workshop, several of us speculated whether we were reaching a plateau or local optimum on toolkits. Many of the toolkits have actually reached a fairly impressive level of maturity. You could argue that some are getting fairly 'long in the tooth.' So if we are on some great plane of incremental evolution, I think it's time to puncture that equilibrium and look at some fundamentally new directions we might go toward.

[Presentation]

**Simunich:** Roger, I have a question to start off the discussion. You said agent modeling is mature and that it's ready to adopt software engineering tools and techniques. You gave good examples of the trends and directions of the software engineering field, which is my field at Argonne. I think that this would be a good way to bring agents into the traditional software engineering field. How do you see agents bringing something in? You're trying to adopt and adapt to traditional software engineering tools and UML and so on. Is there something in agent modeling that can enhance traditional software engineering?

**Burkhart:** Yes, and that's actually what motivated me. I probably spent more time on the counter side of the non-agent systems, and so I should give equal time to the agents. Before I got into Swarm, I wrote a paper saying that I thought that in effect, complex systems simulations needed to be an important part of our classic information system models because there are too many complex, messy things that go on that we can't even express or define in our fairly impoverished, for example, information modeling or even dynamic modeling framework. So I think agent models and the entire class of systems that we apply them to are important to show the gaps and fissures than what our classic business models can even talk about.

I view this very much as a synergy — a way of getting a bigger picture together. However, in the classic IT [information technology] world, there's enough frustration even getting basic capabilities in place that doing crazy things they don't know how to do yet isn't their most near-term priority.

**Simunich:** You had a slide on code generation techniques. Can you see smart agents helping to create and generate the code?

**Burkhart:** That is an additional application area where there's been work, for example, by Ivar Jacobson, who did the Use-Case framework, and UML has formed a company to look at agents — sort of assistance agents, not fine-grained agents — that help and do different tasks in a software development process. They do it automatically for code generation; it's a hard application domain because there is a lot of creative design, and that's, I think, where some generation and transformation logic oversimplifies the creative tasks performed by a good programmer. On the other hand, there's a lot of routine, repeated coding that probably could be implemented. Whether it concerns agents or non-agent techniques is one of these questions of the boundaries between agent problem-solving techniques and more classical, traditional techniques.

**Simunich:** Maybe we'll finally get to the point where the computer will do what we intend, not what we actually said it should.

**Burkhart:** Right.

**Rod Sipe:** Rod Sipe, New Science Partners. You and John Deere are justifiably famous in our little corner of the world for the work you've done. In my own humble experiences, once an executive suite gets a working understanding of the application of complexity science in general to their business, it transforms their way of thinking and their sense of what's possible and therefore gives them a new vocabulary to express what they might want. How have you seen that evidenced in John Deere, which has to be one of the longest cases of people having thought that way?

**Burkhart:** We've had perhaps one of the longest continuous involvements, but I would not say the deepest in terms of internal applications of agent models because of the reasons that I went through, which is why I've started to switch into these other more visible direct product applications to raise that visibility. For example, recently, we've been making headway talking to the business people, so our next step is to get ownership by the business people, including some of these internal operational roles, supply chains, and customer distribution. And so the research has been very interesting. The crossover into the mainline business is still in progress.

**Claudio Cioffi-Revilla:** Roger, much of what you said resonates with many of us, including those of us that teach graduate courses in computational social science. Jackie Barker and I will be co-teaching a new course next spring on object-oriented modeling in social science; it hinges fundamentally in a very important way on the use of UML in the construction of social science simulation models.

So while the need for this is acknowledged and felt by many of us, there's a certain frustration because we have an implementation problem. I wonder whether you have ideas about how in practice one can disseminate the importance and the use of UML in, for example,

professional venues such as this one, to encourage its use, and, as I said, you expressed the need. How in practice is this implemented? Perhaps papers that present and express the UML design of models should be given slight preference so that things are equal in the interest of communication and dissemination of this approach.

**Burkhart:** I think that papers and actual concrete examples that use particular sections of UML and specific roles are the most productive way to move forward. UML, as we found in our systems engineering use, really sprawls all over the place, and now that I've been inside the sausage factory where it gets made, UML still needs a lot of fundamental clean-up and conceptual clarification. I think UML should be used selectively and judiciously; examples of how that's actually been done will be the most effective way to get broader use and understanding.

**Pam Sydelko:** My question is more specific to when you're talking about operationalizing agent models and putting them into systems like this. One of the challenges that we've had with our customers [like for homeland defense and logistics modeling] — I'm curious about what your thoughts are on this. A series of events happens, real-time events, and sets off a simulation. So now we want to know, what will emerge given these sets of things?

Then they [our customers] want to say, "Well, we don't know a lot of real-time data, but we'll have little points in time that we might be able to say, 'Well, actually, this is where this vehicle is.'" They want to come back in the simulation, and they want the entire simulation to basically readjust itself to real-time data and then move forward. That's really challenging because you don't know all the agents of change. You know one or two, and you have to interpret that, "Well, if those things are not where we thought they are, then the simulation's probably off by this much," and adjust the whole thing. I thought maybe you might have some thoughts on that.

**Burkhart:** Yes, it's definitely part of this idea of operational use of simulation and effect as part of a control system or decision-making system. You've got a feedback control if you're trying to get desirable results, and running simulations is part of how you test the state that you can observe. I think scaling and distributed execution apply to a whole family of models — many different levels of refinement, detail, and synchronization with the real state of the world.

Los Alamos had a transportation simulation that actually ran a bunch of fine-grain micro-simulations of individual cars going through intersections just to calibrate the state that was fed into the mainline simulation. But you couldn't afford to do that on the entire big network, so it was very selective just to calibrate the model at the next level up. In principle, there should be, in effect, a vessel to run all sorts of models at different levels of detail fidelity and synchronization, all of which could affect the accuracy as a result.

**Scott Christley:** Roger, you put forward a declarative approach for these agent-based models and in the artificial intelligence community. There's been discussion against declarative models because of their efficiency in implementation. Can you give your thoughts on how these declarative models can be made efficient, or if there has been any progress in that area?

**Burkhart:** Yes, I mentioned that even in a declarative world you have to limit the form in which you express things. In some cases, the range of what you can express in order to be tractable for execution purposes, but the real question of efficient implementation, if you do have

a solvable model, is this whole approach of transformation or generation. A declarative says *what* you're going to do, but not necessarily how you do it. It's just the launching point to generate something that is driven by it. But the pure functional programming subsets with all the garbage collection and one-time assignment and everything that's part of those evaluations are actually surprisingly efficient, even measured against traditional programming. I think that's an entire front that, in the practical world of applied programming, there have been functional programming contests, and they consistently outperform what the imperative programmers can possibly hope to express in solving these problems. Yet, it's hardly crossed over out of academic circles into applied practice.

**Simunich:** Thank you, Roger.

# Overview of Methods, Toolkits, and Techniques





## OVERVIEW OF METHODS, TOOLKITS, AND TECHNIQUES

M.J. NORTH,\* Argonne National Laboratory, Argonne, IL

### ABSTRACT

This paper considers future development directions for agent-based modeling and simulation methods and toolkits. Several major areas are identified for possible work, including methodologies and toolkit features for elucidating model runs; exposing model designs and implementations; extending models to better support theory-grounded modeling; exploring and exploiting social theories; and extracting commonality.

**Keywords:** Agent-based modeling and simulation, agent-based toolkits, agent-based methods, narrative simulation

### INTRODUCTION

This overview considers future development directions for agent-based modeling and simulation (ABMS) methods and toolkits. Along the way, it identifies several major areas for possible future work. It should be noted that there are example methodologies and toolkit implementations that address the issues raised in some of these areas. Many of these examples are cited in the detailed discussions in this paper. However, these areas are classified as future work rather than as past accomplishments since at least one of the following questions currently must be answered “no:”<sup>1</sup>

- Are they expected practices?
- Are they widely used practices?
- Are they supported by, or even possible with, today’s ABMS methods and tools?

### ELUCIDATE RUNS

Most models produce “final” results in the form of graphs, reports, and so forth.<sup>2</sup> However, this output rarely captures the individual behavior and rich interactions found in many agent models. What is needed for today’s models are automated “narrative simulation” or automated “story-and-simulation” capabilities (Hutto, 1997; EEA, 2004) in which the narratives are automatically constructed by the simulation itself.

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<sup>1</sup> The “no” answers are not a criticism of current efforts in these areas. Rather, they simply indicate the need for further research, development, or wider education.

<sup>2</sup> Obtaining these outputs often requires significant manual intervention.

Aspect-oriented programming, combined with logging tools, such as JUnit or NUnit, can be used to provide this capability in a gross way (Table 1) (North and Hood, 2004). A more smoothly integrated methodology would incorporate convenient mechanisms built into toolkits. A hypothetical example is provided in Table 2. Of course, the hypothetical results in Table 2 might be significantly improved with careful consideration of the model's domain.

**TABLE 1** Example automated narrative simulation using logging tools (JUnit or NUnit)

Time	Message
1781	MyrinetNIC 4.send(Message 103)
1781	MyrinetNIC 4.getNetwork()
1796	MyrinetNIC 4.sendInterrupt()

**TABLE 2** Hypothetical automated narrative simulation output

Time	Event
81.3	Jim offered Jane \$25,000 for the car.
83.4	Jane immediately accepted.
88.6	Jim regrets offering so much.

## EXPOSE MODELS

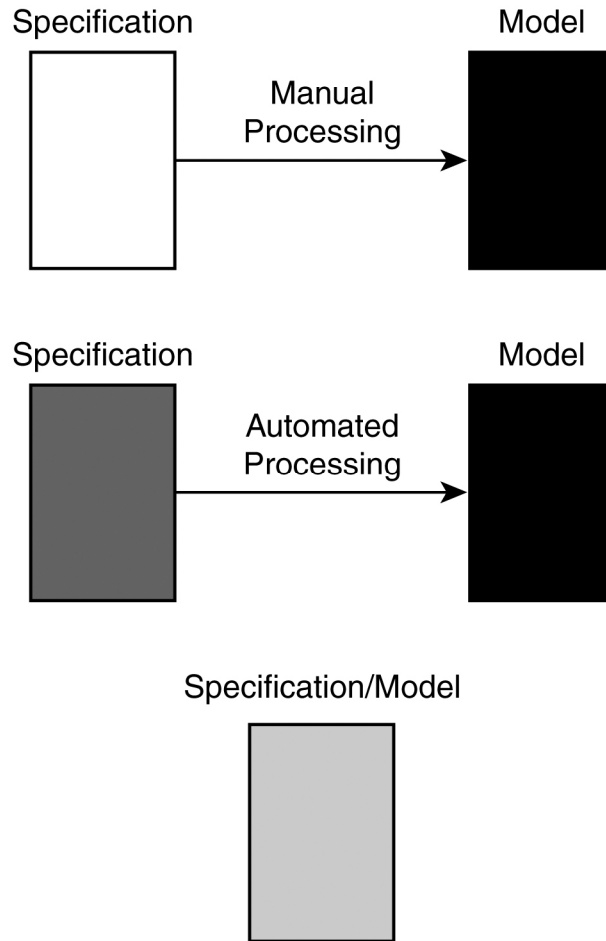
Today's models are at best translucent and are often opaque to their users. Specifications may be available for opaque or translucent models. However, software experts are often needed to determine what a model really does.

Models written with scripting languages, such as *Mathematica*, may be less opaque to some users. Models built using "round trip" diagramming tools, such as general UML or agent UML tools, may also be less opaque. However, significant technical expertise is still needed to understand these systems. Figure 1 shows a diagram that compares opaque, translucent, and transparent models.

In the future, models need to be transparent to their users. We need either models or fused specifications that can be understood without deep technological expertise:

- Easily read models are ideal.
- Fused specifications can also work. With this approach, models are automatically generated from easily read specifications and vice versa.





**FIGURE 1** Opaque (top), translucent (middle), and transparent (bottom) models

## EXTEND TOOLS

Many, but certainly not all, of today's models use theories that were chosen because of ease of modeling rather than appropriateness. This choice often is not the fault of modelers because of the difficulty of implementing almost any complex model. The resulting mixture might be called "model-based theories," as opposed to "theory-based models." The situation can also be viewed as a "chicken and egg" modeling tools issue:

- Modelers (the chickens) select theories that are in one way or another easier to model than other theories.
- These theories yield models and tools (the eggs) that make modeling the *chosen* theories even easier.

Theories that are outside of this loop tend to be disregarded and thus become increasingly difficult to model as compared to the chosen theories. Clearly, we need to extend current modeling tools to better represent a wider range of substantial theories. What is needed is

evolution of both the chickens and the eggs, so that theory selection depends less on ease of modeling and vice versa.

## EXPLORE AND EXPLOIT THEORIES

Any one model can only be run a finite number of times. How much can we get out of these runs? If the underlying theories contain an unbounded number of special cases, the results may only be valid for special cases. If the underlying theories can be advanced to provide bounded equivalence classes, more general conclusions can be reached.

An example from another domain, namely, the four-color theorem from mathematics, illustrates how bounding can be used to advance science:

- In 1853, Guthrie conjectured that a standard map can be covered with only four colors.
- The theory remained unproven until 1976, when Appel and Haken bounded the problem to 1,476 special cases.
- Appel and Haken then used computers to show that all 1,476 cases can be covered with four colors each.<sup>3</sup>

Can this approach be used for ABMS? If so, the results might be called theory-bounded models. It may be possible to achieve theory-bounded agent models, but it is unlikely the bounds will ever be as tight as with the four-color theorem. However, the tighter the theoretical bounds, the clearer the modeling results can become. Faster model construction will likely be needed to allow social scientists to bound processes through efficient “experimentation with alternate ontologies” (Sallach, 2003). It is important to note that even with tight bounds the number of cases to be studied is likely to be huge.

Often, even the best modeling situations have a huge number of potential input combinations, not to mention the need for stochastic replications. ABMS tools need to leverage new technologies to address the growing need for computational power:

- Computational grids and utility computing software, such as Argonne’s Globus ([www.globus.org](http://www.globus.org)) and the Global Grid Forum technologies ([www.gridforum.org](http://www.gridforum.org)) might be used.
- Large-scale computing clusters, such as Beowulf systems and other networks-of-workstations (NOWs), might be used.

Support for these new high-performance computing platforms needs to be built into toolkits to lower the barriers for modelers. Drone for Swarm is a pioneering example of this kind of work.

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<sup>3</sup> There have been some questions about the use of computers in the proof, but overall it has been accepted.

## EXTRACT COMMONALITY

Running simulations on large-scale open computational grids suggests the need for standards. However, Tanenbaum (1988) has noted that the “nice thing about standards is that there are so many to choose from.” Among the current choices are the Foundation for Intelligent Physical Agents’ (FIPA) specifications, the Knowledgeable Agent-oriented System architecture (KAoS), and the High Level Architecture (HLA), to name just a few. It may be that we do not need one rigid standard but a set of reasonable conventions that allow modelers to:

- Take advantage of shared resources, such as computational grids, without excessive duplication of effort and
- More directly discuss what their models really do rather than what their models are supposed to do.<sup>4</sup>

Of course, there must be some commonality to extract, which may not always be the case. Docking, or rigorously showing the equivalence of both models and tools, is needed. Certainly, docking does not prove that models or tools are “correct”; it may in fact prove that two models are equally wrong! Nonetheless, docking can be useful in two ways:

- As a form of verification, docking can increase our confidence that models and tools are properly implemented.
- Docking can provide a rigorous foundation for standards or widely shared conventions, in whatever form the standards eventually take.

## OTHER GOALS

A few other long-term goals bear mentioning. For example, it would be good if more models could be made available publicly. Numerous agent models have been developed, but few of these models are available to the public. Obstacles to the public release of models include the following:

1. Extra work is needed to make a model ready for public release (e.g., much more documentation is needed).
2. There are reasonable concerns about support costs (e.g., it is difficult to determine who pays for answering e-mail questions).<sup>5</sup>

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<sup>4</sup> This is consistent with the goal of increasing model transparency.

<sup>5</sup> Concluding that support will not be provided for publicly released software is more difficult than many realize. On a practical basis, users often (1) ask for help even when they are not supposed to and (2) brand software as “buggy” when help is not provided, even if the software itself is not actually at fault. This is not to say that publicly releasing software is prohibitive, only that successful public releases usually involve much more than simply posting files on a Web site.

3. Developers need to protect their proprietary advantage and intellectual property.<sup>6</sup>

The published research needs to do a better job of referencing previous work. Originality is clearly important, but there should be less focus on novelty and more on building upon existing work. A related goal is to encourage more independent replication of results, where feasible.

Fully endogenous emergence should be the long-term goal of ABMS, as long as we do not fall into the trap of equating “not emergent” with “not good.” Many results from ABMS are not emergent but are useful. We should expect fully endogenous emergence to take some time to achieve.

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<sup>6</sup> It is difficult to balance the scientific community’s need for independent replication of results with an individual researcher’s need to maintain proprietary advantage. This balance can become ever more difficult as research becomes increasingly applied due to many factors, including the potential use of proprietary data and the potentially greater immediacy of the results. Striking a fair balance among reporting results, describing methods, and repaying research investments has few easy solutions and will likely remain a long-term topic of debate.

**DISCUSSION:****OVERVIEW OF METHODS, TOOLKITS, AND TECHNIQUES****(Thursday, October 7, 2004, 10:30 to 11:00 a.m.)***Michael J. North, Argonne National Laboratory***Overview of Methods, Toolkits, and Techniques**

**Unidentified Speaker:** Regarding having enough models, you still might not know what a model is doing because the implications of the equations are not obvious.

**Michael North:** I want to make things clear; I'm not saying that analytical modeling is perfect. In fact, you have to understand quite a bit of math to comprehend those models, and that's a barrier for many people. I'm not saying that the modeling approach is perfect. There is a valid criticism that you need to see the source in order to understand the model, but you also need to understand the details. The source is a barrier for many people. But that's a problem with many systems. Clearly, anything that involves any type of what we call technology or advance representation has some sort of barrier. So if you're in optimization, you're not sure what the optimization did. If it's just pure math, just analytical proof, you still need to understand that — whatever level of math is necessary. So it's not a perfect solution, but the idea is to move toward models that are more transparent in this regard. Writing everything in Java, for instance, creates a barrier and some problems; writing in C++ or anything like that does the same thing. I'm not claiming to have a perfect answer for all these things. I'm merely saying these are long-term needs that are present in a community.

**Zhen Lei:** That's a very interesting perspective from the traditional understanding of the agent-based model at the aggregated level. The question is: How competent are we for those when we see this is the person who's making this decision? How much confidence can we have that it was expected?

**North:** Oh, you're talking about, in terms of elucidating runs or ...

**Lei:** Yes, you know, if we keep track, put that sensor ... the agents and ...

**Unidentified Speaker:** My understanding is that it's a stochastic process or simulation. How do we interpret this kind of behavior?

**North:** That's a good question. And one thing I'll note here, this is intended to be somewhat controversial. The second thing I'll say very quickly is that I'm talking about long-term problems. Also, I'm not claiming I have a perfect answer for all of them.

Let's say, for instance, that the behavior was drawn from a random distribution. We're basically saying either this is the most knowledge we have or the most we're willing to invest in the modeling effort to understand the behavior. Let's say the decision here in terms of whether you're going to accept the offer is a random draw from a distribution, so it's weighted toward saying no, but there's a chance of saying yes. In that case, you'd say that the agent did a random

draw against this distribution. You'd probably try to translate that into higher levels. Those data are actually drawn from, say, known purchase histories. On the basis of previous purchase histories, there was an  $x$  percent chance of probability of purchase. Probably it drew a number indicating a purchase and there you are. And so the closer you can get to a domain, the better you are in terms of this output, but there will be natural limits. In some cases, you'll simply say it was a draw, and that's all you can infer. In many cases, though, we can go a lot further because when we get into the complex processing logic, we can say it went through this logic. It went into the area where it was either highly receptive to a purchaser or not very receptive. These types of things could be added to the system. There's a lot then that we can do to track things.

Now, I should be very cautious here and say that — well, I'm already not being cautious. I guess that's a problem, but I'll try to be cautious for a second. I'm not saying there's anything wrong with aggregate outputs. It's a perfectly valid thing. I am saying that we can go beyond. We should in a certain sense believe our own religion here, saying we talk about the importance of individual interactions. That is, we talk about the importance of individual interactions — why it matters so much that we're tracing, or at least simulating, specific people, organizations, entities — and so why not actually do that? And watch what they're doing to you?

**Unidentified Speaker:** Yes. I agree with you. I think it is very important not to have all the problems ... a user. The aggregate ... from the ... population ... the decision was made within the ... organization ...

**North:** Yes. And that's part of that. And the key is to do the best you can. In some cases, you know you may just have to draw a line and say that all we know is that it was drawn from a distribution. Maybe we can talk a little about why the distribution was chosen. This represents the aggregate decisions of 1,000 customers or something like that, but then we do the best we can. In many cases, though, we can actually say quite a bit about what happened.

Putting things in a narrative format, I could also have a potential value even if it is about distributions. Just being able to say that this is what happened in the simulation and not needing to trace through some binary file to figure this out is actually a step forward in a lot of cases. I think a lot can be done by embedding it in as toolkits in a way that's so natural that it automatically tends to get done versus forcing people to add lots of logging at the last minute; this is important, too.

**Rod Sipe:** In billing and allocation for natural gas pipelines in which the scarce capacity of the pipeline has to be allocated among all those nominees, we purposely turned out of the model in the first place to justify one of the nominees — place in the ultimate allocation of the volume. You couldn't do that just in the end result. You have to have the intermediate process for them to be able to see how they are being treated in relation to the rest of the candidates. A second example is when we work over asset optimization — when the probability of the use of a tool is taken into account as to whether or not to order one. In that instance, a 10% probability of use 10 times aggregated to the need for one tool is interpreted differently than a 50% probability of the need of the tool twice.

**Steven Guerin:** I want to make sure that you don't finish your presentation and ask a question.

**North:** Okay. That's right. Thank you. That's helpful, actually.

**Guerin:** At SIGGRAPH a couple of years ago, there was also a big move to do automated cinematography.

**North:** Yes.

**Guerin:** So out here you have a script that you're producing, but now how do you move the camera and adjust to see the details of a scene?

**North:** That's a really good point, and the idea is that this leads into all sorts of uses. Once something like this becomes available, then exactly as Steven is saying, you can start to generate other things; not only just what I said, which is kind of the Word document in which you present what happened and say read it. You could also do things like animating this in different ways that are completely separated from the  $x$ ,  $y$  coordinates of a simulation, and all these types of things would be very possible. In fact, the entire story in a simulation step is in fact a design to take information from a simulation and take it out of the usual "just animating" — something moving around in a plane — and put it into a more visually pleasing context where you can actually see it in terms of a movie at a higher level. So that's absolutely right, and that's a very good point. These are some of the things we were trying to get to. We're trying to do these individual-level simulations. Let's get individual-level data that are actually intelligible at more than a binary level.

In terms of exposing models, the idea is that we really want to move toward clarity. Every modeling approach requires some technical knowledge. You're going to need technical knowledge of math, you're going to need technical knowledge of optimization theory, and on and on. I think right now that we require too much technology and too much computer technology. Being an expert on Java should not be a requirement to be sure that the model really works, for example, and that's something we should be able to move toward over time.

[Presentation Continues]

**North:** Are there additional questions?

**Seth Tisue:** Can you give an example of what you mean by the results of an ABM being useful even though they're not emergent?

**North:** Yes. First, it depends somewhat on what we're talking about in terms of emergence. If you're talking about emergence, for instance, having system-level results that depend on individual decisions, in that sense, you would want it to be emergent. I'd take emergence to be a little different where you're seeing — fundamentally, Jim Crutchfield and other people have, or at least are starting to develop — a rigorous mathematical definition of emergence. I'll talk about it on an intuitive level. If you talk about it as being a counterintuitive result, emergence is — what's the right way to put it — quicksand. Why, because what's counterintuitive to you may not be counterintuitive to me. And so, the word itself becomes a problem.

But, for example, one of the models that we could talk about is a networkcentric warfare model for the Navy. Is it emergent? Well, the agents work together; they are able to keep the communications protocols running at the same time in a complex battlefield. They're able to keep bandwidth going by staying close enough to one another to be able to hop messages over

radios. And maybe that's emergence or maybe it's not, but the people we're working for don't really care about that. What they care about is being able to quantify what the individuals are doing, seeing if they're getting the bandwidth that they need, understanding what the barriers are in getting the bandwidth that they need, and deciding what protocols are needed to keep the bandwidth going. And so emergence isn't even really a question. It's just a matter of tying the overall system structure to the individual behavior. So that's an example of a model where emergence isn't really the issue. Does that make sense? To me there's also a very serious question. Emergence is, aside from Crutchfield and others' mathematical definition, a bit of a quicksand or tar pit, if you will, because your emergence and my emergence may be different.

**Charles Macal:** I think we have time for one more question or comment because we need to be moving on.

**North:** Is it okay if we get the non-Argonne question? Yes?

**Russ Abbott:** Russ Abbott, not from Argonne. It seems that the goal of complete transparency of models is basically unachievable because the problem is that if you have any kind of complexity in a model, it's hard to understand, no matter how it's expressed.

**North:** Sure, absolutely.

**Abbott:** The difficulty is in understanding the complexity in whatever it is you're modeling.

**North:** Absolutely. Of course, the same thing could be said of modeling in general, and we can't model everything in the world and understand it completely. Perfect or complete transparency goes deeper than modeling. Language can't be perfectly or completely transparent. There's always indexicality; there's always some imperfection in terms of my understanding versus your understanding. But I think we could go a lot further than we have. I would not claim to ever be able to produce a perfectly transparent model. If there is one, it's probably this: it's like the real world, right? Everything else, we're working downward from, but I think that we can do a lot to improve the transparency of models because if you really want to know what a model does, you end up digging into Java or C++ or something like that. I think that that could be improved, but we don't have to go quite that far. But perfect transparency ...

**Mark Fossett:** ... expressed somehow.

**North:** Absolutely. That's right. But that somehow doesn't have to be pointers or class structures. What's your background? Is it computer science? From a computer science perspective, it's not so bad. But if you're coming in as a sociologist, it's horrible. And how many sociologists are here? What do you think? Do you think coding is good?

**[Unintelligible...]**

**North:** Yes, but, no, and we're not trying to get you to say anything is wrong with that. You have to rigorously specify things. If you end up in math, you need to know something about math. If you end up in other areas, you need to know things about those areas. But I think we can go much further than what we were doing right now, which is Java or something like that. That,



to me, is a very unclear way to specify things for nontechnical people. But I think we can improve.

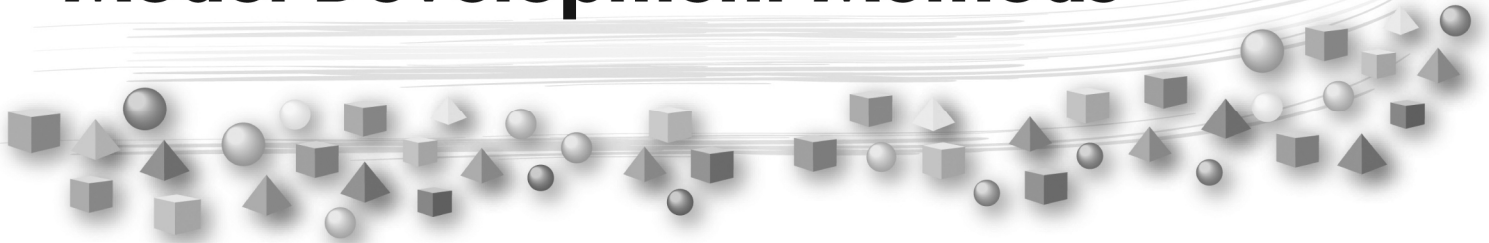
**Macal:** I'd like to thank Mike for an excellent introduction to the methods, toolkits, and techniques-dedicated day. As you can see, the discussions are very stimulating, and they could go on for hours.

**North:** With me, even if you're not here, I'll go on actually, yes.

**Macal:** Yes, with Mike involved, yes. Mike is always happy to talk to you about methods and toolkits; any place and any time.



# Model Development Methods





## **SIMSEG AND GENERATIVE MODELS: A TYPOLOGY OF MODEL-GENERATED SEGREGATION PATTERNS**

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R. SENFT, Amber Waves Software, Lancaster, PA

### **ABSTRACT**

SimSeg Learning Edition is a Windows-based computer program intended for use in undergraduate and graduate instruction focusing on agent-based models of residential segregation. Presently in beta distribution and review, SimSeg is the product of a multi-year collaboration, funded by the National Institutes of Health, in which Amber Waves Software has transformed a research-oriented prototype program into a robust, user-friendly program suitable for use by students and nonspecialists. SimSeg faithfully implements an agent-based model rooted in social scientific research on residential segregation dynamics and situates it in a program with ease-of-use features and performance expected of commercial-quality Windows software.

**Keywords:** Residential segregation patterns, ethnic preferences, SimSeg, agent-based modeling

### **INTRODUCTION**

SimSeg makes it possible for students to run simulation experiments dealing with residential segregation patterns without having to first learn specialized programming languages or skills. Students interact with the model via familiar Windows-style menus that present meaningful, substantive choices in non-technical terms. A graphical representation of the city landscape depicts household movements in real time and provides an easy-to-understand visual representation of segregation patterns as they emerge from agent behavior. Significantly, students can assess segregation patterns without having to master the technical literature on segregation measures. SimSeg also produces a wealth of reports summarizing model parameter settings and segregation patterns using standard measures found in the social scientific literature on residential segregation. These data are made available via formatted reports and predesigned figures that can be exported to other Windows programs (e.g., Word, PowerPoint) for incorporation into papers and presentations via the Windows' "clipboard" or standard "cut-and-paste" operations.

SimSeg is designed to be intuitive and easy to use so students need only minimal faculty guidance to be able to begin running experiments and observing how different simulation scenarios produce different patterns of residential segregation. Students select simulation scenarios, run experiments, and examine results via the simple point-and-click operations of the Windows graphical user interface (GUI). These features enable students to quickly perform "hands-on" analyses and consider the implications of simulation results for substantive issues.

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A variety of learning tools in SimSeg help faculty and students become familiar with agent-based models of residential segregation. For example, “Quick Start” scenarios gives users the ability to select from a library of predesigned simulation scenarios crafted to feature selected segregation dynamics, such as ethnic preferences, socioeconomic inequality, and housing discrimination, operating in various combinations. Other “Quick Start” scenarios give users the ability to load predesigned scenarios crafted to demonstrate “generative dynamics” that will produce particular residential segregation patterns, including integration, concentric zone patterns of status segregation, ethnic sectoring, ethnic checkerboarding, ethnic clustering, and even “hypersegregation.” Finally, an easy to use menu allows faculty and students to design their own simulation experiments by manipulating model parameters through menus that list meaningful choices described in intuitive language. A “scenario wizard” is available to guide novice users through the steps of designing an experiment. An “experiment wizard” (currently under development) will help students generate data needed to compare results obtained using alternative scenarios.

This paper introduces SimSeg Learning Edition, a Windows-based computer program developed with the goal of making it easy and compelling to use agent-based models of residential segregation in undergraduate and graduate instruction. SimSeg has many noteworthy features. First and foremost, it implements the core elements of Schelling’s (1971) celebrated agent-based model of residential segregation. The Schelling model is the best known agent-based model of segregation and has generated important insights regarding how micro-level residential choice behavior can produce complex aggregate-level patterns of ethnic residential segregation.

Schelling’s work on preferences and residential segregation has been influential in many disciplines, including sociology, economics, demography, political science, geography, and social psychology, and his agent-based simulation model is routinely cited as an exemplar of how seemingly simple, micro-level behavior can produce nonobvious emergent structure in spatial networks (Macy and Willer, 2002). Some thirty years after Schelling’s landmark paper, his work continues to inspire theory and research (e.g., Clark, 1991; Krugman, 1996; Epstein and Axtell, 1996; Young, 1998; Wasserman and Yohe, 2001; Fossett and Waren, 2004a,b; Fossett, 2004a; Fossett, 2005a,b) on segregation dynamics. Perhaps the most important insight to emerge from agent-based simulations of segregation is that spatial integration is a surprisingly fragile condition. Surprisingly high levels of segregation can emerge even when no individual in the population wishes to reside in the type of ethnically homogeneous neighborhoods found in highly segregated cities. SimSeg makes it possible for faculty to introduce this powerful insight to undergraduate and graduate students by running compelling simulations in real time in the classroom. In addition, because the program is easy to use and results are easy to understand, students can run simulations on their own to explore the model and its implications in more detail.

SimSeg provides an attractive implementation of the Schelling model, but that is just part of its value for instruction that focuses on the dynamics of residential segregation. SimSeg refines the Schelling model by drawing on the broader theoretical and empirical literature on residential segregation to implement features that make it useful in exploring a wide variety of factors that shape residential segregation in urban areas. Specifically, SimSeg implements features that give users the capabilities to:

- Specify ethnic demography in terms of number of groups and the relative sizes of each group,

- Specify ethnic preferences in more detail than in previous implementations of the Schelling model,
- Specify the level of socioeconomic inequality within and between ethnic populations,
- Specify a variety of housing discrimination dynamics,
- Specify household-level preferences regarding neighborhood status and housing quality,
- Implement urban spatial structure in the form of city-suburb differences in housing quality, and
- Systematically evaluate segregation patterns by using measures that are widely used in empirical research on residential segregation.

This rich set of features makes SimSeg the most sophisticated agent-based model of segregation in existence and gives its users the capability to explore many different perspectives regarding residential segregation in urban areas.

Significantly, while SimSeg implements a sophisticated, science-based model, it is designed to be used by students with little background in agent-based modeling or the research literature on residential segregation. A user-friendly interface shields students and novice users from the technical details of agent-based modeling. Students interact with the model by using familiar Windows-style menus that allow them to make meaningful choices regarding model specification. They choose from a simplified palette of intuitive, easy-to-understand options. Context-sensitive Help screens provide further assistance in guiding students through choices and alerting them to relevant theoretical and empirical literatures.

In similar fashion, SimSeg presents simulation results in ways that are engaging and easy to understand. It uses a graphical representation of the city landscape to depict the residential location of households from different ethnic groups and updates the movement of these households in real time. The result is a dynamic visual representation of emerging segregation patterns that is intuitive and nontechnical, yet very effective in communicating segregation patterns.

The combination of ease of use and ease of interpretation of results means that students can be trained to run and interpret simulation experiments using SimSeg very quickly, usually after just one lecture period. Beta testing by approximately two dozen experts in the field of segregation research indicates that faculty and students find the program engaging and easy to use. With only minimal faculty guidance, students can learn the basics of using the program and begin running sophisticated simulation experiments to gain an appreciation of how different simulation scenarios can produce fundamentally different patterns of residential segregation.

SimSeg can be used by a broad audience because it also incorporates features that appeal to advanced users. For example, it provides tools that allow faculty and students to craft user-designed experiments. Significantly, the user does not need to learn specialized programming languages or develop special programming skills. SimSeg also gives users access to a

comprehensive database of settings for model parameters and state-of-the-art quantitative measures of segregation outcomes. At the same time, it permits students to manipulate model parameters and assess the resulting impact on segregation outcomes without requiring them to deal directly with the technical issues associated with setting model parameters and measuring segregation patterns.

This paper provides a brief introduction to the SimSeg model. In the next section, we describe the features and capabilities of the SimSeg program and note the goals guiding its development. We then demonstrate the capabilities of the model by reviewing a typology of segregation patterns that the model produces under varying combinations of model parameters. We conclude by reviewing the standing of agent-based models in the literature on residential segregation and noting our assessment that SimSeg has good potential to serve as a tool for introducing students to agent-based models of residential segregation.

## **SimSeg LEARNING EDITION**

### **Model Description**

SimSeg Learning Edition is an agent-based simulation geared to undergraduate and graduate education. The program is distributed by Amber Waves Software (AWS) of Lancaster, Pennsylvania. Dr. Richard Senft, principal of Amber Waves Software, directed the development effort, supported by funding from the National Institutes of Health. The effort involved transforming a research-oriented prototype into a robust, commercial-quality program suitable for use in undergraduate and graduate instruction. SimSeg implements the core elements of SimSeg Research Edition (SimSeg RE), an agent-based model developed by Mark Fossett of Texas A&M University for use in academic research investigating segregation dynamics (e.g., Fossett, 2004b, 2005; Fossett and Waren, 2004a,b).<sup>1</sup> The key contribution of the AWS development effort is that in addition to faithfully implementing a sophisticated, science-based simulation model, AWS has produced a program that makes this model accessible to nontechnical audiences. They have embedded the model in an engaging, user-friendly program that is easy, and even fun, for nonspecialists to use. At the same time, it allows them to conduct sophisticated agent-based simulations to explore residential segregation dynamics.<sup>2</sup>

SimSeg is geared to two primary audiences. The first is faculty, who can use the program as a teaching tool in the undergraduate classroom to illustrate different patterns of residential segregation and the dynamics that can contribute to their creation and/or maintenance. The second audience is undergraduate students, who can use the program to perform simulation experiments for out-of-class exercises and research projects.

SimSeg has several notable features that make it especially attractive to its target audiences. Perhaps the most important is its refined user interface. That interface shields faculty

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<sup>1</sup> Unless noted otherwise, all references to SimSeg refer to SimSeg Learning Edition. SimSeg RE is a research and development tool used by Dr. Fossett and his graduate assistants.

<sup>2</sup> SimSeg implements all crucial elements of the full SimSeg RE model; however, it represents model parameter choices to users in simpler, less technical ways.



and students from the technical details of the model and gives them two convenient options for running sophisticated and substantively interesting simulation experiments. First, it provides users with a library of “Quick Start” scenarios — pre-designed experiments crafted to illustrate a variety of teaching points. Quick Start scenarios make it possible for the user to select and run experiments quickly and easily with just a few mouse operations. These scenarios are geared for lecture presentations in the classroom. They also are ideal for giving students “hands on” experience running simulation experiments, with minimal investment in training and instruction.

SimSeg also provides a powerful, easy-to-use, menu-driven experiment design option that permits faculty and students to change values of model parameters to craft their own user-designed experiments. Faculty can use this capability to prepare specialized examples for lectures. Students can use this capability to perform out-of-class exercises and research projects. SimSeg guides the user through the basic choices in the model and makes it very easy to design and run agent-based simulation experiments focusing on segregation dynamics in ways never before possible. Model choices are scientifically grounded and substantively meaningful, but they are presented in intuitive, nontechnical terms. Careful attention has been given to ease of use. Accordingly, only a few mouse operations are needed to modify model parameters and run a new simulation experiment.

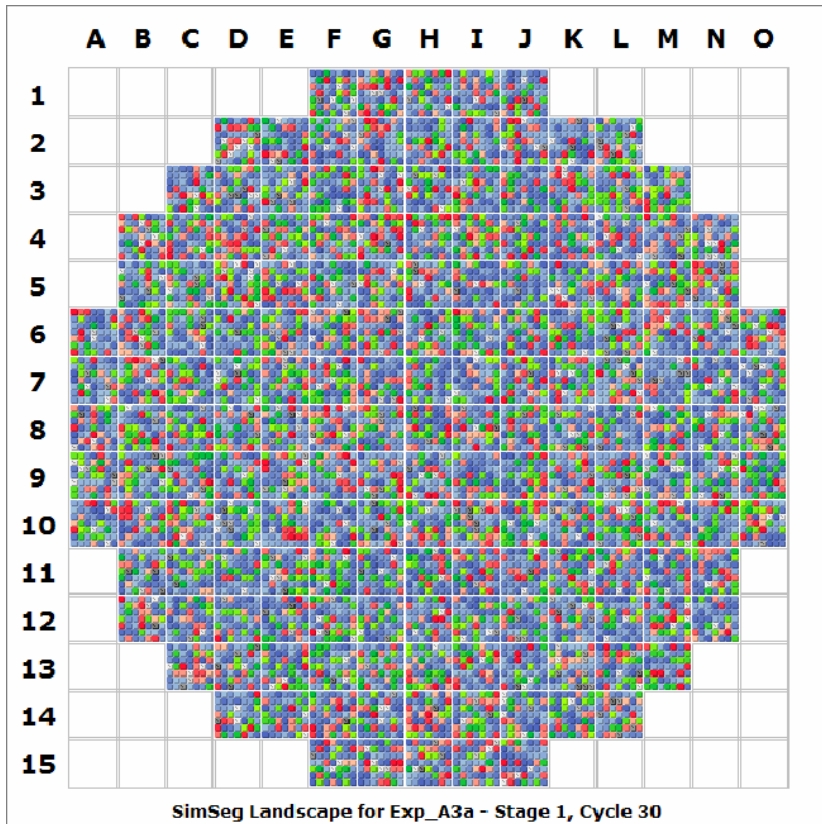
Another hallmark of SimSeg is that it presents model results in a variety of forms that meet the needs of both novice and advanced users. For novice users, it presents segregation patterns via a graphical representation of the “city landscape” depicted in Figures 1 and 2.

This graphical display conveys segregation patterns quickly and intuitively. Students can immediately “see” as many as four distinct dimensions of residential segregation within a matter of seconds by visually inspecting the city landscape. The dimensions of segregation that are evident include:

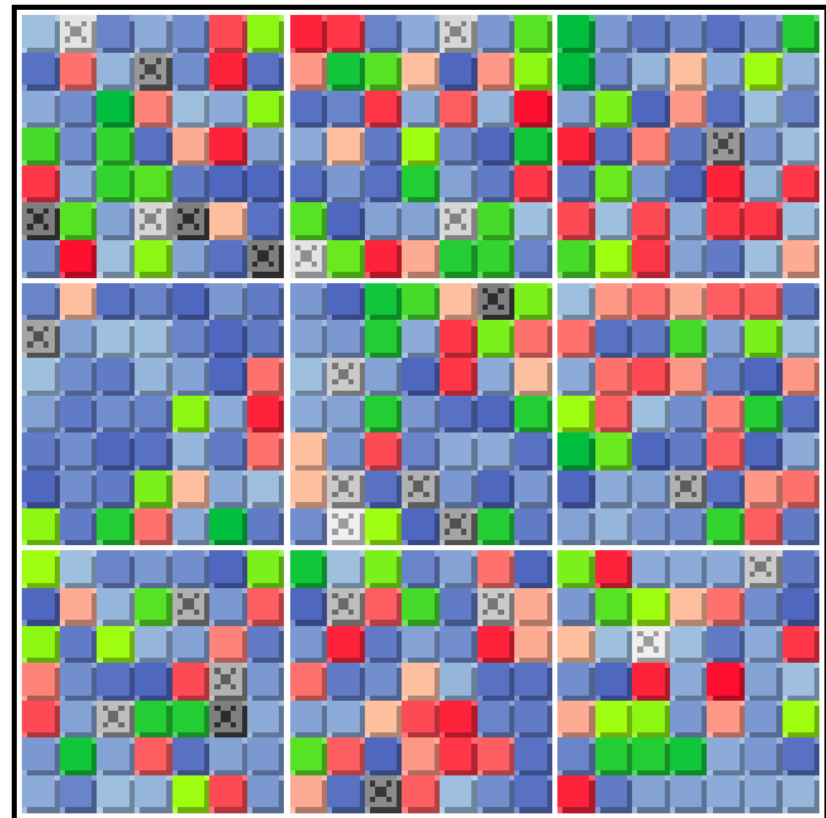
- The uneven spatial distribution of ethnic groups;
- Group “isolation” based on concentration in ethnically homogeneous areas;
- Group clustering, or “ghettoization,” in large, ethnically homogeneous regions; and
- Group differences in centrality.

Materials distributed with SimSeg provide guidance on how to recognize these four dimensions of segregation in the city landscape and interpret their levels as high or low, both across simulation experiments and in relation to empirical patterns in real cities. For example, these materials include city landscapes for real cities prepared with census data and geographic information system (GIS) software. The color schemes and presentations are crafted to maximize the correspondence between SimSeg city landscapes and the patterns seen in real cities.

Faculty can use the city landscape and other graphical displays to introduce students to complex, multi-dimensional patterns of ethnic segregation without requiring them to master the highly technical literature on quantitative measures of segregation patterns. SimSeg also computes a comprehensive set of quantitative measures of segregation outcomes and makes them



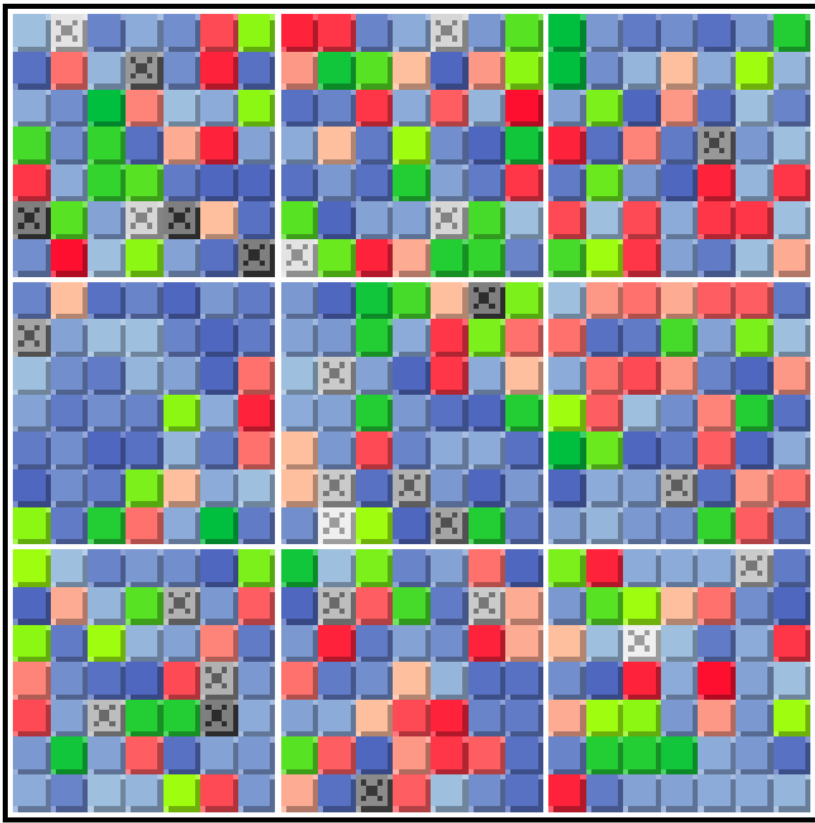
**City Landscape**



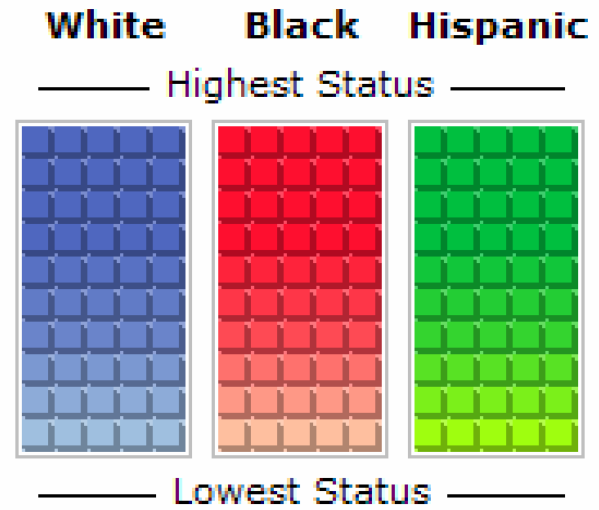
**Detail of Nine Neighborhoods**

*Graphical Elements:* The city landscape is a collection of neighborhoods arranged in a square neighborhood grid. Neighborhoods are collections of housing units arranged in a housing grid within the neighborhood.

**FIGURE 1** The SimSeg city landscape with nine area detail



**Detail of Nine Neighborhoods**



**Legend**

*Graphical Elements:* Housing units depicted as squares. Neighborhoods depicted as collections of housing units arranged in a square grid. Ethnic and socioeconomic status of occupied housing units signified by color and shading (see legend). Vacant housing units signified by gray square with “X.”

**FIGURE 2** Housing units, households, and neighborhoods

available in easily accessible, formatted reports. Instructional materials distributed with SimSeg explain the different measures and provide guidelines for interpreting their scores. In classroom use, however, the striking visual patterns in the graphical display of the city landscape provide a convenient means for quickly reviewing segregation patterns generated by a particular simulation experiment.

## Elements of the SimSeg Model

The characteristics and capabilities of the SimSeg program have been outlined in considerable detail in Fossett (1998). In the context of the present paper, space permits only a brief overview of the selected aspects of the model.

### *Agents and Their Characteristics*

The first concept is that of the agent. In this case, agents are virtual households that have the ability to search in a virtual housing market and make residential choices (possibly subject to certain constraints). Households possess *ethnic status* and belong to one of three ethnic groups that may be represented in the simulation — Whites, Blacks, and Hispanics.

Households also possess *socioeconomic status* scored on a scale ranging from 1 to 99. This scale establishes their socioeconomic standing within the population. It also establishes their purchasing power in simulations where housing differs in quality and value, and access to housing is means-tested.

Households hold *ethnic preferences* — preferences for levels of residential contact (co-residence) with members of different ethnic groups. Included are preferences for *in-group contact*, specified in terms of desired minimum levels of co-ethnic presence in neighborhoods. Also included are preferences for *out-group contact*, specified in terms of desired minimum levels of out-group presence in neighborhoods. The SimSeg model permits ethnic preferences to be specified separately by ethnic group. When ethnic preferences are active, a household's satisfaction or dissatisfaction with their residence will depend in part on how the ethnic mix of their neighborhood compares with their ethnic preference.

Households also hold *preferences for housing quality* and *preferences for neighborhood status*. In simulations where these preferences are active, households seek the highest quality housing they can afford. All else being equal, they also seek higher-status neighborhoods over lower-status neighborhoods.

These three preferences — ethnic preferences, housing quality, and neighborhood status — influence how households evaluate their level of satisfaction with their current residence and their potential level of satisfaction with any residence they may consider moving to. The evaluation of residential options is discussed in more detail below.

## *Housing Units and Their Characteristics*

Households reside in *housing units* found at fixed locations in a two-dimensional virtual city landscape (discussed below). Housing units differ in housing “quality” or value measured on a scale of 1–99 corresponding to the scale for household socioeconomic status. Households seek higher-quality housing but can only move to housing units they can “afford” as determined by comparing their socioeconomic status to the value of the housing unit.

Households can only move to vacant housing units. When households move, they leave their origin housing unit unoccupied, and it is added to the pool of “available” housing units. Their destination housing unit becomes occupied and is removed from the pool of available housing units.

## *City Landscape*

Housing units are arranged in a virtual city landscape as shown in Figures 1 and 2. The default city landscape is roughly circular. It consists of a collection of small “bounded areas” arranged within a “neighborhood” grid. Each bounded area contains a fixed number of housing units arranged in a square housing grid within the neighborhood. In the simulations presented in this paper, the neighborhood grid is  $15 \times 15$ , which means that the city spans 15 neighborhoods at its maximum height on the north-south dimension and on its maximum width on the east-west dimension. Neighborhoods within this grid are “developed” and contain housing units if they are within a fixed distance from the city center. Otherwise, they are undeveloped and have no housing units. This arrangement gives the city landscape its approximate circular form. In the simulations reported in this paper, a total of 177 bounded areas are developed. Each contains 49 housing units arranged in a  $7 \times 7$  housing grid. Thus, the city has 8,673 housing units.

## *Urban Structure: City Size and Shape*

The size of the city can vary from small to medium to large. Larger cities have more neighborhoods and more housing units. In this work, the city landscape is set to a large size for all simulation experiments considered. At present, city shape is limited to the circular city form described above. Future versions will include the option of choosing from a variety of city forms, including patterns fashioned after real cities and abstract patterns, such as a boundless torus.

## *Ethnic Demography*

The ethnic mix of the city can vary in two major respects. First, the city can have either two (White and Black) or three (White, Black, and Hispanic) ethnic groups. Second, the relative sizes of the groups can vary. Current choices parallel patterns commonly found in American metropolitan areas. Whites are a numerical majority of from 60% to 90%, and minority ethnic populations constitute up to 40% of the population in varying mixtures.

### *Urban Structure: Area Stratification*

The distribution of high-quality housing can vary in its spatial distribution. When area stratification is low, high-quality housing is randomly distributed such that all neighborhoods have similar mixtures of low- and high-quality housing. When area stratification is high, high-quality housing is concentrated in suburban neighborhoods (i.e., bounded areas on the city perimeter), and low-quality housing is concentrated in central neighborhoods. This model parameter influences where high-status households and population groups are most likely to reside in the city.

### *Status Inequality*

Socioeconomic status varies in the degree to which it is equally or unequally distributed across households. At one extreme, low-status inequality, the relative gap between low- and high-status households, is moderate. At the other extreme, high-status inequality, the relative gap between low- and high-status households, is large. This model parameter can influence the degree to which low- and high-status households and population groups are residentially segregated.

### *Minority Status Disadvantage*

Minority ethnic groups can be subject to status disadvantage relative to Whites. When minority status disadvantage is set to low, minority groups and Whites have identical status distributions and, thus, similar ability to purchase high-quality housing. When minority status disadvantage is set to high, minority groups have much lower status distributions and lesser ability to purchase higher-quality housing. This model parameter can influence whether minority ethnic groups can afford to live in neighborhoods where Whites reside.

### *Discrimination Dynamics*

Households' efforts to search for and move to new residential locations can be subject to discrimination in various forms. All households can be subject to *ethnic steering*, whereby households are not "shown" a random selection of housing but instead are more likely to be shown housing in neighborhoods where their ethnic group is concentrated. Minority households can be subject to *minority exclusion*, whereby a substantial fraction of their attempts to move to predominantly White neighborhoods are blocked. Similarly, minority households can be subject to *discrimination in credit qualifying*, whereby their purchasing power is lower than that of White households with similar socioeconomic status. These model parameters influence the degree to which White and minority households are residentially segregated from each other.

### *Neighborhoods and Neighborhood Evaluations*

Neighborhoods are relevant when a household evaluates a housing unit. Households can evaluate the ethnic mix of the neighborhood in which the housing unit is located. They also can evaluate the socioeconomic status of the neighborhood in which a housing unit is located. In

SimSeg, neighborhoods are delimited in two ways. The first is the “bounded area” described previously in the discussion of the city landscape. All households within the bounded area are treated as neighbors for purposes of evaluating neighborhood ethnic mix and neighborhood socioeconomic status. In the case of ethnic mix, group percentages for the bounded area are compared against the household’s targets for in-group and out-group contact to determine the household’s satisfaction with ethnic mix. In the case of socioeconomic status, the average socioeconomic status of households in the neighborhood is compared against the household’s own socioeconomic status to determine the household’s satisfaction with area socioeconomic status.

In addition, households can also consider immediately adjacent bounded areas when evaluating the ethnic mix of a neighborhood. In this case, group percentages are computed for the population residing in adjacent areas. These percentages are then compared against the household’s targets for in-group and out-group contact to determine satisfaction with ethnic mix. Satisfaction with the ethnic mix in adjacent areas is then averaged with satisfaction with the bounded area, with the latter counting twice as much as the former.

Future versions of SimSeg will include more options for specifying neighborhoods. One is the option of specifying larger bounded regions or districts analogous to school districts. Another is the option of specifying “site-centered” neighborhoods, that is, neighborhoods delimited in terms of households residing within a fixed distance (in housing units) from a reference housing unit.

## **SIMULATION EXPERIMENTS**

### **Initialization, Housing Search and Movement, and Duration**

At initialization, the city housing stock is created on the basis of the settings for city size and shape, socioeconomic inequality (which establishes the distribution of housing values), and the level of area stratification (which determines the spatial distribution of low- and high-quality housing). Next, the city’s population of households is created on the basis of the settings for overall socioeconomic inequality, ethnic demography, and minority status disadvantage. The households in the population are assigned preferences for housing quality, neighborhood status, and neighborhood ethnic mix on the basis of active settings for the simulation.

When the population for the city is created, the households are randomly assigned to housing units with the one restriction that they must reside in a housing unit with a value that matches their socioeconomic status. At initialization, the only systematic segregation that exists is segregation that results from the interaction of socioeconomic inequality (within and between ethnic groups) and area stratification.<sup>3</sup>

During a simulation experiment, households are randomly chosen and given the opportunity to search for housing. A searching household is presented a random selection of

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<sup>3</sup> Future versions of SimSeg may also allow for the option of starting with a segregated landscape. This feature is demonstrated in some of the examples presented in this paper but is not scheduled for inclusion in the initial release of SimSeg.

available housing units. If moves are means-tested (the default condition), the housing is screened on the basis of the household's purchasing power. If discrimination dynamics are active, the housing the household "sees" may be subject to further screening.

The searching household evaluates each available housing unit it is shown and assesses it according to the preferences that are active in the simulation. Separate satisfaction scores are computed on housing quality, neighborhood socioeconomic status, and neighborhood ethnic mix. These scores are then summed to obtain an overall satisfaction score. If the score for the most satisfying available unit is higher than that for the household's current residence, the household attempts to move. If discrimination dynamics are active, a minority household's efforts to move may be blocked. Otherwise, the household moves to the new location, and a vacancy is created in its previous residential location.

In a small fraction of cases, households are required to move even if they would prefer to remain in their current residence. All households are subject to a "forced move" if they have not previously moved during the simulation. Most of this movement is concentrated in the very beginning of the simulation. It ensures that all households reside in a location that they have chosen through search. Later in the simulation, households are subject to forced moves on the basis of a low random probability. This procedure simulates fundamental demographic dynamics of residential turnover, such as household formation and dissolution, in- and out-migration, and so on. One significance of this dynamic is that the city landscape moves toward a dynamic equilibrium because household movement ceases only when the duration specified for the simulation has been completed.

Time is represented in the simulation in units termed cycles. Cycles are periods of time during which housing search and movement take place. Their duration is controlled by the fraction of households that are given the opportunity to search during the cycle.<sup>4</sup> The settings for this parameter generally produce levels of residential movement that are roughly comparable to those observed in a "real city" over a 6- to 12-month period. The standard duration for an experiment is 30 cycles. This length of time is normally more than adequate to reveal the pattern of segregation that will be generated under the settings in effect.

## **Model Inputs**

SimSeg provides a library of formatted reports and graphical figures that can be easily accessed to summarize and document the settings in effect for model parameters in the simulation. These tools are relatively straightforward and easy to interpret. Accordingly, we do not review them in detail in the present paper.

## **Segregation Outcomes**

As noted earlier, SimSeg documents segregation patterns with the continuously updated graphical representation of the city landscape. Color choices register the ethnic status of households at different residential locations. Shading registers the socioeconomic status of the

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<sup>4</sup> During each cycle, 25% of the city's households are randomly selected and given the opportunity to search for new housing. In any given case, this may or may not lead to a move.



households, with dark shades representing high-status households and lighter-shades representing lower-status households. Figures 1 and 2 illustrate these visual principles. Clustering in the patterns of color and shade on the city landscape reveal segregation by ethnic and socioeconomic status. Or, as is the case in Figure 1, the absence of marked visual patterns indicates the absence of ethnic and status segregation.

SimSeg also computes a battery of standard segregation measures (e.g., the index of dissimilarity, the index of isolation, a centrality index) and maintains these in a database. SimSeg makes the scores available via figures and reports that can be accessed when the simulation is completed. These measures are computed on the basis of summary data for the bounded areas described earlier. We do not review quantitative measures of segregation here because the graphical patterns are more than adequate to establish major differences in the segregation patterns produced by the simulation scenarios considered here.

## **Generative Models and Typologies of Segregation Patterns**

One of the hallmarks of agent-based models is that they make it possible to establish typologies of generative models. That is, the modeling framework makes it possible for investigators to systematically document how particular combinations of settings for model parameters will consistently generate particular patterns in simulation results. Typologies can be established inductively by observing segregation patterns that emerge from simulations with different settings that are considered on an exploratory basis. Or, typologies can be established in a confirmatory way by varying model parameters in combinations that theory would suggest will produce particular patterns.

We follow the second approach in this paper. Guided by theoretical perspectives on residential segregation drawn from sociology and agent-based models, we specify combinations of model parameter settings that should, on the basis of theory, generate particular patterns of residential segregation. We highlight these patterns here for several reasons. One is to establish that the SimSeg model has the capacity to generate a wide range of segregation outcomes. Another is to show that the model has the ability to represent conditions and processes identified by important theoretical perspectives on residential segregation. Finally, this approach also demonstrates that the model's algorithms produce expected results under particular model parameterizations.

The distinction between patterns discovered inductively and patterns strictly implied by theory is not always simple. This difficulty is reflected in the present paper, as some of the segregation patterns documented here can, at this point in time, be described as implied by theory. However, at an earlier point in time this was not the case. In particular, patterns of segregation produced by ethnic preferences were first noticed in exploratory simulation analysis and were not strongly predicted by previous theory. However, their observation stimulated the development of new theory and the refinement of existing theory such that the generating principles can now be stated; however, at an earlier point in time they were unknown.

The typology of segregation patterns reviewed here is produced by varying a small number of factors, namely:

- Area stratification,

- Minority economic disadvantage,
- Whites' preferences for in-group contact,
- Minorities' preferences for in-group contact,
- Adjacent neighborhoods are considered in in-group evaluations, and
- White exclusion of minorities.

Each variable is discussed in more detail below. Although the discussion is brief, it identifies the states the variables take, the relevant body of theory associated with the variable, and basic predictions for the variable's effect.

### **Area Stratification: Low-High**

When the variable is set to low, high-quality housing is distributed throughout the city. When set to high, high-quality housing is concentrated in suburban neighborhoods. This variable is highlighted in urban-ecological theories of residential segregation, especially the Burgess "zonal hypothesis," which predicts that status segregation will emerge on a suburban-central city continuum and will reinforce ethnic segregation when minority groups are disadvantaged in socioeconomic status. It also plays a role in Hoyt's "sector model" of ethnic segregation, which hypothesizes that new, high-quality housing stock usually is built on the periphery of the city and tends to take on the ethnic composition of adjacent areas.

### **Minority Economic Disadvantage: Low-High**

When this variable is set to low, Whites and minorities have identical status distributions. When set to high, minorities have much lower average socioeconomic status. This variable is relevant in urban-ecological theory (per the Burgess-Hoyt model described above) and in spatial assimilation models, which hypothesize that minority segregation tends to diminish when cultural and economic assimilation occur.

### **White's In-group Preferences are Segregation Promoting: No-Yes**

When this variable is set to no, White's in-group preferences are zero. When set to yes, Whites are given in-group targets, which motivate them to seek 90% in-group contact, an amount that exceeds the group's representation in the population (which is 80% in two group simulations and 60% in three-group simulations). Preferences are central in Schelling's agent-based model. Fossett's (2004a, 2005a,b) extensions of Schelling's theoretical analysis predict that Whites' preferences for in-group contact will promote White-minority segregation when Whites' targets for in-group contact exceed the group's representation in the city population.

### **Minorities' In-group Preferences are Segregation Promoting: No-Yes**

When this variable is set to no, minority group goals for in-group contact are fixed at zero. When set to yes, minority groups are given in-group targets, which motivate them to seek 50% in-group contact, an amount that is higher than the group's representation in the population (which is 20%). Again, preferences are central in Schelling's model and Fossett's extensions of Schelling (Fossett 2004a; 2005a,b). These perspectives generate two predictions: (1) minority group preferences for in-group contact above group representation will produce White-minority segregation, and (2) these same preferences will produce minority-minority segregation.

### **Adjacent Areas are Considered in Ethnic Mix Evaluations: No-Yes**

When this variable is set to no, ethnic mix (i.e., in-group presence) is evaluated only for the bounded area. When set to yes, ethnic mix is evaluated for the bounded area *and* for the adjacent areas. The former receives twice the weight of the latter. This variable is relevant in Schelling's bounded area model, in all agent-based models that use site-centered definitions of neighborhood, and in urban-ecological invasion-succession theory. These perspectives all predict that evaluation of adjacent areas will produce ethnic clustering (i.e., ghettoization).

### **Whites Exclude Minorities from Majority White Areas: No-Yes**

When this variable is set to no, minorities can freely enter majority White areas. When set to yes, minorities are systematically blocked from entering majority White areas. This variable is relevant in discrimination theory which predicts that it will produce white-minority segregation.

### **Other Variables**

The six variables summarized above represent only a subset of the variables that can be manipulated in the SimSeg model and, for these variables, only some of the values they can take. However, as illustrated below, manipulating this small set of variables produces a wide range of highly distinctive segregation patterns.

Finally, before presenting the results, we note that several important variables in the SimSeg model are fixed at constant values over all of the simulations reported in this paper. These variables include the following:

- Status and housing preferences are set to active in all simulations.
- City size is the same in all simulations.
- Overall status inequality is set to high in all simulations.
- All residential moves are means-tested.

- City ethnic mix is the same in all two-group and three-group experiments. In two-group experiments it is 80% White and 20% Black. In three-group experiments it is 60% White, 20% Black, and 20% Hispanic.

## Simulation Results

The typology of segregation patterns produced by varying the six featured variables in differing combination is introduced in the figures presented below. Each figure provides a brief summary of the segregation pattern and a brief summary of the “generating mechanisms” operating in the simulations depicted. In each case, representative examples of the city landscape images produced by the simulation design are presented for a two-ethnic-group city and a three-ethnic-group city. To assist in making comparisons across experiments, Table 1 presents an overview of the settings for the key variables in each simulation, and Table 2 presents an overview of the segregation patterns produced by each simulation.

### *Basic Patterns*

Segregation measurement theory identifies several different dimensions of residential segregation (Massey and Denton, 1988). The two most widely studied dimensions of ethnic segregation are uneven distribution and group isolation. Uneven distribution of ethnic groups is evident in city landscape images when ethnic group colors (blue, red, and green) are not distributed evenly. Ethnic isolation is seen when an ethnic group’s color is predominate in some areas and absent others. Not surprisingly, uneven distribution and isolation often occur together. But as will be evident in some examples discussed below, they also can vary independently. Two other important dimensions of segregation, clustering and centralization, also can be easily seen in city landscape images. Clustering is evident when areas of ethnic homogeneity form a few broad regions rather than many small areas. Centralization is evident for an ethnic group when it is concentrated in central areas and is low when the group is concentrated in outlying or suburban areas.

When segregation is high on three or more dimensions at once, the pattern is termed hypersegregation. Massey and Denton (1989) report that the condition of hypersegregation is found in many American cities. It is especially common for Blacks and is also sometimes seen for Hispanics.

Segregation between socioeconomic groups can also be seen in city landscape images. In this case, the patterns involve uneven distribution of shades (lighter and darker) rather than colors.

### *Patterns of Segregation from Six Variables*

This review focuses on the patterns of segregation that the SimSeg program will produce when running experiments based on scenarios with varying combinations of the six featured variables. These “generative models” include:

- Random distribution (no segregation by socioeconomic status [SES] or ethnicity),

**TABLE 1** Summary of generating mechanisms and their states across different simulation experiments

Figure	Description	Area Stratification	Minority Economic Disadvantage	White Ethnic Preferences Promote Segregation	Minority Ethnic Preferences Promote Segregation	Ethnic Mix Evaluations Consider Adjacent Areas	Whites Exclude Minorities
3	Random ethnic and status distribution	None	None	No	No	No	No
4	Random ethnic distribution in a Burgess zonal city	High	None	No	No	No	No
5	Random ethnic distribution in a zonal city with minority disadvantage	High	High	No	No	No	No
6	Ethnic checkerboarding	None	None	Yes	Yes	No	No
7	Ethnic checkerboarding in a zonal city	High	None	Yes	Yes	No	No
8	Ethnic clustering	None	None	Yes	Yes	Yes	No
9	Ethnic sectoring	High	None	Yes	Yes	Yes	No
10	Minority hypersegregation	High	High	Yes	Yes	Yes	No
11	Minority checkerboarding variations	None	None	Yes	No/Yes	No	Yes
12	Minority checkerboarding variations in a zonal city	Yes	None	Yes	No/Yes	No	Yes
13	Minority clustering variations	No	None	Yes	No/Yes	Yes	Yes
14	Minority sectoring variations	Yes	None	Yes	No/Yes	Yes	Yes
15	Minority hypersegregation variations	Yes	High	Yes	No/Yes	Yes	Yes

**TABLE 2** Summary of segregation patterns evident in simulation results<sup>a</sup>

Figure	Description	Low SES-High SES Uneven Distrib.	White-Minority Uneven Distrib.	Minority-Minority Uneven Distrib.	White Isolation	Minority Isolation	Ethnic Cluster Patterns	White Centrality	Minority Centrality
3	Random ethnic and status distribution	Low	Low	Low	Medium	Low	None	Medium	Medium
4	Random ethnic distribution in a Burgess zonal city	High	Low	Low	Medium	Low	None	Medium	Medium
5	Random ethnic distribution in a zonal city with minority disadvantage	High	Medium	Low	Medium	Low	Low	Low	High
6	Ethnic checkerboarding	Low	High	High	High	High	None	Medium	Medium
7	Ethnic checkerboarding in a zonal city	High	High	High	High	High	None	Low	High
8	Ethnic clustering	Low	High	High	High	High	High A	Medium	Medium
9	Ethnic sectoring	High	High	High	High	High	High B	Medium	Medium
10	Minority hypersegregation	High	High	High	High	High	High B	Low	High
11	Minority checkerboarding variations	Low	High	Low/High	High	Low/High	None	Medium	Medium
12	Minority checkerboarding variations in a zonal city	High	High	Low/High	High	Low/High	None	Medium	Medium
13	Minority clustering variations	Low	High	Low/High	High	Low/High	High “A”	Medium	Medium
14	Minority sectoring variations	High	High	Low/High	High	Low/High	High “B”	Medium	Medium
15	Minority hypersegregation variations	High	High	Low/High	High	Low/High	High “B”	Low	High

a Notes: Minority-Minority Uneven Distribution: In Figures 11–15, “Low/High” indicates “Low” when minority preferences are not segregation promoting and “High” when minority preferences are segregation promoting. Ethnic cluster patterns: High “A” clusters are SES integrated; High B clusters are SES zoned. Minority Isolation: in Figures 11–15 “Low/High.”

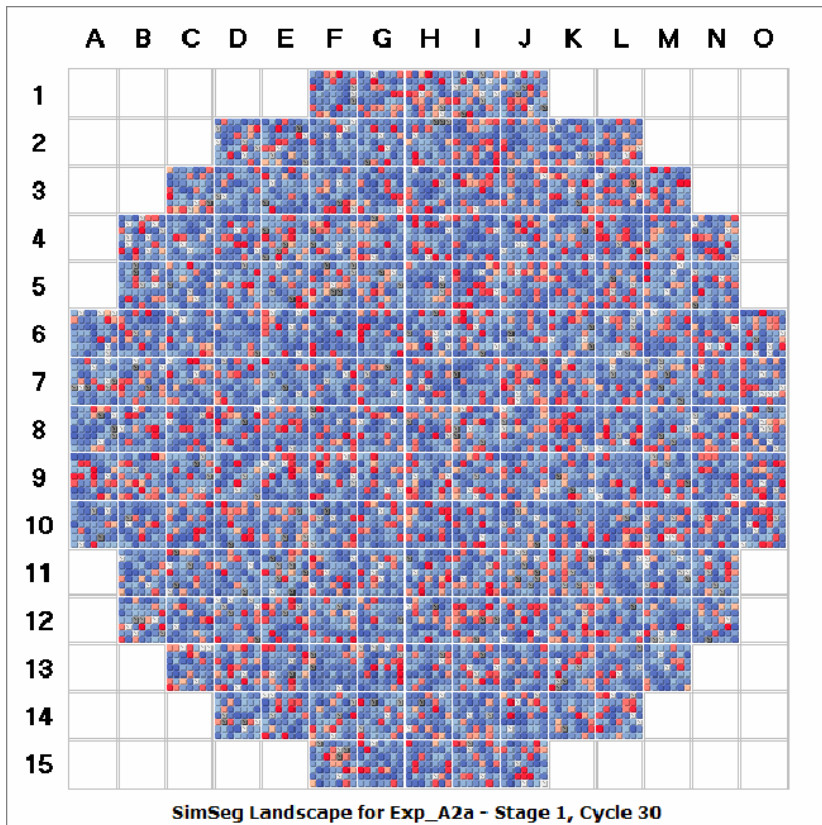
- “Zonal” patterns of status segregation (per Burgess),
- “Checkerboard” patterns of ethnic segregation,
- “Clustered” patterns of ethnic segregation (ethnic ghettos),
- “Sectored” patterns of ethnic and status segregation (per Hoyt), and
- “Hypersegregation” of minorities.

In Figure 3, the six variables featured in this study are all set to low values for the simulations. The city landscapes produced under this scenario exhibit very low levels of ethnic and socioeconomic segregation. Low levels of ethnic segregation is seen in the fact that White, Black, and Hispanic households (depicted in blue, red, and green, respectively) are found in all neighborhoods. Likewise, lower- and higher-status households (depicted in lighter and darker shades, respectively) are found in all neighborhoods.

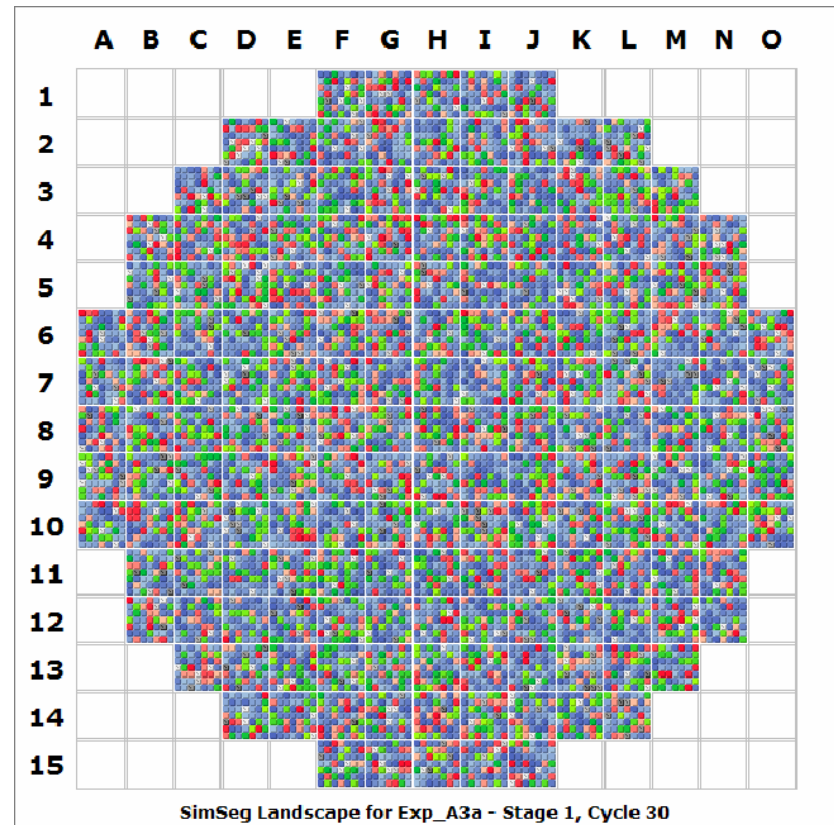
In Figure 4, the previous scenario is changed by modifying one setting: area stratification is set to high. This implements a Burgess “zonal” pattern in the distribution of housing values, with high-quality housing being more common in suburban areas and low-quality housing more common in central areas. The change produces a clear zonal pattern of status segregation as high-status households follow high-quality housing. The zonal organization of status segregation is seen in the fact that households in the center of the city are of lighter shades (signifying lower socioeconomic status), while households in the suburban areas are of darker shades (signifying higher socioeconomic status). The zonal pattern of status segregation produces centralization and clustering of low-status households. Low-status households are found in central areas, and central areas form a broad region of lower-status. In addition, high-status households experience low centralization and clustering, because high-status areas form a suburban ring surrounding the central city. Significantly, area stratification by itself produces little ethnic segregation. The different ethnic groups are again found in all areas of the city in roughly population proportions.

In Figure 5, the scenario used in the previous simulation is modified in one additional way: the setting for minority status disadvantage is changed from low to high. The combination is often posited to be one that plays a major role in promoting ethnic segregation. The previous zonal pattern status segregation is again evident in the city landscape images. In addition, there is a noticeable but modest increase in ethnic segregation. Suburban areas have higher concentrations of White households (depicted in blue) than in Figure 4, while central city areas have higher concentrations of Black and Hispanic households (depicted in red and green, respectively). Ethnic segregation remains low overall, however, since all ethnic groups are found in all neighborhoods throughout the city. This result illustrates a finding reported in many previous studies: the combination of area stratification and minority status disadvantage contributes to ethnic segregation but does not by itself produce high levels of ethnic segregation.

In Figure 6, all ethnic groups are given preferences for in-group contact that exceed their group’s representation in the population. The other four featured variables are set to low states. The scenario produces a striking pattern of ethnic segregation known as checkerboarding. In checkerboarding, many small, ethnically homogeneous areas emerge. Significantly, however, while almost all individual neighborhoods are ethnically homogeneous, the ethnically



**Two Groups**

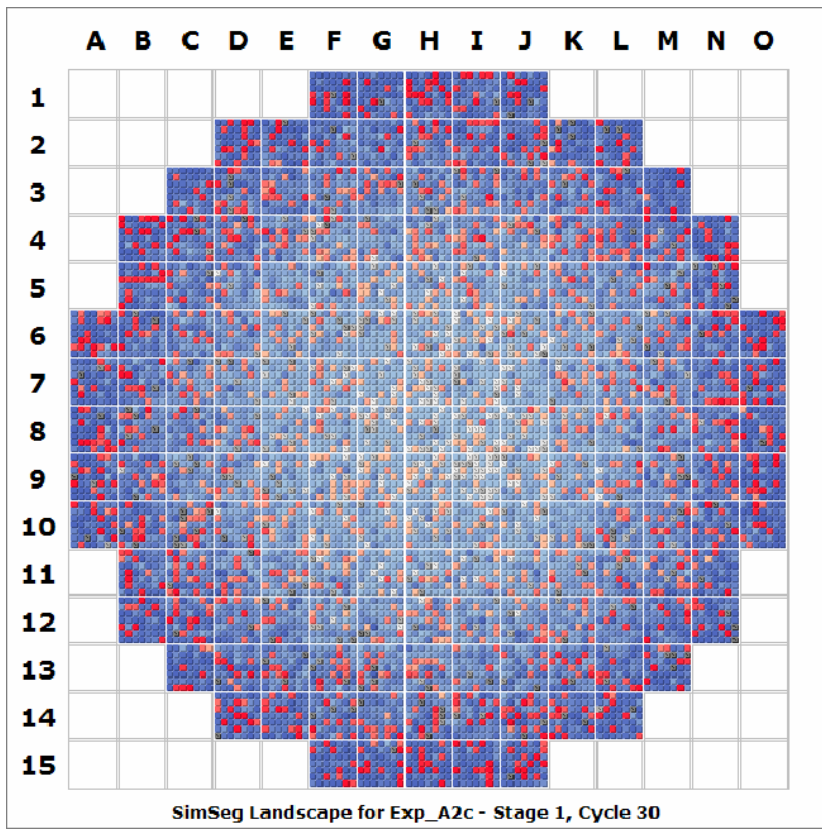


**Three Groups**

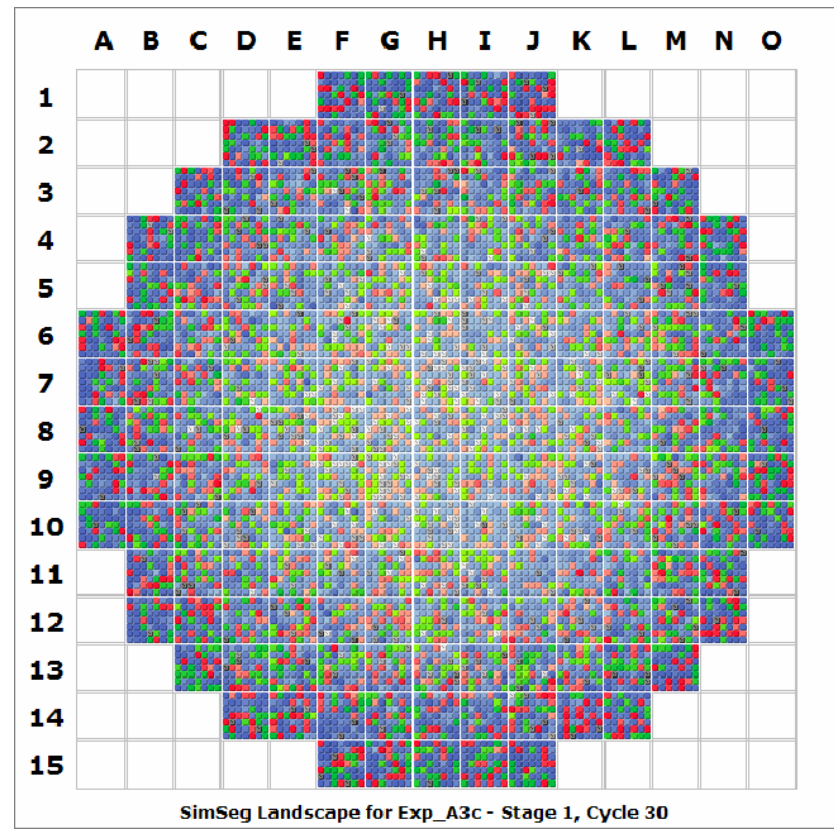
*Characteristics:* No systematic ethnic or status segregation. Distributions are random. (Note, this is different from “exact” even distribution.)  
*Generating mechanisms:* Random assignment of housing values in space. No ethnic dynamics.

**FIGURE 3** Random ethnic and status distribution





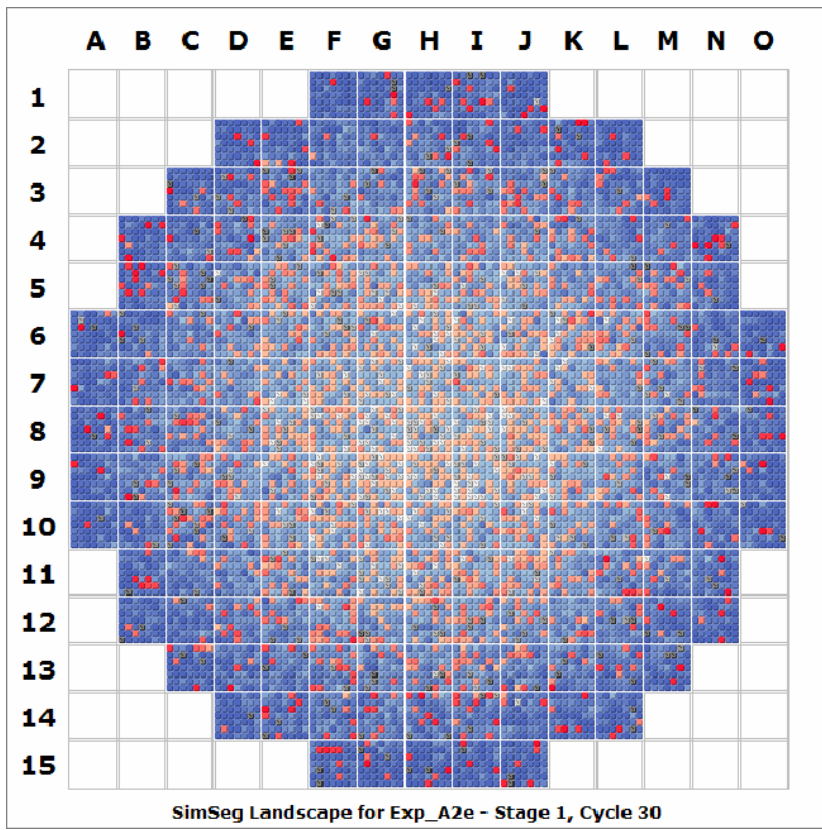
**Two Groups**



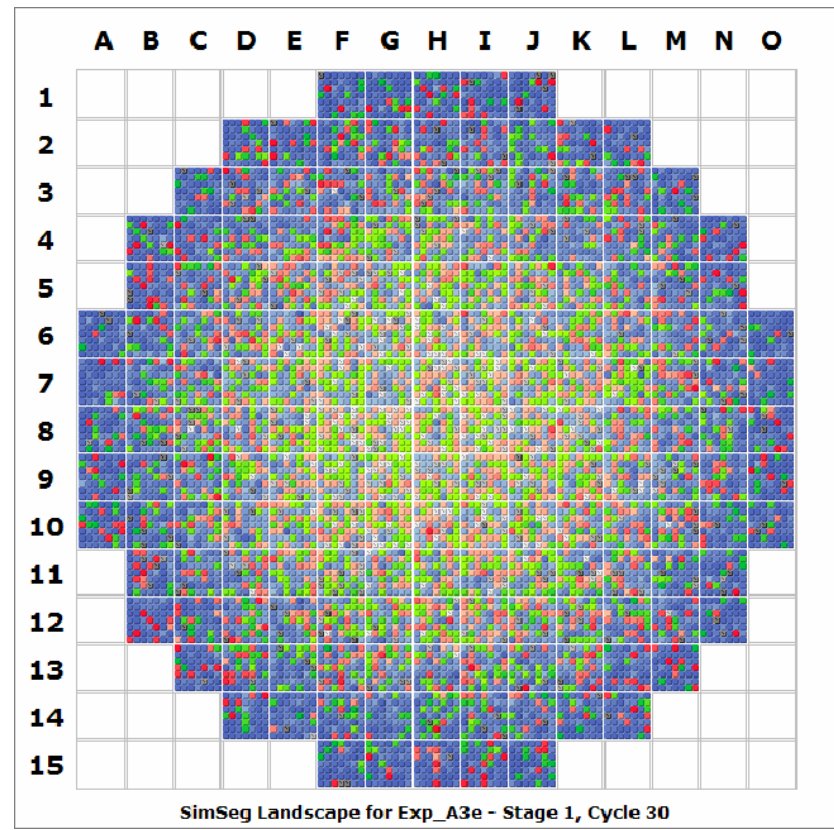
**Three Groups**

*Characteristics:* Status segregation by SES “zones,” but no ethnic segregation (i.e., ethnic distributions are random).  
*Generating mechanisms:* Area stratification in housing values. No ethnic dynamics.

**FIGURE 4** Random ethnic distribution in a Burgess “zonal” city



**Two Groups**

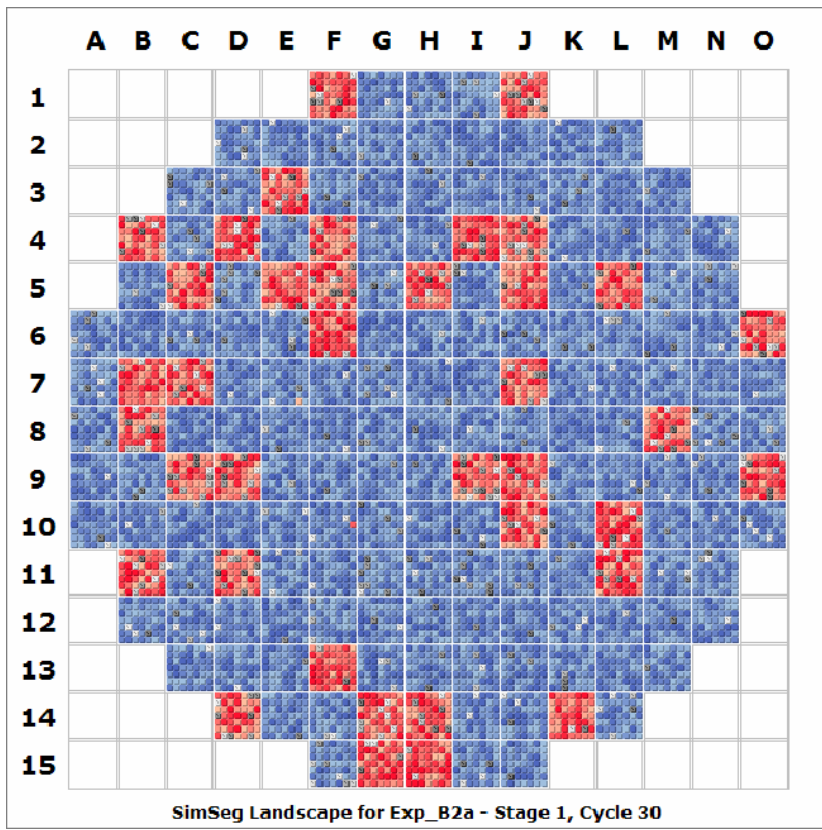


**Three Groups**

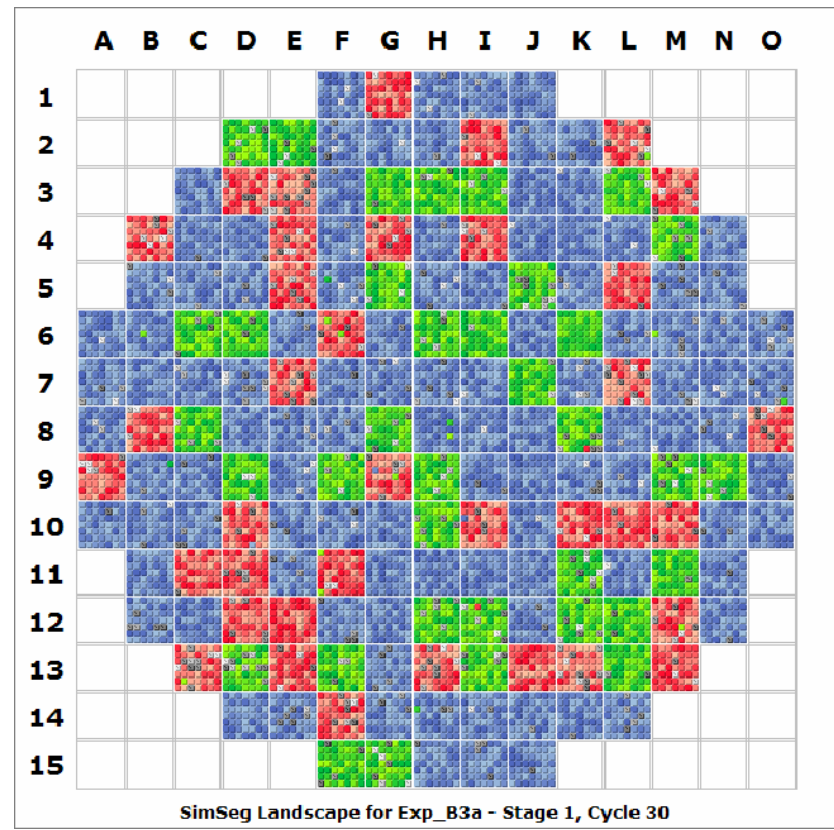
*Characteristics:* Status segregation by SES “zones.” Some ethnic segregation is produced by status dynamics.

*Generating mechanisms:* Area stratification in housing values. Minority status disadvantage. Status dynamics, but no ethnic dynamics.

**FIGURE 5** Random ethnic distribution in a “zonal” city with minority economic disadvantage



**Two Groups**



**Three Groups**

*Characteristics:* Uneven distribution and isolation of ethnic groups, but no clustering or centralization. No status segregation.  
*Generating mechanisms:* Random assignment of housing values in space. Households have ethnic preferences (for immediate area only).

**FIGURE 6** Ethnic checkerboarding (uneven distribution without clustering)

homogeneous areas for a particular group are not clustered together to form large regions or ghettos.

In Figure 7, area stratification is added to the previous scenario. The combination of segregation promoting in-group preferences with area stratification produces ethnic checkerboarding (as seen in Figure 6), which is overlaid on a zonal pattern of status segregation (as previously seen in Figure 5). The combination yields ethnic segregation and status segregation as seen in these previous examples. It also yields something not previously seen — status segregation *within* ethnic groups. This is evident in the fact that individual areas tend to be homogeneous with respect to both ethnic mix and socioeconomic status as low- and high-status households within ethnic groups live apart from each other.

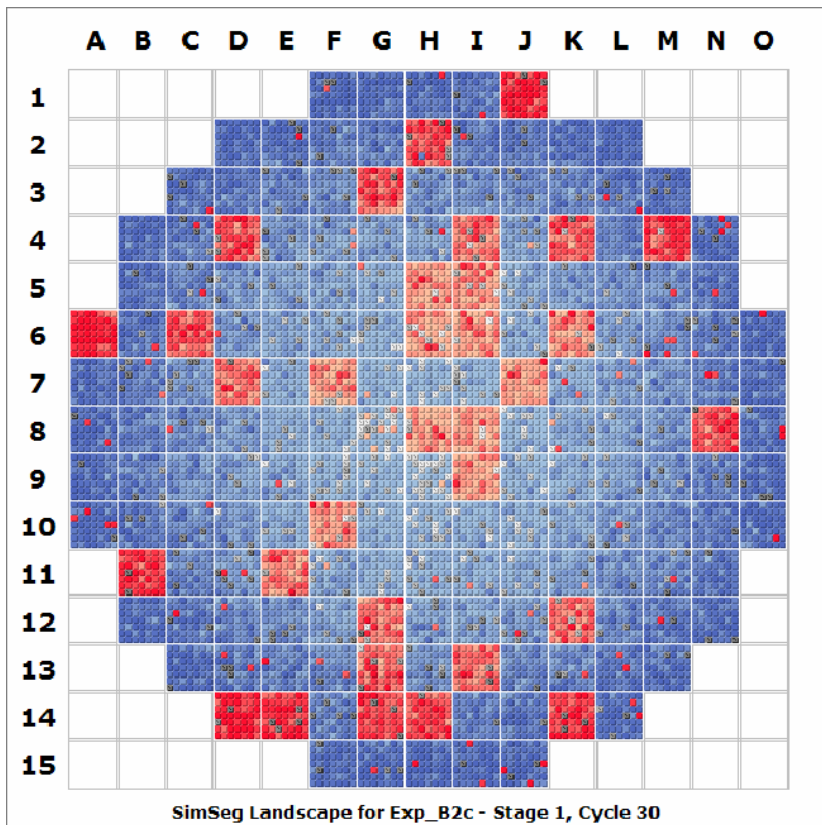
The simulations shown in Figure 8 implement a different variation in the scenario shown in Figure 6. Here all ethnic groups are given preferences for in-group contact that exceed their group's representation in the population. In this case, however, households evaluate neighborhood ethnic mix for adjacent areas as well as for the immediate bounded area. This change produces a pattern of ethnic segregation characterized by high levels of clustering or “ghettoization” instead of the checkerboarding seen in Figure 6.

Figure 9 adds area stratification to the scenario used in the simulations shown in Figure 8. The results is a distinctive pattern of segregation termed ethnic sectoring. By itself, area stratification produces a zonal pattern of status segregation. By itself, the combination of ethnic preferences and evaluation of adjacent areas produces large ethnically homogeneous regions. When these occur together, ethnically homogeneous clusters align across status rings to form ethnic sectors (i.e., wedges or pie slices) that begin in the central city and extend out toward the suburban ring. These sectors are large, ethnically homogeneous regions characterized by a striking pattern of ethnic-group-specific status segregation. Lower-status households in the ethnic group are found in the inner-city portion of the sector, and higher-status households in the ethnic group are concentrated in the suburban portion of the sector.

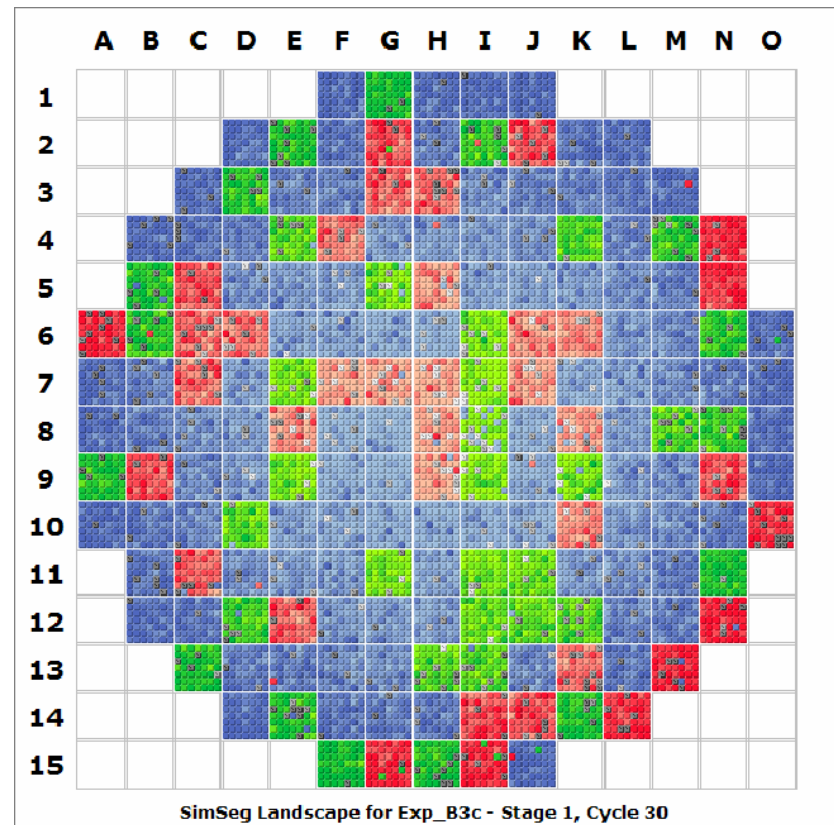
The patterns seen in Figure 9 begin to approximate the patterns of hypersegregation seen in many American cities. Ethnic groups are unevenly distributed and reside in large ethnically homogeneous clusters (ghettos), where they are isolated from other ethnic groups. Minority centralization/White suburbanization is the dimension of segregation not observed in these city landscapes.

Figure 10 shows city landscapes produced when minority status disadvantage is added to the last simulation scenario. The results exhibit maximum hypersegregation as minority status disadvantage produces a strong pattern of minority centralization and White suburbanization. The chief difference from the pattern seen in Figure 9 is that minority ethnic sectors are “fatter” in the central city and do not extend as far into the suburban ring because (due to minority status disadvantage) minority households are over-represented at lower-status levels and under-represented at higher status levels.

The simulations presented in Figures 11–15 are all variations on the three-group simulations presented in Figures 6–10. The correspondence is summarized below.



**Two Groups**

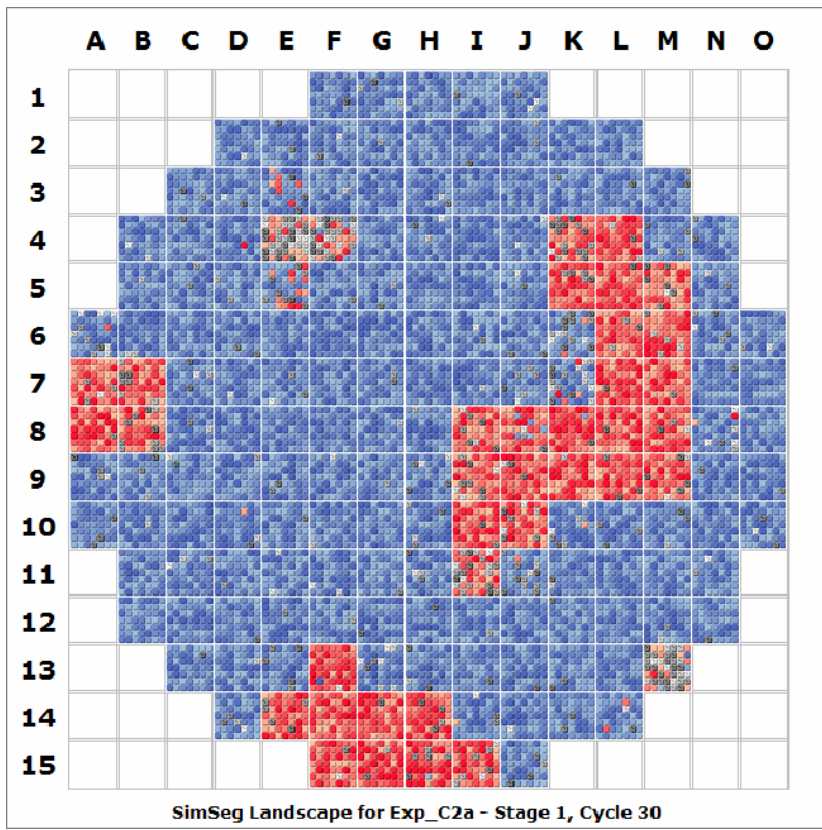


**Three Groups**

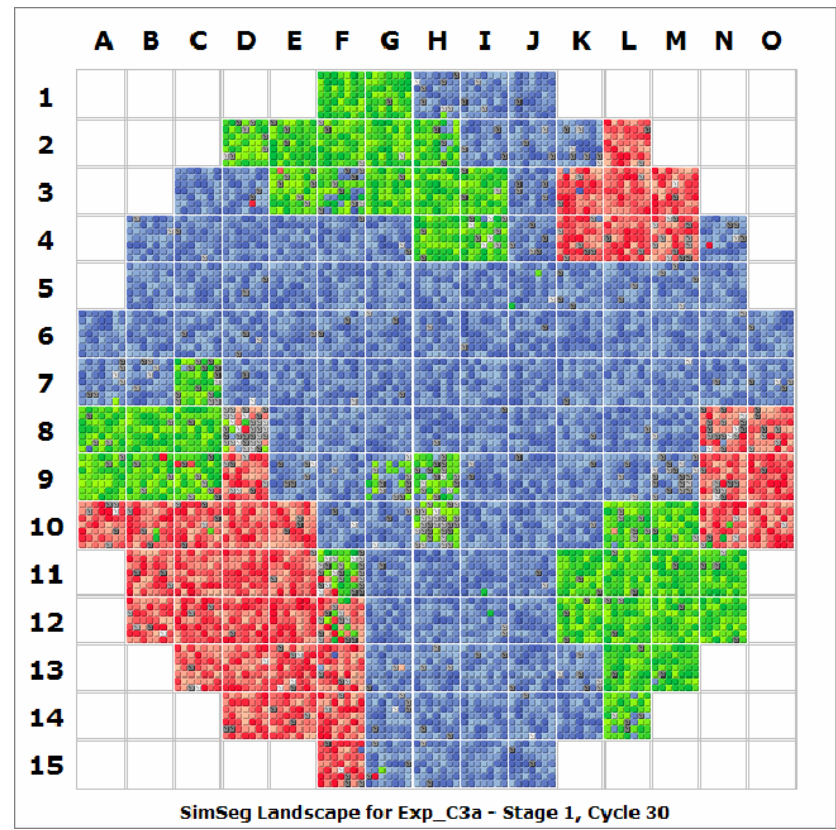
*Characteristics:* Uneven distribution and isolation, but no clustering or centralization. Status segregation by SES “zones.”

*Generating mechanisms:* Area stratification in housing values. Households have ethnic preferences (for immediate area only).

**FIGURE 7** Ethnic checkerboarding in a “zonal” city



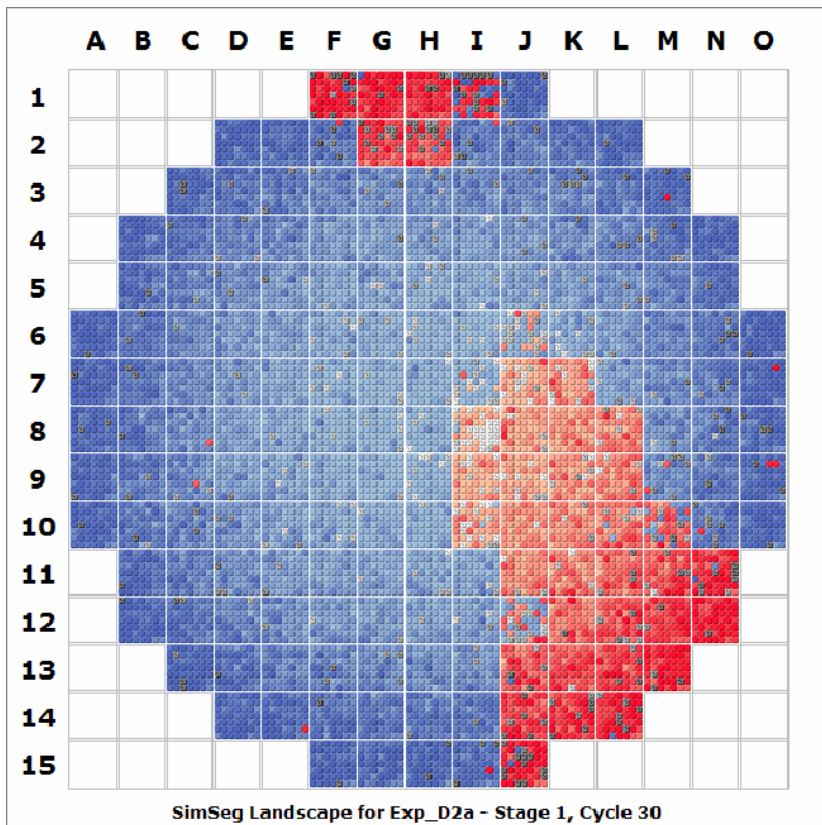
**Two Groups**



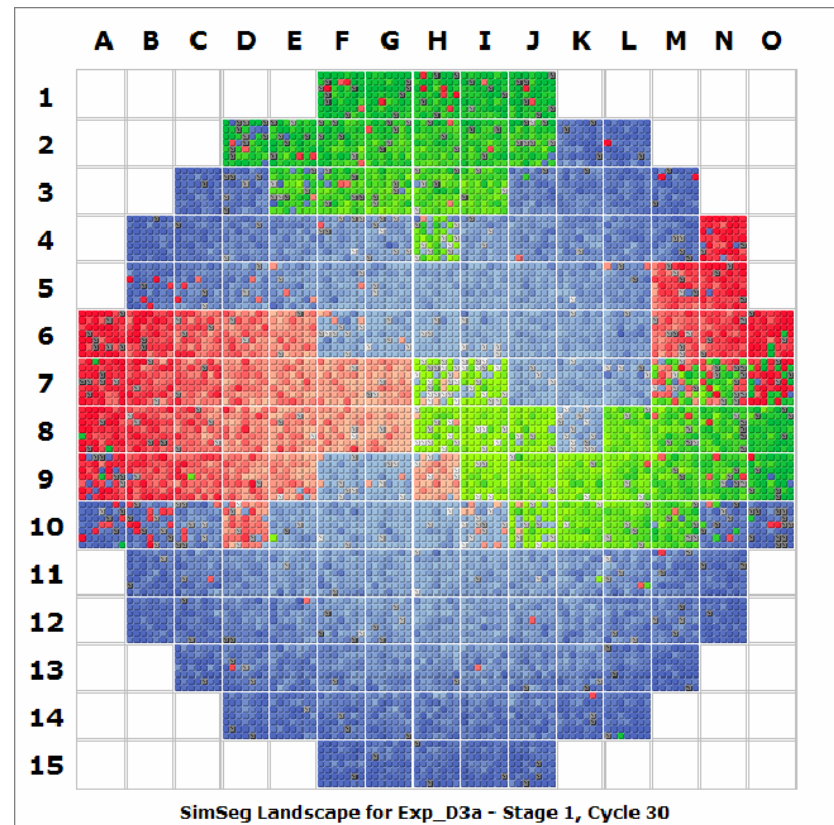
**Three Groups**

*Characteristics:* Uneven distribution, isolation, and clustering, but no centralization. No status segregation.  
*Generating mechanisms:* Households have ethnic preferences for both immediate and adjacent areas.

**FIGURE 8** Ethnic clustering



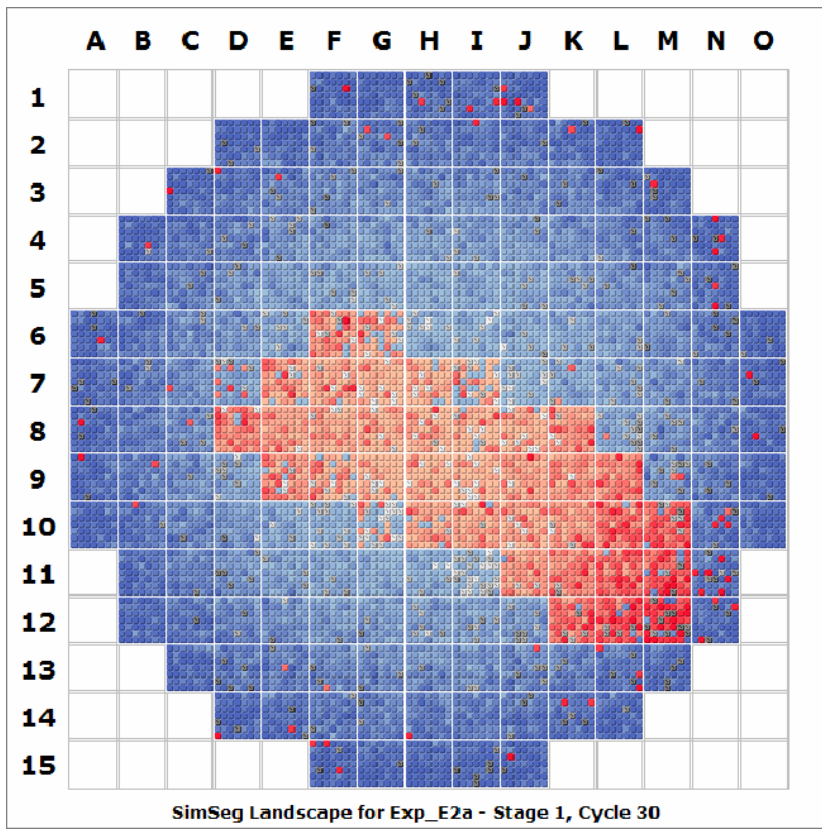
**Two Groups**



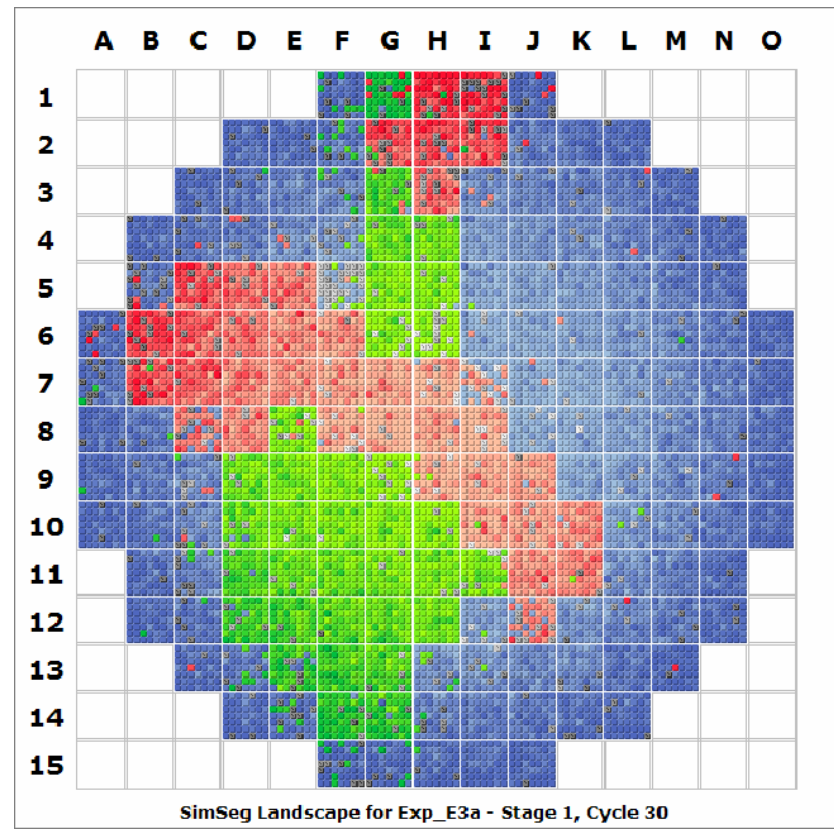
**Three Groups**

*Characteristics:* Burgess-Hoyt pattern – status segregation by SES zones with ethnic segregation by sectors or “wedges.”  
*Generating mechanisms:* Area stratification and ethnic preferences for both immediate and adjacent areas.

**FIGURE 9** Ethnic sectoring — ethnic clustering in a “zonal” city



**Two Groups**

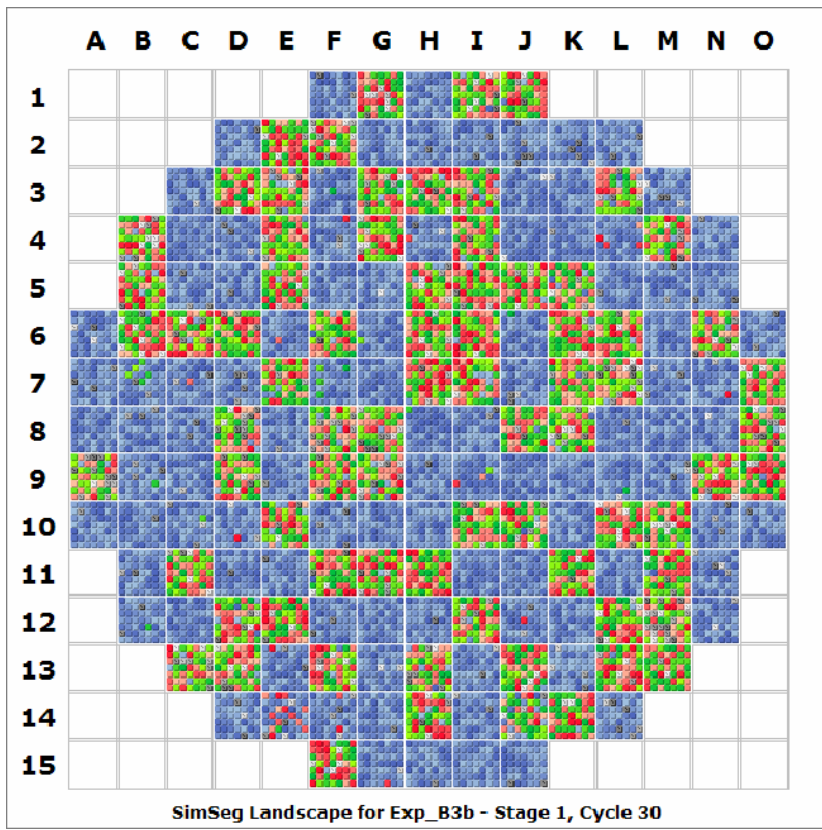


**Three Groups**

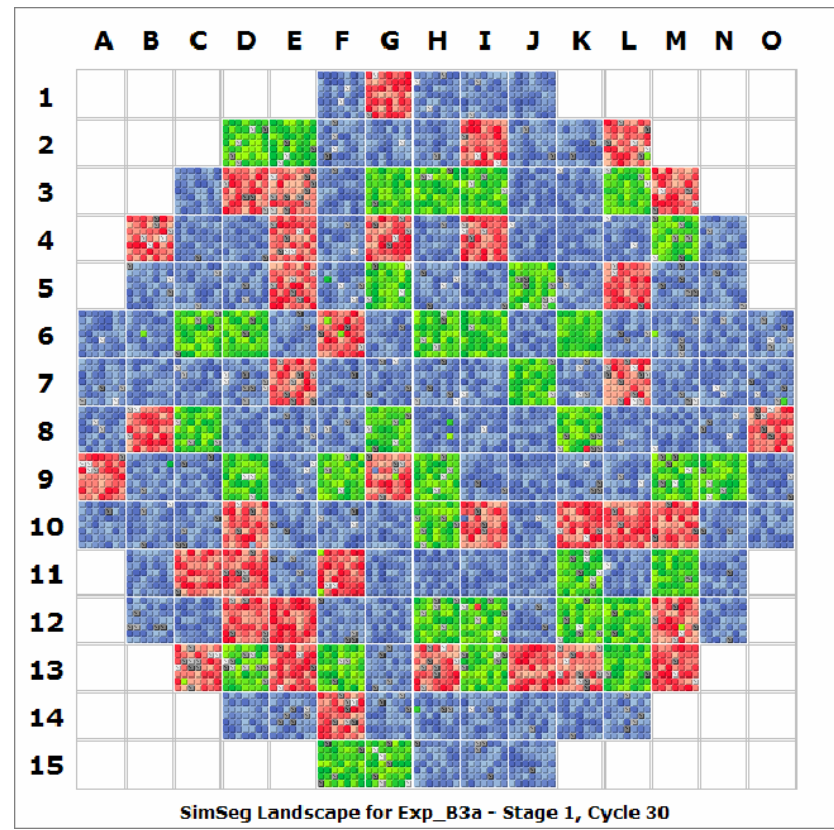
*Characteristics:* Burgess-Hoyt pattern with minority segregation on four dimensions (uneven distribution, isolation, clustering, centralization).  
*Generating mechanisms:* Area stratification, minority status disadvantage, ethnic preferences for immediate and adjacent areas.

**FIGURE 10** Minority hypersegregation





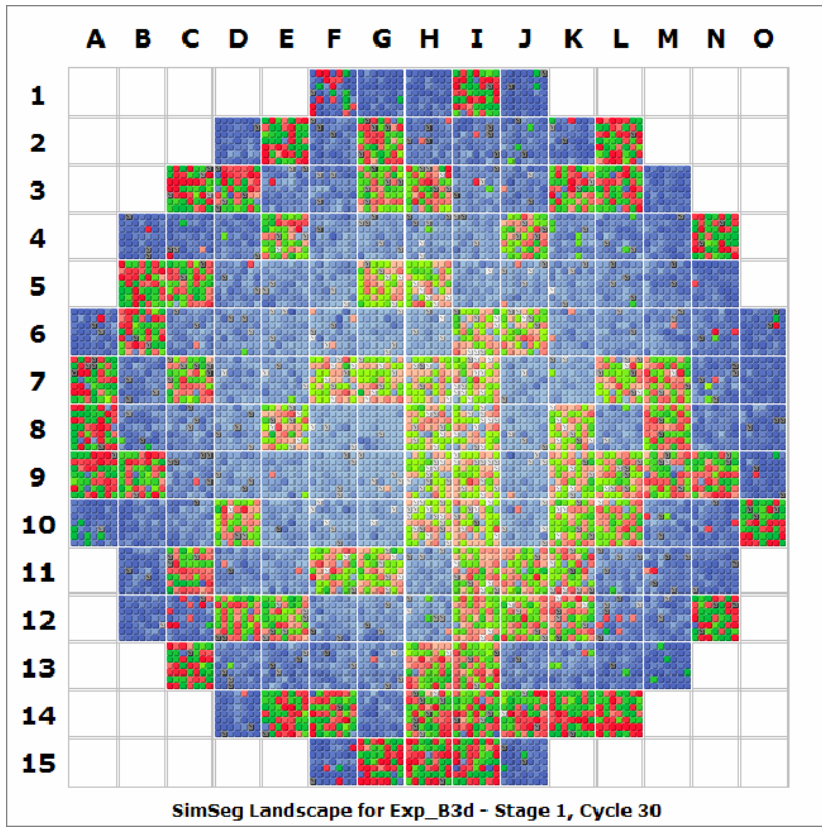
**Minority Segregation from Majority Only**



**All-Way Segregation**

*Characteristics:* Uneven distribution and isolation for minorities, but no clustering or centralization. Minority-minority segregation varies.  
*Generating mechanisms:* Active ethnic preferences for immediate area only, majority exclusion and minority preferences vary.

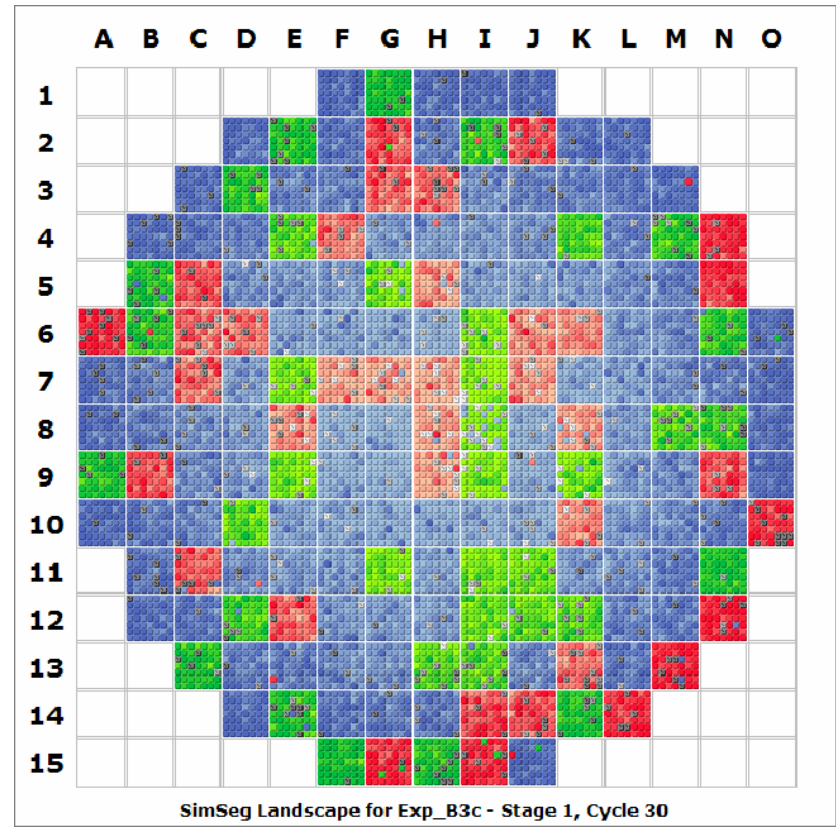
**FIGURE 11** Minority checkerboarding variation



**Minority Segregation from Majority Only**

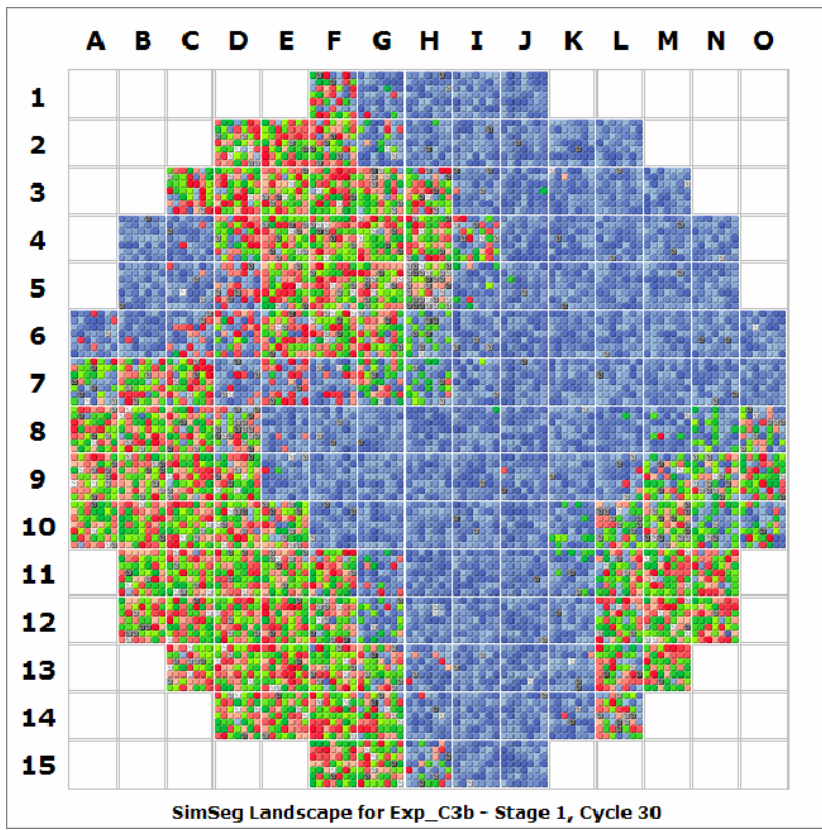
*Characteristics:* Uneven distribution and isolation for minorities, but no clustering or centralization. Minority segregation varies. Status segregation by SES “zones.”

*Generating mechanisms:* Active ethnic preferences for immediate area only, area stratification, majority exclusion and minority preferences vary.



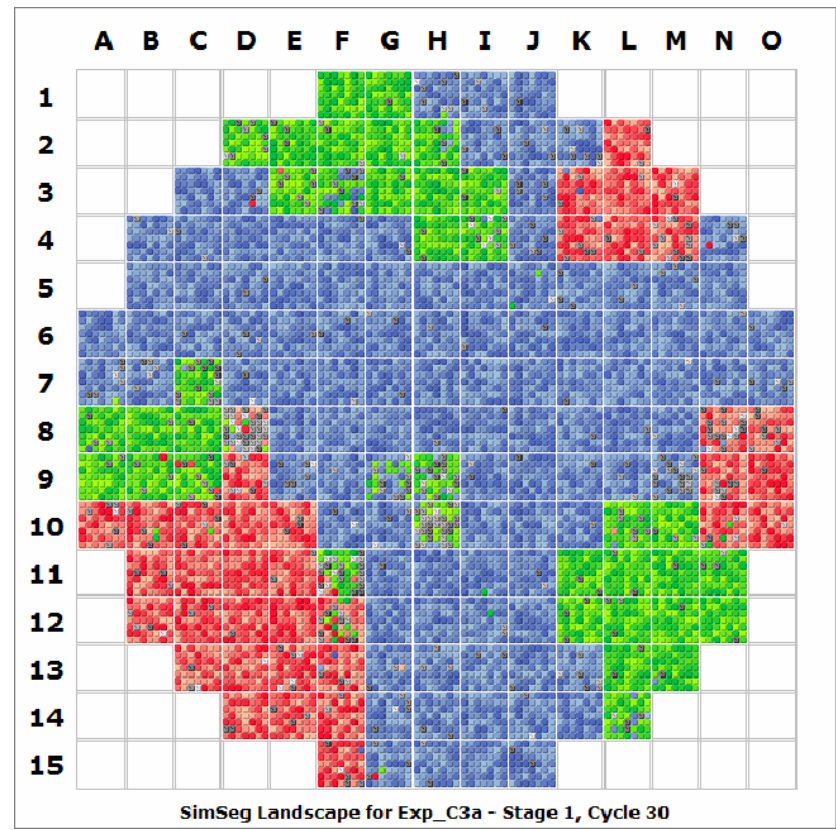
**All-Way Segregation**

**FIGURE 12** Minority checkerboarding variation in a “zonal” city



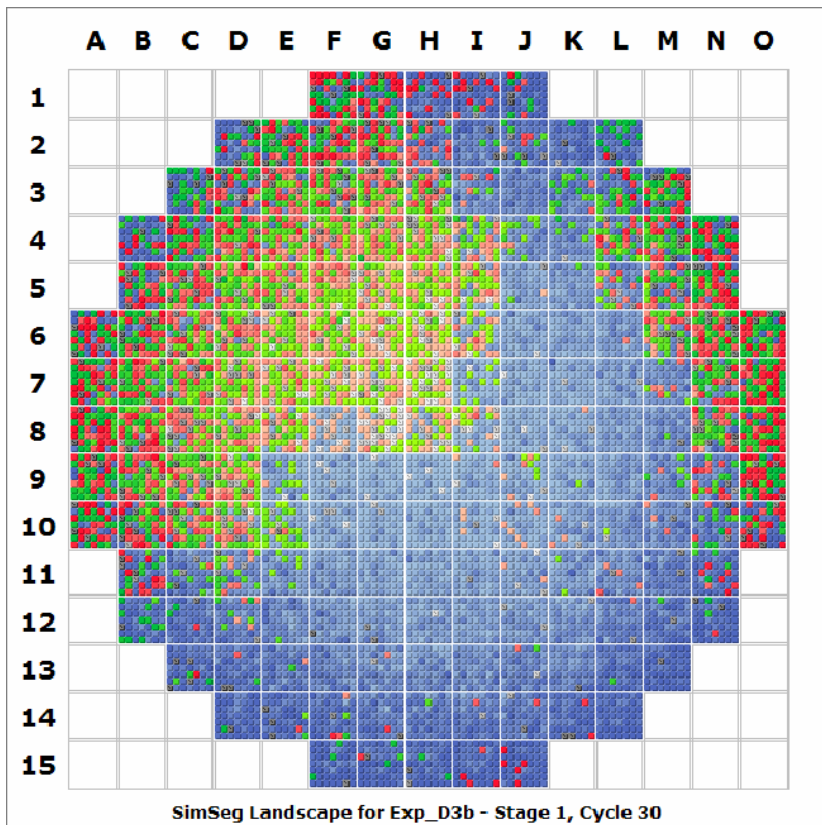
**Minority Segregation from Majority Only**

*Characteristics:* Uneven distribution, isolation, and clustering for minorities, but no centralization. Minority-minority segregation varies.  
*Generating mechanisms:* Active ethnic preferences for immediate and adjacent areas, majority exclusion and minority preferences vary.



**All-Way Segregation**

**FIGURE 13** Minority clustering variation

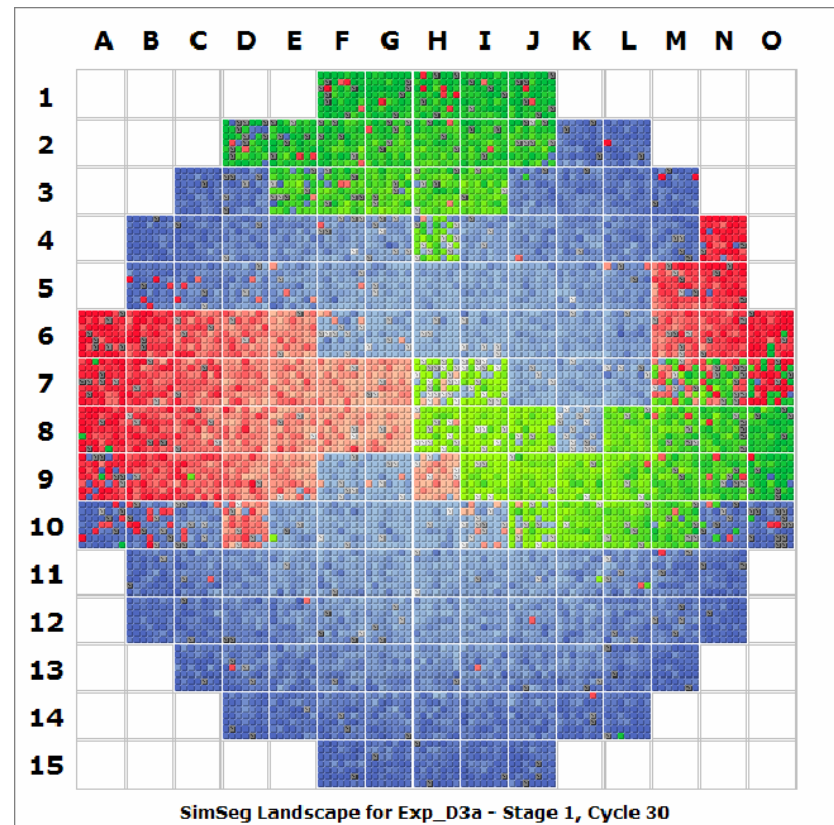


**Minority Segregation from Majority**

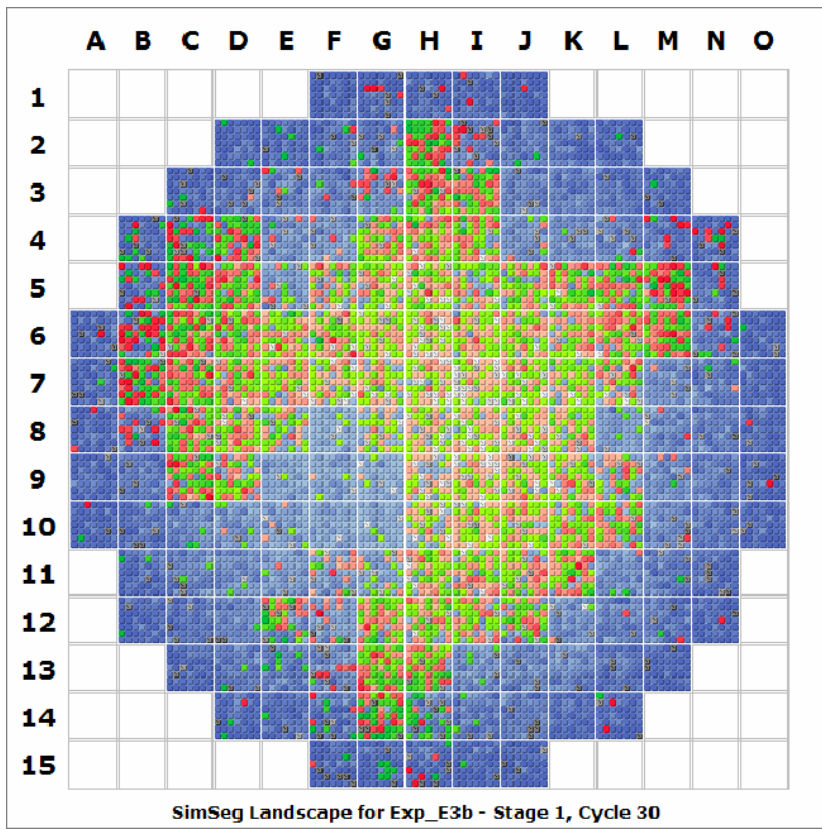
*Characteristics:* Uneven distribution, clustering, and isolation of minorities, but no centralization. Minority segregation varies. Status segregation by SES “zones.”

*Generating mechanisms:* Active ethnic preferences for immediate and adjacent areas, area stratification, majority exclusion and minority preferences vary.

**FIGURE 14** Minority zonal-sectorial variation



**All-Way Segregation**

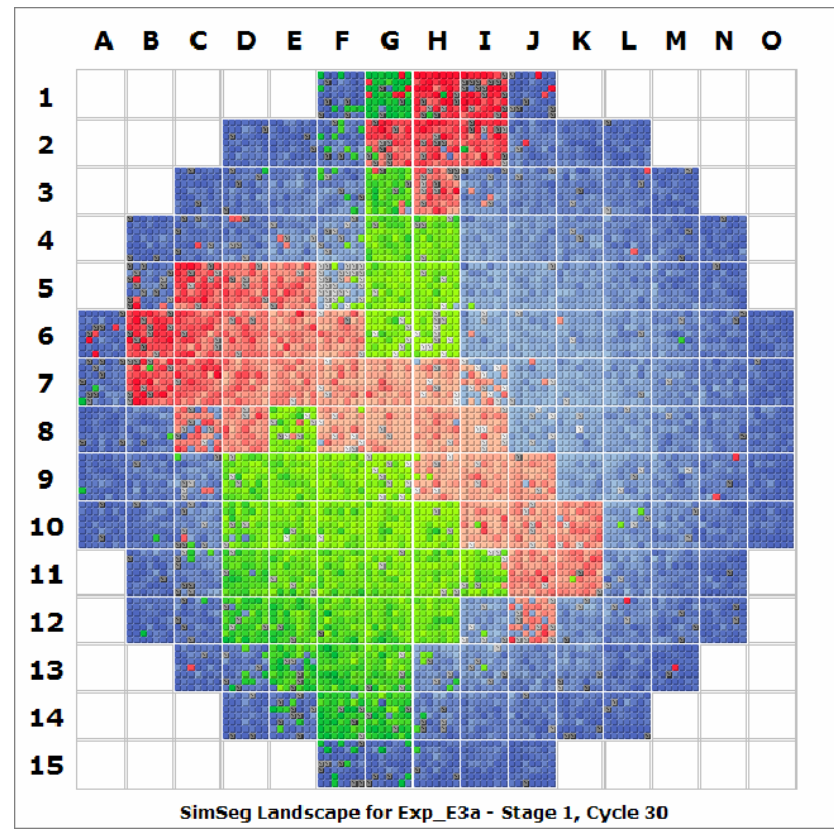


**Minority Segregation from Majority Only**

*Characteristics:* Uneven distribution, isolation, clustering, and centralization for minorities. Minority-minority segregation varies. Status segregation by “zones.”

*Generating mechanisms:* Ethnic preferences for immediate and adjacent areas, area stratification, minority status disadvantage, majority exclusion and minority preferences vary.

**FIGURE 15** Minority hypersegregation variation



**All-Way Segregation**

In each figure, the city landscape on the right side of the page is the landscape presented earlier for the three-group simulation for the reference simulation experiment. In each figure, the city landscape on the left side is a new landscape generated by a simulation experiment that varies from the reference simulation.

The variation implemented is the same in all cases and can be described as follows. In the experiments reported in Figures 6–10 all ethnic groups are given segregation-promoting, in-group preferences (i.e., preferences for in-group contact at levels above population representation). In the new experiments reported in Figures 11–15, only Whites are given segregation-promoting in-group preferences. In-group preference targets for Blacks and Hispanics are set to zero (i.e., households in these groups have no preferences for in-group contact). Accordingly, housing search by minority households will take them to any neighborhood where they can satisfy their desires for high-quality housing and high-status neighborhoods, regardless of the ethnic mix of the neighborhood. But, a new dynamic is added to the original scenario for these simulations — a simulated process of minority exclusion is implemented. The consequence of this dynamic is that minority households trying to enter majority White areas are systematically blocked from entering.<sup>5</sup>

The impact of these changes in the simulation scenarios is easy to summarize. In broad terms, city landscapes on the left side of the page manifest high levels of White-minority segregation but low levels of minority-minority (Black-Hispanic) segregation. In contrast, city landscapes on the right side of the page manifest high levels of both White-minority segregation and minority-minority segregation. The minority-minority integration in the landscapes on the left side of the page also leads to lower levels of minority isolation and ghettoization. More precisely, minority isolation and ghettoization are evident, but levels of Black and Hispanic isolation and ghettoization are much lower than in the reference simulations.

## *Conclusions*

This set of simulation results highlights an important finding from agent-based models of ethnic segregation. This is the interaction of ethnic preferences and ethnic demography, which in this case is dramatically evident in the impact that minority preferences have on minority-minority segregation patterns. Schelling (1971) called attention to this interaction, and Fossett (2004a) has explored it in considerable depth. He offers the following conclusion. The implications of ethnic preferences for segregation cannot be assessed by examining the preference itself. One must consider the preference in relation to the ethnic demography of the city. Preferences for in-group contact become segregation promoting only when the level of in-group contact sought begins to equal or exceed the group's population representation. As a result, groups that are demographic majorities can hold preferences for relatively high levels of in-group contact without generating ethnic segregation. On the other hand, groups that are demographic minorities can hold preferences for relatively low levels of in-group contact that will generate high levels of ethnic segregation. Fossett (2005b) terms this counter-intuitive pattern the “paradox of weak minority preferences.”

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<sup>5</sup> This pattern simulates White owners refusing to sell to minority households or systematically favoring co-ethnic households over minority households.

The contrasts between Figures 11–15 and Figures 6–10 highlight the fact that agent-based models of segregation contribute important insights to a more complete understanding of ethnic segregation. From Schelling forward, segregation research drawing on the agent-based modeling framework has stressed that agent-based models show that surprisingly complex, counter-intuitive patterns of segregation can arise from the interplay of seemingly simple conditions and dynamics. The segregation-promoting implications of minority preferences represent a key example of this fundamental insight. Even today, the broader literature on ethnic segregation has tended to ignore the role of minority preferences. Descriptive studies of ethnic segregation in real cities rarely report minority-minority segregation patterns. General theories of segregation are overwhelmingly geared to explaining majority-minority segregation and give almost no attention to explaining minority-minority segregation although it is the norm in most American cities. Agent-based studies thus address an important blind spot in the broader literature on residential segregation.

The broader literature on ethnic segregation has also tended to ignore a fundamental insight that orients adherents of the agent-based modeling perspective. Agent-based models have a strong appreciation of the fact that the implications of particular conditions and dynamics for segregation may not always be obvious and should never be casually presumed on the basis of discursive theory and intuitive reasoning. Agent-based modeling adherents believe instead that discursive theory and intuitive reasoning should be given formal representation and carefully explored using a rigorous modeling approach. We return to this point in the concluding section of this paper.

### **SimSeg AND PEDAGOGY**

The segregation patterns presented in Figures 3–15 are compelling and highlight the educational value of SimSeg’s implementation of agent-based models of residential segregation. First, as Figure 10 shows, SimSeg is able to produce simulation results that manifest the kinds of complex, multidimensional patterns of segregation by ethnic and socioeconomic status seen in real cities. This itself is a significant modeling achievement.

Second, SimSeg presents these complex patterns of segregation in a form, namely, the city landscape, that can be easily understood and appreciated by students with little technical background in segregation measurement. Moreover, while not directly evident here, SimSeg illustrates segregation principles in a dramatic way by generating these patterns of segregation in real time in the classroom. Thus, for example, city landscapes for the simulations shown in Figure 10 are ethnically integrated at initialization. But when the simulation experiment is run, the visual pattern of ethnic integration transforms into a striking pattern of maximum hypersegregation within a matter of seconds. This can be repeated for effect and easily and quickly compared with simulations using other scenarios that do not produce maximum hypersegregation.

Third, and perhaps most importantly, SimSeg shows how the complex pattern of segregation seen in Figure 10 is built from the interaction of several separate dynamics. If any one of these dynamics is removed from the simulation scenario, something less than maximum hypersegregation is produced. This kind of demonstration simply cannot be accomplished using data for real cities. The reason for this, of course, is that the states of the crucial factors contributing to segregation patterns in real cities are “naturally occurring” (in the sense of

beyond the investigator's control). They cannot be manipulated by outside observers, and many combinations simply never occur.

In our opinion, simulation analysis presents the best alternative for exploring the effects of these separate dynamics and demonstrating how they come together to create complex segregation patterns.

Multivariate statistical analysis is the chief method used to assess the effects of different factors on segregation outcomes in the social scientific literature. But it is not a viable alternative for instruction. For one thing, it is difficult for undergraduate students to understand the results of such analyses. Lectures and readings must emphasize statistical analyses of multiple quantitative indices of segregation (to get at the multiple dimensions of segregation), which to undergraduates are technically challenging and hard to interpret. Similarly, the notions of statistical control and interaction effects, crucial to a full explanation of the dynamics involved, are unfamiliar to most undergraduates. Finally, and perhaps most important of all, many combinations of settings for the factors involved never occur "naturally," so statistical analysis of observational data on real systems simply cannot provide a basis for assessing the independent contributions of these factors and their interactions with other factors.

Theoretical analysis is the other major alternative for instruction, but it is inferior to simulation analysis on several counts. The relationships involved are complex and, at least to date, have defied theoretical deductions and "proofs" of complex effects. This, of course, is the type of situation where simulation analysis provides an important option for theoretical analysis. Theoretically relevant conditions and processes can be implemented and manipulated within a simulation program and the implications of the complex model can be assessed inductively by observing the results generated by the model.

To summarize, SimSeg is an attractive pedagogical tool for several reasons. The constructs and algorithms in SimSeg reflect the key conditions and dynamics identified in sociological theories of segregation. SimSeg provides a means for exploring these theoretical perspectives in "real time" in the classroom setting. SimSeg gives students the opportunity to engage in empirical research and test hypotheses about residential segregation. SimSeg exposes students to the power of using experimental methods to test ideas against empirical evidence.

## **THE STANDING OF AGENT-BASED MODELS OF SEGREGATION**

Agent-based models have generated important theoretical insights about the dynamics of residential segregation in urban areas. As noted earlier, Schelling (1971) introduced the best known and most celebrated example of agent-based models of segregation. Today, more than three decades past the date of initial publication, his theoretical analysis drawing on agent-based models stands as a key contribution to understanding of how micro-level residential choice behavior can produce complex aggregate-level patterns of ethnic residential segregation. The Schelling model has been influential across many disciplines, including sociology, economics, demography, political science, geography, and social psychology. It is routinely cited as an exemplar of how seemingly simple, micro-level behavior can produce nonobvious emergent structure in spatial networks (Clark, 1991, 1992; Epstein and Axtell, 1996; Krugman, 1996; Young, 1998; Wasserman and Yohe, 2001; and Macy and Willer, 2002;) are among the many scholars and researchers who have explored different aspects of Schelling's model and endorsed



his conclusions that spatial integration is a surprisingly fragile condition and that high levels of segregation can occur even when no individual in the population wishes to reside in the type of ethnically homogeneous neighborhoods found in highly segregated cities.

Theoretical insights derived from agent-based models are celebrated by many, but their influence in the broader theoretical and empirical literatures on residential segregation is mixed at best. Notable scholars (e.g., Clark, 1991, 1992; Thernstrom and Thernstrom, 1997; and Glazer 1999) have argued that Schelling's work has important implications for social science understandings of ethnic residential segregation. In the main, however, it is fair to say that agent-based modeling efforts have been viewed with skepticism by sociologists, geographers, and political scientists. Thus, for example, important surveys of the field (Massey and Denton, 1993; Yinger, 1995; Charles, 2000, 2001, 2003; Farley et al., 2001) severely discount the relevance of Schelling's theoretical work for understanding segregation in the real world.

What accounts for this situation? It is not weakness in Schelling's theoretical analyses; they have withstood the test of time. The few scholars who have criticized Schelling's preference models of residential segregation (e.g., Massey and Denton, 1993; Yinger, 1995; Krysan and Farley, 2002) have not offered any formal critiques of his mathematical or simulation models.<sup>6</sup> Their critiques have instead relied on discursive reasoning and a variety of arguments that the Schelling model is not relevant for "real world" segregation patterns because it is too abstract, too simplistic, and too artificial.

One might respond that this type of criticism of Schelling, and agent-based models of segregation generally, is rooted in a view that places little value on the task of building theoretical models with rigorously grounding in basic principles. There is at least circumstantial evidence to support this view. Social science research on residential segregation is highly developed in the area of *description and documentation* of macro-level patterns of segregation and the micro-level dynamics that are involved. But it is severely undeveloped in the area of formal modeling frameworks that tie micro-level dynamics to macro-level patterns in rigorous ways. Thus, there is a clear tendency for segregation researchers to emphasize description over model development.

Nonetheless, agent-based modelers are not free of responsibility for this situation. One of the limitations of this literature is that agent-based modeling efforts are largely divorced from the broader theoretical and empirical literatures on residential segregation. Agent-based modeling efforts rarely use measures of segregation that are standard in the broader literature. They often make modeling choices (e.g., implementing city landscapes as a torus), that unnecessarily weaken the correspondence between model systems and empirical systems, often for reasons that are obscure if warranted at all. As a result, agent-based studies appear strange and artificial to conventional segregation researchers, and theoretical insights derived from agent-based models have been viewed with skepticism by most sociologists.

The SimSeg model seeks to address at least some of these problems and achieve closer integration of agent-based modeling traditions and conventional traditions of research on

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<sup>6</sup> A recent study by Laurie and Jaggi (2003) purports to identify significant problems with Schelling's insights regarding segregation dynamics. But Fossett and Warren (2004) show that Laurie and Jaggi's modeling approach and conclusions based on it are flawed. Fossett and Warren also show that when the flaws in the Laurie and Jaggi modeling approach are corrected, the results provide strong support for Schelling's position.

residential segregation. As noted earlier, SimSeg combines the core elements of the Schelling model together with elements of important theories of urban-demographic spatial structure. The model draws on standard measures of residential segregation and makes it easy to compare results from simulation analyses with results from traditional descriptive analyses of segregation.

The interaction between traditional researchers and researchers drawing on agent-based modeling frameworks need not be antagonistic. Indeed, there are many reasons for anticipating productive exchange and debate. A good simulation model must embody sociological theory and knowledge and thus rests on the identification of basic constructs, conditions, and behavioral processes relevant to residential segregation. Consequently, agent-based modeling needs to draw on the broader empirical literature on segregation, including both quantitative descriptive studies of segregation patterns and quantitative and qualitative studies of the dynamics involved in segregation. Agent-based modeling efforts can stimulate the broader literature because model building requires development of formal representations that can be implemented in unambiguous ways in the context of a model. The task of model building thus exposes conceptual ambiguity and gaps in knowledge. In addition, the representations of theory and assumption in concrete ways in simulation models invites criticism and productive debate.

We offer SimSeg in precisely this spirit. The model incorporates insights and approaches taken from agent-based modeling traditions. But it also seeks to represent constructs and dynamics not previously examined in agent-based studies. The SimSeg modeling effort should be seen as a significant step forward but hardly the last step along this pathway.

Finally, and perhaps most importantly, the SimSeg project strives to make agent-based models accessible to broader audiences that are not versed in the technical details of the modeling framework. SimSeg's user interface allows students to explore basis insights from agent-based modeling perspectives, without initially having to directly confront the more difficult conceptual and practical issues that occupy the attention of agent-based researchers. Agent-based models yield compelling insights about segregation dynamics. We believe SimSeg can be an important tool for bringing these insights to larger and broader audiences.

## ACKNOWLEDGMENTS

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## SYSTEMS DEVELOPMENT LIFE-CYCLE METHODOLOGY FOR AGENT-BASED MODEL DEVELOPMENT

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### ABSTRACT

Systems development life-cycle (SDLC) methodologies are used to plan and execute a wide variety of software development efforts, ranging from traditional custom applications to rapid applications using prototyping. Consultants use SDLC methodologies in the commercial delivery of their services to show their how they can plan and execute software development while properly controlling scope and cost. As agent-based models (ABMs) take their place in the list of capabilities of custom software development companies, a variation on the traditional SDLC methodologies will be needed to control the ABM development process. This paper presents a methodology for developing ABMs that defines the phases, activities, and deliverables of the process. It also provides some insights and comments on favorable circumstances for the application of an ABM and the nature of the dialogue between the developer and the client.

**Keywords:** Agent-based modeling, systems development life-cycle methodology, SDLC, project management

### INTRODUCTION

All of us at this conference believe in the future of agent-based models (ABMs). To some, ABMs represent a paradigm shift in the way we see human systems of all sorts that will lead to a revolution in the way we understand and manage our way in the world. To others, ABMs represent the latest generation of modeling techniques — more efficient and effective than the last generation.

If correct, over the next few years, in order to apply these models in business, we will increase our knowledge of how to create them; refine their capabilities and sophistication and what they can tell us; and move out of the research and development (R&D) phase of our experimental efforts and into the world of standard business systems, in which embracing the concepts and utilizing the capabilities of ABMs will become the standard, not the exception.

Along the way, the size and complexity of the projects that create the models will increase with the size and complexity of the modeling objectives, and we will find ourselves (indeed, we already find ourselves) facing a problem of structure and organization that precisely parallels the issues that have always faced computer application development projects, namely, how to manage and control the systems development life cycle (SDLC).

This paper presents an SDLC methodology for ABM development, in the hope that such an effort will contribute to the ongoing dialogue on the issue among the modelers. That dialogue

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may lead to a heightened awareness and understanding of the fundamentals of large-scale application development projects and, perhaps more important, of the standards and practices already in place in corporate America for those projects. If we are lucky, we will have to deal with those standards as the capabilities and popularity of the discipline gradually work their way into the best practices of critical decision makers in business.

## BUSINESS CASE FOR AN SDLC METHODOLOGY

I first participated in complexity-science-based systems development projects as liaison from Ernst & Young's consulting practice to Biosgroup, Stu Kauffman's company. Kauffman is fond of comparing the behavior of a deregulating industry to the Cambrian explosion in the fossil record, citing the parallels in the proliferation of candidate solutions to the new paradigm and in the gradual winnowing away of the suboptimal to a steady state of winning solutions (Kauffman, 1995). Like the early efforts in a deregulating industry, we are in the early stages of an investigation of the nature and capability of ABMs and of our ability to build them effectively and efficiently. We are operating in an R&D mode, in which the project of building the model is as much a research effort into the feasibility of the application of the science as it is a systems development project. Our customer to date has been the "visionary," as defined by Geoffrey Moore in *Crossing the Chasm* (Moore, 1991). Whether the visionary is a corporate finance executive frustrated with his inability to set effective risk management policy or a hard-bitten operational manager faced with multi-million-dollar scheduling decisions on a daily basis, he sees the world as it could be and is willing to invest in our research just in case we might be able to improve his bottom line. To the visionary, who is used to big bets, the risk of the investment is justified by the potential of the payoff. My first big project with Biosgroup was the development of an ABM for a natural gas pipeline. It modeled the pricing mechanisms of natural gas at a physical pricing point in Louisiana called the Henry Hub. The funding came from the marketing department, to whom the prospect of a strategic advantage was well worth the investment.

In the introduction to *It's Alive*, Christopher Meyer and Stan Davis say, "Our information systems themselves will become adaptive — otherwise, our businesses cannot be. By the end of the decade, business management, information systems, and biological concepts and technologies will converge around a common view of how change happens" (Meyer and Davis, 2003). This theme of seeing the organization as a living, breathing being rather than a Newtonian clock, as you are well aware, has been gathering momentum for some time. From Peter Senge's learning organization (Senge, 1990) to Margaret Wheatley's "zeitgeist of interconnectedness" (Wheatley, 1999), the notion of harnessing the power of ABMs to model the behavior of the organization is well formed in the minds of the visionaries. As usual, the concept is fully articulated far in advance of the reality. Whether ABMs will indeed fulfill their promise as the thinking engines of a whole new generation of systems that are able to adapt themselves to the environment or will go the way of artificial intelligence remains to be seen. I believe that the effectiveness and efficiency of the development projects themselves can be a very positive factor in the ongoing success of the effort, lending credibility to ABM development in the eyes of our "investors," those who would risk their software budgets on our efforts. And that depends, in part, on the method.

In *Crossing the Chasm*, Moore acquaints us with how information-systems-based products are born with a model he calls the "technology adoption life cycle" model. In this model, "innovators" and "early adopters" put up with the fits and starts of an R&D approach in

which one of the legitimate outcomes is “it didn’t work,” in order to get what they want. They are the means by which a software product is born, but they do not constitute a large enough market to sustain success. To reach a larger market, the entrepreneur, armed with his product and the innovator’s endorsement as a happy first customer, must cross Moore’s chasm and do battle with a very different sort of a buyer, the “pragmatist” (Moore, 1991). Wrapped in the cloak of corporate custom and heavy with the responsibility of “due diligence,” the pragmatist is the gate keeper of corporate funding. He wants to see your work plan. He wants to talk to a happy customer. He wants it on time and within budget, and he wants to know exactly what “it” is. Even in the earlier stages of development while the visionary is still working on an R&D basis, the visionary is often “shadowed” by the corporate technology control network, busy ensuring the standardization and interoperability of all corporate software products and services.

It is through this portal that the funding for the realization of agent-based modeling (ABM) lies. As we get better and better at modeling; as our track record improves; as we enjoy mass exposure for early, significant successes; as our object libraries fill up with standard customer behavior entities and blind auction modules; as our interface engines evolve, combine, and connect; as our software moves from custom, one-of-a-kind, stand-alone modules to integrated, corporatewide, real-time systems — one of the enabling technologies of this success will be the methods and standards that govern the development process.

Further, because the project in question is one that attempts to do something that no one has ever done, the customer has a reason to be nervous about its outcome and will require even more hand-holding during the process than is usual.

So, the business case for an ABM SDLC methodology is simply the need to put what we want to do into a format that is recognizable by those who have to pass judgment on it (and who are often responsible if it is out of specifications), to keep them informed during the process, and to give them the comfort that we are conducting our business in a disciplined way and are not going to embarrass them with that thing most feared: a “problem” project that is over time or budget or, worse, ineffective in its results.

## TECHNICAL CASE FOR AN SDLC METHODOLOGY

In my 30 years as a practitioner of application development, I have participated in countless methodology training sessions and seminars and have been a principal in the development and deployment of methodologies from four full generations of thought on the subject. In all those years, I still come back to 1975’s *The Mythical Man Month* by Frederick P. Brooks, Jr., as the best book ever written on the subject of large-scale systems development projects. Now out in a 20th anniversary edition with four new chapters, it still reminds me of what I once knew but had forgotten.

The heart of much of the technical miscommunication between the pragmatist buyer and the model developer, when it is there, is described in the text on the “programming systems product” on the very first page of Brooks (1975). He identifies a program, which is “complete in itself, ready to be run by the author on the system on which it was developed,” and three escalations of that state. The first is a “programming product,” which is “a program that can be run, tested, repaired, and extended by anybody.” The second state, a program improved in a different direction, is a “programming system,” which is “a collection of interacting programs,

coordinated in function and disciplined in format, so that the assemblage constitutes an entire facility for large tasks.” The happy marriage of “program product” and “program system” yields the third state, “programming system product,” which the author notes costs nine times as much to develop as does the program.

It is my observation that the developers of ABMs are often writing programs, the customers are often expecting programming system products, and the lack of some fundamental best practices within the project sometimes delays the discovery of this miscommunication until it has escalated into a major problem.

It’s fine to just be writing a program. As a matter of fact, as we shall see in the methodology, that’s exactly what must be done in the prototyping phase, to prove the concept before real money is provided for its development. The point is that descriptions of the deliverables that are early and effective are much less likely to be misinterpreted by the customer and are one of the primary objectives of a good method.

Because of the parallel between the methodological needs of ABM development projects and of traditional systems development projects, it is fair to say that all the problem areas in the latter apply to the former. Project planning, work plan development, project team training, scheduling, requirements gathering, module design and testing, data architecture development, training, and implementation — all are traditional areas of focus and deserve the attention of the ABM developer. Like its traditional counterpart, the ABM development project is susceptible to delays and missed deadlines. While these project execution issues are items of interest and concern to the ABM developer, who is focused on perfecting the application of the science, they are items of ominous portent to the pragmatist project controller, focused on controlling the scope of the project.

In addition, whereas the developers of a new accounts receivable system start the project with a common understanding of what one of those systems does, the ABM development project team must add the burden of the conceptual development of how the model will work in the real world, what it will do, and how that will be better, to the already lengthy list of things that must be attended to during the project. This puts a particular emphasis on a skill set that is usually a minor sidebar in a traditional project: facilitation. One does not need to get a group of subject-matter experts together to discover the fundamental concepts behind accounts receivable; the concepts have been well documented for 400 years or more. However, if you are building an ABM of the pricing mechanism of the Henry Hub, you do have to get a group, because no one has ever done that before. In my pipeline project example, it took several intensive group sessions with the executives of the company to get closure on the fundamentals of the design of that system, far longer than would have been necessary in a traditional development project. Each executive had his own opinion, forged in the fire of his personal experience, about a matter that was central to the success of the company. Identifying the agents, their environment, and their behaviors became a war of wills within the executive camp, with implications that went far beyond the model itself. Had we not prepared the customers for this eventuality, they might very well have taken it as evidence that the model was not feasible rather than a natural consequence of the creative process.

Variances in the work program like this are not a problem if you have anticipated them and prepared the customers for the effort. They become a problem only if you let your customers compare the project to their only frame of reference, the traditional project, and if you don’t



point out to them the ways in which ABM development differs. In summary, from a technical point of view, an ABM development project has all of the old issues plus some new ones, and the keys to success are to educate the customer about what those differences are, keep the customer informed about the status of the project, and do a good job of scheduling and executing the tasks that are necessary.

## METHODOLOGY

### Origins

The need for a methodology to control the ABM development process emerged immediately when I became involved with the discipline during my first few major assignments. The methodology was not, and is not, an effort to control the creative process of the developer but rather to align the development process with the expectations of the customer, a customer who is used to doing business in a certain way as it relates to controlling software projects. The fact that a good methodology is all about collecting and using the best practices of the discipline to make development more efficient and effective is a beneficial, but secondary, objective.

My interest in the development and formalization of a methodology has increased in recent years because of the changing nature of the customer. Winning key assignments with very sophisticated objectives and big budgets in my current work with NuTech ([www.nutechsolutions.com](http://www.nutechsolutions.com)), Biosgroup's successor, when each assignment has been more integrated with the business (and therefore the "line" organization) than the last, has brought the need for this sort of a formalized method out of the "nice to have" category and into the "must have" category. Because of this growing need, over the last year, I have formalized a methodology for a systems development project that is based on the application of complexity science. Attachment 1 provides a level 1 process model for this method. Because the assignments often employ a variety of techniques drawn from complexity science, the method is not specific to ABM development, although many of its applications have, in fact, been ABM development projects.

In the spring of 2002, as I was launching New Science Partners, I attended the conference called *Capturing Business Complexity with Agent-based Modeling and Simulation: Useful, Usable and Used Techniques* at Argonne National Laboratory. Here I saw Michael North's excellent presentation entitled, "The ABMS Paradigm," in which he presented a "high level visual roadmap of ABMS development and use" (North, 2002). With North's permission, I have included some of the features of his paradigm, particularly with respect to his steps in the attribution of model behavior. These help bring my generic model down to a specific application of ABM development. Attachment 2 is an excerpt from Michael's presentation that presents an overview of his method.

Attachment 3 is an analysis of the components of the two methods, which told me, in part:

- My entire first phase was an expansion of North's first step.
- We were in general agreement about the steps in model development, but North's model provided a clearer explanation of the entity identification and attribution steps and of the creation of the global environment in which the entities would operate.
- North's "use phase" was, in general, the same as my "model application phase," but my phase extended into the first level of results feedback from the initial application of the model.
- North's model had some of the flavor of "build a capability, then see what business problems we can solve with it," whereas mine had more of a flavor of "prove to me up front you can make this thing work, and maybe I'll give you the money to try." This caused me to move some of North's "experimental design" step (the first one in his ABMS use phase) all the way up to my prototype phase.
- My "integrate model into production" phase was in need of detailing because it was where the standalone models finally found their way into the corporate mainstream and it was outside of the scope of North's method.

Also, because of my experiences with the actual application of this method, I have broken the model development phase into two activities: "baseline model development" and "model refinement." This is a concession to an orderly management of the process that the business community can understand and help us execute. I wanted the basic operation of the model to be in hand before the sophisticated work of detailed attribution got under way, and this two-step approach accomplished that objective.

In addition, this exercise led me to the realization that there were several different potential definitions of a successful project, depending on what the model was being asked to do and by whom the model would be operated. This led me to Attachment 4, which is an identification of five different levels of deliverables. The proof of concept, baseline model, and refined model levels are all required to deliver an "expert interpretation" system, but additional work is required to escalate that deliverable to the decision support or "integrated production" level.

## **Overview of the Five Phases**

Attachment 5 is an overview of the five phases of the SDLC methodology, which are governed throughout the project by a set of activities that manage the project, control change, and maintain the client relationship.

Phase 1, proof of concept, includes the initial identification of a "business value proposition" in which the modeler and the customer conspire together to find an application for

the science in business and describe the application and its potential value to the business. The model developer then creates a prototype, the purpose of which is to test the feasibility of the objective and conclude whether the application of the science has a reasonable chance of achieving the business value expected.

Phase 2, basic model development, defines the architecture of the model, including any development tools that will be used in its creation, and builds the initial model. Since the identification of the agents in the model and the attribution of behavior to them are such fundamental features in the process, Phase 2 attempts only to “stub in” the agents, describe the landscape of their environment, implement their basic interaction with that environment and each other, and “baseline” the model for further development. Because of this approach, it is easier for the business community to see if we have the fundamental relationships right, before the model is clouded with subtle and sophisticated interactions.

Phase 3, model refinement, asks for the participation of the business community to help bring the attribution of the behavior of the agents up to a “significant” level, meaning that we can begin to see real-world-like interactions in the execution of the model. This phase, in my experience, is where the model must gain the confidence of the business community. It is iterative and intensive and, when successful, leads to a growing customer confidence that the model will have real value in the business.

Phase 4, model application, is always the first mode of operation, regardless of the ultimate plans for more sophisticated implementations in the future. In the hands of subject matter experts in the customer’s organization, the model is loaded with production data, the model attributes are set, the model is iterated, and the results are analyzed for business implications. Feedback loops lead back to the model refinement phase for finding errors and making enhancements to the model. An investigation of the business consequences of applying the model’s results completes the phase.

Phase 5 is model integration. Phase 4 may be the end of development, in that a stand-alone module run by a specialized subset of the business community may have been the objective all along, or Phase 4 may be a proving ground for further escalation of the use of the tool to include automatic interfaces or a wider user community. In either of these cases, model integration is the process of aligning the model with the production system standards in place in the organization, and includes the modifications required to make the model, in the words of Brooks (1975), a “programming systems product.”

## **Project Management**

Project management is an ongoing effort throughout the project to control the SDLC process in a businesslike manner, thereby increasing our probability of success and, just as importantly, keeping those who control our funding happy. It consists of three components.

The first component, project management, is the total of our efforts to plan the project, develop schedules for executing it, staff those schedules with our own and customers’ personnel, gauge and report progress on a regular basis, and make adjustments to the project plan for any number of unanticipated events and distractions that will threaten the project during its lifetime.

The second component, change control, is a formal system in which the excellent ideas about what else we could do that are offered by everyone during the project are duly recorded for posterity. They are included in the project only when the specific permission of the customer, fully knowledgeable of the cost and time implications of the inclusion, has been given. This preserves the relationship between the cost of the project and the scope of the project.

The third component is customer relationship management. Since ABM development is not the same as accounts receivable development, particular attention must be paid to maintaining a clear, open, and frequent line of communication with the customer. From the funding authority, through project managers, down to the actual members of the project team, frequent, frank, and informative communication of the project status is necessary to keep everyone “on the same page.”

## **PROJECT ORGANIZATION**

### **Project Organization Chart**

Attachment 6 is a typical project organization chart for an application development project. The need for a formal process and data integration grows with the number of detail teams running in parallel. In a small project, the project manager usually performs both of these roles, but in a larger one, the two roles are required to keep the design/development teams coordinated.

### **Design Session Facilitation**

As I mentioned earlier, because of the exploratory nature of the ABM development project, facilitation is far more important here than it usually is. It is an art in itself and supported by much literature. A good facilitator is worth his weight in gold when toiling away all day to extract the fundamentals of the business out of a room full of headstrong department heads, each with a hidden agenda that usually doesn't have anything to do with the project. Further, it is not a skill that is widely practiced, particularly in the development community.

Because the attribution of the agents in the model can be an iterative process, the busy customer may tire of repeated requests for dialogue on the subject or, worse yet, stop returning our phone calls (he has a railroad to run, you know). It is incumbent upon us to use his time wisely, extract as much information as possible at each session, consolidate and remember the results of Session 1, and make sure that Session 2 moves us forward and doesn't just go over Session 1 again. A solid approach to facilitation will ensure a happy customer and get closure on the critical information-gathering tasks in the design phase.

## **SUMMARY**

Obviously, I have presented the framework for a methodology, and it falls far short of providing the level of detail and depth of content that a formal SDLC method contains, whether

it is an internal standard at a major corporation or a standards package offered for sale by a major software organization.

My motivation for developing this framework is that the lack of its existence has, on occasion, caused difficulty and miscommunication between an eager customer and a talented developer who happened to be working on an application of ABM that promised to be a real advancement of the science. It seems that the larger and more important an opportunity is, the more likely it is that issues would arise among the customers, technical community, and developer, thereby taking energy away from the objective and sometimes dampening the momentum of the effort.

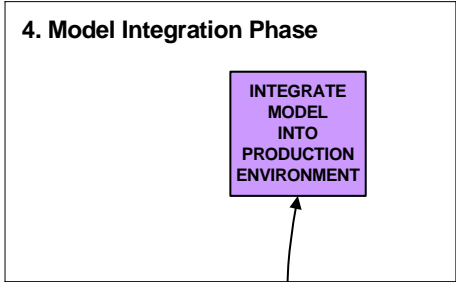
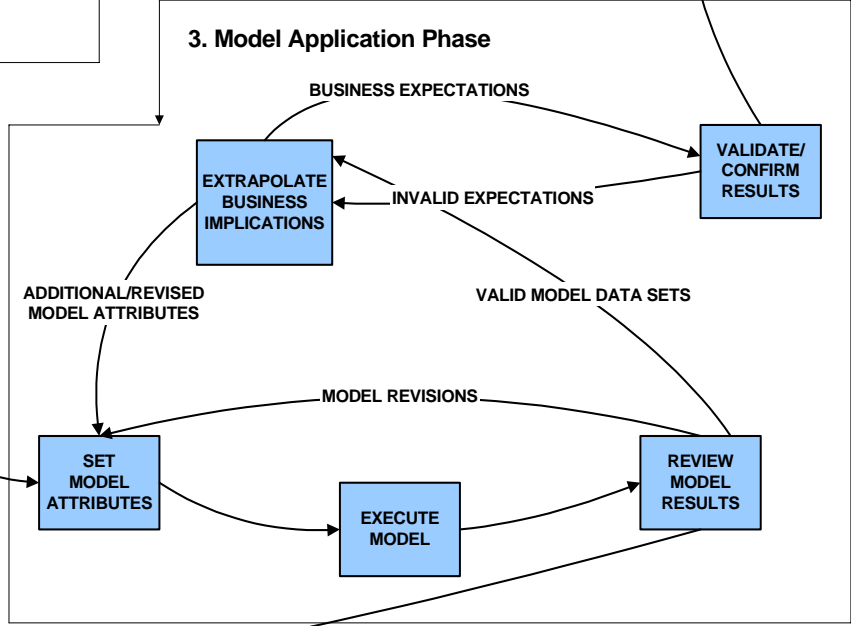
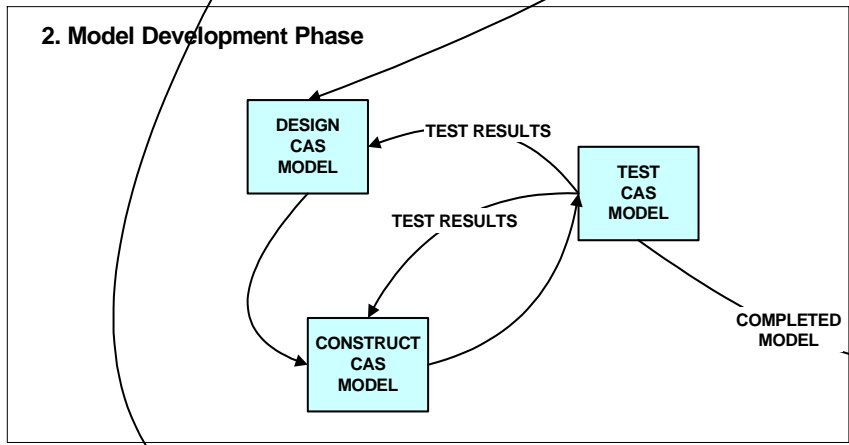
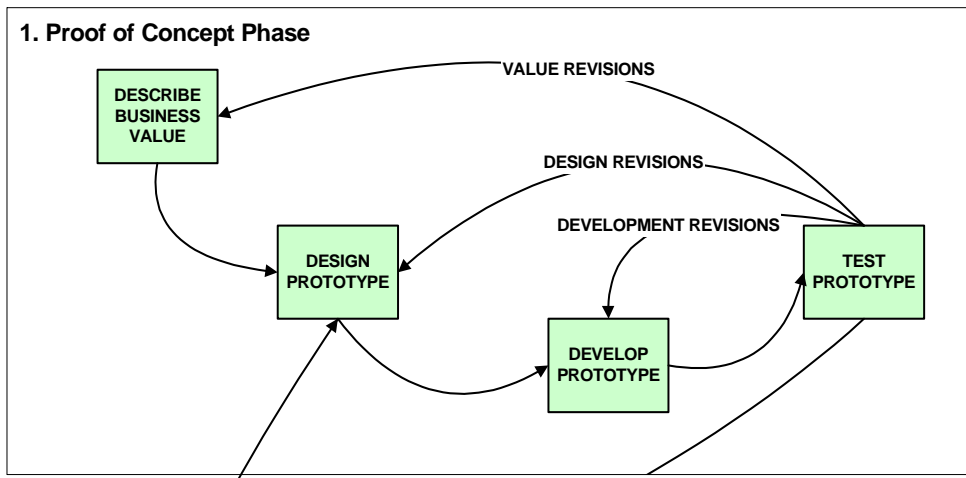
Understanding and being able to present our processes in the native language of the customer, so that he is comfortable with our approach and can focus on more important things, is just good business, particularly when that business is the furtherance of a discipline that all of us believe will become a very important one in the years to come.

Finally, many of you may well have begun your own efforts in methodology, and I welcome your comments and offer you this model as a contribution to that effort. I continue to expand this methodology. Currently, I am working on definitions and best practices for the project management components, and I already have detailed process models of the phases.

The best use of a methodology, in my opinion, is not as a cookbook, in which every step must be observed, but as a library, from which those things that are important to the effort at hand are extracted. If nothing more, use this SDLC methodology as a checklist. Ask yourself if you have done the task, and if not, why not? And it doesn't have to be a huge tome to be effective. A simple memo to your customer citing your understanding of an important issue may well uncover fundamental misconceptions, easily corrected in the short term but much more difficult to unravel on the day that the model is delivered.

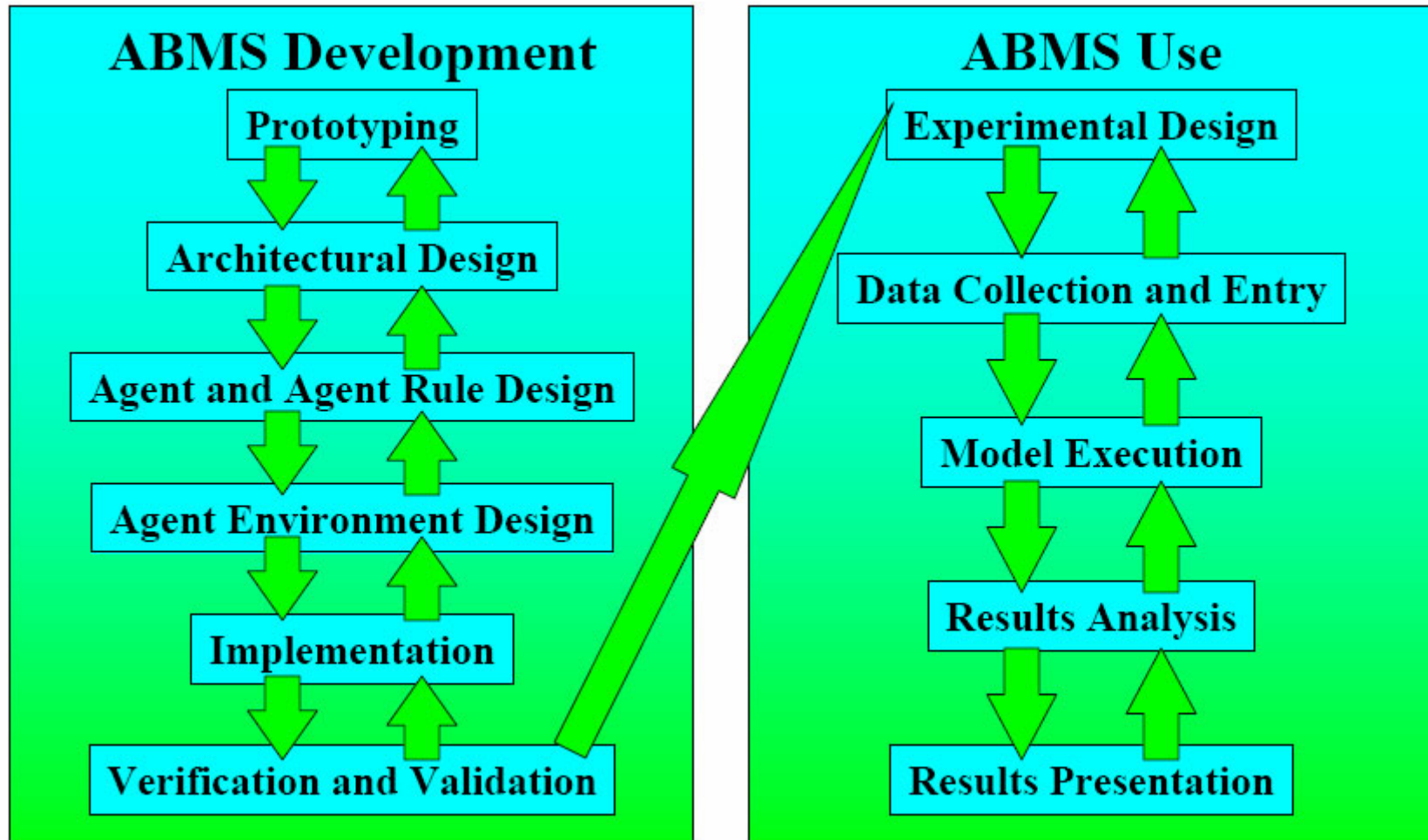
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REVISED MODEL SPECIFICATIONS

**ATTACHMENT 1** Complexity-science-based development methodology



ATTACHMENT 2 Visual ABMS roadmap containing two main parts: model development and model use (North, 2002)

			Rod Sipe's Agent Based Model Development Methodology												
	Michael North's "Visual Roadmap"		Proof Of Concept Phase				Model Development Phase			Model Application Phase					Integrate Model into Production Environment
	Development		Describe Business Value	Design Prototype	Develop Prototype	Test Prototype	Design CAS Model	Construct CAS Model	Test CAS Model	Set Model Attributes	Execute Model	Review Model Results	Extrapolate Business Implications	Validate/Confirm Results	
	Prototyping	X	X	X	X										
	Architectural Design						X								
	Agent and Agent rule Design						X								
	Agent Environment Design						X								
	Implementation							X							
	Verification and Validation								X						
	Use														
	Experimental Design														
	Data Collection and Entry									X					
	Model Execution										X				
	Results Analysis											X			
	Results Presentation											X			

**ATTACHMENT 3** Methodology comparison

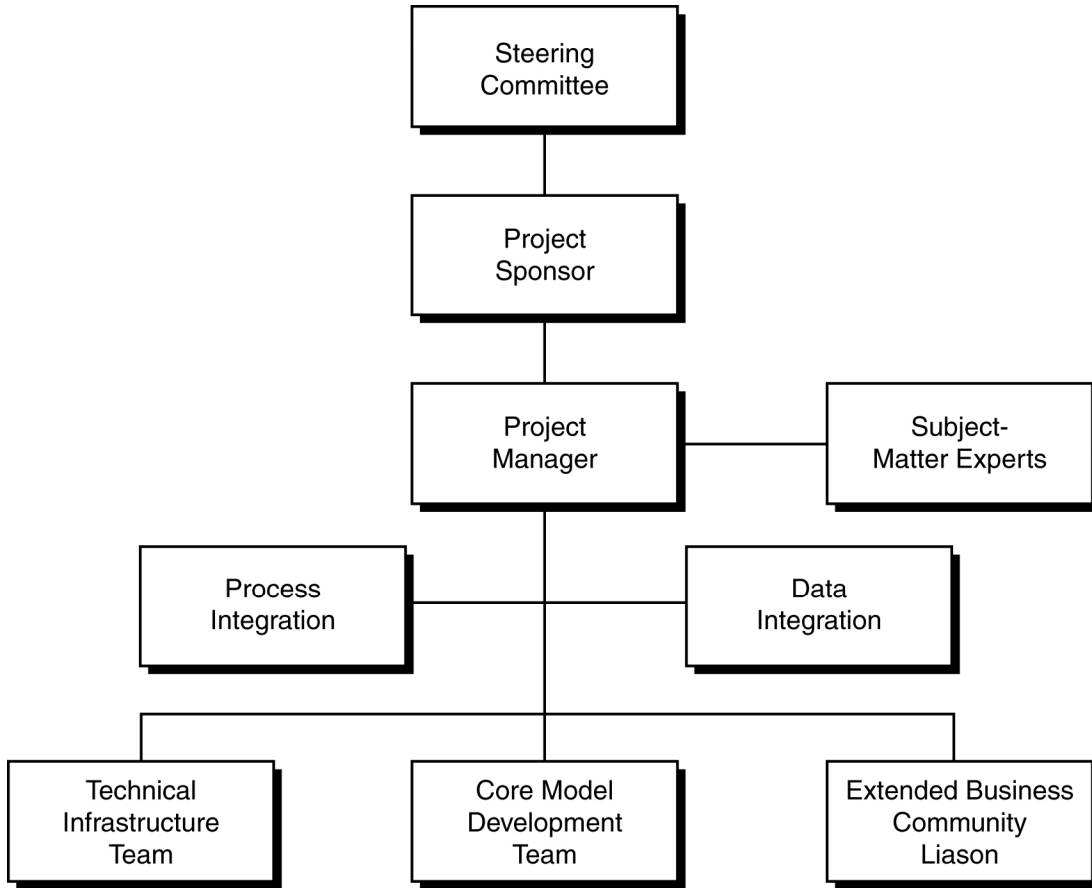


Model Type	Description	Objective	Value	User	Data Sources	Frequency of Execution
Proof of Concept	Feasibility of the application of ABM concepts to the problem at hand	Determine if the science applies before major investments are made in model development	Getting funded in the first place	The core development team develops this model and reports on its execution to the funding authority	Core Development Team developed test data	Iterated during proof of concept
Baseline Model	Establishes the development environment, the global features of the application, identifies the agents and proves the fundamentals of their interaction	Establish the correct functioning of the basic model before additional complexity is introduced into the interaction of the agents	Phased approach assists in getting closure on basic model performance	Core Development Team, Subject Matter Experts	Representative data samples from the business environment	Iterated until Baseline Model meets design specification
Refined Model	Complete attribution of behavior to the agents and their interaction	A model that is complete enough to begin answering questions about the business	Business insight through the observation of the interaction of the agents	Core Development Team, Subject Matter Experts	Robust data samples which emulate actual production data	Iterated until Refined Model meets design specification
Expert Interpretation	The first level of production software. The system is operated by subject matter experts, who interpret it's outputs and extrapolate the business implications	Answer specific, situational questions about the business	Answer specific, situational questions about the business	Subject Matter Experts	Actual production data	Depends on the intent of the model
Decision Support	Model answers pre-specified questions which occasionally occur in the business	Provide expert advice on the resolution of unanticipated issues	Interrupt recovery	"Super Users" in the line organization	Actual production data	As required
Integrated Production	Model plays a role in regularly scheduled production procedures	Harness the power of agent interaction in recurring decisions	Optimization of production	Line personnel		Within the regular schedule of business

**ATTACHMENT 4** Variation in design and function of agent-based models

PROJECT MANAGEMENT				
1.0 PROOF OF CONCEPT	2.0 BASIC MODEL DEVELOPMENT	3.0 MODEL REFINEMENT	4.0 MODEL APPLICATION	5.0 MODEL INTEGRATION
1.1 Identify Business Application 1.2 Describe Business value 1.3 Design Prototype 1.4 Develop Prototype 1.5 Test Prototype Feasibility	2.1 Design Architecture 2.2 Design Agents and Agent Rules 2.3 Design Agent Environment 2.4 Develop Model 2.5 Verify and Validate Model	3.1 Refine Agents and Agent Rules 3.2 Refine Agent Environment 3.3 Verify and Validate Model	4.1 Identify and Access Data 4.2 Set Model Attributes 4.3 Execute Model 4.4 Analyze Model Results 4.5 Extrapolate Business Implications 4.6 Validate/Confirm Results	5.1 Define Production System Requirements 5.2 Design Model Interface/Enhancement 5.3 Design Data Access Interface 5.4 Modify/Enhance Model 5.5 Test Production System 5.6 Prepare for Implementation 5.7 Implement Model in Production

**ATTACHMENT 5** Agent-based modeling systems development methodology overview



**ATTACHMENT 6** ABM development project team organization structure



**DISCUSSION:****MODEL DEVELOPMENT METHODS****(Thursday, October 7, 2004, 11:00 a.m. to 12:00 p.m.)**Chair and Discussant: *P. Sydelko, Argonne National Laboratory***SimSeg and Generative Models: A Typology of Model-generated Segregation Patterns**

**Pam Sydelko:** I'd like to begin by saying, "Wow!" The two speakers this morning [Burkhart and North] have really set us up and started the juices flowing. I don't know about anybody else, but not only have they shown where so much promise is, but they also have laid down a gauntlet for how challenging it's going to be to get there. One of the issues I think is really important, as a nonprogramming modeler, is the trend I've seen this morning — that we need to do whatever we can to make things more intuitive to those people who might not know how to put everything in a code base. When we look at this meta-modeling-type approach, getting all the way there may not be necessary, but getting closer would certainly be nice. I like the trend that I've seen in the two talks this morning.

This morning we're going to start with the "Model Development Methods" session. We have two speakers. We're going to start with a talk by Mark Fossett called "SimSeg and Generative Models: A Selected Typology of Model-generated Segregation Patterns." Mark is from the Department of Sociology at Texas A&M. It's interesting in the model development session that we're taking some of these things out of the research and development arena and trying to push them into other arenas — in this case, into education — giving people the ability to test theories by using these kinds of models. I think it's very interesting. So I'll hand it over to Mark.

[Presentation]

**Sydelko:** Are there any questions or comments? Yes, Tom?

**Tom Howe:** First, I want to commend you for doing this work. I think this is what Mike [North] was talking about when he said that we need to get models out in a more public way so that people can explore them and start to understand what they're doing. This is exactly what he was talking about: give students the chance to play around with their underlying assumptions from the perspective of the theoretical ideas that have gone into it. In light of that, I wonder if you plan on bringing other social theories into this model, such as institutional memory, for example, because you start with a somewhat unrealistic perspective that everyone is purely and completely integrated, instead of having some sort of institutional memory.

**Mark Fossett:** In the test bed, we have that, and we have to deal with a handful of very important, real-world problems. One is that if we develop a tool, we ask ourselves if somebody will use it. We're getting feedback from the field that people are using it in the classroom. We're trying to find out how far the students can go with this in a given class and how many ideas they can put in front of students and feel like it's being effective. We're getting two kinds of

feedback: one is to give people more realism, more detail, institutional memory. This is a starting point where the segregated world is something we can do and may with the next grant try to do that and some other things. On the other hand, people are also telling us that they'll use this for a week or two weeks, and in the context of that time frame, be able to explore about six ideas. Someone in class or somebody writing a thesis or dissertation would go a lot farther with it and really zero in on that. We have a list of things that we've accumulated by going through feedback from workshops we've conducted and from people using the program. We're trying to prioritize that list and add more things.

**Craig Stephan:** I'd also like to commend you on the work you've done. It seems like a very interesting tool to get into the business of ABM. I'd also like to reference Michael North's talk. I forget which 'E' it was, but he talked about the idea of showing individual interactions. This seems like an ideal vehicle for doing something like that. Could you, in fact, have a segment where you could watch an individual agent make a decision about where to move or how to exclude somebody or whatever, to show what's actually going on?

**Fossett:** We can't do that at this moment. This is definitely a very intriguing idea, and I can see the merit of that, so we'll be taking notes and discussing how feasible that is. I've only shown you a few model outputs. We have outputs where you can look at individuals and see what their preferences are and what kind of neighborhood they're currently living in. You get some unusual things, such as somebody saying that they don't care about the ethnicity of their neighbors, yet they live in a neighborhood that's ethnically homogeneous. We have the ability to do a little bit of that, but not with the sophistication you're talking about. That would be really attractive though.

**Sydelko:** We have time for one more question.

**Brian Pijanowski:** I'm interested in how you actually get the students to work with the software. What is the classroom environment like? Are they doing individual work with the model, or are they working in small groups and teams? How do you give the assignments, and do they work outside the class?

**Fossett:** All of the above. We have faculty from universities, a handful of universities around the country, who are using it, and I've used it for years and have pestered some other people into using it. Sometimes their students do very simple exercises using support materials that we've developed that guide them through running six quick-start scenarios and writing up what they saw. We also guide them through building a simulation and reporting the results — hypothesis testing and so forth — and they may work individually or in groups. That's an instructor's decision. But the software is so easy to use that you could ask people to work individually, and it would not be very difficult; it would not require a high level of support.

**Pijanowski:** Just to follow up. I've introduced tools into the classroom before, and you always have the group of students that just take it and run with it. They come back to you with things that you never thought about. There's also another group of students that just are terrified of the computer — terrified of technology or very suspicious of it. You've also got a large population of students in the middle that are just a little clumsy. They can do some things with it, so I'm wondering whether your experiences have been similar in your classes.

**Fossett:** Yes.

**Pijanowski:** How do you actually solve that where you ....

**Fossett:** I won't ask my students if I've solved it, but I feel like I have something quite workable. That is, I have structured exercises that I make everyone do. They're fairly straightforward, and you can give the students the actual list of instructions; the quick-start scenarios are great for that. I ask them to contrast this one against that one, and then reflect on what that could mean for the model and then for social reality. I also offer the opportunity to do term papers or extra credit projects for those people who want to take it and run with it. I just try to work with two audiences, but I want everyone to use it directly. In some cases, for example, one task might be with generative models. I might show them an outcome, and then, without giving clues, I might say that there are basic components that they can manipulate. I ask them to find a combination that generates an outcome like this, and then ask them to tell me. So it's like a little scavenger hunt. The options are restricted enough that they can play with them to do it. When the software is set up and installed, the interface, thanks to the work at Amber Wave Software and Richard Senft's team, the feedback we're getting, is that no one worries about the difficulty of using it. I have had students who put the CD into the crack between the CD drive and the 3.5-inch drive. They need support, but for the people who can get it in the slot, the menus are easy enough to use, and with a little bit of support, they're going to do okay. We're real pleased with that.

**Sydelko:** Thanks Mark. I would like to also say that I think Mark's work is very important because one of the things we talk about is the challenge of trying to get these technologies useful to decision makers. Certainly one way of doing that is to hit the future decision makers, making them comfortable with these kinds of tools and letting them see how they might be useful. So I think this is really a step in the right direction.

## **Systems Development Life-cycle Methodology for Agent-based Model Development**

**Pam Sydelko:** Rod Sipe is now going to talk about "Systems Development Life-cycle Methodology for Agent-based Model Development." Rod is with New Science Partners. When I read his paper, I found it interesting that he, too, is in an educational mode because one of the things he sees as challenging about agent-based modeling and to some traditional types of software development cycles is educating people on what it means and what it does. I'm hoping he'll touch on that a bit, too.

**Rod Sipe:** Thank you. I'm also a little bit out of water. It is a tribute to Michael North's eclectic personality that he invited me to make this speech. I'm a retired Ernst & Young consulting partner and spent my entire career building systems for corporate America. I spent 30 years in corporate America, cruising the halls, trying to understand what those people were saying and what they meant, building very large systems — \$400 million worth of implementations over 20 years at Ernst & Young, with 20- and 30- and 40- and 50-people projects that lasted for three, four, five, and six years, which is an interesting environment and one that causes you to have to go to school on the way corporate America behaves, particularly in the IT substructure.

The connection to complexity sciences at the end of my tour of duty at Ernst & Young, I was fortunate enough to get involved with Chris Meyer, director of the Center for Business

Innovation in Cambridge, which was Ernst & Young's think tank and their development and creation of the Bios Group, which was one of the early for-cash ventures out of the Santa Fe Institute. So my proudest designation is probably that I still hold the post of lead guitar in Stu Kauffman's after-hours blues band called the Strange Attractors. I spent a considerable amount of time with them, and I'm still aligned with NuTech, which is the company that bought the assets of Bios Group, and Stu is on the board of directors, along with Bob MacDonald.

So the social dynamic in terms of this talk is the relationship between the developer and the customer. New Science Partners is my company. I'm in the business of trying to make money out of the commercial application of complex adaptive systems and the kind of business results that you can create for them, which is an interesting point of view.

[Presentation]

**Sipe:** Value and use — I offer these to you as a starting place. If you're dealing with corporate America over a contract, these are more important issues than they might be otherwise.

**Sydelko:** First, I have a comment that many of the things that you talked about definitely carry over to my area for government agencies that are actually funding research and development. It's research and development, yet, there's a lot of impatience for wanting to get here quickly. I know the iterative cycle of software development — I truly believe in it, but sometimes find it difficult because I might have somebody who's funded me that's higher in the chain of command, but I'm actually delivering to somebody in the lower level. They understand the need for this iterative cycle because we're doing knowledge engineering at the same time, but the person on the top is saying, "I don't have time for that."

**Sipe:** Exactly. You can at least prepare those people for the eventuality if you're able to lay out a methodology and say that this is a little different than traditional systems development. It's different right here and right there and right there, and here is how it's going to be different. That helps them to understand that when we get into iteration over attributing behavior to a model, that that's just the way this one works, and it's not a signal as it might be in a traditional project that this is not going to work because you don't know what you're doing.

**Sydelko:** It's the interpretation sometimes. Are there any other questions? Chick?

**Charles Macal:** In your life-cycle methodology, there were sprinklings of agent references here and there, but we all know that the data issue and the verification and validation issue can be overwhelmingly large aspects of any project. How would you characterize the agent-based modeling approach? Do you do 90% of the work and then add on the agent aspects, or is the process much different somehow, with agent development changing the process in a fundamental way?

**Sipe:** Do you mean changing the actual business processes in the company?

**Macal:** Well, no, I mean in terms of how you actually develop agent models for a particular project.

**Sipe:** The only way I know how to do this is — and the way I have done it in the past — is to take the executive group. I can give you a good example. The first one that I did was for a



high-flying, sharp-dressing bunch of natural gas marketers from Houston, Texas, who wanted to know what the pricing mechanisms were around the Henry Hub, which is a physical gas trading point in Louisiana where natural gas is traded because pipes come in from three or four different directions. It's just a natural place.

The project turned into a debriefing and almost a counseling session with the four or five major executives because they each had their own mental model of how the business worked, but the production guys' mental model was completely different than that of the marketing guys. First, we had to get everybody's views out on the table and build this theoretical model of all the factors that affected the price of gas at the Henry Hub. The facilitation of the different points of view of the executives was a roadblock that had to be passed before we could identify all the factors. Once we did that, we could build a model and see if we could make it behave that way. So, first we have to consolidate the corporate knowledge about the business process into a logical model of the agents and their attributed behavior.

**Macal:** I have one brief comment on your answer. It seems that you have a fundamentally different starting point in how you're analyzing system — where you're starting with how the people think of the system ...

**Sipe:** Right.

**Macal:** ... in the sense that they are the agents, as opposed to a view that takes a look at the system as a process and seeks to somehow optimize [or improve] it.

**Sipe:** It also depends on where you're at. My work for my company is just an 8-crayola box, not a 64-crayola box. All we care about is that we've got trucks and roads and well equipment, so there are not a lot of moving parts to this model. In fact, you can start with an analysis of the current physical behavior of the system, but if you're shooting for pricing mechanisms or any sort of social interaction, it's a fundamentally much deeper problem than the one I'm trying to solve.

From a commercial point of view, I'm trying to do the least amount of innovation in the delivery as possible because I want the greatest potential for success. If I can give a 5% improvement on the utilization of the resources around the well work over in the Permian Basin, I'm a hero without having to get out on the ragged edge of the behavior of the tool operators where I'm not so sure I can be successful.

**Sydelko:** We have time for one more question.

**Unidentified:** You've been describing a methodology, and we work with the capability maturity model, which is a product of Carnegie Mellon, for software engineering. There's something coming out, called CMM Integrated, for systems engineering. How does your methodology fit in with this overall picture, and how does it compare with the things that might come out of the cookie-cutter approach to systems engineering and software development?

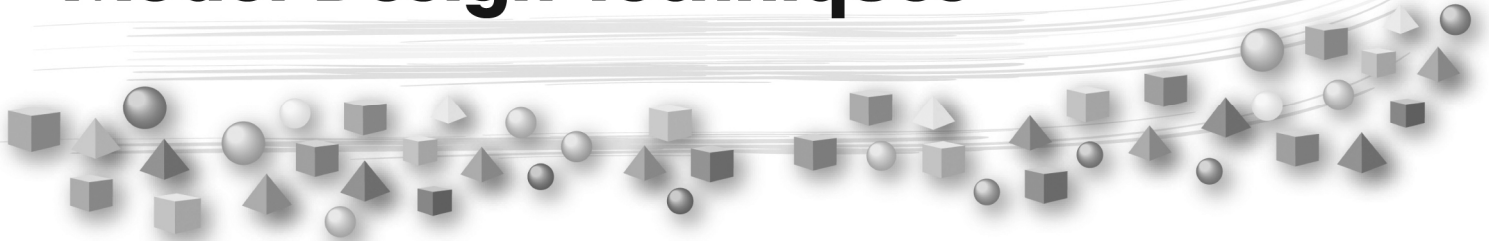
**Sipe:** I don't know the answer because I don't have detailed knowledge of the model you reference. What do you think — if you know them both — because I don't?

**Unidentified:** One of the issues with the CMM [Capability Maturity Model] is that it is a kind of meta-process, a process by which you define the process. It's up to people to figure out what their process is, and they probably go to the books and start to put together a number of steps, which leads to even more steps.

**Sipe:** Right, a model of the model. It makes you dizzy to think about it.

**Sydelko:** We're out of time. I'd like to thank everyone for their comments.

# Model Design Techniques





## TO DECEIVE OR NOT TO DECEIVE? MIMICRY, DECEPTION, AND REGIMES IN TAG-BASED MODELS

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### ABSTRACT

The tag-based computational model of cooperation described by Riolo et al. in *Nature* (2001) was extended in a series of experiments that examined the impact of tactical deceptive mimicry on cooperation, tolerance, and the emergence of regimes. Under all conditions, tactical deceptive mimicry increased the population cooperation above that of the base case. Allowing deceptive tolerance or deceptive propensity to evolve as separate traits (from the base case) increased the average life span of a regime. In addition, endowment gains through cooperation were associated with the emergence of regimes, while endowment gains through deception occurred when no groups were dominant. Not allowing deceptive tolerance or deceptive propensity to evolve as separate traits inhibited the emergence of regimes but yielded the highest overall cooperation levels.

**Keywords:** Tag-based cooperation, indirect reciprocity, social algorithm, deception, organizational simulation

### INTRODUCTION

In general, the explanation of why individuals cooperate at a cost to themselves has been somewhat problematic. Much of the confusion is based on the wide variety of contexts within which cooperation may or may not occur. Cooperation necessarily involves more than one individual; therefore, cooperation is a construct that must be socially defined. Consequently, given the range of contexts and possible social situations, as well as the wide definitions of “individuals” that may underlie them (ants, apes, or economic agents), it is not unexpected to see disparate perspectives, assumptions, or theoretical underpinnings associated with this topic.

The basic model described in this paper is based on the genetic algorithm method of Riolo et al. (2001). It requires no agent assumptions of specific social memory typically associated with cooperation, such as direct or indirect reciprocity (Sober and Wilson, 1994; Nowak and Sigmund, 1998; Henrich and Boyd, 2001; Sethi and Somanathan, 2003), or direct sanctions (Boyd and Richerson, 1992). Rather, tactical cooperation decisions are determined by a simple behavioral rule that is influenced through a specific and common social process: to mimic the strategy of the agents whose performance is better than yours. The decisions themselves are based on a simple and common social constraint: to cooperate only with those who are similar to you. The tactical decisions are based on the particular values of the mimicked strategy, and the values of the mimicked strategy are determined by the best performing agents in the group.

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In the model, a strategy is composed of two independent values: a tag and a tolerance. A *tag* is an identifier (in our case, an integer  $\tau$ ) that obviously can be compared for similarity — like the “green beard” hypothesis in evolutionary biology (Dawkins, 1996) — but can also be readily adopted or changed by other agents. For example, tags can represent a way of dress or perhaps a dialect. On the other hand, a *tolerance* is a value (in our case, an integer  $T$ ) that represents the flexibility in an agent’s perception of similarity. Specifically, one agent considers another agent as being similar to it only if the absolute difference between the two tags is less than or equal to the agent’s tolerance.

In this model, the cooperation context is defined as when one agent solicits a donation from another agent, and cooperation is defined as when the donation occurs. In such an exchange, the donor suffers a cost of donation, and the recipient gains a benefit. The tactical rule for donation, therefore, is the following:

*Social Donation Rule.* Agent  $x$  will donate to agent  $y$  iff  $|\tau_x - \tau_y| \leq T_x$ .

Thus, an agent cooperates with (donates to) another agent only if the tag of the other agent is sufficiently similar to its own (i.e., within its tolerance). Each agent is given several donation opportunities to randomly interact with other agents in any given generation.

The social comparison rule used for adjusting the strategic values, on the other hand, is adjusted each generation and is based on the performance (as defined by the endowment  $E$  [a real number]) of the other agent as follows:

*Social Comparison Rule.* Agent  $x$  will adopt the tag ( $\tau_y$ ) and tolerance ( $T_y$ ) values of another agent  $y$  iff  $E(y) > E(x)$ .

By using this model, Riolo et al. (2001) demonstrated that substantial cooperation levels can emerge and be sustained. Chen and Prietula (2003) replicated their findings and explored this model further by looking at the particular regimes that emerge with varied population sizes, perceptual errors, and generation lengths. In particular, they tracked the value of the tags and defined a *regime* as a state in which at least 80% of the agents have adopted the exact same tag value. In this paper, we explore mimicry a little further by examining the effects of mimicry when applied to the social donation rule.

### **Adaptive Mimicry: Joining a Group**

Both the Riolo and Chen models examine tag-based cooperation from the standpoint of agents in the donor role, where donors make decisions to donate and where agents in the recipient role have no direct impact on that decision. Future cooperation decisions are influenced through *intergenerational* mimicry opportunities given at the end of a generation. Thus, in these models, mimicry is an adaptively strategic mechanism designed to achieve a particular social goal: to gain the most cooperation possible by adopting the look and behavior of the most successful agents. If we interpret this strategy as adopting norms of conduct for a group that is identified by a tag range, then the strategy is not unlike joining a particularly successful group. As research has consistently demonstrated, group influence on individual behavior can be substantial (e.g., Asch, 1956; Milgram, 1974; for comparison, see Crano, 2000), and imitation is a core component of cultural emergence and adoption (Dugatkin, 2000).

## Deceptive Mimicry: Deceiving a Group

Tags, as visible signs of membership, can be mimicked not only for making a strategic membership change, thereby satisfying a rational social goal, but also for satisfying a different and more tactical but nonetheless rational social goal: immediately gaining the most cooperation you can by *temporarily* mimicking the look (i.e., tag) of the proximal agent. As an extension of the Riolo and Chen models, we incorporate such an *intragenerational* mimicry component to be made by agents in the requesting role. When an agent encounters a situation in which a donation is to be requested from another agent, there is an opportunity for the requesting agent to temporarily mimic (at a cost) the tag of the potentially donating agent *before* making that request. We refer to this as *deceptive* mimicry. This was accomplished by adding a social deception rule:

*Social Deception Rule.* Agent  $x$  will temporarily adopt the tag value ( $\tau_y$ ) of another agent  $y$  at a cost ( $z$ ) iff [*tolerance conditions*] and [*deception conditions*] hold.

We ran a  $2 \times 2$  factorial experiment that examined four forms of the social deception rule and compared them to the base case (Chen model) results. The forms were derived by manipulating two constructs of the rule: the tolerance condition and the deception condition. The four forms were defined by the resulting combination of the condition types.

The *tolerance conditions* define the situations under which the social deception rule is relevant. Consistent with the Riolo and Chen models, the tolerance conditions test the extent to which the potential donator agent's tag is similar to the requesting agent's tag. If the values are not sufficiently similar, then the requesting agent would consider applying the social deception rule. Two tolerance conditions were defined on the basis of whether the tested tolerance trait was the same as the trait used by the tag, or if there was a special trait for that decision:

1. *Same Trait.* The social deception rule used the same tolerance trait as the social donation rule, but the results were inverted:

Agent  $x$  will consider deceiving agent  $y$  iff  $|\tau_x - \tau_y| > T_x$ .

2. *Different Trait.* The social deception rule used a different and separately evolving tolerance trait  $T'_x$  for the rule:

Agent  $x$  will consider deceiving agent  $y$  iff  $|\tau_x - \tau_y| > T'_x$ .

The *deception conditions* define the likelihood of the social deception rule being applied, given that the tolerance conditions are satisfied. Accordingly, two types of deception conditions were examined on the basis of whether deception was certain or determined by the value of a separately evolving trait:

1. *Certain Deception.* If the social deception rule is relevant, it will be applied.
2. *Deception Trait.* There is a separate inheritable trait ( $\delta$ ). Deception will occur if the value of this trait for the agent exceeds the average propensity value of the population for that generation  $g$ ,  $E(\delta_g)$ .

## METHOD AND PROCEDURE

Following the general form of Riolo et al.’s model (2001), in the base case, agents have two inheritable traits: a tag  $\tau \in [0,100]$ , and a tag tolerance threshold  $T \in [0,100]$ . Cooperation occurs when an agent donates to another agent. Donation is done at a cost ( $c = 0.1$ , plus the 1.0 donation) to the donating agent, with the recipient of the donation achieving a benefit ( $b = 1.0$ ). A population of 100 agents was used, with the initial values for tags and tolerances selected randomly from a uniform distribution  $[0,100]$ . On average, for each generation, an agent ( $x$ ) has three opportunities to donate to other agents ( $y_i$ ) via random pairings. For each pairing, if agent  $x$ ’s tag is sufficiently similar to the tag of the other agent  $y_i$  (i.e.,  $|\tau_x - \tau_y| \leq T_x$ ), then agent  $x$  will donate to agent  $y_i$ . At the end of a generation, each agent is compared with another randomly selected agent, and the agent with the lower score adopts the tag and tolerance levels of the higher-scoring agent. This strategy results in the traits of higher-scoring agents being replicated about two times faster than the traits of lower-scoring agents in the population, with the traits of the lowest-scoring agents not being replicated at all.

In the base case and for each manipulation below, 30 replication runs were made per cell. For each replication, there is a 0.1 probability of replication error in any trait. A run consisted of 3,000 generations. Apart from the stated manipulations, all other elements of the simulations were the same as those in the base case. The forms of the social deception rule were made as indicated in Table 1. The specific inheritable traits are shown in parentheses.

**TABLE 1** Classification of manipulations

Deception Condition	Tolerance Condition	
	Same Trait	Different Trait
Certain deception	Form 1 ( $\tau, T$ )	Form 3 ( $\tau, T, T'$ )
Deception trait	Form 2 ( $\tau, \delta, T$ )	Form 4 ( $\tau, \delta, T, T'$ )

### Form 1: Same Tolerance Trait, Certain Deception

Conditions were similar to the base case and two traits were used: tag and tag tolerance. Before the social donation rule was invoked, agent  $x$  would deceive the donor agent by temporarily mimicking agent  $y$ ’s tag if the tags of the paired agents were *not* within the tag tolerance of  $x$  (i.e.,  $|\tau_x - \tau_y| > T_x$ ). In other words, agent  $x$  would deceive those it does not consider “its kind.”

### Form 2: Same Tolerance Trait, Deception Trait

An inheritable trait was added to the base case: *deception propensity*,  $\delta$ . Therefore, agents had three inheritable traits: tag, tag tolerance, and deception propensity. Deception propensity was initialized via a random draw from a uniform distribution  $[0,100]$ . The soliciting agent  $x$  would deceive a potential donor agent  $y$  only if  $x$ ’s tag differed from  $y$ ’s tag as defined by its tag



tolerance (i.e.,  $|\tau_x - \tau_y| > T_x$ ) and if  $x$ 's *deception propensity* exceeded that of the population average of that generation.

### Form 3: Different Tolerance Trait, Certain Deception

A *deceptive tolerance* trait was added to the base case model. Agents had three inheritable traits: tag, tag tolerance, and deceptive tolerance. Each agent now had two tolerance traits defining two thresholds (i.e., tag tolerance threshold  $T$  and deceptive tolerance threshold  $T'$ ), reflecting the dual decision contexts in the game (i.e., cooperation, deception). For each pairing, agent  $x$  would deceive agent  $y$  if the difference between tags exceeded  $x$ 's deceptive tolerance threshold (i.e.,  $|\tau_x - \tau_y| > T'_x$ ).

### Form 4: Different Tolerance Trait, Deception Trait

The two inheritable traits examined in Form 2 (deception propensity  $\delta$ ) and in Form 3 (deceptive tolerance  $T'$ ) were combined. Agent  $x$  would deceive potential donor agent  $y$  if the difference between their tags exceeded  $x$ 's deceptive tolerance threshold (i.e.,  $|\tau_x - \tau_y| > T'_x$ ) and if the deception propensity  $\delta$  of  $x$  exceeded that of the population average at generation  $g$ ,  $\delta_x > E(\delta_g)$ .

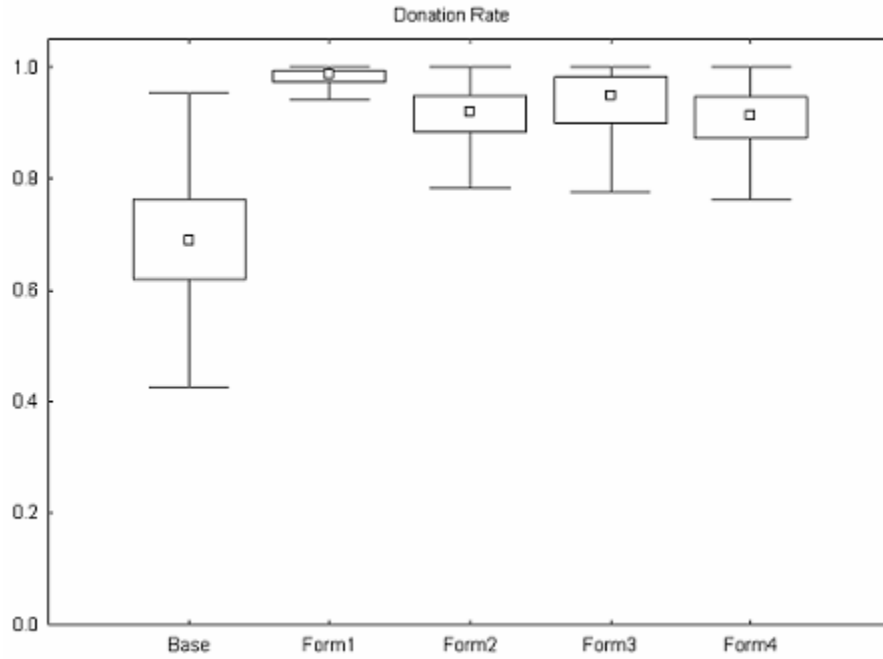
## RESULTS

A brief overview of the results follows. The simulation results indicate that the average level of cooperation achieved (i.e., the donation rate) is more than 90% in all four manipulations and higher than the levels achieved in the base case model (Figure 1). Thus, agents learn that it is economically beneficial to deceive (at a cost) in order to gain tactical advantages (via donations) over other agents. The consequence of this is that substantially more agents are deceived into cooperating through the use of deceptive mimicry. This study is small and necessarily constrained; therefore, our embryonic findings are presented as assertions rather than conclusions; they should be examined later in depth.

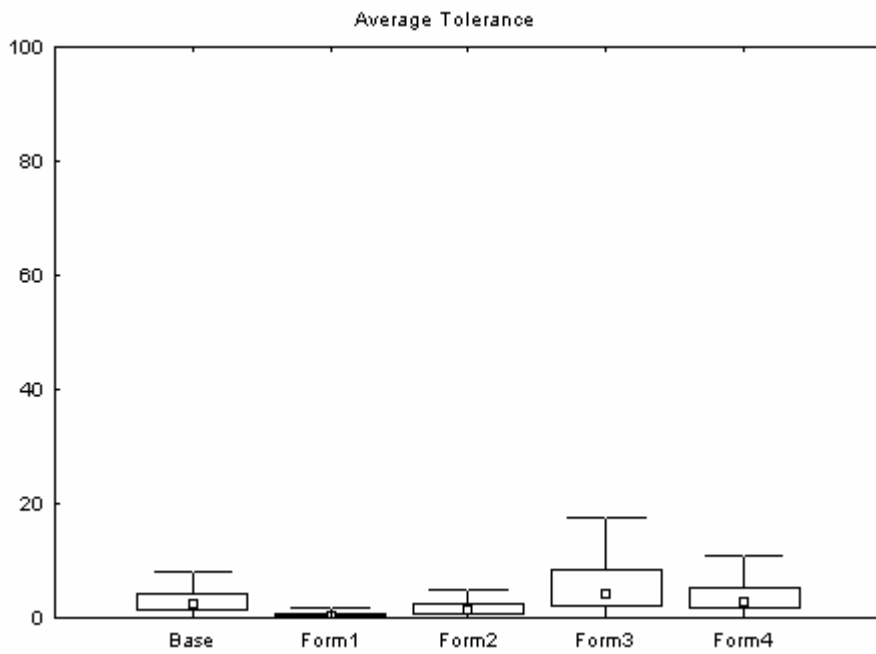
*Assertion 1.* Deception (as deceptive mimicry) generated higher cooperation levels (and less variance) than equivalent groups without such deception.

An examination of Figure 1 shows that the highest donation rates and lowest variance in the study are found in Form 1. Recall from Table 1 that this form retains the same two traits as the base case but adds a decision procedure (deceptive mimicry) that relies on those two traits. The reason for this can be found, in part, by examining one of those traits: tolerance,  $T$ , as shown in Figure 2, indicating the low tolerance of Form 1.

Here, we compare the two cases (base and Form 1). In essence, the base case has two driving forces (see Chen and Prietula, 2003). First, high-tolerance results in more donations at a cost to the donor; therefore, tags of highly tolerant agents will be replicated at a comparatively lower level, so the associated high tolerance will be propagated at a lower rate. Second, the agents that benefit from donations are those whose tags fit within the tolerances. Consequently,



**FIGURE 1** Donation rates for base case and all manipulations



**FIGURE 2** Average tolerance  $T$  for all manipulations

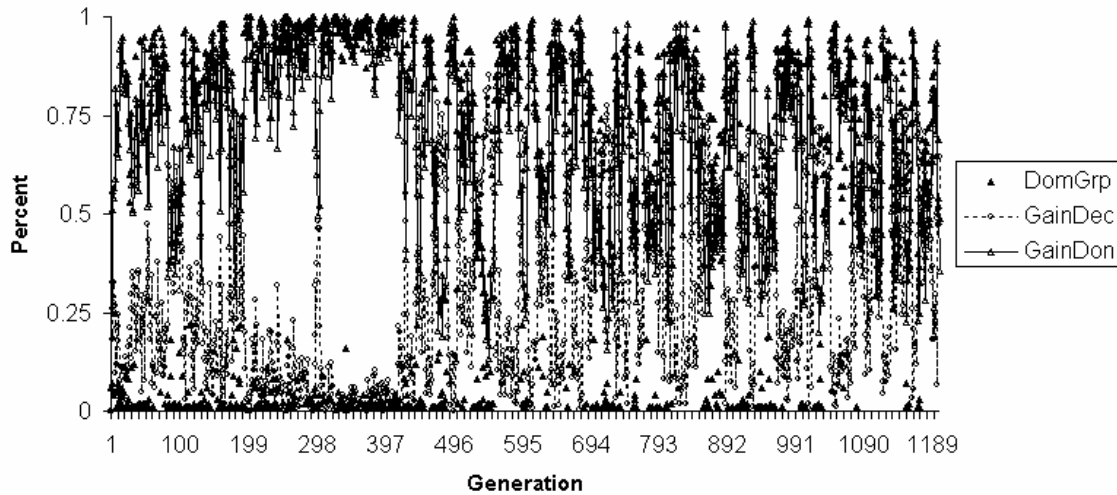
as lower tolerances propagate, the tags associated with the lower tolerances propagate. This results in a rapid “takeover” of one type of tag into a regime, since tags that are not similar do not receive donations. Thus, there is a forced, albeit opportunistic, convergence to a particular tag value as the tolerance converges.

Once a regime dominates, the likelihood of one agent encountering another agent that has a substantially different tag drops, and so does the value of having a small tolerance, since it becomes nondiscriminatory. However, through mutation, agents that have tags that are not the same but that are sufficiently similar emerge, and they can receive donations from agents in the dominant regime. Furthermore, some of these agents will have comparatively smaller tolerances, which will make the donations asymmetric (i.e., they are similar, so they receive donations, but they have smaller tolerances, so they will not donate). These free-rider agents will rapidly propagate and take over as a new regime. As can be seen, however, each regime lays the foundation for its own collapse, and all regimes bear the same fate: they collapse from within. As a consequence of this pattern, the base case tolerances oscillate with high variance, causing a wide variance in donation rates.

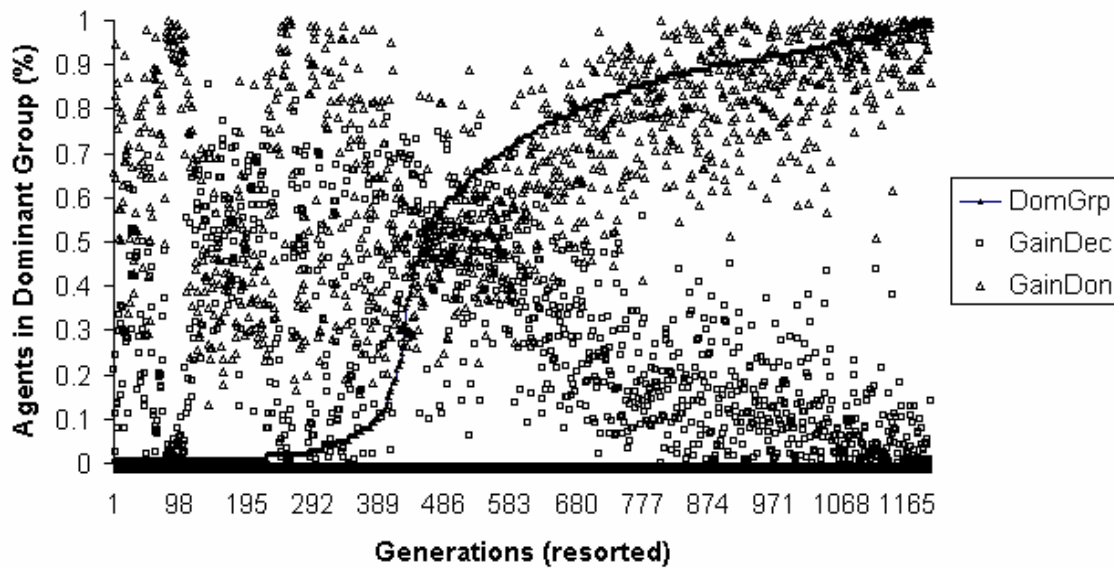
Form 1 affords a slightly different twist. As in the base case, agents with higher tolerances donate more (via the social donation rule), resulting in lower endowments and lower propagation rates (via the social comparison rule). Accordingly, the average tolerance in the population falls. In this group, however, agents also incorporate the social deception rule, which results in higher donation rates for agents that deceive other agents that are not like themselves. This condition also results in movement toward lower tolerance values. Figure 2 shows the low tolerance  $T$  of Form 1 resulting from this confluence of pressure. The results from the two are remarkably high donation rates (see Figure 1).

Note two other influences. As in the base case, there is pressure to adopt similar tags (to fit within the tolerances and receive donations), which leads to the emergence of regimes. However, there is also indirect pressure to be different (via low tolerance to afford more opportunities to deceive others and receive donations), which resists the emergence of regimes. What this implies is that although regimes emerge, additional events lead to their demise because not only is there a subsequent emergence of free-riders (as in the base case), but there is also an emergence of deception. When all agents are sufficiently similar (i.e., during a regime), tolerance generally is not selective (in the base case), but in this form, low tolerance can be quickly exploited by shifting to a deception strategy. The consequences are shorter regimes and periodic shifts of deception. In other words, when regimes emerge, deception is low. Then deception sets in, and gains by deception dominate gains by donation. Figure 3a illustrates a typical sequence of the cycling between generations. In this figure, the percent of agents in the dominant group is depicted as black triangles (which may or may not be a regime), gains by donation are depicted as white squares, and gains by deception are depicted as black squares. Note that gains by donation are closely aligned with the emergence of the dominant group and that overall, deception strategies account for a relatively lower percentage of gains overall. This can be seen by viewing the same data as shown in Figure 3a but sorted by the size of the dominant group (lower to higher, Figure 3b). When no particular group is dominant (left of inflection), there is turbulent competition between strategies (donation, deception). When a regime takes over, however, donation strategies (among the dominant agents) are used most often and are most successful. An analysis of the data revealed similar results for all manipulated conditions.

*Assertion 2.* Deception is a strategy whose frequency (as an indicator of success) varies inversely with group dominance.

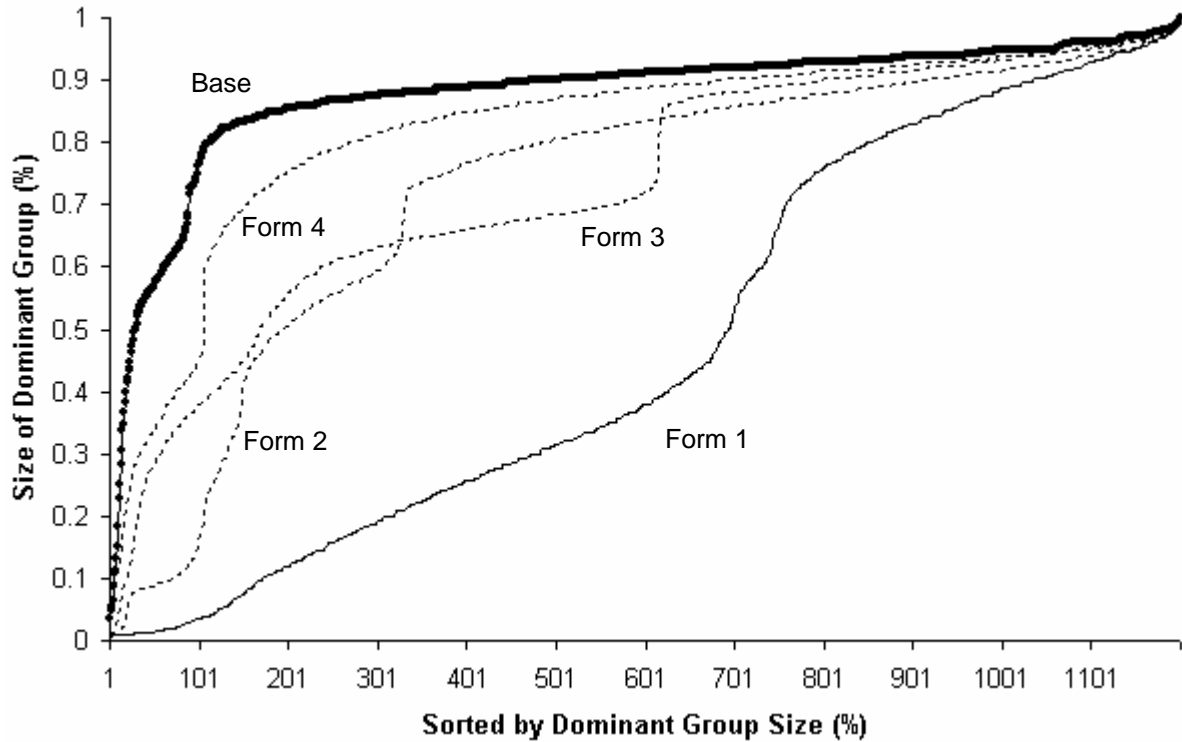


**FIGURE 3a** Source of endowment gain and size of dominant group (form 1)



**FIGURE 3b** Source of endowment gain sorted by size of dominant group (form 1)

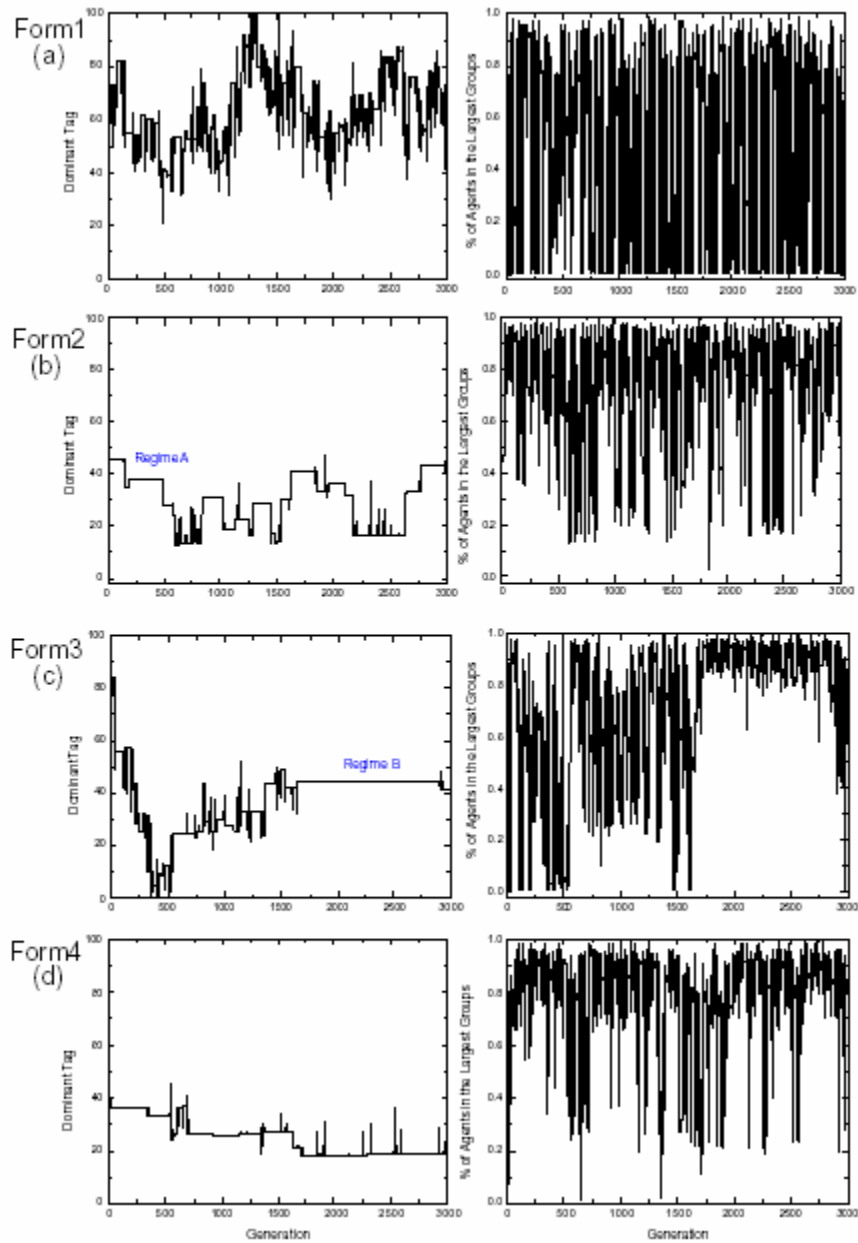
Our final assertion is based on examining the impact that deception has on regimes. In the base case, regimes were limited but could last for a substantial time, and regime takeovers were rapid. This can be shown by taking the average size of the dominant group (in percentage of total agents) over generations for a set of runs, then putting them in ascending order in a graph. The resulting *regime graph* shapes will reflect the relative time spent in regime dominance and transitions. Because of Assertion 2, the shapes will also reflect the relative time spent with groups of agents behaving with cooperative or deceptive strategies; more dominance indicates more gains by donations than by deception. Figure 4 shows such a graph. Note that the base case



**FIGURE 4** Average sorted dominance sizes for all forms

has the smallest number of small dominant groups (reflective of nonregimes), while Form 1 has the largest number. Forms 2, 3, and 4 reside within the two extremes. Figure 5 illustrates specific examples of regime emergences in the four forms. As can be seen, when the social deception rule was given the opportunity to vary traits independently (i.e., Forms 2, 3, and 4), two effects occurred. First, the impact of deception on regime emergence and sustainability was mitigated. Regimes now emerged and were sustained, but not to the higher levels of the base case (sans deception). Second, cooperation (as donation rate) was reduced, but not to the lower levels of the base case (see Figure 1). The reason for the differential effects was the *decoupling* of the traits of the rules underlying the strategies. In the base case, the behavior (deception) was introduced with little flexibility and independence. The consequence of this was high cooperation but minimal emergence of regimes. When additional degrees of freedom were added (via traits), levels of cooperation dropped, but regimes could emerge.

*Assertion 3.* Regime emergence is affected by the flexibility (independence) of deception strategies.



**FIGURE 5** Dynamics of regimes

## CONCLUSION

Riolo et. al (2001) demonstrated that cooperation can emerge in groups where decisions to cooperate are based on simple rules of social comparison embodied in the social donation rule and the social comparison rule. We explored that model further and examined how minor adjustments and the addition of deception can impact cooperation and the emergence of agent groups (regimes). We can view the set of rules we have described as a portfolio of routines or social algorithms in which an agent will engage in response to events in the social environment, where the social environment is defined perspective as “the other agents.” As events relative to

the routines change, the agents have the ability to change components of the routines themselves. Note that in the rules described, the behaviors are invariant, but the *conditions* under which they are engaged are variable, and it is these condition components of the rules that adapt over time. In this research, we essentially modified how different rules (and therefore behaviors) were interlinked and examined the resulting impact on cooperation and group/regime emergence.

We explored how the structure of routines and interactions can impact behaviors, not the intentionality of the routines themselves. These agents do not have active goals, but we may assume that the routines are derivative of goals and intentionality. Note that the social goal in this work is simple, implicit, and individualistic (i.e., to maximize endowment), but the effects of the social routines brought to bear on this goal have social (sometimes beneficial) consequences, such as the formation of groups and cooperation. Thus, regimes and cooperation in these models are by-products of (and barometers for) strategies interacting with collective behavior over time.

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## ONTOLOGY FOR AGENT-BASED MODELING AND SIMULATION

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### ABSTRACT

Ontologies provide a formal methodology for establishing a common vocabulary; for defining concepts and the relationships among those concepts with a particular domain; and for reasoning about the objects, behaviors, and knowledge that constitute the domain. We present an ontology for agent-based modeling and simulation, which has become an important and popular paradigm for the computational social and natural sciences. However, this paradigm tends to be applied in an ad-hoc fashion, leading to questions about underlying assumptions in an agent-based model, verification of the software implementation as a representation of that model, and validation of hypothesized conclusions inferred from data produced by computer simulation experiments. An ontology provides a formal, logical knowledge representation that supports automated reasoning. Such reasoning capability provides for consistency checking of the concepts and relationships in an agent-based model, can infer the assumptions inherent in a model, can infer the assumptions and the parameters inherent in a simulation or software representation of a model, and can enforce adherence to formal methods or best practices for verification and validation testing. These reasoning tasks direct, or at least inform, the modeler relative to relevant techniques and methods in the agent-based paradigm. The reasoning capability also provides a framework for automated generation of software code, automated design and execution of simulation experiments, and automated generation and execution of validation tests for those experiments. We use the standard Ontology Web Language (OWL) to provide a complete, detailed ontology of agent-based modeling and simulation, and we show how the ontology is used as part of the modeling and simulation process.

**Keywords:** Agent-based modeling, agent-based simulation, automated reasoning, ontology, artificial intelligence, discrete-event simulation

### INTRODUCTION

Agent-based modeling and simulation has become an important and popular paradigm for the computational social and natural sciences; however, this paradigm tends to be applied in an *ad hoc* fashion based on a subjective understanding of the agent-based concept. Different techniques for construction of the model and implementation of computer simulations are often accompanied by underlying assumptions that are unknown to the researcher or cannot be explicitly characterized for the particular model. In addition, manifestation of artifacts in the computer simulation can lead to legitimate questions about the verification of the implementation and validation of hypothesized conclusions. Model-to-model comparison, or docking, can expose

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these issues because it forces the researcher to confront some of these underlying assumptions while analyzing differences between the two models. However, this still is no guarantee against situations where the two models can inadvertently hide possibly relevant assumptions.

Ontologies provide a formal methodology for establishing a common vocabulary; for defining the concepts and the relationships among those concepts within a particular domain; and for reasoning about the objects, behaviors, and knowledge that constitute that domain (Russell and Norvig, 1995; Miller et al., 2004). We present an ontology for agent-based modeling and simulation. The ontology is general in that we define the terms, concepts, and relationships for the process and objects of agent-based modeling and simulation without reference to a specific application domain. Such an ontology provides a solution to the issues of ad hoc construction and subjective interpretation in three ways. First, the establishment of a common vocabulary provides unambiguous interpretation of terms. Next, the definition of concepts and their relationships makes explicit the assumptions that accompany those concepts. Finally, the reasoning capability of this ontology provides a framework for automatic generation of software programs, automatic composition of agent-based models to form new simulations, automatic design and execution of simulation experiments, and automatic generation of validation tests for those experiments. We use the standard Ontology Web Language (OWL) to provide a complete, detailed ontology of agent-based modeling and simulation. Our ontology is too large to include in this paper, but the files can be obtained from our Web site (Christley, 2004). To better associate the discussion with the ontology, in the remainder of this paper, we use *italics* when referring to specific classes or properties in the ontology.

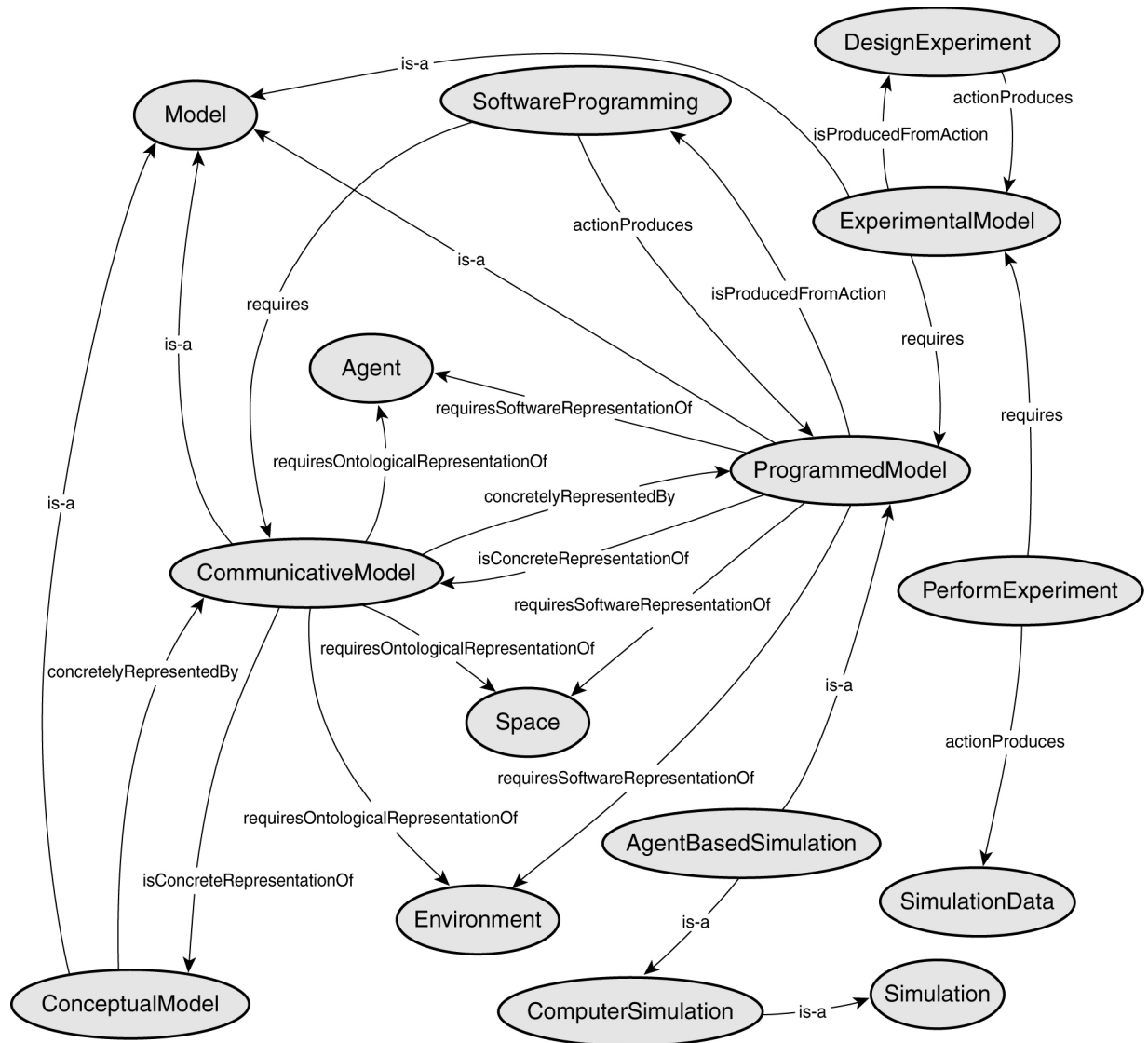
## **AGENT-BASED MODELING AND SIMULATION**

The three basic reasons for using simulation are (1) to design something that does not yet exist, (2) to train people when the real task is costly or dangerous, and (3) to understand some real-world phenomena as part of scientific study. Although the design task and scientific inquiry can be considered similar to each other, all three uses have different processes and techniques. We concentrate on using simulation to understand real phenomena. Simulation provides (1) finer control over the complete system than is usually possible with the real system and (2) the ability for extensive what-if analysis through tweaking of parameters and altering the assumptions in the underlying theory. However, simulation injects a new problem into the scientific method in that a model of the theory for the phenomena must be implemented in a concrete representation so that it can be manipulated and simulated. Thus, the question becomes not just is the theory consistent with the real phenomena, but also is the concrete model representation an accurate description of the theory and is the execution of that model an accurate representation of the processes in the theory? The analysis needs to be taken one step further to the question: Are the implications of the simulation consistent with the implications of the theory? If not, the simulation does not provide the logical step required to determine whether the theory correctly captures the real phenomena. Most of the work with modeling and simulation involves doing the proper checks to provide a high degree of confidence for taking that logical step.

Although we focus on agent-based simulation, much is shared with general discrete-event simulation (Banks, 1998; Banks et al., 2001). Therefore, we highlight the differences where appropriate while relying on core fundamentals that have made discrete-event simulation a successful field. Despite being called agent-based simulation, the methodological differences lie more in the constructed models versus the implementation of those models in a computer

simulation. When viewing a phenomena through the agent-based paradigm, one sees agents interacting with other agents within an environment and within a spatial structure. An agent is the conceptual unit of interest, and there may be multiple agents. The concept serves to define a boundary between what is internal to the agent versus what is external. By agent, we are referring to a prototypical concept and not an individual. The environment and space can also be considered agents because they may have interaction mechanisms, but they are generally differentiated since their boundaries are not well defined. The environment (or possibly multiple environments) represents state information that is external to the agents. The environment could be global state for all agents, or it may be local state in conjunction with the spatial structure with its defined notions of locality. Space can be two or three dimensional physical space, or it may be a virtual construct, such as a network. Space is different from the environment in that it provides measures, like distance or connectivity, and typically only holds state specific to those measures. Multiple spaces can exist, each with its own set of measures. A cognitive agent maintains, among other things, internal state about what it perceives about the environment and space; so in a simulation, the environment and space represent actual truth versus what a cognitive agent might perceive as truth.

By modeling, we refer to the process of representing something with something else; it can be an abstract model whereby the representation simplifies or removes extraneous detail to capture the conceptual properties, or it can be a concrete model, which, oppositely, specifies a more detailed representation. By simulation, we refer to the process of enacting the model to learn consequences and to compare against the real phenomena of interest. Four key modeling concepts represent different model types: *ConceptualModel*, *CommunicativeModel*, *ProgrammedModel*, and *ExperimentalModel* (Balci, 1998). The *ConceptualModel* is a verbal, abstract model that states the theory or hypotheses for the proposed agent-based representation and the goal and objectives of the corresponding agent-based simulation. A *ConceptualModel* also provides descriptive specifications for the agent, the environment, the space, and the actions and properties for those constructs. A *ConceptualModel* is made more concrete by constructing a *CommunicativeModel*. In our process, the *CommunicativeModel* is a domain-specific ontology that fits within the general agent-based ontology. Objects in the model, such as agents, environment, and space, are represented through subclasses of those concepts in the general ontology. Subclasses are also created for the properties of those objects as well as their actions. Through *SoftwareProgramming*, a *ProgrammedModel* is constructed from the *CommunicativeModel* by representing the ontological concepts with concrete implementation in software code. A *ProgrammedModel* is one that can be executed as a *ComputerSimulation*. In a later section we discuss how the *ProgrammedModel* can be automatically generated from the *CommunicativeModel* using a reasoner. Finally, *DesignExperiment* involves using a *ProgrammedModel* to produce an *ExperimentalModel*, and *PerformExperiment* will cause the *ExperimentalModel* to produce *SimulationData*. *Validation* can use a *StatisticalTest* to compare the *SimulationData* against *EmpiricalData*. This is a simplified example of the modeling and simulation process as there are many more actions and concepts involved. Figure 1 shows a portion of the semantic network representing our formalized knowledge about agent-based modeling and simulation.



**FIGURE 1** Relationships among models and agent, space, and environment

## ONTOLOGY FOR AGENT-BASED MODELING AND SIMULATION

When developing an ontology for agent-based modeling and simulation, we must clearly distinguish between the concepts and relationships that comprise the process of modeling and simulation versus the agents and behaviors in the domain of interest; yet these two are intimately related. The latter is called the domain-specific ontology, and the former is called the general ontology. The relationship between the two is simply that the domain-specific ontology provides more detail concepts and properties. For example, the general ontology has the concept of an agent that has some undefined properties and behaviors, but the domain-specific ontology will have the concept of a *SoftwareProgrammingAgent* that has defined properties like skill and resources and defined behaviors like writing code and fixing bugs.

Our ontology is implemented in OWL (2004) using Protege (2004). OWL represents knowledge as a semantic network with nodes as classes and directed edges as properties. We have more than 100 classes in our ontology, with a similar number of properties. The root classes include *Agent*, *Environment*, *Space*, *Action*, and *Property* for concepts in the agent-based paradigm. *Action* and *Property*, along with *Model*, *Simulation*, *Representation*, *DataSource*, *Test*, and *Assumption*, are root concepts for the process of modeling and simulation. *Measure*, *Time*, and *Event* are concepts that appear in any general ontology. *Action* and *Property* are both concepts about the modeling process as part of the model, so we have *AgentAction*, *EnvironmentAction*, *AgentProperty*, and *EnvironmentProperty* subclasses for those concepts in the agent-based model; while, *ModelerAction* and *ModelProperty* subclasses are concepts about the modeling process. The classes that refer to concepts in the agent-based model stop at a general description, so more specialized subclasses would be provided by the domain-specific ontology.

Our ontology focuses on the process of modeling and simulation, so *ModelerAction* includes subclasses like *InputModeling*, *ParameterEstimation*, *DesignExperiment*, *Verification*, *Validation*, *ModelToModelComparison*, and others. The *Model* class encapsulates all types of models, although we concentrate on *ConceptualModel*, *CommunicativeModel*, *ProgrammedModel*, and *ExperimentalModel* as described in the previous section. *Simulation* can be split between *ComputerSimulation* and *PhysicalSimulation*, with *AgentBasedSimulation* as a subclass of the former. *Representation* deals with representational forms like *OntologyRepresentation* as given by a *CommunicativeModel* or *SoftwareRepresentation* as embodied in a *ProgrammedModel*. The *DataSource* class conceptualizes all sources of data, such as *EmpiricalData*, *RandomNumberGenerator*, and *SimulationData*. *Test* refers to all forms of testing, especially specialized classes of *StatisticalTest* used in *InputModeling* and *Validation* actions. Finally, we have the concept of *Assumption*, which our reasoner will use to categorize the assumptions within the agent-based model. All of the concepts in the general ontology establish a common vocabulary that can be shared across domain-specific ontologies and provide unambiguous interpretation of conceptual terms.

In addition to classes, OWL has properties that define the relationships among concepts. The properties themselves are concepts that can form an inheritance hierarchy. Many properties are found in most ontologies that represent general relationships such as composition with *isPartOf* and *isBunchOf*, dependencies like *requires*, ordering of events with *isBefore*, *isAfter*, *overlapsWith* among others, or actions like *has* and *produces*. We specialize many of these relationships for agent-based modeling so that we can perform more accurate reasoning tasks. For example, a *NormalDistribution* *hasParameter Mean* and *hasParameter Variance*; thus, we will be able to reason that a simulation using a *NormalRNG* to produce normally distributed random numbers will require two parameters to define the distribution. Likewise, *PerformExperiment* *requires* an *ExperimentalModel* that *isProducedFromAction DesignExperiment* and that *ExperimentalModel* *requires* a *ProgrammedModel* that *requiresSoftwareRepresentationOf Space, Environment, and Action*. As for classes, the properties establish a common vocabulary for relationships, and the properties and classes together form our complete knowledge base for agent-based modeling and simulation.

## ONTOLOGICAL REASONING

An ontology formalizes our knowledge base, so it is possible to perform automated reasoning on the process of modeling and simulation as well as on the models and simulations themselves. Reasoning on a model and its corresponding simulations provides us with a set of inferred assumptions for the model, a set of inferred assumptions for the representation of the model as a simulation, and a set of inferred parameters for the simulation. Reasoning on the process of modeling and simulation provides the potential for automating many of the primary tasks in the process, including software programming of the simulation, design and execution of computer simulation experiments, and validation of experimental results. We describe each of these capabilities in more detail in the following sections.

### Inferred Assumptions

An *Assumption* can be further categorized into a *DataAssumption* or a *StructuralAssumption*. A *DataAssumption* refers to questions about how data are collected and analyzed, so *InputModeling* of *EmpiricalData* to come up with an appropriate probability distribution introduces a *DataAssumption* that the distribution is an appropriate representation of the *EmpiricalData*. A *GoodnessOfFitTest* can be used to validate that assumption. A *StructuralAssumption* refers to questions about the composition of the model and the conceptual representations in the model. Concepts in the model and the relationships among those concepts, as abstract constructions of reality, imply assumptions about how those constructs are represented and whether the relations are correct. Viewing a *CommunicativeModel* as a semantic network, a *StructuralAssumption* asks whether the nodes are appropriate concepts, whether the edges are appropriate properties, and whether concepts linked by an edge is an appropriate relationship. Assumptions can either be falsified or failed to be falsified (validated), much like a null hypothesis, if an appropriate test can be performed. For the *InputModeling* example above, the *GoodnessOfFitTest* performs this function, while experiments and tests would need to be performed to provide *Validation* of a *CommunicativeModel*.

Not all assumptions can be tested, such as whether a *CommunicativeModel* accurately represents the concepts in a *ConceptualModel*, because the *ConceptualModel* is a verbal model lacking a formal description. The best that can be performed is a *SubjectiveTest* such as *FaceValidity*. The reasoner is able to infer all of the assumptions in an agent-based model from the *CommunicativeModel* through to the *ExperimentalModel*, and our goal is for the reasoner to determine whether these assumptions can be validated and what appropriate test should be used. The assumptions can be inferred by looking at the properties of the classes and questioning whether the relationship among the classes implied by the property is correct. With all of the assumptions clearly laid out, the modeler obtains a broader view of how the agent-based model can be validated and may gain insights into model changes to strengthen the overall theory.

### Inferred Parameters

A *Parameter* is a *ModelProperty* that is considered as an input to the model. A *Parameter* may be given a value through the *ParameterEstimation* action, or the modeler may *AssignParameterValue* as part of *DesignExperiment*. The *Parameter* may have a constant value throughout the simulation, or it may be attached to a *DataSource* like *EmpiricalData* or

sampled from a *Distribution* created by a *RandomNumberGenerator*. An *InitialCondition* is a *ModelProperty* similar to a *Parameter*, but an *InitialCondition* assigns values to state variables for just the start of the simulation. In contrast, a *Parameter* is persistent through the whole simulation run. Like a *Parameter*, an *InitialCondition* may be assigned a specific value or sample values from a *DataSource*. The reasoner has the capability to determine all of the *Parameters* and *InitialConditions* in an agent-based model. It can do this because the ontology encodes knowledge of the properties of agents, environment, and space, so a logical query on the properties provides the list. The result of such a logical query becomes part of the automatic design and execution of experiments, whereby the query results are presented to the modeler for specification of input values.

## Automated Software Programming

Complete automated software programming of the simulation requires more than a *CommunicativeModel* embedded within the agent-based ontology because it does not provide sufficient detail to generate source code for all agent and environment actions. Attempts to provide high-level specification of software can fail because too many assumptions must be made about the functionality and purpose of the software, or the specification process may be more cumbersome than directly writing the code (Rich and Waters, 1988; Flener and Popelmsky, 1994). However, we believe an intermediate approach is both feasible and useful. The *CommunicativeModel* can be translated into the high-level structure of the *ProgrammedModel*. This process includes generation of the object-oriented classes for the agent, environment, and spatial constructs in the model with instance variables for the properties of those constructs, and accessor, constructor, and stub methods for the constructs' actions. Such an intermediate approach means the modeler can focus upon the software implementation for the fundamental behaviors in the model while much of the "glue code" required to make the simulation work is handled automatically.

## Model Composition

Another fruitful area of automation is the composition of multiple, separate *CommunicativeModels* into a single *ProgrammedModel*. These *CommunicativeModels* can be created by the same modeling group or different groups. Composition of *CommunicativeModels* requires semantics of the interactions among the models. We separate the composition process into two situations according to whether these *CommunicationModels* consist of the same or different collection of entities:

1. Two *CommunicativeModels* representing the same collection of entities that interact together over time: We consider these two *CommunicativeModels* as representations of the same world phenomena. One of the research groups at the University of Notre Dame models the evolution of natural organic matter (NOM, a complex mixture of molecules that is heterogeneous in structure and composition) by using the agent-based modeling approach (Xiang et al., in press). As NOM passes through an ecosystem, it is acted upon by a variety of reactions. To satisfy different research interests, two communicative models are developed. One models the physical reaction behaviors of NOM, and the other models the chemical reactions between NOM and its environment.

A new, third model can be generated that includes both of these two behaviors by composing the two *CommunicativeModels*.

2. Two *CommunicativeModels* representing a different collection of entities that interact together over time: The two *CommunicativeModels* are considered as representations of different world phenomena. In the example we describe above, the microbes, fungi, and bacteria exist in the natural environment and interact with NOM; in the current *CommunicativeModels*, they are represented as a set of environment state variables. It is more realistic that these microorganisms be represented as agents in the NOM world and their interaction with molecules be explicitly modeled. When there is an existing model that models the life cycle of the microorganisms (microorganisms can reproduce themselves and die) with an agent-based modeling approach, creation of the new model can benefit from the composition of these two existing models.

The composition of *CommunicativeModels* requires merging different domain-specific *CommunicativeModels* together. This merging process can be automated with ontological reasoning. Three possibilities for semantics arise for these two situations: the semantics may either be already described in both *CommunicativeModels*, in only one model, or in neither of the models. In the first situation, both *CommunicativeModels* most likely have the same semantics. In the second situation, the semantic are most likely existing in one *CommunicativeModel* but not in another (partially overlapped).

One important task residing in the merging process is determining whether two domain-specific concepts are the same in two *CommunicativeModels*. Determining the “structural equivalence” of two concepts by comparing the incoming edges and outgoing edges of these two concepts is one way to complete the task. Much research has addressed matching the concepts by using sophisticated algorithm and artificial intelligence techniques, such as machine learning (Noy and Musen, 2000; Doan et al., 2003). The merging process may involve integration of new knowledge, such as specifying the new interaction among agents, which requires the input from model developers. With complete knowledge representation, the composition process can be done automatically.

## Automated Design and Execution of Experiments

Automated design of simulation experiments can be implemented through manipulations of the *ProgrammedModel*. Such manipulations include basic assignments of values to *Parameters* and *InitialConditions*, enabling or disabling of *Actions* for the *Agents*, *Environment*, and *Space*, or even completely different implementations for those constructs. Here we take the viewpoint that an experiment works within the framework of a *CommunicativeModel* and that manipulations to that model fall outside the domain of the *ExperimentalModel*. However, most model manipulations can be supported as long as the possible changes are encapsulated through ontological concepts in the *CommunicativeModel*. For example, suppose you have designed a model and corresponding simulation whereby the agents interact in a two-dimensional continuous space using an Euclidean distance neighborhood measure, and you decide you want to replace the space with a random network structure connecting the agents. Changing the spatial



structure will create a logical inconsistency because a network does not have a Euclidean-distance neighborhood measure. The inconsistency is resolved by manual alteration of the *ProgrammedModel* to utilize a different neighborhood measure. In contrast, if the original *CommunicativeModel* had both spaces, then a general concept would have been required to encapsulate the neighborhood measure; the result being the *ProgrammedModel* that allows for automatic manipulation, via a *Parameter*, of the spatial structure through use of a generalized neighborhood measure. This is not to say that one is more capable than the other, but because we have taken an intermediate approach to software code generation, inconsistencies due to model changes outside of the *ExperimentalModel* may not be automatically resolved within the *ProgrammedModel*.

Once an *ExperimentalModel* has been designed, it can be executed to produce *SimulationData*, which can then be validated. One execution of a simulation is not sufficient; numerous executions, or replications, of the *ExperimentalModel* must be performed with different seed values for any *RandomNumberGenerator* in the simulation. The reasoner can automate these replications because knowledge of the seed values is part of the ontology. Likewise, a modeler does not generally design a single experiment; experimentation is often an iterative process whereby experimental results are analyzed, changes are made to the *CommunicativeModel*, those changes flow through to the *ProgrammedModel*, and a new *ExperimentalModel* is designed. This iterative process continues until the modeler feels that the *CommunicativeModel* has been sufficiently validated. At this point, the next step depends upon the purpose of the simulation. Presuming that the simulation is for scientific discovery, *SensitivityAnalysis* is an example action that can be performed to better understand the role of the model parameters, or experiments with different model parameters or design may be performed to generate hypotheses that can be tested against the real world phenomena.

## Validation of Simulation Experimental Results

*Validation* is the process of comparing a model against the real world phenomena it represents. All *Validation* is based on a *Test* that decides whether two things are same or not. There are weak tests and strong tests. A weak test is a *SubjectiveTest* that does not have a well-defined decision procedure. A *SubjectiveTest* includes such things as a *VisualTest*, whereby you make a visual comparison of two graphs, or *FaceValidity*, whereby a knowledgeable user makes a determination if the model appears reasonable. A strong test is generally associated with a *StatisticalTest* where a formal mathematical decision procedure exists to objectively make a determination. Computers have difficulty performing *SubjectiveTests*, but they excel at *StatisticalTests*, so the reasoner can perform automatic validation provided it has sufficient knowledge about what type of *StatisticalTest* is appropriate for the *SimulationData* provided by an experiment. Many statistical tests exist, and formalizing all of them in our ontology is a large task; however, we incorporated many of the standard techniques like *GoodnessOfFitTest*, *ConfidenceInterval*, *AnalysisOfVariance*, *TestOfMeans*, and *TimeSeriesAnalysis*.

One particular form of *Validation* introduced by Axtell, et al. (1996) is *ModelToModelComparison*, by which two simulations are compared. The original definition has the same *CommunicativeModel* but different *ProgrammedModel*, possibly written in different programming languages or using different simulation toolkits, and correlated *ExperimentalModels* are designed and their *SimulationData* are compared. *ModelToModelComparison* provides a good test to validate that the *ProgrammedModel* is an

accurate representation of the *CommunicativeModel*, so differences indicate that artifacts exist in the *ProgrammedModel*. Takadama and Fujita (2004) propose the notion of cross-element validation that makes small changes, one element at a time, in the *CommunicativeModel* and compares the experimental results. For such an experiment, the Bonferroni approach can be used, if the *SimulationData* is a fixed sample size, to produce a confidence level of whether the two models are statistically similar or different. We consider both the original definition and cross-element validation to be forms of *ModelToModelComparison*. Likewise, our iterative description of the experimental process allows for the possibility of *ModelToModelComparison* between *CommunicativeModels* as they evolve from one iteration to the next. With knowledge of multiple programming languages and multiple simulations toolkits, the reasoner can automatically generate multiple *ProgrammedModels* from a single *CommunicativeModel*, allowing for greater experimentation.

## FUTURE WORK

Our discussion of simulation in general has been brief; we described key areas that we consider relevant to agent-based modeling and simulation but omitted some areas completely. In the areas covered, our discussion is not as encompassing as we would like. However, we have presented a high standard for automation of many simulation tasks. Going forward, we intend to implement tools specific to agent-based modeling that can perform these tasks and put them in practice on a couple of actual agent-based simulations. This should help elicit more issues that are not apparent just from the theory. One of our key assumptions is the completeness of our ontology, which makes many of the automated tasks possible. A more realistic scenario is to assume incomplete knowledge as well as uncertainty; then we use a probabilistic reasoner for making decisions and a learning algorithm to accumulate additional knowledge. This is very much what a modeler does as part of the scientific inquiry into a phenomenon; a useful tool will work alongside the modeler, helping to increase the knowledge base while automating many of the mundane tasks.

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## USE OF ROBUST AND EFFICIENT METHODOLOGIES IN AGENT-BASED MODELING: CASE STUDIES USING REPEATED MEASURES AND BEHAVIORAL COMPONENTS IN THE MABEL SIMULATION MODEL

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### ABSTRACT

In recent years, the modeling of realistic relationships by agent-based models (ABMs) has been gaining significant ground because of the ability of ABMs to overcome the generalizations and statistical moment assumptions of traditional modeling approaches. ABMs follow a bottom-up approach to modeling, allowing issues of scale, time, and space to be taken into account simultaneously. This paper uses case studies as examples to demonstrate these significant properties in an ABM environment that also incorporates and utilizes traditional statistical assumptions and properties at an individual agent level. In this way, the design of individual agents can be used to more accurately represent existing real-world relationships and reduce the level of uncertainty in predicting individual and collective agent behaviors for sustainable futures. Specific case studies from the Multi Agent-based Behavioral Economic Landscape (MABEL) model are used to illustrate the usefulness of the proposed methods for studying land use change, natural resource management, efficiency, and environmental-specific considerations that affect the decision-making capabilities of the agents. These methods are designed with the end user and decision maker in mind, so that robust and efficient outcomes can be back-propagated to the model in ways that enhance the adaptivity and veridicality of our experiments.

**Keywords:** Agent-based model, MABEL, Bayesian belief networks, Monte Carlo experiments, robustness, decision making

### INTRODUCTION

In recent years, the modeling of realistic or “real-world” relationships by agent-based models (ABMs) has been gaining significant ground. ABMs are an appropriate tool for modeling such relationships because of their ability to overcome the generalizations and the statistical moment assumptions of traditional modeling approaches. They follow a bottom-up approach to modeling, allowing issues of scale, time, and space to be taken into account simultaneously in a simulation environment. This paper uses case studies as examples to demonstrate these significant properties in an ABM environment. Furthermore, the paper showcases the ability of ABM environments to incorporate and use traditional statistical assumptions and properties at an individual agent level. In this way, individual ABM designs can be used to more accurately represent existing real-world relationships and reduce the level of uncertainty in predicting

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individual and collective agent behaviors for sustainable futures. Specific case studies from the Multi Agent-based Behavioral Economic Landscape (MABEL) model are used to illustrate the usefulness of the proposed methods for studying land use change, natural resource management, efficiency, and environmental-specific considerations that affect the decision-making capabilities of the agents.

The use of repeated measures as Monte Carlo replication experiments can help (1) improve the constructability of the agent-based architecture (by testing the accuracy of the agent's performance by comparisons to historically observed changes) and (2) increase the confidence with which changes can be predicted over time (by reducing the uncertainty of the estimates and providing the necessary near-term range of scenarios for sustainable futures). The examples here show how these replication experiments can be designed and incorporated as an integral part of the ABM environment and, at the same time, be used as reference and accuracy-assessment tools that use external performance metrics in both statistically and environmentally based assessment schemes. This linking of the ABM environment with accuracy-assessment metrics is important and establishes the degree of confidence required by decision makers and end users of the simulations.

The range of confidence in the simulation replication experiments can be also used as a transition step for achieving the necessary predictability and confidence level for near- and long-term predictions and sustainable-future scenarios. When the ABM exercises are addressed as an integral part of a holistic approach to sustainable futures, it is often desirable to use prediction ranges instead of individual predictions. Then the simulation veridicality can be advanced by incorporating uncertainty considerations (such as behavioral changes of individual agents and collective cognitive estimates of agents participating in a simulation) into a simulation environment that is more stochastic than deterministic. Designing and constructing cognitive and behavioral changes in an ABM requires an adequate number of plausible and realistic scenarios that are able to differentiate the agents' behavior at the desired degree of abstraction, provide realistic simulation outcomes, reduce the level of uncertainty in the decision-making process, and provide a clear and comprehensive picture of the sustainable futures. This paper provides examples of the procedural steps that can be followed in such an ABM environment.

The approach to modeling proposed here attempts to reveal a working environment for ABM architecture that it is not limited to traditional computational science considerations but also takes into account, in advance, the considerations and assumptions that are necessary to take the simulation results one step further. In other words, it is designed with the end user and decision maker in mind, so that robust and efficient outcomes can be back-propagated to the model in ways that enhance the adaptivity and veridicality of the experiments.

## **Modeling in the Context of Epistemology**

The epistemological framework upon which the ABM approach is built represents a very important concept in designing and implementing an agent-based simulation. Our ability to construct theoretical arguments that go beyond the framework of a single simulation experiment, thus extending our understanding of the real world, depends on the epistemological content and context (Kuhn, 1996).

Here we enhance the epistemological content of our approach to ABMs by widening the magnitude and the dimensions of our understanding of what the elements of change are and how these changes emerge, and also by addressing questions on why these changes emerge and what their broad meaning is in terms of real-world changes. We suggest that the individual elements, experiments, and case studies can be assigned a broader meaning only if they are thought of and conceived of as a part of a series of inferences to the epistemological context.

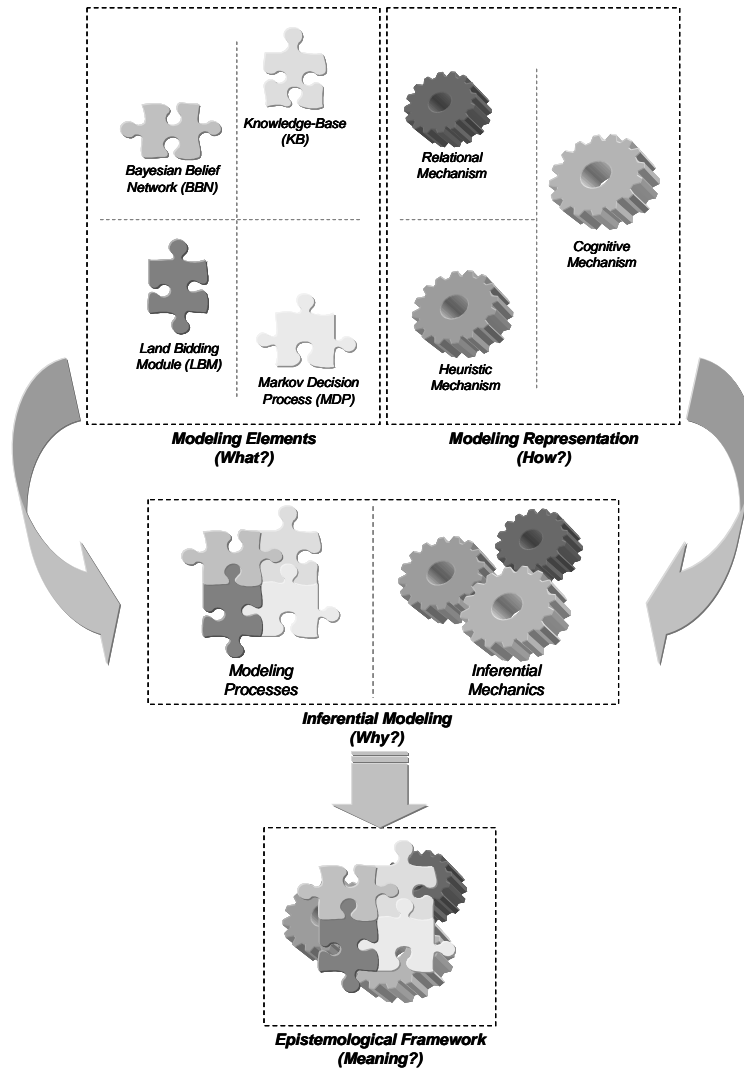
An epistemological framework like the one we employ for the MABEL model architecture is neither purely mechanistic, in the sense of the Descartes mechanistic representation (Rouanet et al., 1998; Erion, 2001) and the 20th century philosophy of science, nor purely stochastic, in the sense of the early game-theoretic approach and social and cognitive discipline approaches to modeling (Innocenti, 2004; Milchtaich, 2004). It perceives these approaches as being complementary to each other, and it proceeds to construct a scientific hypothesis in terms of both “what the world is like” and “how the world can be.” It expands the perceptual limits of the first notion by using a diverse array of modeling elements and tools to capture the emergent properties of the systems that are present in the modeling environment. This allows us to understand what the objects and subjects of change are, what is changing and what is not, and what is important to our understanding of reality. It also enhances our understanding of the second notion by confining the mechanistic character only to the modeling representation and by explaining how a mechanism emerges, how changes occur, and how these changes reflect back to the modeling elements and their properties. These two approaches are shown in the first part of Figure 1.

Consequently, our effort to understand why the world changes requires an understanding of both the specific elements of change and the underlying mechanisms of these changes. The MABEL modeling architecture presents a synthesis of modeling processes and their inferential mechanics that can be called inferential modeling (second part of Figure 1). This synthesis is the essence of the epistemological framework we employed and describe here, which allows us to derive the broad implications and consequences of the changes we model. We live in a less-than-perfect world; there are no single truths that can provide answers to all of our questions. Often our answers and suggestions have numerous and broad implications on policy and implementation that can direct future changes in one direction or another within an ensemble of alternative futures. Exploring such a broader meaning (final part of Figure 1) can often allow us to distinguish between alternative futures in a larger sense and between sustainable futures in a desired sense.

Perceiving and implementing an ABM within such an epistemological framework is often a complicated task, since it requires an enhanced ability to move within and across scales, involves different levels of complexity, and demands a clear understanding of the broad implications and interactions involved. These issues are discussed further.

## **Dealing with Multiple Scales**

The question of the multiplicity of scales in such an agent-based simulation is important to consider, especially when the complexity in the simulation and/or representation of reality is great. There are numerous simulations over a multiplicity of single scales. Few go beyond the single-scale representation and examine the interactions emerging across dualities of scales.



**FIGURE 1** Constructability of the epistemological framework for the MABEL model (Our ability to freely transcribe our modeling simulations and exercises to meaning — both content and context — depends heavily on how we construct the mapping of different scales of perception.)

Traditional statistical techniques allow for the discovery of patterns across pair-wise comparative scales. When the scale dimensions exceed two, the problem becomes nontrivial, since the covariation across and within such scales introduces a significant challenge in the study of emergence and its mechanisms.

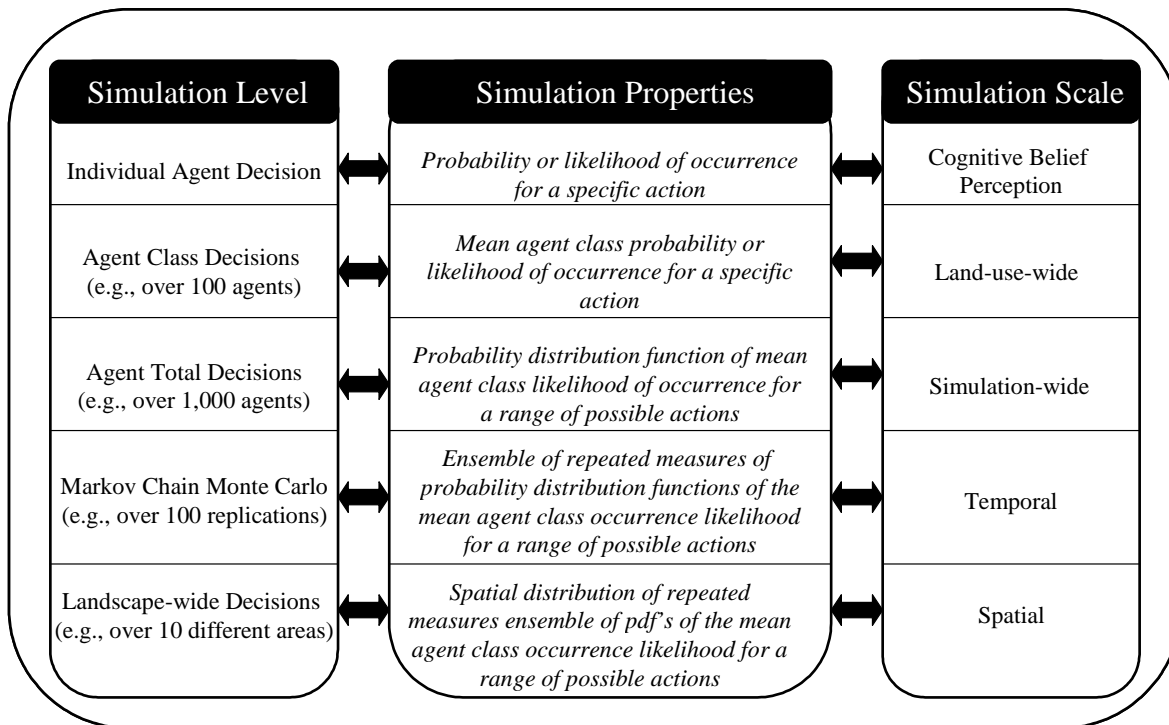
An example of the computational and statistical complexities involved in such a attempt at representation is shown in Figure 2. Starting from the bottom, the smallest perceptual unit is the cognitive belief perception of each agent. This is a microcosmic representation of the simulation scale, as the decisions by individual agents are being considered. If we denote as  $p(a_i)$  the probability that an agent would select a specific action  $a_i$  based on his beliefs, rules, and properties, then the mapping of these probabilities across the simulation state space (all the



agents or entities participating in the simulation) presents us with the fundamental simulation scale via a transition probability model  $P(a_i)$ . Such a transition probability model varies across agents belonging to the same class (homogenous), so that we can represent agent class decision making as an ensemble of decisions made by individual agents. The transition probability model varies across agent classes (heterogeneous) as well, by means of various beliefs, rules, and properties. Across an entire simulation with multiple agents and multiple agent classes, the representational scale is a probability density function *pdf* that maps the densities of the homogenous agent decisions across all heterogeneous agent classes.

Such a mapping is a “snapshot” of the underlying reality of the world at the agent-based perceptual level. It does not take into account the variability and uncertainty of changes in the agent’s decisions as the simulation advances through time. It represents just one possible future out of a wide variety of possible futures. Especially in the cases where stochastic simulation is employed, the discovery of alternative futures and the conditions under which one would expect these futures to emerge is important. These are cases where, for example, we want to simulate a hypothetical situation or predict a possible change, as opposed to cases where simulation properties are deterministic and correspond to a historical sequence of events or actions.

If the simulation is a spatial one, the probability mapping described above defines a third dimension in a three-dimensional (3-D) scale map (e.g., dimension  $z$  on an  $\{x, y, z\}$  plane, where  $x$  and  $y$  are the latitudinal and longitudinal spatial coordinates, respectively).



**FIGURE 2** Statistical and computational complexity in multiple scales (Movement within scales [horizontal dimension] and across scales [vertical dimension] dictates the level of complexity involved and thus the number of representational elements required to visualize them.)

As is often pointed out, the relative level of complexity encountered within ABMs is very important. It can have many consequences on our ability to accurately depict changes that occur in the real world (i.e., in the case of structural complexity) and/or our ability to represent and communicate these changes in a meaningful and comprehensive way (i.e., in the case of representational complexity). Carley's (2002) discussion on the difference between transparency and veridicality provides good insight into the issues associated with the level of complexity and on the implications of the complexity on modeling representation. Similarly, Agarwal et al. (2002) provides a 3-D insight on different complexity scales that is based on a thorough examination of 19 different land-use models in use.

### **MABEL SIMULATION APPROACH: MODELING ELEMENTS AND MECHANISMS<sup>1</sup>**

The MABEL model framework presents a comprehensive, dynamic, and interactive way to simulate land-use changes over time and space, accounting for environmental, socioeconomic, and cognitive factors. It is based on the Swarm ABM architecture (Swarm Intelligence Group, 2000) but has several major added distributed architectural tools and simulation elements that advance the simulations' capabilities and present a departure from traditional ABM techniques. First, both the agents as well as the simulation as a whole acquire a spatial intelligence character by incorporating geospatial and geographic information system (GIS) components and visualization elements. Second, it integrates the spatial dimension (2-D) with the socioeconomic (SE) dimensionality of the decision makers, thus transforming it into  $n$ -D. An agent in MABEL is therefore both a parcel of land (with its associated geospatial and GIS attributes) and a decision maker (with the parcel owner's associated SE attributes). Third, an agent's decision-making process is associated with an underlying cognitive mechanism, namely a Bayesian belief network (BBN) model. An agent's decision-making intelligence is closely associated with such a BBN model, as it interactively provides learning and adapting capabilities for the entire simulation.

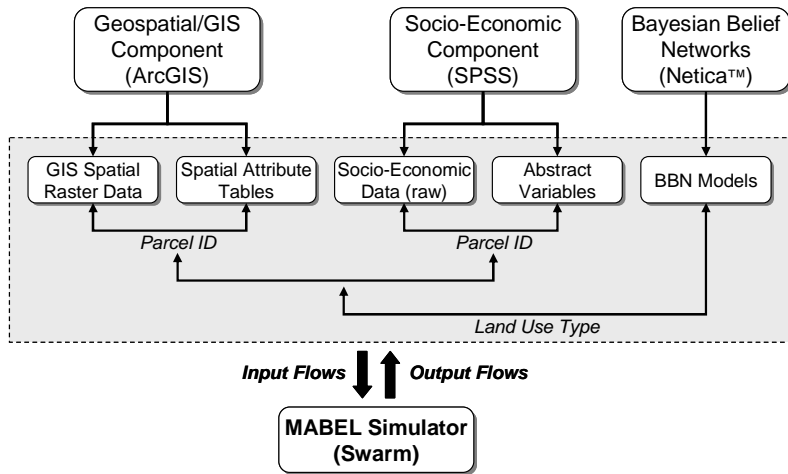
The relational mechanism that precedes the actual simulation is a part of the MABEL model's initialization stage. Figure 3 illustrates the procedure itself and how identification proxies are used throughout the simulation.

The SE component of the knowledge base (KB) allows us to map the possible transitions from state-space ( $S_i$ ) to action-space ( $A_i$ ) by using alternative configurations of cognitive mechanisms (different BBN models, corresponding to homogenous agent classes). The conceptual diagram in Figure 4 demonstrates such a process.

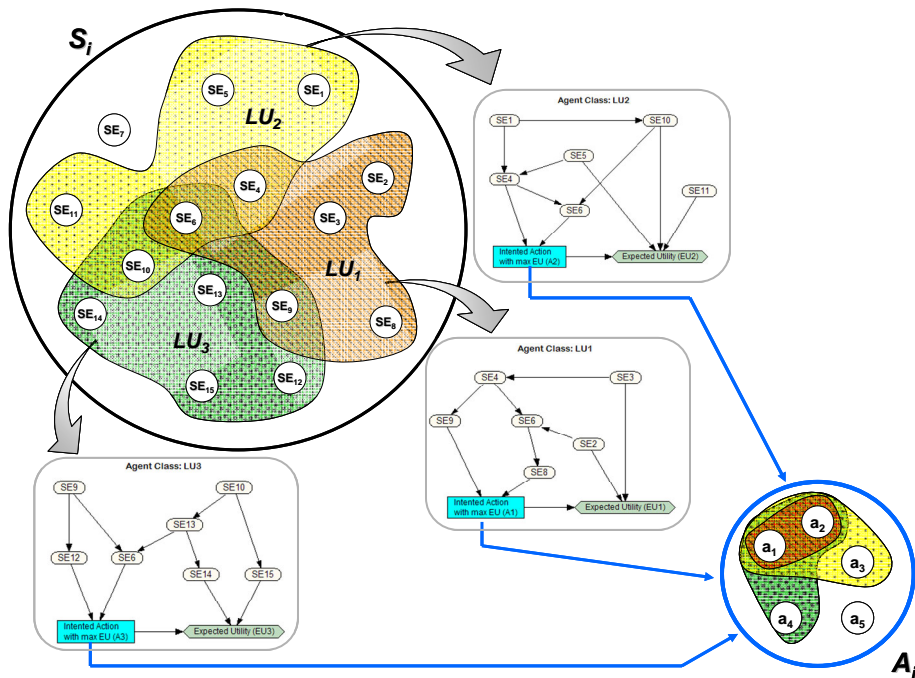
Through the simulation, the sequential decision-making process exhibits the properties of a Markov mechanism. It is referred to as a Markov decision process (MDP), and for each time step, an agent has to derive an evaluating ranking of its intentions via an expected utility maximization rule. The specific formulation of the MDP model elicits the use of a set of States ( $S$ ) – Actions ( $A$ ) – Transition Models ( $P$ ) – Reward Functions ( $R$ ) to achieve the maximization

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<sup>1</sup> This section provides a very brief overview of the MABEL simulation framework. A detailed description of the MABEL model is provided in our recent papers (Alexandridis et al., in revision; Lei et al., 2005). Contact the author for further details.



**FIGURE 3** Acquisition of knowledge base (KB) in MABEL (The rectangles represent elements of the KB, and the shaded area represents a type of a relational mechanism [Source: Lei et al., 2005]).

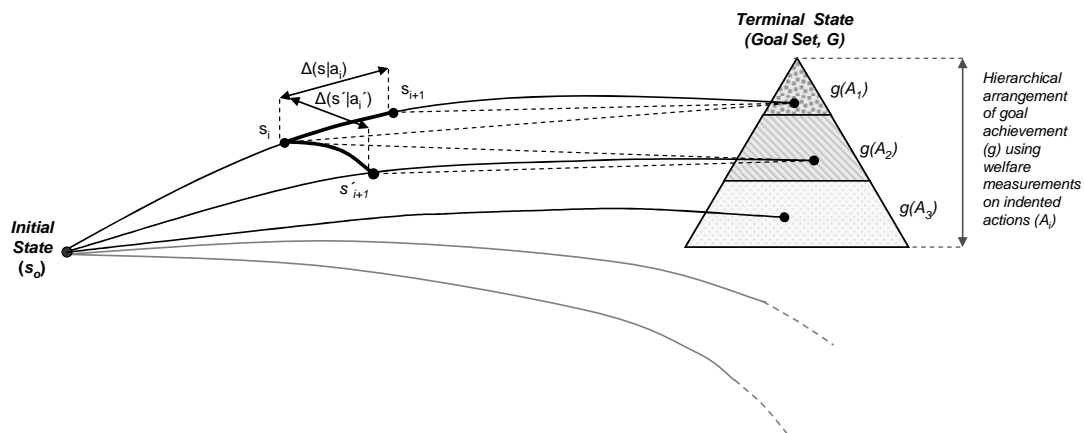


**FIGURE 4** Mapping state-space to action-space in the MABEL model (In addition to the KB, BBN, and MDP modeling elements, identifiable modeling mechanisms are also present. They are the relational mechanism, which links the variable-space of the KB to action-space, and the cognitive mechanism, which consists of the BBNs for agent classes.)

of the expected utility (MEU) principle (see Alexandridis et al., in revision, for details). Although in a deterministic simulation, this procedure alone would be adequate to derive an optimal path toward a given goal, in any real-world situation, such an assumption is, in a practical sense, inadequate for providing long-term efficiency assessment measures. The reason is that real-world goals associated with long-term dynamics cannot be defined in advance; in other words, the simulation faces an infinite horizon MDP problem formulation. To overcome this problem, the use of a heuristic mechanism is required. Instead of asking whether or not an agent reached a given goal, we can define the goal set ( $G$ ) as a wider terminal state, where goals are elicited as hierarchical arrangements of goal achievements by using welfare measurements of intended actions. The theory of social scale development and social psychology provides us with many alternative ways to achieve such a hierarchical arrangement (Petty and Cacioppo, 1996; Eagly and Chaiken, 1993). We can evaluate and elicit relative distance measurements of the degree of change between two sequential time steps. In Figure 5, an example of such a heuristic is provided for an agent's transition from a given time step  $s_i$  to the next one,  $s_{i+1}$ . The alternative pathways between the initial state  $s_o$  and any of the goal sets  $g(A_i)$  describe a given sequence of actions, analogous to the way that a DNA string denotes a given sequence of genes.

The heuristic distance between the current state  $s_i$  a goal set  $g(A_i)$ , denoted as  $d[g(A_i)-s_i]$ , can be estimated in terms of an expected utility measure (EU), and it is the shortest path distance measure. The differences between two alternative states,  $s_i$  and  $s'_i$ , in the example is simply  $\Delta(s/a_i) = d[g(A_i)-s_i] - d[g(A_1)-s_{i+1}]$  and  $\Delta(s'/a_i) = d[g(A_2)-s_i] - d[g(A_2)-s'_{i+1}]$ . By comparing the two differences, we can say that if  $\Delta(s/a_i) > \Delta(s'/a_i)$ , then the agent should stay on the path (toward achieving some relaxed set of terminal goals). But if  $\Delta(s/a_i) < \Delta(s'/a_i)$ , the agent's path sequence is a not an optimal one; thus, an alternative action strategy for achieving the terminal goal state(s) should be actively sought. This inferential rule is equivalent to the MEU rule. The grayed paths in Figure 5 denote nonrational agent action sequences.

Another relational mechanism is the land bidding module (LBM) in the MABEL simulation. The module negotiates "biddings" between buyer and seller agents within a time-step sequence. MABEL considers the decisions coming out of the initial MDP model to be intentions



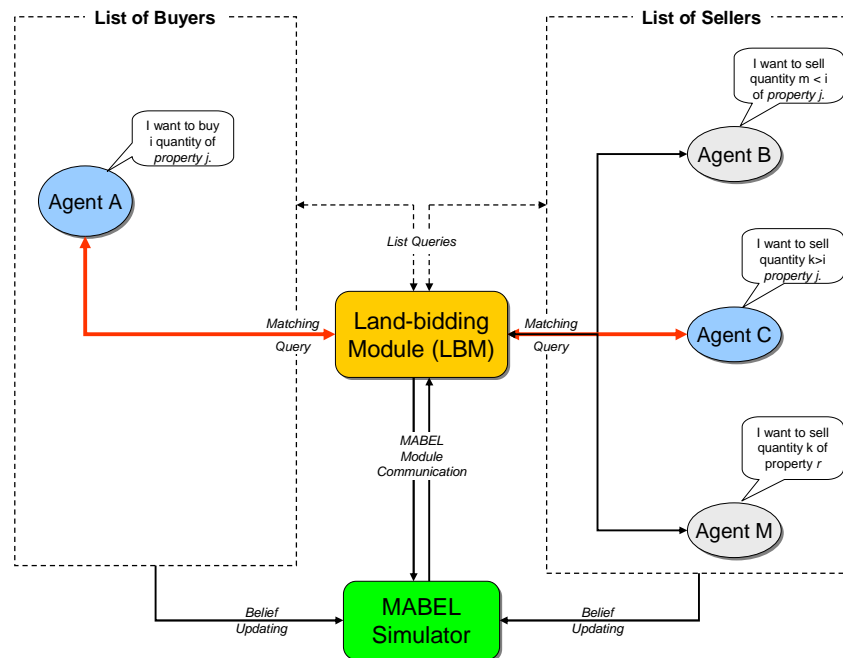
**FIGURE 5** Procedural representation of the MABEL decision-making sequence (The terminal goal state is a stochastic one; thus, the procedure achieves its performance by using a heuristic mechanism.)

and thus to not represent actual changes in the agents' attributes. They can be considered as latent variables, which are used to indicate the degree and strength of an agent's willingness to engage in a specific action (e.g., buying and selling land). The purpose of the LBM relational mechanism is to attempt to match such transactions as efficiently possible. The final outcome of the bidding process can then be considered the final (and actual) action that an agent will perform in the next time step. Figure 6 illustrates the LBM procedure.

The variance that emerges between intended and performed actions across agents raises the question of how accurate the initial estimation of the agent's welfare measures is, especially in cases where the difference between intentions and actions undertaken is significant. The use of an iterative sequence of prediction-correction processes addresses this question. These processes are performed by the Bayesian learning and Bayesian updating procedures in the belief networks (Berikov and Litvinenko, 2003; Shachat and Walker, 2003; Wong et al., 2004). The use of these processes is illustrated in a later section by a case study example.

## Inferential Modeling

In this section, we use specific modeling exercises as case studies to illustrate the relative importance of the MABEL modeling approach to the conceptual elements and their underlying mechanisms. The details associated with these exercises can be found in the respective papers from which they were drawn. (It is not the purpose of this paper to replicate the explanations).



**FIGURE 6** Formulation of the land bidding module (LBM) in MABEL (An agent negotiates its intended actions [derived from the MDP] and achieves its final decisions. This is an intermediate simulation stage between belief prediction and correction. It is also a type of relational mechanism, linking intentions with actions.)

These exercises are vehicles to show the importance of the epistemological framework and how phenomenically diverse modeling exercises address different yet equally important aspects of our understanding of the world around us.

Two broad exercises are examined here. The first involves understanding the landscape changes that emerge around us as a result of individual decision making related to land use and assessing the accuracy of the spatial aspects involved in the MABEL agent-based simulation. The second showcases the use of the BBNs as a cognitive mechanism and the potential effect of their use on the agent's learning capability and intelligence.

### **Monte Carlo Replication Experiment for Landscape Dynamics of the MABEL Model <sup>2</sup>**

The main goal of the experiment was to assess the parcelization algorithms that are designed within the MABEL modeling architecture. Historical data from 1970 to 1990 were used to initiate different MABEL simulations that modeled historical land-use change sequences. The agents were assigned a set of deterministic goals that were based on a series of assumptions. For example, the temporal sequence was fixed so that the initial terminal states of the simulation would correspond to the intermediate observed changes (i.e., from the decade observations for 1970, 1980, and 1990, the number of agents that changed equaled the number of parcels that historically changed within each land-use and agent class). Other assumptions were used to achieve exactly the opposite: introduce an adequate level of stochasticity on the simulation factors that were irrelevant to the exercise goals. For example, the focus was on the shape and pattern characteristics of the parcels that changed; thus, the spatial (locational, e.g., centroids' mean longitude and latitude) arrangement of the agents as well as of the cognitive and SE elements had to be random.

To enhance the reliability of and confidence in the simulation, a series of Monte Carlo replications were performed (100 replications for each of the three alternative modeling configurations). An ensemble of search- and scan-based pattern recognition algorithms was tested; the algorithms were tested simultaneously, and the use of functional metrics allowed their performance in the simulation to be tested. These metrics are the occupancy area ratio *OAR* and width/height ratio *WHR*, as follows:

$$OAR_i = \frac{AREA_i}{AREA_{\min CR(i)}},$$

where  $\min CR(i)$  is the smallest confined rectangle containing the agent  $i$ .

$$WHR_i = \frac{X_{\min CR(i)}}{Y_{\min CR(i)}}.$$

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<sup>2</sup> Based on the simulation experiments performed in Alexandridis et al. (in review).

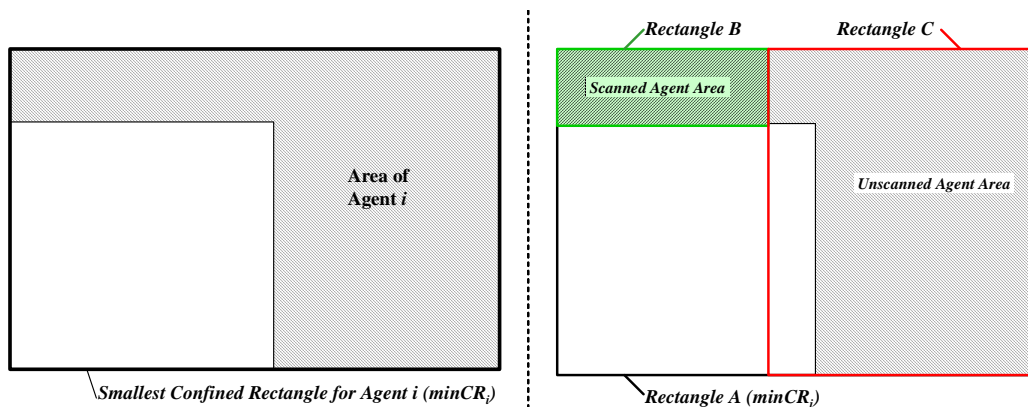
For a certain partition algorithm  $i$ , the optimal value  $OPT_i$  is used to describe the “correctness” of the shape partition. This can be expressed as follows:

$$OPT_i = \frac{AREA_{new\ agent} \times (w_1 \times OAR_{new\ agent} + w_2 \times WHR_{new\ agent})}{AREA_{seller\ agent}} + \frac{AREA_{remaining\ seller\ agent} \times (w_1 \times OAR_{new\ seller\ agent} + w_2 \times WHR_{remaining\ seller\ agent})}{AREA_{seller\ agent}},$$

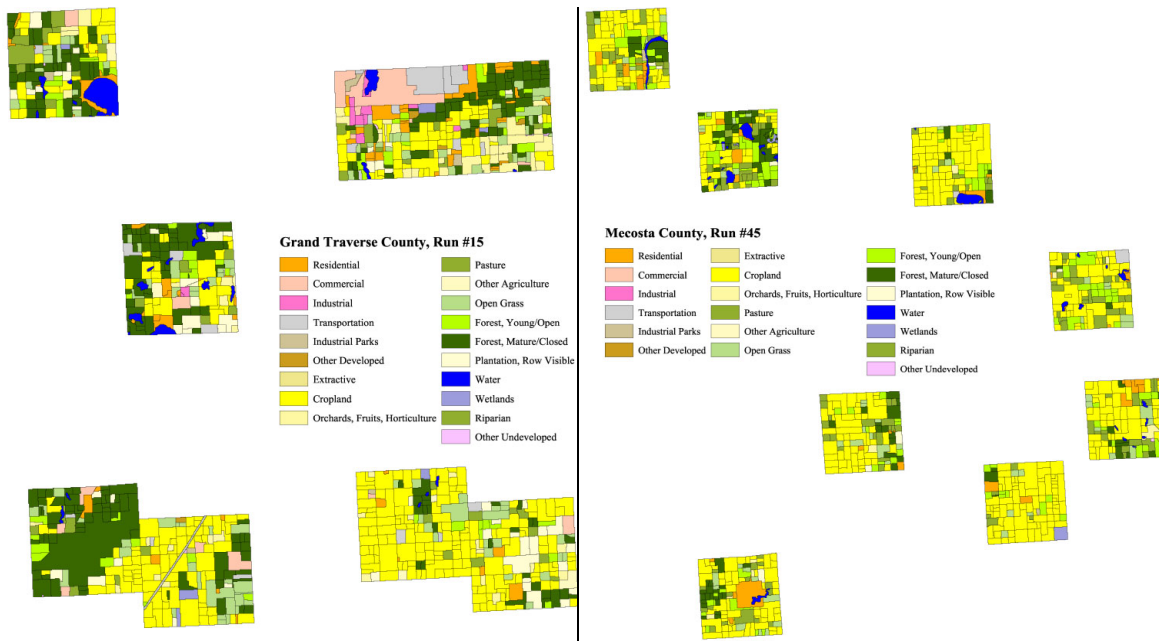
where  $w_1 + w_2 = 1$ , and  $w_1$  and  $w_2$  are defined as the relative proportions of  $OAR$  and  $WHR$  of the optimal shape, respectively. A graphical display of the spatial configuration of the partitioning algorithm is shown in Figure 7.

The simulation’s focal area involved the entire Midwest region of the United States, as it was divided into sampling areas by county blocks. Each county block contained eight  $3 \times 3$ -mi<sup>2</sup> blocks, each with a distribution of land-use parcels. The distribution and data development methods were derived from Brown et al. (2001). For computational and analytical purposes, we focused on two of these county blocks in two counties in Michigan — Grand Traverse County and Mecosta County — containing eight  $3 \times 3$ -mi<sup>2</sup> blocks each. An example of a visualization of the simulation results’ area is shown in Figure 8.

To assess the accuracy of the simulation results, the landscape metrics were employed (McGarigal and Marks, 1994; McGarigal et al., 2002). The relational and inferential mechanism of such a modeling exercise is relatively complex. The interpretation and export of the simulation results in a form that can be used for a spatial accuracy assessment are



**FIGURE 7** Example of quantity measurements of optimal shape in a hypothetical MABEL agent (Left: The smallest confined rectangle for agent  $i$  is denoted by the thick-bordered rectangle and contains the entire area of the agent  $i$  [shaded area]. Right: Rectangle A denotes the smallest confined rectangle for agent  $i$ . Rectangle B denotes the scanned area for agent  $i$ . Rectangle C denotes the unscanned area for agent  $i$ .)



**FIGURE 8** Example of the MABEL Monte Carlo replication experiments (Left: Grand Traverse County Blocks, 1970–1980, Replication No.15. Right: Mecosta County Blocks, 1980–1990, Replication No. 45. The dimensions of each sample block are  $3 \times 3$  mi<sup>2</sup>. The blocks across counties appear to be different sizes in this display because of the differences in county area sizes. [Source: Alexandridis et al., in review]).

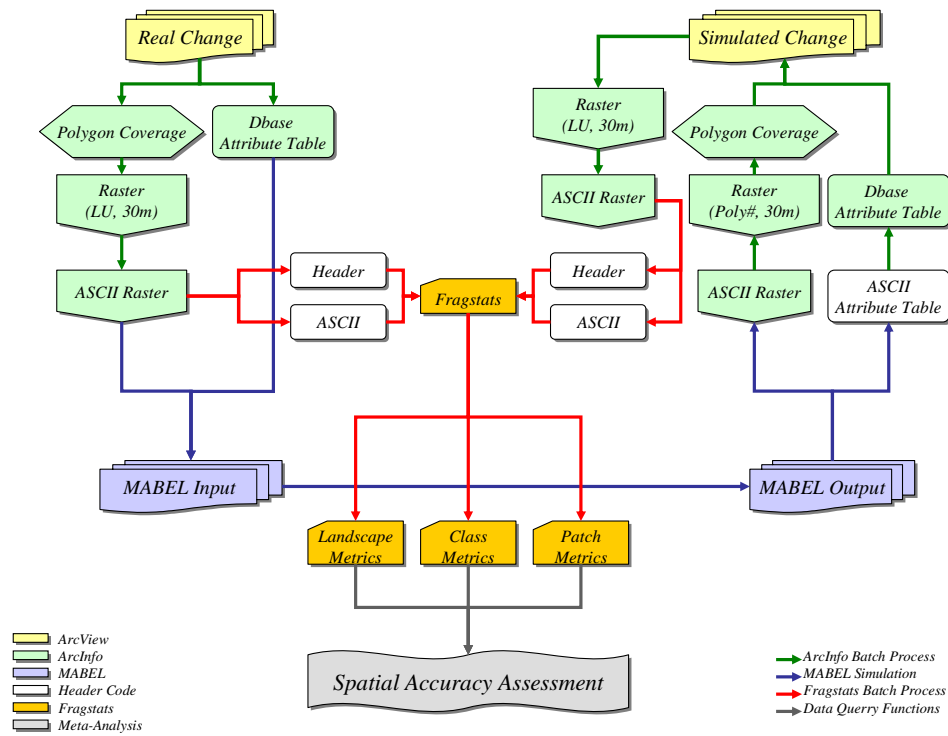
complicated, as shown in Figure 9. Several alternative landscape and class metrics were employed. The landscape metrics presented some inferential properties both for the spatial configuration of the agents' parcels and for the agents' classification as homogeneous (at the landscape level) and heterogeneous (at the class level). The functional forms of these metrics are shown in Table 1.

These metrics were used to calculate and draw the simulation results. A subset of these results is shown in Figures 10 and 11. The results seem to confirm the accuracy of the MABEL model parcelization algorithms. Additional tests (using a Kolmogorov-Smirnov test) indicated that the results differ from a random distribution. A reliability analysis indicated that the simulation displayed a significant level of reliability with regard to our process in terms of capturing the variability observed in the real-world changes (Alexandridis et al., in review).

### Assessing the MABEL Cognitive Mechanism by Using Bayesian Belief Networks

The example that follows showcases the value of the BBN modeling elements in the context of the MABEL decision-making process. The example was purposely chosen to be an oversimplification of the reality that encompasses the true elicited attitudes and beliefs that people use when faced with similar decisions, simply because of its transparency attributes. Since the point to be made here is not about the BBN elicitation or constructability but about the intelligent learning properties that the agents participating in the simulation are implied or inferred to have, unnecessary veridicality was avoided.





**FIGURE 9** Relational mechanism and procedural steps involved in performing a spatial accuracy assessment

The BBN shown in Figure 12 was initially elicited to present a simple situation in which a farmer-agent faces a land acquisition decision to either buy land, sell land, or do nothing. At each time step, the agent observes directly only a weather forecast (that has a relatively biased correlational relationship to the actual weather) and the yield of the land parcel at any given planting period, and the agent has a risk aversion potency toward his or her decisions. On the other hand, the weather (especially past weather experience) affects the weather forecast, land yield, and achieved price levels that exist in the market. Both prices and yield, in turn, affect the income from the farm (which, in the long run, affects the agent's risk aversion properties). The elicitation of the welfare measurements in terms of the expected utility (EU) allows both the price and farm income levels to affect the scale representation index of these measurements.

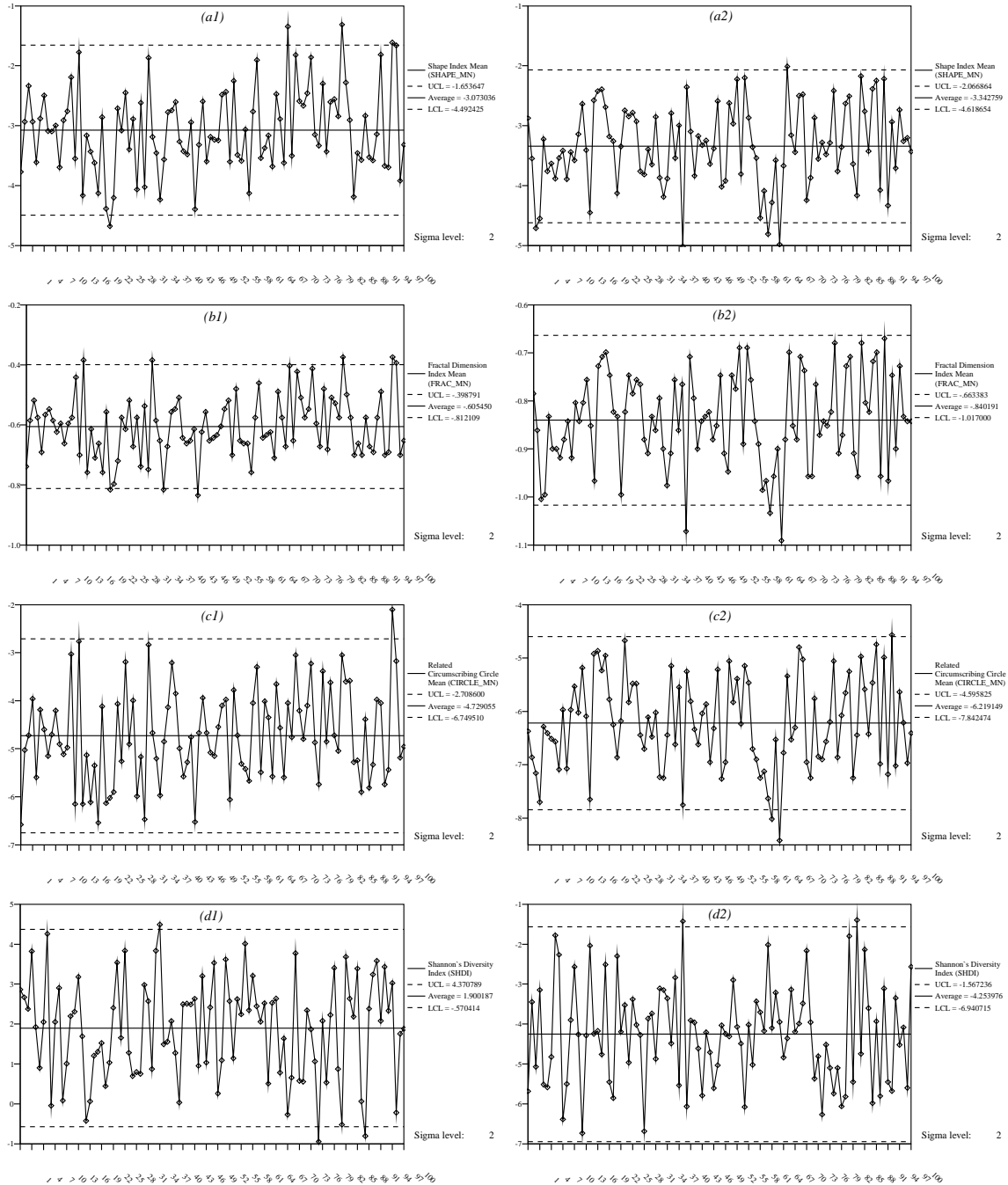
The welfare (EU) index representation is then used to derive the EU distribution for the land-use decision node, by weighting the probability value of each of the alternative decisions with its corresponding utility index value. The MEU principle in MABEL requires that the action with the highest EU should be considered as the intended action and should be message-passed to the LBM for further processing. A set of 100 sequential observations used for three of the BBN nodes (weather, weather forecast, and yield achieved) was used to enter evidence into the model, and the changes in the maximum EU were monitored (Figure 13).

**TABLE 1** Landscape and class metrics and their inferential properties for the MABEL agents

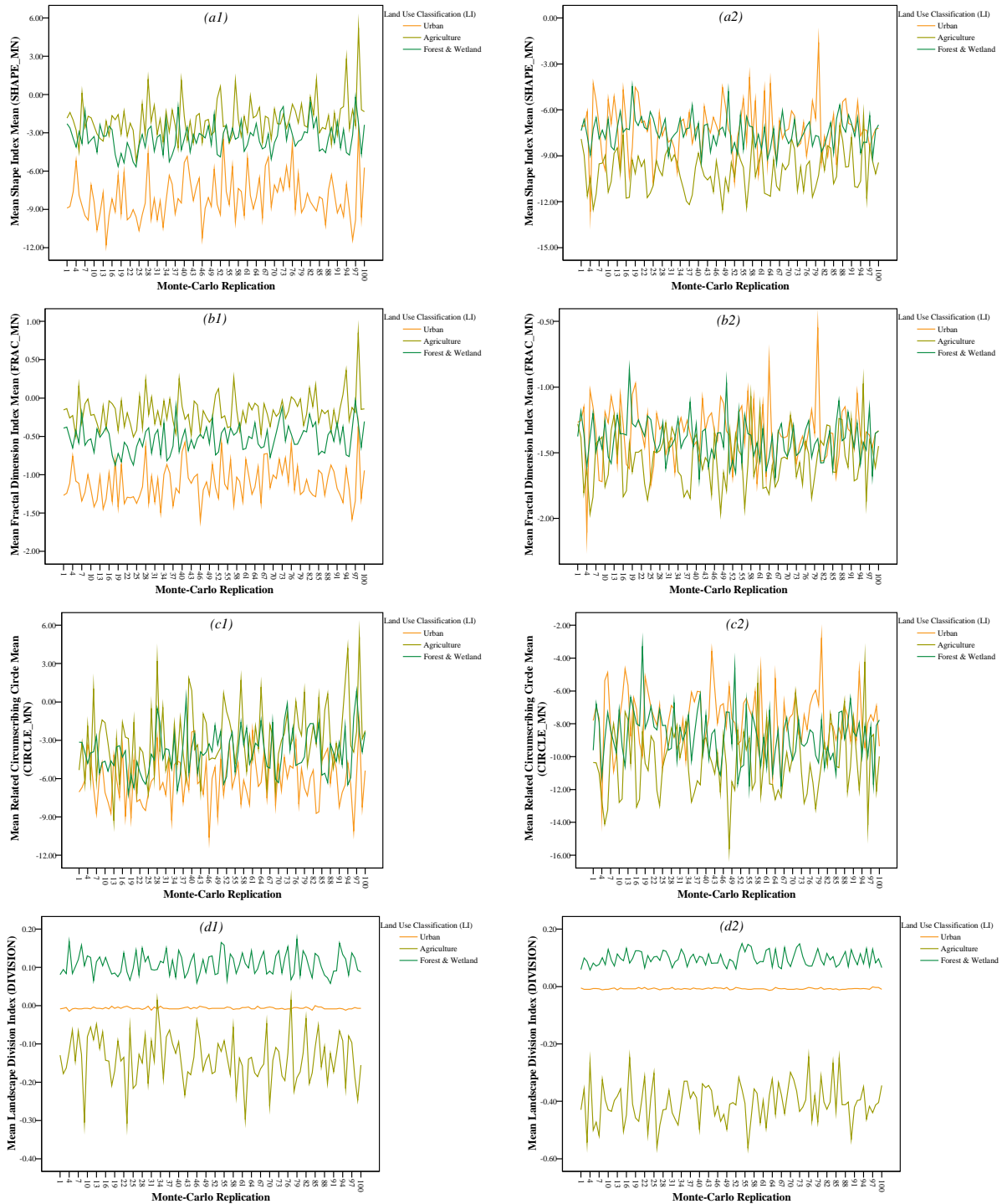
<b>Landscape Metrics (Heterogeneous Agents)</b>		
<i>Mean Shape Index</i>	$SHAPE\_MN = \frac{\sum_{i=1}^m \sum_{j=1}^n \left[ \frac{p_{ij}}{\min p_{ij}} \right]_{ij}}{N}$	Measures the complexity of a parcel shape at a landscape level. Equals 1 for square parcels, and it increases for more irregular ones.
<i>Mean Fractal Dimension Index</i>	$FRAC\_MN = \frac{\sum_{i=1}^m \sum_{j=1}^n \left[ \frac{2 \cdot \ln(0.25 p_{ij})}{\ln a_{ij}} \right]_{ij}}{N}$	Measures the degree of complexity in a parcel shape, as a departure from Euclidian shapes. Ranges from 1 to 2. The larger its value, the more complex the parcel's shape is.
<i>Mean Related Circumscribing Cycle</i>	$CIRCLE\_MN = \frac{\sum_{i=1}^m \sum_{j=1}^n \left[ 1 - \left( \frac{a_{ij}}{a_{ij}^s} \right) \right]_{ij}}{N}$	Similar to shape index, but uses the smallest circle instead of square. Ranges between 0 and 1, and approaches 1 for elongated, relative linear parcels.
<i>Shannon's Diversity Index</i>	$SHDI = -\sum_{i=1}^m (P_i \cdot \ln P_i)$	Measures the level of diversity in the informational entropy of a landscape. The index asymptotically approaches 0 for homogenous landscapes, and it increases for heterogeneous ones.
<b>Class Metrics (Homogeneous Agents)</b>		
<i>Mean Shape Index</i>	$SHAPE\_MN \approx \sum_{c=1}^c (SHAPE\_MN_c)$	Similar to the relative landscape level metric, but is computed separately for different land use (agent) classes.
<i>Mean Fractal Dimension Index</i>	$FRAC\_MN \approx \sum_{c=1}^c (FRAC\_MN_c)$	
<i>Mean Related Circumscribing Index</i>	$CIRCLE\_MN \approx \sum_{c=1}^c (CIRCLE\_MN_c)$	
<i>Landscape Division Index</i>	$DIVISION = \left[ 1 - \sum_{j=1}^n \left( \frac{a_{ij}}{A} \right)^2 \right]$	Denotes the probability that two randomly chosen parcels in the landscape do not belong to the same land use (agent) class. Ranges from 0 to 1. For homogeneous landscapes, it approaches 0.

Since, by definition, the nondecreasing character of the utility concept does not allow the long-term consequences of the actions selected to be accounted for and thus also does not discriminate between positive and negative actions, a very simple, balanced reward index was implemented on this example (+1 for buying, 0 for doing nothing, -1 for selling). The reward function then was derived by weighting the MEU by its corresponding reward index. The simulation results are shown in Figure 14.

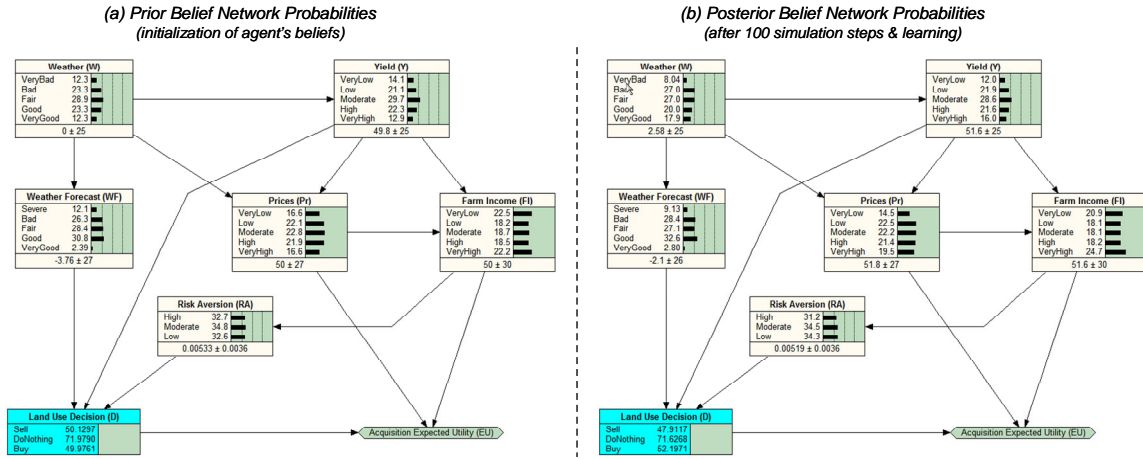
An examination of the cumulative reward distribution over time shows that by almost the first two-thirds of the simulation, the achievement made by the farmer-agent toward his or her goals was highly volatile, making it difficult to interpret the results. During the last third of the simulation, the results indicate a clear potency for significantly increasing the welfare. Yet a further examination of these results indicates that the agent faced a potentially consistent trend. If we compute the moving average of these cumulative rewards for the time-step sequence of the



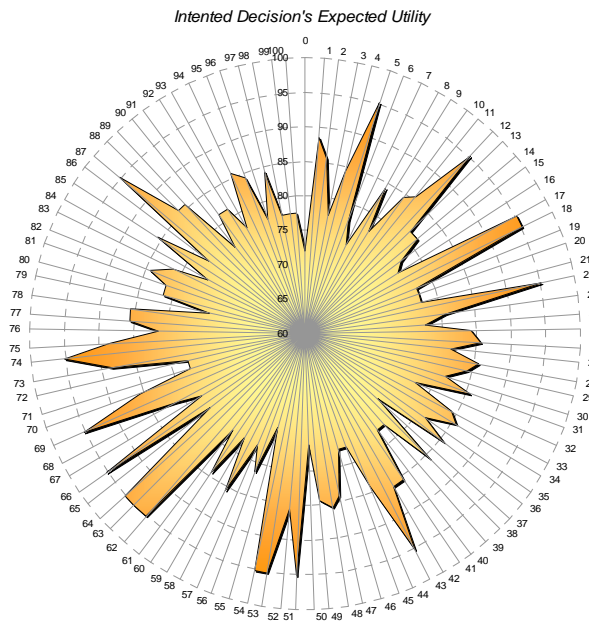
**FIGURE 10** Landscape metrics results for the MABEL Monte Carlo replication experiment in Grand Traverse County (Column 1 = 1970–1980. Column 2 = 1980–1990. Row a = mean shape index [SHAPE\_MN]. Row b = mean fractal dimension index [FRAC\_MN]. Row c = mean related circumscribed circle [CIRCLE\_MN]. Row d = Shannon's diversity index [SHDI].)



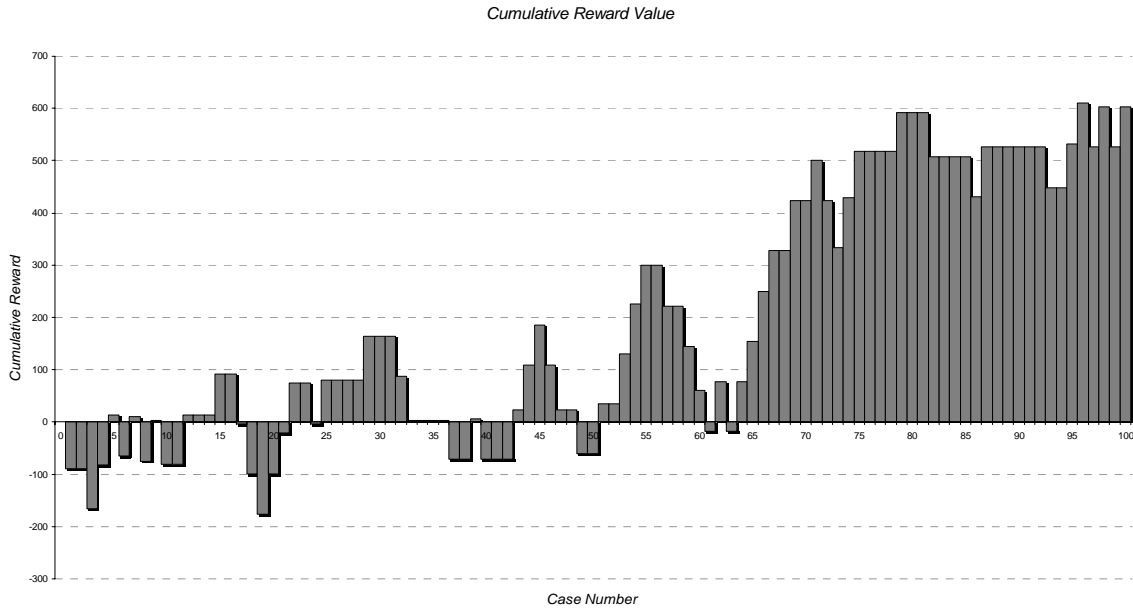
**FIGURE 11** Class metrics results for the MABEL Monte Carlo replication experiment in Grand Traverse County (Column 1 = 1970–1980. Column 2 = 1980–1990. Row a = mean shape index [SHAPE\_MN]. Row b = mean fractal dimension index [FRAC\_MN]. Row c = mean related circumscribed circle [CIRCLE\_MN]. Row d = landscape division index [DIVISION].)



**FIGURE 12** Farm decision simulation experiment (Both prior beliefs and posterior beliefs [a and b] are shown over a 100-step learning simulation from evidence entering the system.)



**FIGURE 13** Distribution of the intended actions' expected utility across the simulation steps

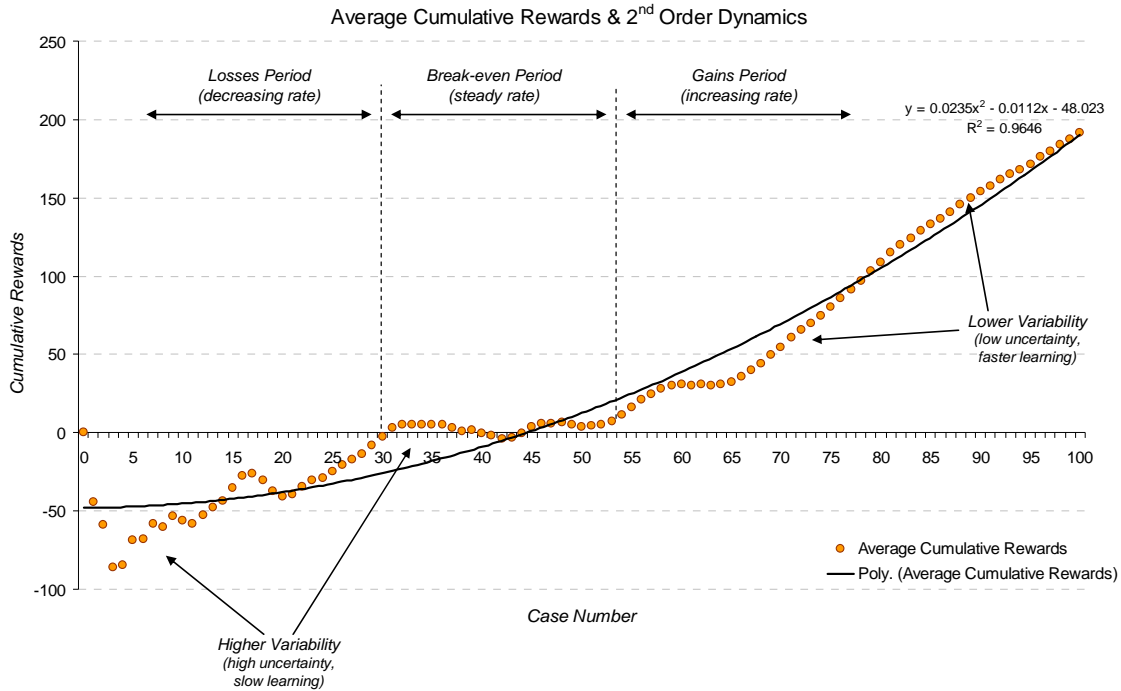


**FIGURE 14** Belief network simulation results in terms of the cumulative reward value of the intended actions, across the simulation steps

entire simulation, we can see that such a consistent pattern emerges. The average cumulative rewards represent the second-order dynamics, as they denote the rate of change of the agent's welfare from the beginning to the end of the simulation. This pattern is shown in Figure 15. The overall simulation properties exhibit three distinct temporal phases. The first one is a period in which there are significant losses in the agent's welfare, which occur at a consistently decreasing rate. The second phase is a break-even period where the welfare level remains relatively constant. The third phase is a period of gain in which the agent's welfare exhibits a consistent and significantly increasing trend.

The BBN mechanism on the MABEL model employs Bayesian learning techniques to adapt to observed evidence and to the experience that an agent acquires through the simulation. At the theoretical level, such adaptive learning is achieved through the use of an expectation maximization (EM) algorithm (Islam, 1999; Laskey and Myers, 2003). The EM algorithm uses maximum likelihood estimation properties for fitting a mixture to data via an information confusion matrix. When the theoretical exponential learning curve of such an algorithm is fit to the data observed in the simulation experiment, there is a high degree of agreement ( $R = 96.5\%$ ). Thus, our model exhibits a consistent learning pattern through time.

The learning components discussed so far present an example of the inferential modeling epistemological formation discussed in the initial section of this paper. In other words, they attempt to answer the question of why we observe the simulation results, given the stochastic simulation elements of a given BBN and the inferential heuristic mechanism of learning. We can take our discussion one step further to explore the meaning of this simulation exercise in terms of its implication on the agent's optimal policies ( $\pi$ ) and action sequences ( $A$ ). As Figure 15 indicates, the data on empirical average cumulative rewards display some interesting



**FIGURE 15** Consistent pattern of change in the cumulative welfare of the agents (The simulation exhibits a three-stage learning pattern, with gradually decreasing uncertainty.)

characteristics. In the initial stages of the simulation, the agents face a high degree of variability in their outcomes because of the greater uncertainty involved in the evidence entering the belief network. This has implications on the relative degree of learning over time (Phase 1). On the other hand, as the simulation advances, the variability of the outcomes significantly decreases to a minimum degree of uncertainty, and a faster learning curve results.

The results displayed in Figures 14 and 15 show that a given agent belonging to this land-use class (farmer-agent) often faces significantly negative welfare measure values. In a real-world context, this would be translated into debt, cost-associated problems, etc. Thus, a question can be formulated on how much loss an agent can withstand without having to change its long-term consistency. This question can now easily be translated into a more comprehensive or more robust postulate in terms of the agent-based simulation framework, as follows: the degree of volatility (i.e., the degree of variability and uncertainty) that an agent can withstand is adequate to keep the agent consistent in pursuing his or her long-term goals. By transforming this question, the inferential modeling framework can be employed to help the decision makers improve their long-term consistency between actions and optimal policies. It also becomes clear that in order to address this question, the simulation design has to shift its scale of perception, since it is not enough to employ only repeated temporal measures (i.e., the simulation observed in this example). The simulation also requires repeated measures (i.e., repeated 100-simulation experiments for different areas, or agent types) within agents and across agent classes in order to discover the confidence intervals associated with the variability in the initial stage.

## Epistemological Meaning Revisited

By taking into account the arguments and case studies presented so far, we can often derive specific meaning from the inferential modeling elements and mechanisms. As an example, we expand here on the previous discussion in order to understand the differences between the homogeneity and heterogeneity of agents throughout a simulation model. During the course of this text, the terms “homogeneity” and “heterogeneity” were used, but no semantic explanation of them was provided. The semantic representation is provided here.

- *Heterogeneous agents* are diverse among themselves; they have different attributes and/or beliefs. They are similar to a population composed of individuals. These agents do not necessarily have to belong to different classes. The natural tendency is for heterogeneous agents to represent the “natural order” of things. We can perceive them to have maximum entropy (a minimum amount of information is contained within them).
- *Homogenous agents* have similarities in their properties and/or beliefs. They are similar to a group of people who have something in common. These agents do not necessarily have to belong to the same classes. This concept of homogeneity implies (or infers) a higher level of organization; thus, the agents contain more informational context.

Homogeneity and heterogeneity are complementary concepts. When we know the level of homogeneity of an agent (or the degree of homogeneity of an agent group), we consequently know its level of heterogeneity (or the degree of heterogeneity of an agent group). If  $p$  is the homogeneity level, then heterogeneity is  $q = 1 - p$ . In informational terms, if entropy denotes or infers a level of homogeneity, then *negentropy* necessarily infers a heterogeneity content, and vice versa.

When we talk about agent homogeneity alone, we imply the existence of agents that belong to the same class (i.e., they have identical class properties in all aspects of their decision-making attributes, and any differences observed among them are solely attributed to the differences that exist in their external agent environment). If we want to differentiate this definition, we can introduce a level of classification that refers to completely or totally homogenous agents. The idea is the same for the properties of heterogeneity. Agents are completely or totally heterogeneous when they share no common decision-making class attributes (i.e., they belong to different agent classes) and when this holds true, even when the agents share a common external environment. In contrast, we can talk about partial homogeneity and heterogeneity of agents. These agents are closer to a real-world cognitive representation, where people are never perceived as being entirely identical (unless they are cloned!). We can define partial homogeneity (with respect to a specific attribute) as the property of agents that have one (or more) specific attribute(s) in common but differ in every other attribute or belief. We can intuitively use the terms “partial homogeneity” and “partial heterogeneity” (with respect to a specific attribute) interchangeably, depending on the properties or attributes being focused on and the common/diverse ratio that they represent. In that sense:

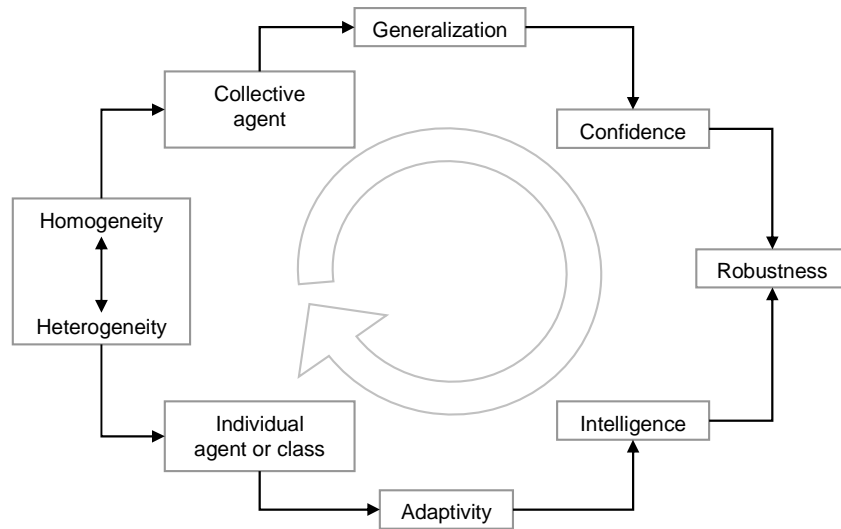
- A set of agents can be considered *partially homogenous with respect to attribute a* when the only common attribute within them is attribute  $a$ .



- Similarly, a set of agents can be considered *partially heterogeneous with respect to attribute  $b$*  when all the other attributes (except attribute  $b$ ) are common within them.
- A set of agents can be considered *partially homogenous with respect to an attribute set*, say  $A = (a_1, a_2, \dots, a_n)$ , when the only common attributes within them are the attributes of the attribute set  $A$ , and  $N \leq 2n$ , where  $N$  is the total number of the agent's attributes, and  $n$  is the number of attributes belonging to the attribute set  $A$ .
- A set of agents can be considered *partially heterogeneous with respect to an attribute set*, say  $B = (b_1, b_2, \dots, b_n)$ , when all the other attributes  $C - B = D$  (and  $C < B$ , where  $C$  is the total attribute set) are common within them, and when  $N \leq 2n$ , where  $N$  is the total number of the agent's attributes, and  $n$  is the number of attributes belonging to the attribute set  $B$ .
- We can take these definitions a little further in accordance with the mathematical definitions of homogeneity and heterogeneity. When differentiating the degree of homogeneity and heterogeneity, we can refer to the "degree of" instead of their generic definitions. In other words, we can say that a set of agents is homogenous of degree  $n$  with respect to an attribute set  $A$ , where  $n$  is the number of attributes contained in the attribute set  $A$ . When  $n = 1$ , the attribute set  $A$  degenerates into a singular attribute element  $a$  or  $A = (a)$ . The definition for the degree of heterogeneity is similar.

The type or the specific properties of the attribute set that postulates the homogeneity and/or heterogeneity properties of an agent group can help in further identifying the nature of homogeneity. Thus, we can refer to different types or classes of homogeneity and heterogeneity, such as spatial, temporal, environmental, physical, natural, economic, technical, social, etc.

While the agents' homogeneity and heterogeneity are interrelated, the definitions themselves reflect different focal areas or areas of interest for the researcher. Homogeneity is related to group attributes and, as such, is subject to a higher degree of generalization within a population of interest (to be modeled). In an agent-based dynamic framework, where a degree of stochasticity in the modeling process is desired and, to an extent, required, higher degrees of generalization infer higher degrees of robustness, higher degrees of confidence, and lower degrees of uncertainty in the simulation outcomes. On the other hand, heterogeneity is related to the diversification derived from individualistic behavior, and, as such, is related to a higher adaptivity and higher degree of intelligence processing of the agents. But an increase in the degree of intelligent processing ability and adaptivity of the agents inevitably provides the basis for the emergence of robustness in a simulation. These emergent properties of the homogenous and heterogeneous agents allow for an abundance of alternative pathways to robustness, as shown in Figure 16. Thus, robustness in the epistemological framework of an agent-based simulation can be defined as a carefully weighted mix of the heterogeneity and homogeneity of agent properties and their underlying mechanisms.



**FIGURE 16** Alternative pathways to agent-based modeling robustness (The level and quality of simulation robustness achieved depend on the meaning or semantic representation of the simulation’s epistemological framework.)

## DISCUSSION

The purpose of this paper is to initiate a wider discussion about the semantics of and the need for a wider epistemological framework for an agent-based simulation that crosses multiple disciplines of scientific research. We provided a comprehensive description of the constructability of such an epistemological framework, and what it may come to represent in terms of asking the right questions for the modeling exercises undertaken. We described the MABEL modeling architecture in terms of this epistemological framework, and we discussed two distinct simulation experiments that served as case studies and revealed two widely opposing modeling approaches to epistemology. The first one showcased how a deterministic agent behavior can reveal emergent properties of the patterns of change and the dynamics of these patterns over time and space. The second one showcased how a stochastic simulation element allows us to explore the horizons of adaptivity and intelligence in the agent properties. Both experiments display a highly significant level of robustness, but they use alternative pathways toward achieving this robustness.

The growing significance of ABM approaches in addressing and solving real-world decision problems, and the increasing reliance of scientific modeling on new, dynamic, and often intelligent approaches to problem solving, dictate the need for a unified framework of scientific thinking, an epistemological construct that has the ability to cut across different and often diverse scientific disciplines. We suggest that such an epistemological construct can address the diverse array of issues involved in an agent-based simulation only when it focuses on both the deterministic processes and the stochastic mechanisms that underly these changes. Furthermore, this epistemological construct must be able to freely move across and within the different possible modularizations (or mappings) across the conceptual and semantic levels. This is the reason why we believe that representing changes as flexible, loosely connected modules of an ABM simulation, rather than “hard-wiring” these modeling elements and mechanisms to a

computer code string sequence, can enhance the understanding and effectiveness of a modeling architecture. The latter approach presents a relatively inefficient way to approach agent-based modeling, since it does not allow for discovering knowledge or testing robust assumptions without undertaking extensive computer recoding and revising.

Finally, we hope that our approach will initiate a broader discussion among scientists, modelers, and researchers involved in all disciplines associated with agent-based modeling. Such a discussion is important for spotting and identifying the important elements of meaning or semantics in our epistemological constructs, and for providing cognitive space for the emergence of new ideas and advances in our knowledge and understanding of our natural and anthropogenic world.

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**DISCUSSION:****MODEL DESIGN TECHNIQUES****(Thursday, October 7, 2004, 1:30 to 3:30 p.m.)**Chair and Discussant: *N. Collier, Argonne National Laboratory***To Deceive or Not to Deceive? Mimicry, Deception, and Regimes in Tag-based Models**

**Charles Macal:** Our first session of the afternoon is “Model Design Techniques,” and the chair and discussant for this session is Nick Collier who is one of the — well, is *the* original — Repast developer for those of you that may not be aware of that. I’ll turn it over to Nick.

**Nick Collier:** As Chick said, this is the “Model Design Techniques” session, and, as before, each presentation has 25 minutes with 5 minutes for questions. We start with Y.Y. Chen who will talk about tag-based models.

**Y.Y. Chen:** Good afternoon. My name is Yuan-yuan Chen. I’m a third year doctoral student in the Business School at Emory University. I will present a preliminary study of work that I have done with Professor Mike Prietula who is currently visiting Florida International University.

[Presentation]

**Collier:** I would like to start with three questions and comments. The first is out of curiosity. You said that you were in the business school. I was wondering what part of the business school this work falls under and what is the school’s justification for this work?

**Chen:** The business school is an online community. This model can be used to study the online community. It can be used to look at people who have never met and who never get familiar with each other. It looks at how they communicate with each other and how they cooperate with each other, so this model can be used to study how the online community emerged and evolved.

**Collier:** Okay. Second, I’ve read some papers about heterogeneity and homogeneity and about how heterogeneity is important for the robustness of a system. As I was reading your paper and watching your presentation, it occurred to me that there’s an interesting kind of heterogeneity here with the deception, in the sense that you get enough homogeneity so that they can cooperate a lot, but then you have the heterogeneity because they’re not really the same; they’re deceiving. I wondered if you had any comments along that line in terms of heterogeneity and homogeneity.

**Chen:** Yes, this is a very good question and a very good comment. This model is basically combined to see the co-inference of the homophili — its homogeneity and also the deceptions and how this too can influence the cooperation. But you’re talking about the heterogeneity. There’s also some heterogeneity in a group, in the entire population. This model

does not have this now because we haven't focused on heterogeneity, but in the future, this is definitely the direction we'll conduct research.

**Collier:** Right. And my last question is really a comment for future research. I'm wondering about changing the model, or tweaking the model, so that you begin with some agents deceiving, but then as they — a notion of assimilation — begin to see that they're part of two groups, and one is deceiving them, they begin to be assimilated by the other group, and they lose their ability to deceive. They're no longer part of their previous group, and they move along. This mirrors at least the experience, the anecdotal experience, of becoming friends with people. You may not really act like them or whatever, but eventually you do act like them. You become one of them, and you're not faking it anymore.

**Chen:** Yes. That's a good point. Your illustration is to add one level in a population that right now we just see is a single level. But if you're adding a group level into the analysis, that will change the intergroup cooperation of things.

**Unidentified Speaker:** I'm trying to figure out where are the data that you're concerned with? Did you use data to calibrate your theories or to generate your parameters?

**Chen:** We generated. We used a simulation model, a coding model, and simulated, and by using an algorithm I introduced it in a presentation. It generates the preliminary data, and we analyzed the data. Am I answering the question?

**Unidentified Speaker:** You got a sample of real people and got their parameters ...

**Chen:** No, no. We didn't do the experimental analysis. We just used the simulation data.

**John Sullivan:** Were there any consequences? You didn't mention it. Were there any consequences for being caught at deceiving? Any tit-for-tat or anything like that?

**Chen:** Yes. We didn't consider that there's punishment. You are talking about the punishment if they're caught. We didn't simulate a punishment in this model because basically in the tech-based model, there's no memory. There's no punishment assumption in the original tech-based model, so we just extended the model to add another deceptive mimicry, this mechanism into the model, so no punishment, no memory are in this model.

**Meredith Rolfe:** I had a question about your definition of cooperation. It seems that you're saying there is basically a unilateral donation, and there's no prisoner slum, if you want to call it that, set up, wherein if you give a donation. The idea is that the other person is absconding, which brings me to asking if your deceptive agents are different than your donating agents, or can the same agent both deceive and donate?

**Chen:** The same agent can both deceive and donate. It's because in each generation each agent has three opportunities to pair with the other agents. It's randomly paired up. If the tech-value difference between this agent's tech value with the other agent's tech value is very similar, then a donation occurred. If it's not similar enough, there's no donation. When we consider the deceived opportunity, if the tech value is not similar enough, the agent we deceived tries to get the donation. That is the increased opportunity to get the donation.

**Pam Sydelko:** I would urge you for future research to seriously consider separating out deceiving from donating agents because I think it sets up a very different dynamic, much more similar to what we think of as the free writer problem, the problems of cooperation, than the current setup, where you can sort of do both.

**Chen:** Okay. That's a good point. Thanks.

**Collier:** Any more questions? Okay, thank you.

## **Ontology for Agent-based Modeling and Simulation**

**Nick Collier:** Next, Scott Christley is going to talk about “An Ontology for Agent-based Modeling and Simulation.” Just give him a minute to get set up.

**Scott Christley:** This presentation is about some work that I started over the summer. I was happy to listen to Roger Burkhart's keynote speech this morning because I think my work plays along in some of the bullet points that he mentioned. And, thankfully, I was listed under one of the future trends, not one of the things in the past!

I'm going to talk briefly about the motivation for this work and the ontology and what I consider ontology for those who are not familiar with this term. Then I'm going to talk more specifically about agent-based modeling. I presume everybody's familiar with it, so I'll cover that rather fast. The major part of my talk deals with reasoning — reasoning systems for inference and automation. Finally, I'll talk briefly about future work.

[Presentation]

**Collier:** First, I want to say thanks. I enjoyed reading the paper. It touched on a lot of things that are interesting to me and also directly into things I do every day. I have two comments/questions. The first goes back to what Roger [Burkhart] was saying this morning and also addresses my own interest in generative programming, that is, create software-creating software. Roger talked about these transformers that could take the visual language of UML, or SysML, or whichever and turn it into some sort of software code — the raw code itself. I've certainly seen, and I'm sure you have too, UML tools take a class diagram and stub out all the classes and the methods for you. I get the sense, or it's actually more than a sense, that you want to do a little more than this, that the inference engine, starting with a knowledge base, using an ontology as opposed to just a visual language, you could go further than this in some way. You could, both with the general agent knowledge base and then with the domain-specific one, possibly generate more code, code that's more specific to the domain. Could you comment on that?

**Christley:** Yes. I agree because when you take a knowledge-based approach, and you could say in a certain sense that UML has some knowledge within it, but there is obviously a difference between syntactical knowledge and semantics. I think UML has a lot of syntactic knowledge, things about interfaces and data types and connections, but that the semantics may be lost or only implicit in it.

So, yes, if you want to go further, I think you have to put more of the semantics into your knowledge. That goes to the point of where, but that's an issue as well, because you need an expert in the system in order to put that in. So I think one of my future works here is learning. It would be nice if this tool learned along with you. Say you're a researcher who's trying to learn about this phenomenon. You're discovering new things. It would be nice if this tool followed you along so that it can continue to be a good assistant.

**Collier:** My second question — again I'm monopolizing things — is that this ontology is both — and this comes across more in the paper — descriptive in the sense that it's a nice formalization of both agent-based models and agent-based modeling. But there's also a prescriptive slant to it, that says it may be that you should write your models this way; you should start with a knowledge base because  $x$ ,  $y$ , and  $z$  are the benefits of doing that. While I can see the benefits, I wonder what experience you have following that trail because in places it seems like this might be a bit cumbersome to go through, defining every little thing. And of course there are benefits to that, but it does seem cumbersome. Maybe that also gets into the idea of the software learning along with you, so you're not throwing every little thing back into your knowledge base. That's a very valid criticism and one that's been around in the AI community for a long time. And I don't think we've found necessarily a good solution to that.

So, yes, you run into this problem where all these formal methods are great, but they add a lot of overhead, and I have to have a lot of knowledge on how to actually use them. I think, though, that the tools we now have are getting better, especially with the semantic Web and Web services becoming a very big thing. The OWL [Ontology Web Language] language that I mentioned is a standard — a Web standard. A lot of people work in it. In the future, although these are hard to work with, the tools are probably going to get better and it won't be as cumbersome. That's a hope.

**Collier:** Any questions?

**Pam Sydelko:** What are your thoughts about being able to take Legacy models and apply this ontology approach to them as a way of documenting them to the point where somebody could use the ontology documentation to understand how the model could be used in junction with another model or see how this model overlaps with another model? Would standardizing ontologies in this way help model integration efforts? It seems it would.

**Christley:** Yes. I'm going to point back to some of the semantic Web services-type of work because it's dealing with basically the same issue. They have these business processes, these interfaces, and services they want to provide, and they're grappling. What's our common vocabulary? People have the same services, but how do they know that they're the same?

I'm not presenting this as a modeling language. I'm a little skeptical about modeling languages. I think there are plenty of those out there. But you can take this knowledge-based approach and find many forms of how you can represent it. OWL is one — it's the semantic network form, but there are expert systems where you use rules. You know, there are things like first-order logic, which some people aren't comfortable with, but it is very declarative and expressive. I think there are a lot of other more practical things where you get into the UML-type descriptives.



As a way of documentation, I think it's helpful to a point, but you're going to need some more tools so that it's useful to other users. If you just put it into the system, if you just encode all your knowledge into a system, and there are no tools or ways to get it out to do queries, then it's kind of lost in space and it's not so useful. Those are my viewpoints.

### **Use of Robust and Efficient Methodologies in Agent-based Modeling: Case Studies Using Repeated Measures and Behavioral Components in the MABEL Simulation Model**

**Nick Collier:** Our next speaker is Kostas Alexandridis, and he's going to be speaking on "The Use of Robust and Efficient Methodologies in Agent-based Modeling."

**Kostas Alexandridis:** I'm going to talk about robust and efficient methodologies in agent-based modeling. The idea is to step back from current and previous work, look at the big picture, and address some of the theoretical uses involved in other approaches we're taking. First, I will talk about the big idea — setting up the framework of thought and putting the MABEL model architecture into those terms. Then I will present some simulation case studies from current work at our facility. Finally, I will synthesize everything to provide some conclusions.

[Presentation]

Therefore, according to the predefined metrics, we see that some of the algorithms are performing much better than others, mostly the numbers from 5 to 8.

**Collier:** [referring to a slide] I notice you say 1980 to 1990.

**Alexandridis:** Yes. That's why I said in the beginning that we did a deterministic because we wanted to be able to compare land-use changes with historical changes, and that's my next slide. We took the number of agents that started in 1970, and we had dates of 1970, 1980, and 1990. We fixed the number of agents that were changing, and we wanted to see how the personalization algorithms were performing, knowing that matching the historical with the simulated .... This is the example of how the percent of change, that is, comparing the real with the simulated changes of the algorithm, happens across different land-use types. The green one is forest and wetlands, the brown one is agriculture, and the orange is urban. So you see, some algorithms are better at representing changes on different land-use scales.

[Presentation]

**Alexandridis:** The second one [referring to the slide] is looking through heterogeneity; looking at the class and the individual agent's behavior, and achieving robustness through greater ability of the agents and intelligence. So robustness can be achieved separately, but a balanced approach is more important for achieving both capabilities of generalizing your arguments and a higher degree of intelligence and adaptability of the agents.

**Collier:** By "robustness" you mean the robustness of your "argument" with respect to what?

**Alexandridis:** It's with respect to how we can get our simulations and bring them into the point where we can start to talk about ideas. That's what I mean by robustness. Some conclusions or ideas that I think are important is that there is a need for a wider epistemological framework in agent-based modeling. [We need to find] how, why, and what's the big meaning behind it. Somehow it should contain both stochastic and mechanistic characters inside it. The robustness can be achieved via alternative pathways, but balanced approaches make a difference. Flexible modulation of modeling components is very important, I think, and it creates a contrast versus the hardwiring of computer code strings.

[Presentation]

**Alexandridis:** I welcome your questions.

**Collier:** All right. Thanks. I want to say one thing first and monopolize again. I'm curious about the process of developing this notion of the big idea, the epistemological framework. You had this very obviously, very complicated MABEL model. Is that when you started to think more deeply about it and came up with this notion of the epistemology that would help you think more deeply about the MABEL model? I'm trying to think; obviously, you used the MABEL model as an example, but I'm wondering what the epistemology brings to the MABEL model, how it helps you think about the MABEL model, and perhaps how it helped you overcome certain problems?

**Alexandridis:** Well, our class of agent-based model deals with environmental modeling, and each of our models involves more real-world realities rather than stochastic simulations or very deterministic ones. So the whole idea is how we use our knowledge and what we gain from our models to infer about how real-world processes work. That's the original motivation starting, even looking at agent-based modeling. On the other hand, as we designed the model to be part of modules as opposed to just building a model — wiring codes for specific components — we were able to test those components separately, and then the entire idea developed that somehow all those things had to come together. Regarding models, it ties up to the older discussion about models talking to each other; I've been seeing a lot of replication on the work of a lot of scientists. At some point, we have to start thinking about such a big idea to couple it with what we're doing. I think that was the motivation. It's also very exciting to get out of the everyday kind of experimental procedure and start going back and start thinking about those.

**Zhian Li:** I have two questions. For the first question, could you go back to your first few slides? You defined the probability as the summation of the probability density function. I do not understand whether you mean the conditional probability or the individual probability. At the beginning, you said a probability of an individual agent is  $PA$ , and you get a summation of all the agents. Then you probably got the probability over 1, yes, right here [referring to the slide]. Yes, the third one. So what do you mean there? You get 1,000 if a 1 ...

I started saying that you have individual agent issues, and so the agent decision is a probability of making it individual action. Then you go into over 100 agents, a whole class of those agents. So you have a sum or weighted average of those decisions, and that's a probability in sample because I don't want to start talking about — a lot of times you have to compare. I saw in those examples in the Monte Carlo that you have to compare the probability distribution function across different scales, different land-use categories. Then you scale up and you start looking at replication experiments and different landscapes. I still didn't understand. We can

discuss it later, but it seems to me that you cannot make a simple summation of the probability distribution function.

**Alexandridis:** No. Those are not the acts or properties, just to represent how the idea of the level of complexity starts and increases when you start piling things together.

**Li:** Right. Then you have a condition of probability.

**Alexandridis:** Not exactly. Well, you're talking about ...

**Li:** Otherwise, you get our 1.

**Alexandridis:** No. You have a conditional belief network, which is different than a conditional probability distribution.

**Li:** Okay. I don't want to take too much time. The second question has to do with your land-use bidding process; you mentioned that you use a 3- by 3-mile metric area. What's your boundary condition? Do you have a repetitive boundary condition or a reflective boundary condition?

**Alexandridis:** No, we don't use boundary condition.

**Li:** What if a person says that he wants to buy this land, and the land is occupied? Do I want to bid with you, or do I want to look at a different place?

**Alexandridis:** No. The land-bidding model involves only agents that have an intention to buy or sell land.

**Li:** So the agents are just concentrated on this area.

**Alexandridis:** Yes.

**Li:** For example, I want to bid in Chicago, not necessarily the city but perhaps the western suburbs, but you don't want to go through the lake. You don't want to bid to build a house on the lake.

**Alexandridis:** Well, when you do simulation, and that's why we started thinking of the entire Midwest because those are counties, but we didn't do them separately. We do them all at once. So all the agents of all those parcels are together, but there is a round area that is missing. Also, because of the computational problems, at one point when you start thinking about larger scales, then you have, if you want to address those issues, you have to start thinking about in-migration, out-migration, and that's ...

**Li:** Sure, yes. That's exactly the boundary condition you can define at the ingress and egress, so that ...

**Alexandridis:** I agree with you.

**Li:** Yes. Are you considering that kind of funding?

**Alexandridis:** No, no. Up to that point, even as it is a model, it is extremely complex, and I think we are away from that point yet. Well, we have it in the back of my mind.

**Michael North:** I have a quick question. From the framework that you laid out here, not just in terms of land use, but in general, it seems that it could be used to help support repeatability of experiments, in particular, repeatability of simulation designs, not only within your group, but between groups, which I think is very valuable. Could you address that in more detail? How would you use this framework to try to do something like that?

**Alexandridis:** Well, I think our case side is examined, not extensively, but looked at those properties ...

**Brian Pijanowski:** ... for another group to come back and repeat....

**North:** ... between locations. Would you say that repeatability between locations?

**Pijanowski:** Well, no, because that's one of the big issues that I see — simulations having repeatability of entire studies and other simulations. In experimental science, we can get another apparatus and set up a similar configuration, a similar state or conscious design. This part would be sort of natural.

**Collier:** You mean, if you could define their model in this scheme, then give the scheme to someone else, it would be a good starting point.

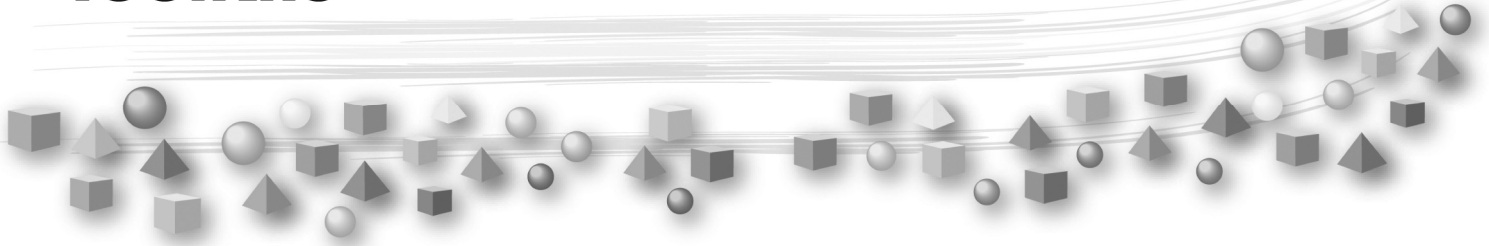
**North:** Exactly.

**Alexandridis:** Well, I agree with you. First, the data for those two case studies are available to everybody who wants to test them. I think putting together a unified and universal thinking about an epistemological framework eventually would help in doing that as well because people would be implementing. Thinking in the same terms, you start being in the same level of comprehensive ... models work. And I couldn't agree more with you on those terms.

**Collier:** Thank you. I think we're reaching the end, so unless anyone has a quick question, we'll stop for now.

**Charles Macal:** Thank you, Nick. Thank you, speakers, for a very stimulating session, taking on some of the larger issues that we're facing in agent simulation. Why don't we take a 10-minute break, and then we'll have a session dealing strictly or specifically with toolkits.

# Toolkits





## NETLOGO: DESIGN AND IMPLEMENTATION OF A MULTI-AGENT MODELING ENVIRONMENT\*

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### ABSTRACT

NetLogo is a multi-agent programming language and modeling environment for simulating complex phenomena. It is designed for both research and education and is used across a wide range of disciplines and education levels. In this paper, we focus on NetLogo as a tool for research and for teaching at the undergraduate level and higher. We outline the principles behind our design and describe recent and planned enhancements.

**Keywords:** NetLogo, agent-based modeling, simulation, modeling toolkits, programming languages, complex systems, complexity, emergence

### OVERVIEW

NetLogo (Wilensky, 1999) is a multi-agent programming language and modeling environment for simulating complex natural and social phenomena (Wilensky, 2002). It is particularly well suited for modeling complex systems evolving over time. Modelers can give instructions to hundreds or thousands of independent “agents” all operating concurrently, in order to explore connections between micro-level behaviors of individuals and macro-level patterns that emerge from their interactions. NetLogo enables users to open simulations and “play” with them, exploring their behavior under various conditions. NetLogo is also an authoring environment that is simple enough to enable students and researchers to create their own models, even if they are not experienced programmers.

We designed NetLogo for both education and research. There has been considerable research on the use of multi-agent modeling in K–12 settings (Wilensky, 1995; Resnick, 1996; Wilensky and Resnick, 1999; Ionnidou et al., 2003; Wilensky, 2003; Wilensky and Reisman, 2004). In this paper, though, we focus on NetLogo as a powerful research tool and as a tool for learners at the undergraduate level and higher.

Historically, NetLogo is the next generation of the series of multi-agent modeling languages including StarLogo (Resnick and Wilensky, 1993; Resnick, 1994). NetLogo is a standalone application written in Java so it can run on all major computing platforms. After five years of development, NetLogo is a mature product that is stable and reliable. It is freeware: anyone can download it for free and build models without restriction. It comes with extensive documentation and tutorials and a large collection of sample models.

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\* Adapted from S. Tisue and U. Wilensky, “NetLogo: A Simple Environment for Modeling Complexity,” International Conference on Complex Systems, Boston, MA, May 2004. S. Tisue and U. Wilensky, “NetLogo: Design and Implementation of a Multi-Agent Modeling Environment,” SwarmFest, Ann Arbor, MI, May 2004.

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As a language, NetLogo is a member of the Lisp family that supports agents and concurrency. Mobile agents called “turtles” move over a grid of “patches,” which are also programmable agents. All of the agents can interact with each other and perform multiple tasks concurrently.

NetLogo is being used to build an endless variety of simulations. Members of our user community have turned turtles into molecules, wolves, buyers, sellers, bees, tribespeople, birds, worms, voters, passengers, metals, bacteria, cars, robots, neutrons, magnets, planets, shepherds, lovers, ants, muscles, networkers, and more. Patches have been made into trees, walls, terrain, waterways, housing, plant cells, cancer cells, farmland, sky, desks, fur, sand, etc. Turtles and patches can be used to visualize and study mathematical abstractions, too, or to make art and play games. Themes addressed include cellular automata, genetic algorithms, positive and negative feedback, evolution and genetic drift, population dynamics, path-finding and optimization, networks, markets, chaos, self-organization, artificial societies, and artificial life. The models all share our core themes of complex systems and emergence.

In the following sections, we offer more detail on all of these topics. We begin with a tour of the application, then back up to outline its history. We then give a more detailed account of the language itself. NetLogo has recently become extensible; we explain why and how. A technical discussion of how NetLogo is implemented follows. Finally, we conclude with a summary of work in progress and future plans.

## APPLICATION TOUR

In this section, we give the reader a brief tour of the NetLogo user interface and Models Library.

### User Interface

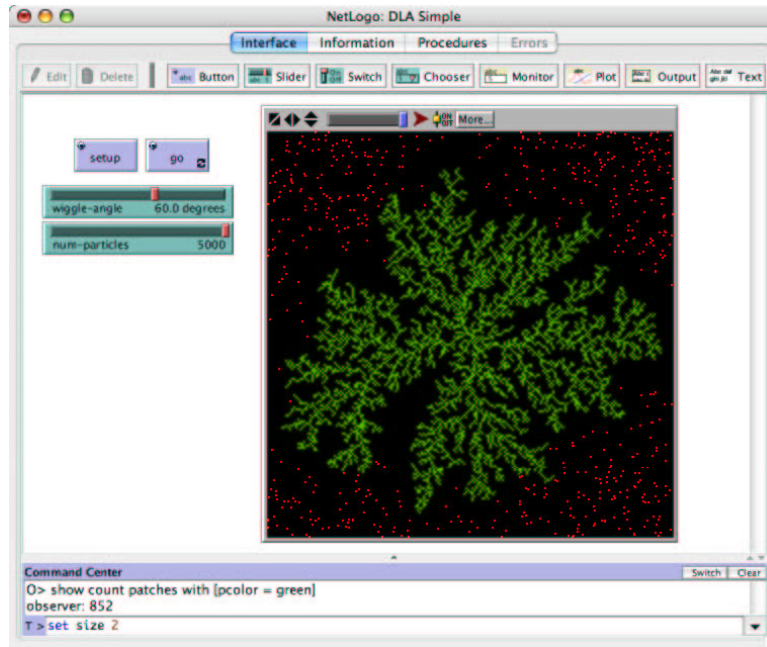
Figure 1 is a screen shot of NetLogo’s user interface after opening and running a model from the Models Library. On the right is the graphics window, in which the “world” of the model is made visible. In the model shown, the turtles represent diffusing particles. They wander randomly. When the model begins, there is a single green patch in the center. When a particle encounters a green patch, it “sticks” and turns green itself. Over time a beautiful, branching aggregate emerges.

On the left are model controls. In this model, they include:

- Buttons for controlling the model. “Setup” initializes the model and “Go” makes it run.
- Sliders that control model parameters. For example, the “num-particles” slider controls the number of particles that build the aggregate.

Note that this is a simple model with only a few controls. For more complicated models, other types of controls are available including switches, choosers, monitors, plots, text boxes, and output areas.





**FIGURE 1** NetLogo’s user interface, with the model Diffusion Limited Aggregation

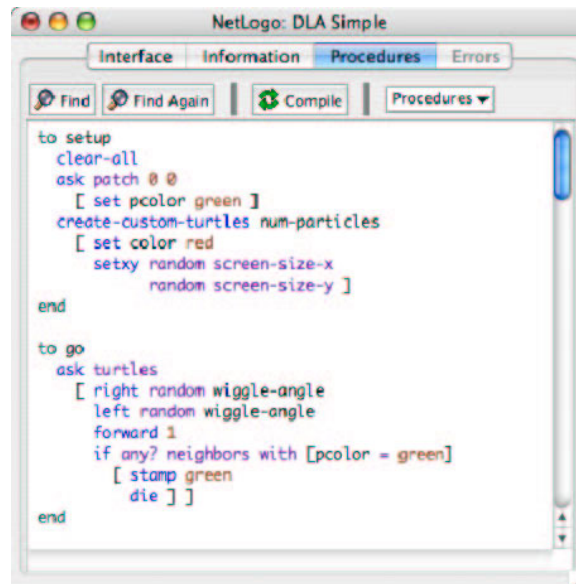
In Figure 1, we see only NetLogo’s “Interface” tab. The Interface tab is also an interface builder. No firm distinction is made between using a model and editing it — you can move, modify, or create interface elements at any time. Agents can be inspected and altered and the code for the model can be changed without restarting the simulation. At the bottom of the Interface tab is the “Command Center,” in which NetLogo commands can be issued, even while the model is running.

The other tabs are:

- Information, where documentation on the model is found. This typically explains the rules behind the model and suggests experiments for the reader to try.
- Procedures, where the actual code for the model is stored. A well written model includes comments in the code explaining how it works.
- Errors (normally disabled), where any incorrect code can be viewed and fixed.

The order of the tabs is meant to follow a user’s typical engagement with a model. Usually people want to dive right in and try out the model first in the Interface tab, then move to the Information tab to more fully understand what they’re seeing. Eventually, they can inspect the code in the Procedures tab to understand the underlying rules and make modifications and additions.

Figure 2 shows the Procedures tab containing the complete code for the model. Language elements are automatically color-coded so the code’s structure is more clearly visible.



```

NetLogo: DLA Simple
Interface Information Procedures Errors
Find Find Again Compile Procedures ▼

to setup
  clear-all
  ask patch 0 0
  [ set pcolor green ]
  create-custom-turtles num-particles
  [ set color red
    setxy random screen-size-x
      random screen-size-y ]
end

to go
  ask turtles
  [ right random wiggle-angle
    left random wiggle-angle
    forward 1
    if any? neighbors with [pcolor = green]
    [ stamp green
      die ] ]
end

```

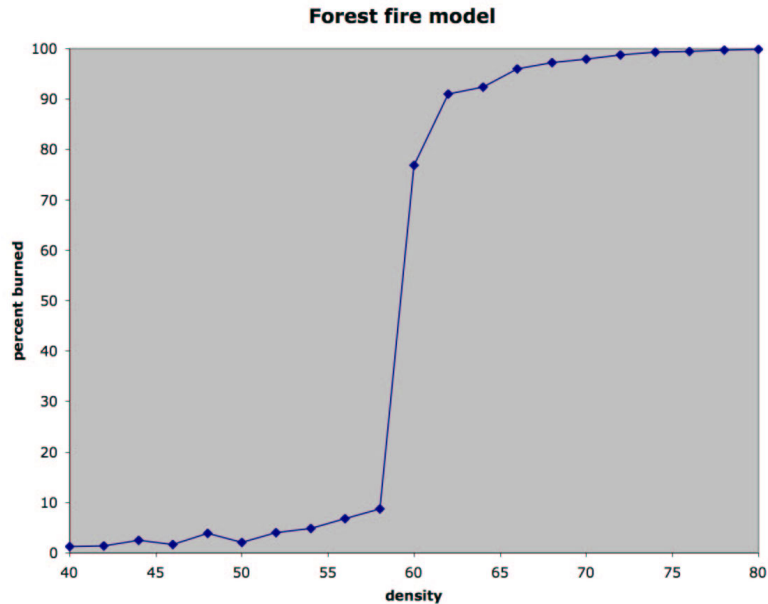
**FIGURE 2** Procedures tab with complete code for the aggregation model

NetLogo can exchange data with other applications. The language includes commands that let you read or write any kind of text file. There are also facilities for exporting and importing data in standard formats. The complete state of the world can be saved and restored in a format that can easily be opened and analyzed with other software. Graphed data can be exported for rendering and analysis with other tools. The contents of the graphics window, or of the model’s whole interface, can be saved as an image, or you can record a series of such images as a QuickTime movie. Finished models can be published on the web or embedded in presentations as Java applets.

NetLogo includes a still evolving tool called BehaviorSpace that allows “parameter sweeping,” that is, systematically testing the behavior of a model across a range of parameter settings. Figure 3 shows an example of using BehaviorSpace to study a forest fire model. Based on the experiment setup entered by the user, BehaviorSpace automatically runs the model many times while varying the “density” parameter. The results show the effect of that parameter on the amount of forest burned.

NetLogo supports not only the construction of wholly computer-based simulations, but also what we call “participatory simulations” (Wilensky and Stroup, 1999a), in which a group of students acts out the behavior of a system, each student playing the role of an individual element of the system. To enable this, NetLogo includes a technology called HubNet (Wilensky and Stroup, 1999b), which enables communication between a NetLogo model operating as a server and a set of clients, which may be handheld devices or computers running HubNet client software.

The most visible area of change in NetLogo 2.0 was graphics. Now, turtles can be any size and shape and be positioned anywhere. Turtles and patches can also be labeled with text.

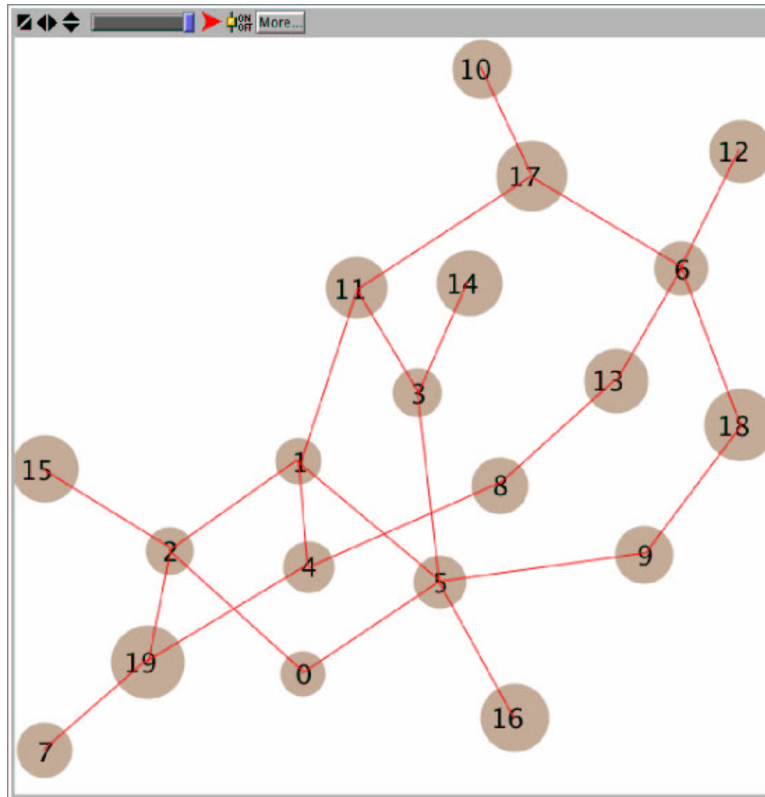


**FIGURE 3** Using BehaviorSpace to study a forest fire model (The density slider is varied from 40 to 80 by steps of 2. We measure the percentage of burned trees at the end of each run. A run ends when no “fire” agents remain. The graph [generated from the BehaviorSpace output by means of a graphing package] shows the results: an abrupt phase transition at the critical density.)

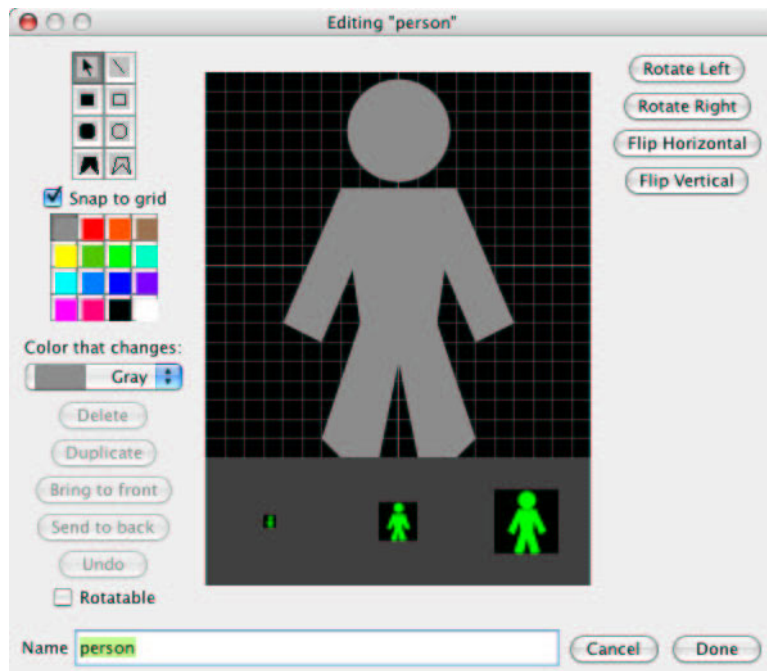
Turtle shapes are vector-based to ensure smooth appearance at any scale. These changes have led to dramatic visual enhancement of models. An example of graphics that were not possible before is the use of turtles to represent both nodes and edges in a network, as in Figure 4.

Significant improvements made for the NetLogo 2.1 release include:

- Improved editor for turtle shapes, to make it easier to customize how a model looks. This is important for data visualization. See Figure 5.
- Parenthesis and bracket matching in the code editor, to make editing complex code easier.
- Detecting individual keystrokes from code. This makes highly interactive models (and games) more usable.
- Adding `let` to the language, so new local variables can be introduced anywhere. This helps modelers write clearer, more concise code.



**FIGURE 4** Nodes and edges, both represented using turtles in the graphics window



**FIGURE 5** New, improved editor for turtle shapes

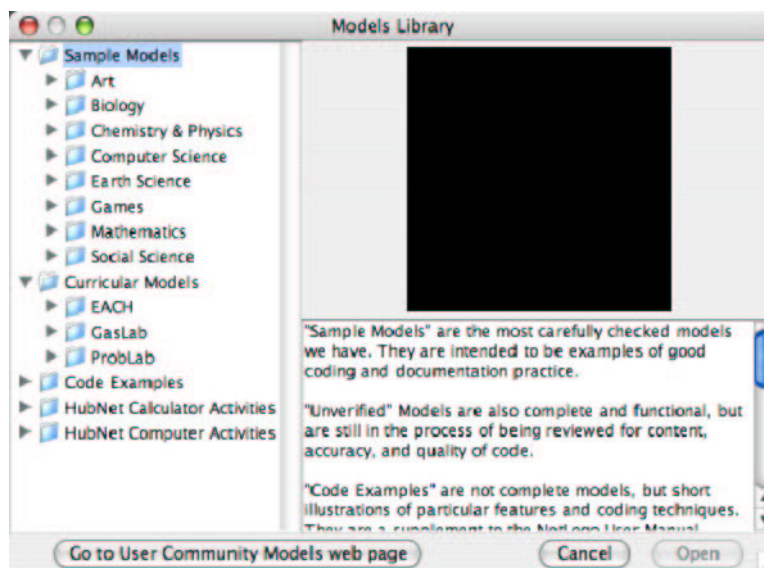
## Models Library

Just as important as NetLogo itself are the materials it comes with. We have devoted almost as much development effort to the Models Library as to the NetLogo application. The Models Library contains more than 150 prebuilt simulations that can be explored and modified. Figure 6 shows the structure of the Models Library. The simulations address many content areas in the natural and social sciences, including biology and medicine, physics and chemistry, mathematics and computer science, and economics and social psychology. All of the models include an explanation of the subject matter and the rules of the simulation and suggestions for activities, experiments, and possible extensions. To aid learning and encourage good programming practice, the code for the simulations is clear, elegant, and well commented.

Our goal for the library is to include as many as possible of the standard, well-known “chestnuts” of complex systems science. This serves several purposes:

- Researchers, already knowing the ideas behind the models, can easily learn the language by studying them.
- Modelers can usually find something in the library to base a new model on, rather than starting from scratch.
- These well-known examples are introduced to a new generation of students of complex systems science.

The Models Library also includes a “curricular models” section. It contains groups of models that are intended to be used together in an educational setting as part of a curricular unit. Most of them include extra associated curricular materials (above and beyond that which we provide with all of our models).



**FIGURE 6** Structure of the Models Library

In addition to the 140 simulations, the library also includes several dozen “code examples.” These are not full simulations, but brief demonstrations of NetLogo features or coding techniques.

## HISTORY AND AUDIENCE

In this section we summarize NetLogo’s history and how it came to be a tool for both education and research, and we explain the benefits of addressing both audiences.

### Origins

NetLogo originates in a blend of StarLisp (Lasser and Omohundro, 1986) and Logo (Papert, 1980); Logo is itself a member of the Lisp family. From Logo, it inherits the “turtle.” In traditional Logo, the programmer controls a single turtle; a NetLogo model can have thousands of them. NetLogo also follows Logo’s philosophy of ease of use, providing a “low threshold” of entry for new users. From StarLisp, a parallel Lisp of the 1980s, NetLogo inherits multiple agents and concurrency.

NetLogo derives from our experience with our earlier environment, StarLogoT (Wilensky, 1997). Even though the original incarnation of StarLogo (Resnick and Wilensky, 1993; Resnick, 1994) was on a supercomputer, it had always been primarily intended for use in schools.<sup>1</sup> But StarLogoT became very popular among researchers. So with NetLogo, we now aim more explicitly to satisfy the needs of both audiences. In the transition from StarLogoT to NetLogo, we redesigned both the language and the user interface. NetLogo includes almost all of StarLogoT’s features and many new ones. Many of the new features of NetLogo are aimed at research users.

### “Low Threshold”

All the multi-agent Logo models have adopted design principles from the Logo language. A central principle is “low threshold, no ceiling.” Low threshold means new users, including those who never programmed before, should find it easy to get started. No ceiling means the language should not be limiting for advanced users. We wanted NetLogo to be just as popular with researchers as StarLogoT had been, so that meant devoting significant attention to the “no ceiling” side of the principle. Logo’s reputation as a language for schools does not do justice to its ample power, as demonstrated by (Harvey, 1997).

We believe researchers should care about “low threshold,” too. Even for such users, NetLogo’s inheritance from educational languages brings several benefits. First, in universities there is substantial overlap between teaching and research, and if a single tool can serve both needs, there are opportunities for synergy. Second, when code is easier to write and easier to read, everyone benefits. Models become easier to build; often researchers can build models

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<sup>1</sup> There were several different early implementations of StarLogo in the first part of the 1990s. The supercomputer version was Connection Machine StarLogo. Later came MacStarLogo (Begel, 1999), of which StarLogoT is a superset.

themselves when otherwise they would have to hire programmers. And models become more easily understood by others; this is vitally important in order for researchers to effectively communicate their results to others, verify each other's results, and build upon each other's work. The goals of scientific modeling are compromised if programs are long, cryptic, and platform-specific. A NetLogo model is less likely to suffer these problems than one written in common general-purpose languages like Java and C++.

## **The Integrated Approach**

NetLogo is its own programming language, embedded in an integrated, interactive modeling environment. The integrated approach to multiagent modeling originates with StarLogo, was refined in StarLogoT and NetLogo, and has also been followed by other all-in-one agent-based modeling solutions such as AgentSheets (Repenning et al., 2000) and Breve (Klein, 2002). "Toolkits" or libraries, such as Swarm (Minar et al., 1996) and Repast (Collier and Sallach, 2001), take a different approach; they make simulation facilities available to programs written in a general-purpose language such as Java.

We see the integrated approach as essential to achieving our "low threshold" goal. The difficulty of programming in Java or C++ isn't due only to the language itself. It's also due to the complication of the environments (whether command line-based or GUI-based) in which programming in those languages is normally done. With the added complexity of getting the environment to talk to a modeling library or toolkit, the initial barrier for entry for new programmers becomes quite high — even before they start dealing with the difficulties of the languages themselves.

In contrast, the NetLogo environment allows a smooth, almost unnoticeable transition from exploring existing models into programming. NetLogo's user interface makes no firm distinction between using a model and editing it. Even the smallest amount of knowledge of the language is immediately useful in creating buttons and monitors or typing commands into the command center, in order to better inspect and control an existing model. The tools for altering the model's rules are only as far away as a click on the Procedures tab.

## **Development History**

NetLogo has been under development since 1999. Since then, we have averaged two to three substantial new releases per year. Version 2.0.2 (August 2004) is mature, stable, and reliable. As of October 2004, version 2.1 is available in beta form and we expect a final release soon. Even though our user base has expanded, the rate of incoming bug reports has slowed to a trickle. Models now run much faster than in earlier versions — our users now find it fast enough for most purposes.

## **Acceptance**

We have much evidence that acceptance of NetLogo in the research and education communities is wide and growing. The software has been downloaded tens of thousands of times. Currently, there are about 50 downloads per day. Our announcements list has over

5,000 members. The NetLogo discussion group (<http://groups.yahoo.com/group/netlogo-users/>) has over 1,600 members and averages about 100 posts per month. Traffic on the discussion group has increased fivefold since 2002. Several organizations have independently conducted workshops on NetLogo for both researchers and teachers. In the summer of 2004, we held our own first annual workshop at Northwestern. A number of university classes are now taught, in whole or in part, using NetLogo. Some of these classes and workshops have rich collections of associated materials available online. The NetLogo web site has an area where users can upload models to share with the user community. More than 100 models have been uploaded so far.

## LANGUAGE

In this section, we describe the NetLogo programming language itself. For further information on the NetLogo language, consult the NetLogo User Manual (Wilensky, 1999), particularly the Programming Guide and Primitives Dictionary sections.

### Language Fundamentals

As a language, NetLogo adds agents and concurrency to Logo. Logo, as originally developed by Seymour Papert and Wally Feurzeig in 1968, is derived from Lisp, but has a friendlier syntax. Logo was designed as a programming language usable by children as well as adults and is still popular today as a powerful general-purpose computer language.

Although Logo is not limited to graphical applications, it is best known for its “turtle graphics,” in which a virtual being or “turtle” moves around the screen drawing figures by leaving a trail behind it. NetLogo generalizes this concept to support hundreds or thousands of turtles all moving around and interacting. The world in which the turtles move is a grid of “patches,” which are also programmable. Collectively, the turtles and patches are called “agents.” All agents can interact with each other and perform multiple tasks concurrently. NetLogo also includes a third agent type, the “observer.” There is only one observer. In most models, the observer gets the ball rolling by issuing instructions to the turtles and patches. Different “breeds” of turtle may be defined, and different variables and behaviors can be associated with each breed.

Some models use the patch world just as a lattice. For example, in a cellular automaton, there are no turtles, only patches. And in some other models, turtles move on the lattice (from patch center to patch center). But the patches are not just lattice sites — they are square sections of a continuous two-dimensional space. Turtle coordinates are floating point values, so a turtle may be positioned anywhere within a patch. For example, in the aggregation model shown above, the aggregate is made up of lattice sites, but particles move freely on the plane.

There are many language elements for talking about space and spatial relations: towards, distance, neighbors, forward and back, left and right, size, heading, patch-ahead, diffuse, and so on. Some of these come from Logo, while others are new.

An important NetLogo language feature, not found in its predecessors, is “agentsets,” or collections of agents. For example, the set of all turtles and the set of all patches are agentsets. You can also make custom agentsets “on the fly,” for example, the set of all red turtles, or a



column of patches (the set of patches with a given X coordinate). Agentsets are responsible for much of NetLogo's expressive power.

In addition to special constructs to support multiagent modeling, NetLogo also includes standard programming constructs such as procedures, loops, conditionals, recursion, strings, lists, and so forth. Both integer math and double-precision IEEE floating point math are supported. The `run` and `runresult` commands can be used to execute code constructed on the fly.

## NetLogo as Logo

Although there is no single agreed upon standard for the Logo language, NetLogo shares enough syntax, vocabulary, and features with other Logos to earn the Logo name. Still, some important differences from most Logos include:

- NetLogo has no symbol data type. Eventually, we may add one, but since it is seldom requested, it may be that the need does not arise much in agent-based modeling. In most situations where traditional Logo would use symbols, we simply use strings instead.
- Control structures such as `if` and `while` are special forms, not ordinary functions. You cannot define your own special forms.
- As in most Logos, functions as values are not supported. Most Logos provide similar functionality, though, by allowing passing and manipulation of fragments of source code in list form. NetLogo's capabilities in this area are presently limited. A few of our built-in special forms use UCBLogo-style "templates" to accomplish a similar purpose, for example, `sort-by [length ?1 < length ?2] string-list`. In some circumstances, using `run` and `runresult` instead is workable, but they operate on strings, not lists.

There are several reasons for those omissions. They are partly due to NetLogo's descent from StarLogoT, which as discussed above needed to be very lean. Many of StarLogoT's limitations have already been addressed in NetLogo (for example, NetLogo has agentsets and double-precision floating point math), but some of the "leanness" remains. This leanness is not only historical, though. Efficiency is always a vital goal for multi-agent systems, since many modelers want to do large numbers of long model runs with as many agents as they can. It is easiest to construct a fast engine for a simple language, and, from a language design perspective, omitting advanced language features and prohibiting the definition of new special forms may actually be desirable for a language in which readability and sharing of code is paramount. We weigh these tradeoffs carefully as we continue to expand the language.

## Reproducibility

One of our core design goals for NetLogo is that results be scientifically reproducible, so it is important that models operate deterministically. NetLogo is a "simulated parallel" environment. In true parallel computing, programs must be constructed very carefully to avoid nondeterminism. We think this is too great a burden for novice programmers, so concurrency in

NetLogo operates deterministically. That means that if you “seed” the random number 8 generator the same way, then a NetLogo model always follows the same steps in the same order and produces the exact same results, regardless of what computer you run it on. Java’s underlying platform-independent math libraries help ensure consistency.

## EXTENSIBILITY

In this section, we describe how NetLogo has recently become extensible through the addition of new “extensions” and “controlling” facilities. Earlier, we described NetLogo as an integrated or “all-in-one” environment. The full NetLogo environment bundles together many components: a programming language, a compiler, an interpreter, a syntax highlighting editor, an interface builder, a graphics engine, BehaviorSpace, and so on. The downside of the all-in-one approach is that “all-in-one” can turn into “all-or-nothing.” We run the risk that if one component does not suit a user’s needs, then that user will not be able to use any of the components, because they are all tied together.

We want to avoid this all-or-nothing trap by letting users extend or replace parts of NetLogo that do not suit their purposes. That way, even users who have unique needs, or just needs we did not anticipate or have not addressed yet, can build what they need themselves in Java, and they will still get the benefit of the rest of our work. These new application programmer’s interfaces (APIs) are steps towards that goal. They lift the “ceiling” on NetLogo’s usefulness and range of applications. The integrated NetLogo environment provides core functionality; our APIs will allow advanced users to move outside that core.

In making NetLogo extensible, we are bridging the gap between integrated modeling environments (easy to use, but potentially restricting) and modeling toolkits (more flexible, but much harder to use).

### Extensions API

NetLogo has always been a full-fledged programming language, so users may write procedures in NetLogo and then use them just like built-in commands. But since NetLogo 2.0.1 we have offered an API for extensions so that users can add new elements to the language by implementing them directly in Java. This lets users add whole new types of capabilities to NetLogo.

We have been using this new API internally for a while now, and have written extensions that let NetLogo:

- Talk to other NetLogos running on different computers, peer-to-peer;
- Pull down data from a web server; and
- Make sounds and music using MIDI.

The sound extension is now included with NetLogo. Full Java source code for it, and a number of other sample extensions, are available from the NetLogo web site. Our hope is that

extension authors will share their extensions with the wider user community, so that everyone can benefit from their efforts.

## Controlling API

We also offer a “controlling” API, which allows external code to operate the NetLogo application by remote control, so to speak. This API includes calls for opening a model and running any NetLogo commands. This permits users willing to do a little light Java programming to automate large numbers of model runs from the command line. This is useful both on a single machine and when distributing runs across a cluster. We already provide an automated parameter-sweeping tool called BehaviorSpace, but the controlling API is still be useful in situations where BehaviorSpace’s present capabilities are insufficient. The API currently requires the full NetLogo user interface to be present, but we are working on removing this limitation so that models can be run “headless” from the command line. (On X11-based systems, it is possible right now to work around this limitation using X11’s “virtual framebuffer” support.)

## IMPLEMENTATION

In this section, we explain how we have constructed the NetLogo software. This section is more technical than the others.

### Background: StarLogoT

StarLogoT succeeded in attracting a large user base from a range of disciplines, but it had important technical limitations that we wanted to address.

The biggest limitation of StarLogoT was that it only ran on Macintosh computers. At the time development on StarLogoT’s precursors began, the introduction of Java had not yet brought cross-platform development of GUI applications within easy reach. Also, the target audience was schools, so the software needed to be compact and fast enough to run even on hardware that by today’s standards was very underpowered. Putting thousands of agents on such machines was only possible if the underlying engine was written in assembly language, which is of course platform-specific.

The need to be fast and small resulted in other limitations as well. Math in StarLogoT was fixed point, not floating point, with only a few digits of precision. Many arbitrary limits were imposed in order for crucial data structures to fit within a small, fixed number of bits. For example, a model could not have more than 16,384 turtles, or a patch grid bigger than  $251 \times 251$ , or a stack depth of more than 64.

StarLogoT’s language design was constrained as well by what could reasonably be implemented. The need for efficiency led StarLogoT’s architecture to become quite complicated. It included three different virtual machines for our three agent types (observer, turtles, and patches). Different agent types had different capabilities and different rules for acting in parallel; this was confusing to users, and some of the restrictions placed on user programs were severe.

## Starting Over

Because of these limitations, we chose to start over and write a new environment, NetLogo, from scratch. We expected Java to permit us to build a cross-platform application that was reasonably fast. Java does not always completely live up to its “write once, run anywhere” promise, but it performed well enough to bring cross-platform development within reach for our small development team. We knew that Java was slower than assembly language but hoped that on newer, faster machines it would not matter too much. The issue of speed is discussed further below.

Using Java offered the additional benefit that individual NetLogo models could be embedded in web pages and run in a browser, without the end user needing to download and install an application. (Initially, we even allowed the full NetLogo authoring environment to run as an applet in a web browser, but later we abandoned this option as not worth the extra development effort.)

Since we were starting from scratch anyway, we took the opportunity to redesign the language to further both our “low threshold” and “no ceiling” goals. Sometimes we had to weigh tradeoffs between those two goals; in other cases, such as agentsets, we were able to reduce barriers to novice entry while also making the language more expressive and powerful. In doing so, we also tried to be compatible with standard, popular Logo implementations whenever possible and reasonable. In particular, we tried not to stray too far from StarLogoT, so our existing user base would not find the transition too difficult.

## Java

NetLogo is written entirely in Java. Java was chosen because both the core language and the GUI libraries are cross-platform and because modern Java virtual machines (VMs) have used JIT (just in time) compiler technology to achieve relatively high performance.

NetLogo 1.3 supported earlier Java versions going back to Java 1.1, but for NetLogo 2.0 we decided to require Java 1.4. The major reasons for choosing Java 1.4 for the new version were as follows:

- The new language version includes much richer libraries. It was increasingly difficult to find developers used to working within the limitations of the antiquated version.
- More recent VMs are higher quality. Before we abandoned Java 1.1, we were constantly working around bugs in the various 1.1 VMs, which was a serious drag on our development efforts.
- Unlike Java 1.1, Java 1.4 offers “strict” math libraries that guarantee identical, reproducible results cross-platform.
- Leaving Java 1.1 behind allowed us to switch GUI toolkits, from the old AWT toolkit to the newer Swing toolkit, which has numerous advantages, including a better look and feel (Figure 7).

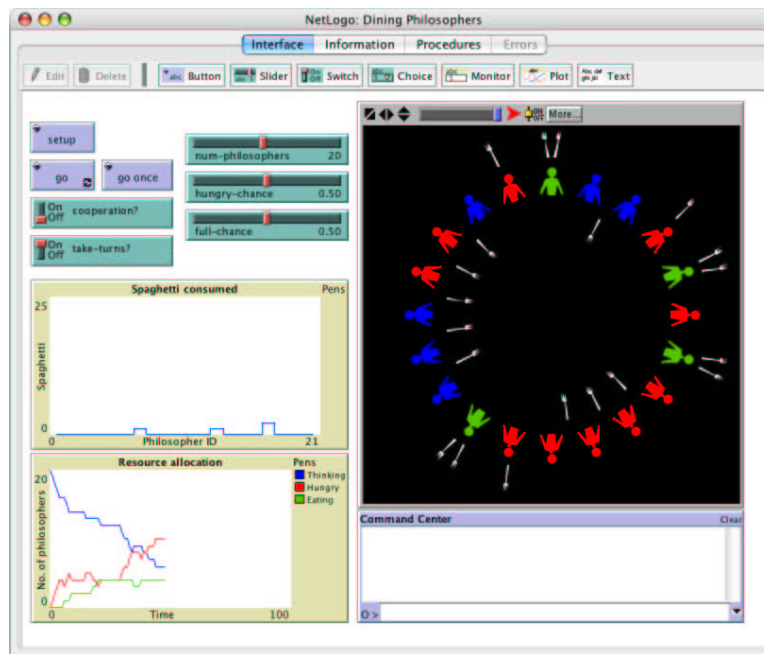
- After a long wait, Apple finally released a high-quality Java 1.4 implementation for Mac OS X.
- Even with the new VM, Apple's support for AWT-based applications on Mac OS X was poor. Mac support is important to us, but a high quality implementation on the Mac was simply impossible without switching to Swing.
- Since Java 1.4 is available for all the major platforms for which 1.3 is also available (not counting Mac OS X 10.0 and 10.1), it seemed unnecessary to be backwards compatible with Java 1.3.

Regrettably, switching to Java 1.4 meant dropping support for users of Windows 95 and Mac OS 8 and 9, since no Java 1.4 implementation is available for those operating systems. However, we continue to offer support and fix bugs for NetLogo 1.3 users.

## Speed

Early versions of NetLogo were slow, but models in later versions run much faster, especially since version 1.3. Most users now find NetLogo fast enough for most purposes. Nonetheless, we plan to continue to improve NetLogo's speed, since agent-based modeling is a field in which users always benefit from more speed.

StarLogoT was written partially in assembly language and was highly performance tuned. NetLogo is written in Java, and the NetLogo language is much more flexible and feature rich



**FIGURE 7** NetLogo's new, Swing-based user interface; note the new graphics features

than StarLogoT. Therefore, you would expect NetLogo to be slower. Surprisingly, that is not always or even usually true. Which environment is faster depends on the nature of the model. In general, StarLogoT is still faster for models with very simple code and large numbers of agents. But NetLogo is usually faster for models with complex code and smaller numbers of agents.

The surprising fact that StarLogoT is not always faster can be accounted for by reference to StarLogoT's unique architecture. As mentioned above, the StarLogoT engine was divided into three virtual machines: one for the observer, written in Lisp, and two for the turtles and patches, written in assembly language. The turtle and patch machines were extremely fast, but crossing the boundaries between the different machines was slow. With simpler code and more turtles and patches, overall speed benefited more from the speed of the turtle and patch virtual machines. In contrast, NetLogo's internal architecture is much more uniform. A single virtual machine handles all three agent types. Therefore, there is no special penalty associated with complex code and no special benefit associated with large numbers of agents.

NetLogo is a hybrid compiler/interpreter. To improve performance, we do not interpret the user's code directly. Instead, our compiler analyzes, annotates, and restructures it into a form that can be interpreted more efficiently.

Earlier versions of NetLogo (1.0 and 1.1) compiled user code into a form suitable for execution by a virtual machine that was stack-based. However, we discovered through profiling that making the virtual machine stack-based actually hurt performance rather than helping it. So, in our current compiled representation, each command is tree-structured so that intermediate results are stored on the Java VM's own stack instead of our stack. This change resulted in an approximately twofold performance gain. Other, smaller engine performance gains in newer versions (since NetLogo 1.0) came from profiling the engine code and addressing inefficiencies in object creation, memory usage, and other areas.

If we want to further increase NetLogo's speed in the future, the most promising approach, relative to the likely development effort required, seems to be to compile NetLogo code to Java byte code instead of our own custom intermediate representation. Informal tests indicate that this would likely result in at least a twofold improvement in speed. We also have considered replacing the Java-based engine with a native one, perhaps written in C. However, general opinion recently is that JITted Java code is not always slower than C code anymore, so this approach may not be fruitful.

So far we have been discussing the speed of NetLogo's core computational engine. But NetLogo's overall performance does not depend only on engine speed. There is also graphics speed to consider. Whether engine speed or graphics speed dominates varies widely from model to model — some are 90% engine, others are 90% graphics. The latter kind of model can always be sped up by using NetLogo's graphics "control strip" to temporarily shut off graphics altogether, but that does not mean graphics performance is unimportant.

Switching our GUI framework from AWT to Swing raised problems for graphics performance. Prior to NetLogo 2.0, graphics window updates were "incremental," that is to say, only agents that moved or changed were redrawn. Incremental painting onscreen, instead of to an offscreen buffer, is not supported under Swing, and on Mac OS X, the performance of painting offscreen was unacceptable. As an experiment, we switched from incremental painting to always redrawing the complete contents of the graphics window every time, expecting that the change

would hurt performance. We were pleasantly surprised: on Macs, graphics performance actually increased, and on Windows, the speed penalty was negligible.

Abandoning incremental updates freed NetLogo's graphics capabilities enormously. Previously, in order to make incremental updates possible, the graphics window was limited in several important respects. Even though NetLogo's world is continuous, turtles in the graphics window were always the same size and appeared centered on their patches, like chess pieces. Since patches did not overlap, it was possible to redraw each patch incrementally and separately. But if incremental updates are no longer performed, then there is no longer any reason to align turtles with the grid. So now, in NetLogo 2.0, turtles can be any size and shape and be positioned anywhere. Turtles and patches can also be labeled with text. Turtle shapes are vector-based to ensure smooth appearance at any scale. These features had actually been available in earlier NetLogo versions, but were slow and buggy. Now they are fast and reliable. These changes have led to dramatic visual enhancement of models (Figures 7 and 8).

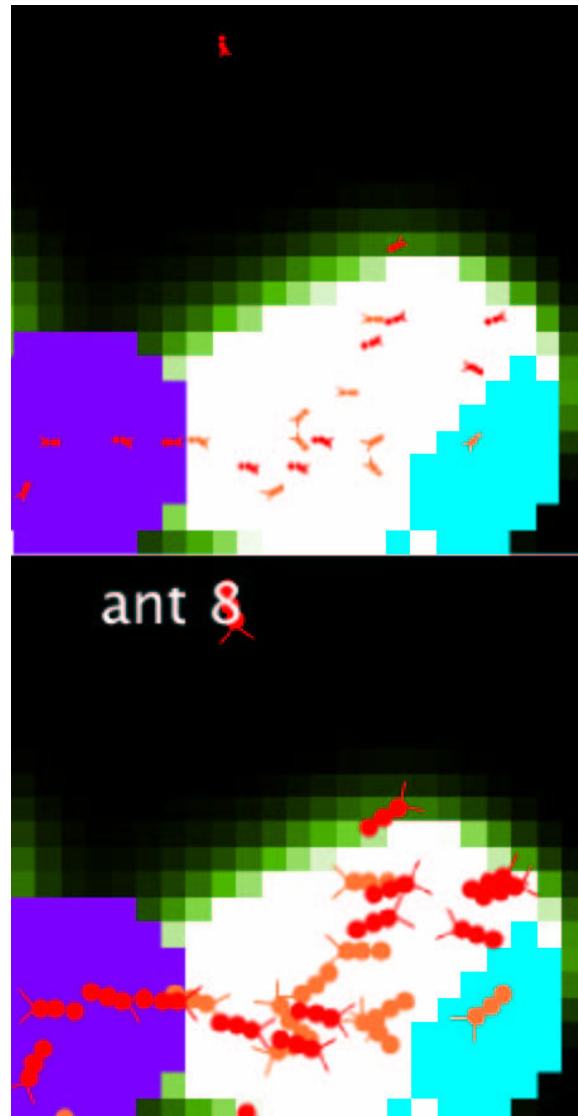
## Concurrency

In many respects the NetLogo engine is an ordinary interpreter. But it also has some unusual features because of the need to support concurrent processes. Concurrency in NetLogo has two sources.

The first kind of concurrency we support is concurrency among agents. If we use the command `forward 20` to ask a set of turtles to move forward 20 steps, we do not want one turtle to win the race before the others have even left the starting line. So, we have all the turtles take one step together, then they all take another step, and so forth. Ultimately, the NetLogo engine is single-threaded, so the turtles must move one at a time in some order; they cannot really move simultaneously. So the engine "context switches" from agent to agent after each agent has performed some minimal unit of work, called a "turn." Because the timing of context switches is deterministic, the overall behavior of the model remains deterministic. We only update the screen after all the agents have had a turn; this visually preserves the illusion of simultaneity. The NetLogo User Manual (Wilensky, 1999) contains a more detailed discussion of the timing of context switches between agents. We provide a command, `without-interruption`, which the programmer can use to prevent unwanted switching.

The second kind of concurrency we support is concurrency among the different elements of the NetLogo user interface which can initiate the execution of code. Currently these are: buttons, monitors, and the Command Center. Buttons and monitors contain code entered by the model author, and the user may enter commands into the Command Center at any time. In all three cases, a "job" is created and submitted to the engine to request that some code be executed by some agents. Jobs are akin to what operating systems call "threads" or "processes." We use the word "job" to avoid confusion. At the operating system level, the NetLogo application is *one* process, and the NetLogo engine is *one* thread within that process.

When multiple jobs are active, the engine must switch between them, just as it switches between the agents within a job. The rule followed is to switch from job to job once every agent



**FIGURE 8** The Ants model, with and without new graphics features

in the first job has had a turn. Here, the NetLogo engine is taking on a task more typically associated in computer scientists' minds with the process scheduler in a cooperatively multi-tasked operating system rather than with a language interpreter.

Concurrency is still an active area of concern for us, and final decisions on how best to support it may still lie ahead. We are presently revisiting and rethinking our current design choices with an eye towards both helping newcomers avoid mistakes and increasing the power available to advanced users.



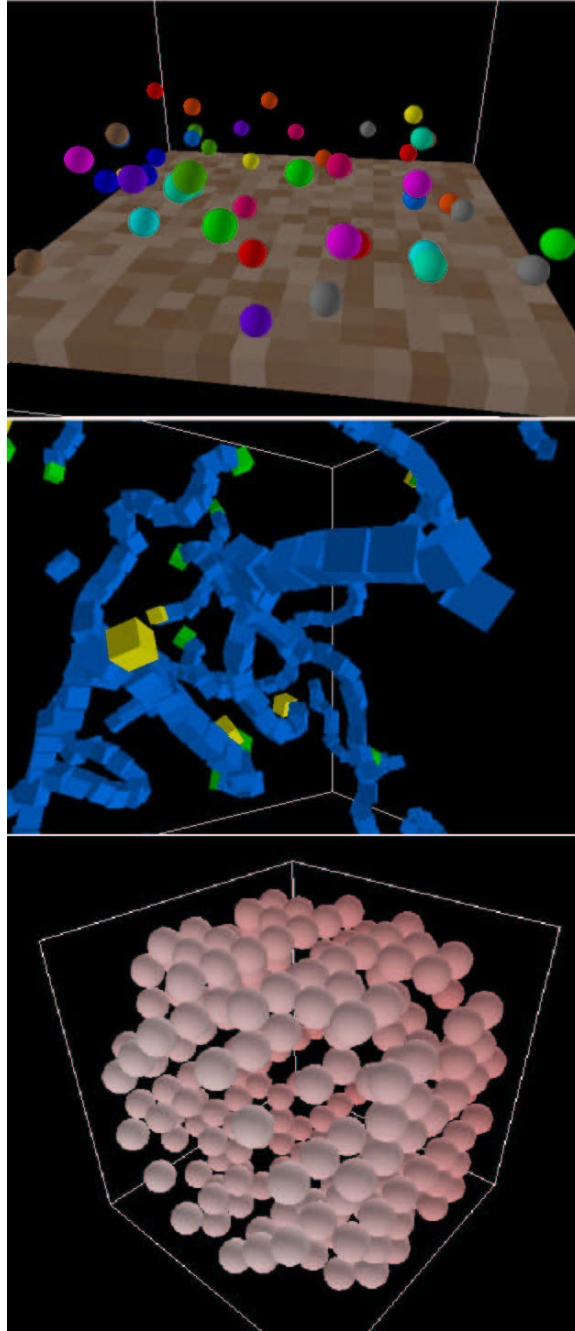
## CONCLUSION

We have already touched upon some goals for future NetLogo versions, such as increased speed and headless operation. Here are some other enhancements for which we already have working prototypes:

- 3-D NetLogo, including language extensions and 13 OpenGL-based 3-D graphics. Some 3-D models are already possible, but language support will make them easier to build and OpenGL will enable much higher quality 3-D visualization. This is a very big job, but we have a working prototype already (see Figure 9).
- Support for different lattices and world topologies, with no extra code required. Currently, the NetLogo patch world “wraps” in the X and Y directions, forming a torus. Some language elements are available in both wrapping and nonwrapping versions. Typically, models that do not want wrapping use the outer layer of patches as a barrier. In a future version, we plan to make wrapping a global option which can be turned off. This is an example of an alternate world topology. Soon, we will also support even-numbered grid sizes and arbitrary placement of the origin of the coordinate plane. In the longer term, we would like to support unbounded plane models. We already have some models that operate on a hexagonal lattice, but their code cannot currently be made as concise as we would like.
- Easier, more flexible randomized agent scheduling. (Random scheduling is already possible by adding extra code, but soon it will be built in.)
- Improved plotting requiring less additional code in the procedures tab. Separating code for agent behaviors from code for data generation and visualization code will improve clarity and conciseness of models.
- A profiling tool for identifying speed bottlenecks in model code.

Networks are currently a very active area of research in the agent-based modeling community. Network models are already possible in NetLogo, but we want to make them easier to build, including making it easier to leverage the capabilities of existing network analysis and visualization tools.

We are also adding support to NetLogo for aggregate modeling. Aggregate modeling, also known as systems dynamics modeling, has historically been supported by separate, non-agent-based modeling tools such as STELLA (Richmond and Peterson, 1990). We are incorporating similar finite difference engine technology into NetLogo so that researchers and students can investigate systems using agent-based and aggregate techniques in tandem.



**FIGURE 9** Some screen captures of our prototype 3-D version of NetLogo

There are ongoing efforts within our research group to further explore NetLogo's potential for research and education. Of particular relevance to NetLogo's future as a research tool are these major ongoing long-term projects:

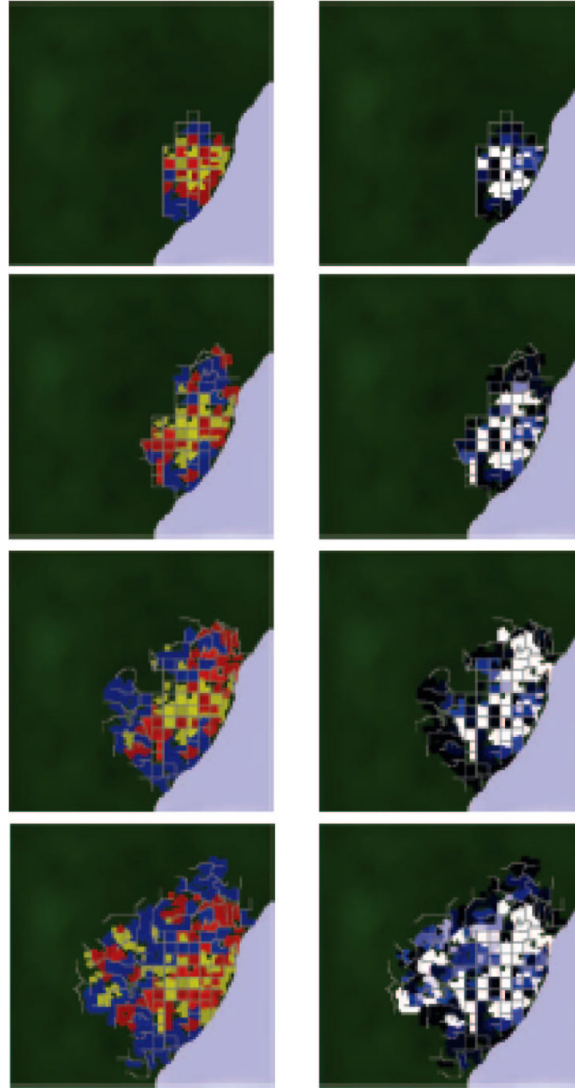
- Integrated Simulation and Modeling Environments (ISME), a project in collaboration with the University of Texas that uses NetLogo to enact “participatory simulations” (Wilensky and Stroup, 1999a) in both classroom and research contexts.
- Procedural Modeling of Cities, a project in which agents “grow” virtual cityscapes for use in architecture, urban planning, training, and entertainment. Preliminary results from the model are shown in Figure 10 (Lechner et al., 2003).
- Modeling School Reform, a project to build models of the potential effects of educational policy decisions, to assist school leaders and policy makers. This work will include social network modeling and analysis. These projects will drive substantial expansion of NetLogo's ability to support large, ambitious modeling efforts. We also have a number of other projects, focused on the use of NetLogo in educational contexts.

### **ACKNOWLEDGMENTS**

Thanks to the members of our user community, and to all past and present members of the Center for Connected Learning and Computer-Based Modeling, for all of their contributions to NetLogo.

Portions of this paper were loosely adapted from the NetLogo User Manual (Wilensky, 1999). We thank Owen Densmore for contributing the network layout model used to produce Figure 4.

We gratefully acknowledge the support of the National Science Foundation.



**FIGURE 10** Growth of a simulated city; left column represents land use, right column represents population density

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## AGENT-BASED MODELING AND SOCIAL SIMULATION WITH *MATHEMATICA* AND MATLAB

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### ABSTRACT

Computational mathematics systems, such as *Mathematica* and MATLAB, can be alternatives or supplements to agent-based model development in the social sciences. *Mathematica* is a symbolic processing system that uses programming paradigms such as functional programming and term replacement, while MATLAB is a numeric processing system that uses a scripting-language approach to programming. These packages and others like them are fully integrated development environments. Their interpretative nature and the seamless integration of their graphical capabilities provide immediate feedback to users during the development process. This feature makes them particularly useful as rapid prototype development tools as part of large-scale model development efforts using agent-based toolkits such as Repast, MASON, or Swarm. Furthermore, they are readily available on the desktop as well as on campus and can be easily integrated into educational courses on social simulation. This paper describes the use of these tools in specific modeling approaches to social simulation.

**Keywords:** Agent-based modeling, social simulation, *Mathematica*, MATLAB scripting languages, computational mathematics systems

### INTRODUCTION

*Mathematica*<sup>1</sup> and MATLAB<sup>2</sup> are examples of computational mathematics systems (CMSs) that can readily be used to supplement agent-based modeling efforts in the social sciences. The reasons for this are twofold:

1. *Mathematica* and MATLAB are powerful, consisting of fully integrated development environments that combine capabilities for programming, graphical display, data import and export, and linkages to external programs.
2. *Mathematica* and MATLAB are convenient to use, are mature, and provide immediate results and feedback to users.

The interpreted nature of these systems avoids the compilation and linking steps required in traditional programming languages and provides immediate feedback to users during the development process. The systems combine a user interface with data import and graphical display capabilities in one package. But most important, these systems are useful as rapid

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<sup>1</sup> *Mathematica* is a registered trademark of Wolfram Research, Inc. ([www.wri.com](http://www.wri.com)).

<sup>2</sup> MATLAB and Simulink are registered trademarks of The MathWorks, Inc. ([www.mathworks.com](http://www.mathworks.com)).

prototype development tools or as components of large-scale model development efforts. Furthermore, they are readily available on the desktop and on campus, and they can easily be integrated into educational courses on social simulation. This paper, which is pedagogical in nature, describes the use of these tools in specific modeling approaches to social simulation.

Several types of modeling approaches have been used as the basis for modeling social systems. Systems dynamics (SD), cellular automata (CA), and social networks (SN) are the main ones that are addressed in this paper. Guetzkow et al. (1972) provide an overview of early social simulations, and Gilbert and Troitzsch (1999) provide one for current approaches.

Many social systems have been modeled by using the SD approach developed by Forrester (Forrester, 1969, 1975; Roberts, 1978; Sedgewick, 1988). Systems dynamics is an aggregate approach emphasizing the interdependencies of system components. Systems dynamics models cast a simulation as a set of simultaneous difference or differential equations. The equations are solved recursively to simulate dynamic social processes as they unfold over time. Both *Mathematica* and MATLAB can readily solve models in the SD style, and both have extensive facilities for statistical analysis and graphic display of results. The MATLAB add-on package, Simulink, is a purely graphical system for constructing dynamic systems models. Other development systems dedicated to SD modeling are also available, including STELLA, VENSIM, and POWERSIM (Dutta and Roy, 2002).

The structure and organization of recent social simulation models tend to be much different than those of traditional social simulations based on SD or discrete-event simulation. This difference arises, in part, because recent social simulations have been based on independently developed simulation frameworks for artificial life. Most notable are Swarm (Burkhart et al., 2000); cellular automata, which are based on a grid structure (Wolfram, 1994); and Schelling's model of segregation (Schelling, 1971), which was based on a grid, although not originally computerized.

Several agent-based models using MATLAB to various degrees have been published recently, including a model of political institutions in modern Italy (Bhavnani, 2003), a model of pair interactions and attitudes (Pearson and Boudarel, 2001), a bargaining model to simulate negotiations between water users (Thoyer et al., 2001), and a model of sentiment and social mitosis based on Heider's Balance Theory (Guetzkow et al., 1972; Wang and Thorngate, 2003). The latter model uses Euler, a MATLAB-like language. Thorngate argues for the use of MATLAB as an important tool to teach social simulation programming techniques (Thorngate, 2000). The primary references for grid-type simulations using *Mathematica* for social network models include Gaylord and Nishidate (1994), Gaylord and Wellin (1995), Gaylord and D'Andria (1998), and Gaylord and Davis (1999).

This paper focuses on modeling agent-based social systems by using the grid and SN approaches with *Mathematica* and MATLAB. Section 2 briefly describes computational mathematics systems and the MATLAB and *Mathematica* packages. Section 3 describes the fundamental operations for agent-based social simulation for two of the most common underlying structures in social simulation: (1) two-dimensional grids as in cellular automata, and (2) social networks, in which agents are related to each other in social space rather than spatially. We present examples of using MATLAB or *Mathematica* for these topologies. Section 4 summarizes and presents conclusions on the role of MATLAB and *Mathematica* in social simulation.



## COMPUTATIONAL MATHEMATICS SYSTEMS

MATLAB and *Mathematica* are examples of CMSs, which allow users to apply powerful mathematical algorithms to solve problems through a convenient and interactive user interface. CMSs supply a wide range of built-in functions and algorithms. MATLAB, *Mathematica*, and Maple are examples of commercially available CMSs. Their origins go back to the late 1980s. CMSs are structured in two main parts: (1) the user interface that allows dynamic user interaction, and (2) the underlying computational engine, or kernel, that performs the computations according to the user's instructions. Unlike conventional programming languages, CMSs are interpreted rather than compiled, so there is immediate feedback to the user, but some performance penalty is paid. The underlying computational engine is written in the C programming language for these systems, but the user does not see the C coding. The most recent releases of CMSs are fully integrated systems that combine capabilities for data input and export, graphical display, and the capability to link to external programs written in conventional languages such as C or Java by using interprocess communication protocols. The powerful features of CMSs, their convenience of use, the need for the user to learn only a limited number of instructions, and the immediate feedback provided to users make CMSs good candidates for developing agent-based social simulations.

A further distinction can be made among CMSs. A subset of CMSs — called *computational algebra systems* (CASs) — are interactive programs that, in contrast to numerical processing systems, allow mathematical computations with symbolic expressions. Computations are carried out exactly, according to the rules of algebra, instead of numerically with approximate floating point arithmetic. CASs owe their origins to the LISP programming language, which was the earliest functional programming language (McCarthy, 1960). Macsyma ([www.scientek.com/macsyma](http://www.scientek.com/macsyma)) and Scheme (Springer and Freeman, 1989; [www.swiss.ai.mit.edu/projects/scheme](http://www.swiss.ai.mit.edu/projects/scheme)) are often mentioned as important implementations leading to current CASs. Typical uses of CASs are equation solving, symbolic integration and differentiation, exact calculations in linear algebra, simplification of mathematical expressions, and variable precision arithmetic. Computational mathematics systems consist of numeric processing systems or symbolic processing systems, or possibly a combination of both. Especially when numeric and algebraic capabilities are combined into a multi-paradigm programming environment, new modeling possibilities open up for developing sophisticated agent-based social simulations with minimal coding.

When it comes to social simulation (as in most types of coding), the most important indicator of the power of a language for modeling is the extent and sophistication of the allowed data types and data structures. As Sedgewick (1988) observes:

For many applications, the choice of the proper data structure is really the only major decision involved in the implementation; once the choice has been made only very simple algorithms are needed.

The flexibility of data types plays an important role in developing large-scale, extensible models for agent-based social simulation.

## MATLAB

MATLAB, originally termed the “Matrix Laboratory,” is a commercially available numeric processing system with enormous integrated numerical processing capability ([www.mathworks.com](http://www.mathworks.com)). It uses a scripting-language approach to programming. MATLAB is a high-level matrix/array language with control flow, functions, data structures, input/output, and object-oriented programming features. The primary data type is the *double array*, which is essentially a two-dimensional matrix. Other data types include logical arrays, cell arrays, structures, and character arrays. The user interface consists of the MATLAB Desktop, which is a fully integrated and mature development environment. In addition, an application programming interface (API) allows programs written in C, Fortran, or Java to interact with MATLAB. There are facilities for calling routines from MATLAB (dynamic linking), routines for calling MATLAB as a computational engine, and routines for reading and writing specialized MATLAB files.

Figure 1 shows the MATLAB desktop environment. The desktop consists of four standard windows: a command window, which contains a command line, the primary way of interacting with MATLAB; the workspace, which indicates the values of all the variables currently existing in the session; a command history window, which tracks the entered command; and the current directory window. Other windows allow text editing of programs and graphical output display.

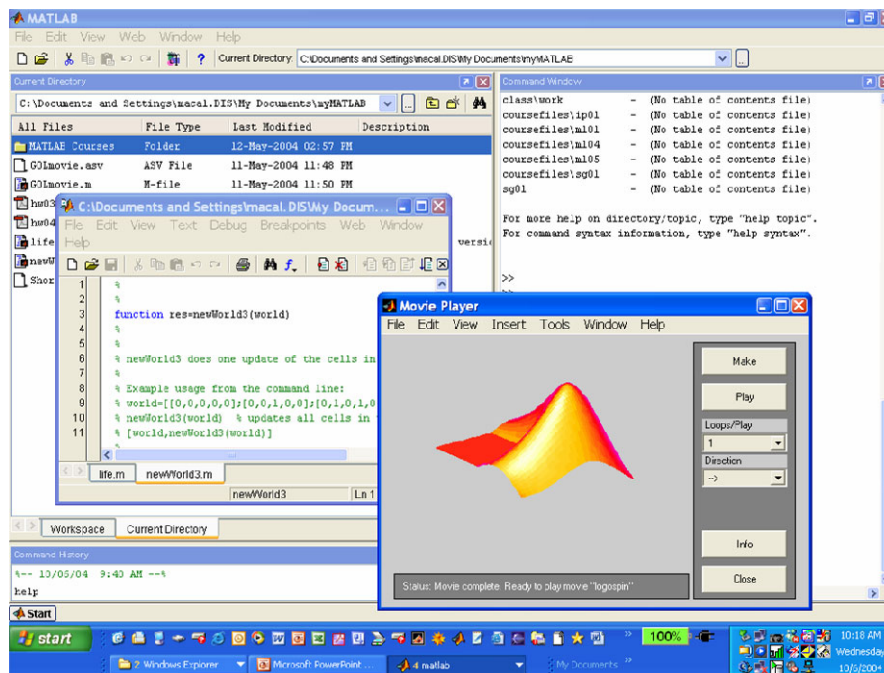


FIGURE 1 MATLAB desktop environment

## Symbolic Processing in MATLAB

MATLAB also has symbolic processing capability provided by a nonstandard, add-on package — the Symbolic Math Toolbox (SMT). Symbolic processing means that variables can be used before they have values assigned to them. The SMT extends the functionality of MATLAB to symbolic processing by defining a symbolic object as a new data type (Higham and Higham, 2000). The toolbox must be purchased as an extra to the standard MATLAB software. The toolbox is based on the Maple kernel, which performs the symbolic and variable precision computations.<sup>3</sup> Unlike MATLAB, Maple is a computer algebra system. (A comparison of *Mathematica*, MATLAB, and Maple for general mathematical computations can be found at <http://amath.colorado.edu/computing/mmm/index.html>.)

Maple is interactive, and the programming language is interpreted. Maple’s programming language is procedural but includes a number of functional programming constructs. Maple is not strongly typed like C and Pascal, but types exist, and type checking is done at run time. Maple has a rich set of composite data types, including list, array, table, and record, along with a large set of standard functions for manipulating the data types (Heck, 2003). Maple does not appear to have extensive pattern matching capabilities, such as those available in *Mathematica*. Without pattern matching capabilities, it is not clear how the symbolic capabilities of Maple could significantly extend MATLAB’s capabilities for constructing agent-based social simulations.

## *Mathematica*

*Mathematica* is a commercially available numeric processing system with enormous integrated numerical processing capability (Wolfram, 1999; [www.wolfram.com](http://www.wolfram.com)). It is a fully functional programming language. Unlike MATLAB, *Mathematica* is also a symbolic processing system that uses term replacement as its primary operation. In contrast, a numeric processing language requires that every variable have a value assigned before it is used. In this respect, although *Mathematica* and MATLAB may appear similar and share many capabilities, *Mathematica* is fundamentally much different than MATLAB, with a much different style of programming, ultimately resulting in a different set of capabilities.

*Mathematica*’s symbolic processing capabilities allow programming in multiple paradigms, either as alternatives or in combination. Programming paradigms include functional programming, logic programming, procedural programming, rule-based programming, and even object-oriented programming. Like MATLAB, *Mathematica* is an interpreted language, with the C-based kernel of *Mathematica* running underneath the notebook interface. In terms of data types, everything is an expression in *Mathematica*. An expression is a data type with a head and a list of arguments in which even the head of the expression is part of the expression’s arguments.

Figure 2 shows the *Mathematica* desktop environment. The *Mathematica* user interface consists of a notebook. A notebook is a fully “integratable” development environment plus a

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<sup>3</sup> Maple is a product of Maplesoft ([www.maplesoft.com](http://www.maplesoft.com)).

## GAME OF LIFE (GOL)

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April 18, 2004: 4 pm

### ■ Import Libraries

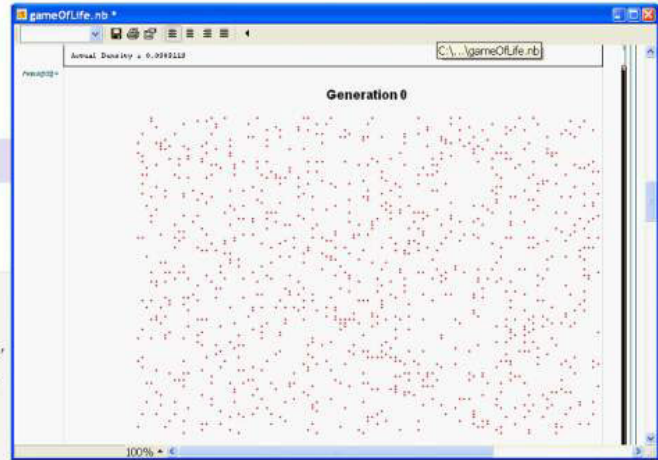
```
In[1]:= << LinearAlgebra`MatrixManipulation`
```

### ■ Create initial lattice.

Example 3: Randomly seeded.

```
In[33]:= latticeSize = 101;
density = 0.10;
gameBoard = Table[If[Random[] < density, 1, 0], {latticeSize},
Print["Actual Density = ", N[Plus@@Flatten[gameBoard]
latticeSize^2]];

(*Print[gameBoard//MatrixForm] (* gliders *) *)
displayLatticeGOL[gameBoard, 0, imageSize -> 750];
```



**FIGURE 2** *Mathematica* desktop notebook environment (A *Mathematica* notebook is displayed in its own window. Within a notebook, everything is a cell, and the notebook cell structure has underlying coding that is accessible to the user.)

complete publication environment. The *Mathematica* API allows programs written in C, Fortran, or Java to interact with the kernel. The API has facilities for dynamically calling routines from *Mathematica* as well as for calling *Mathematica* as a computational engine.

## AGENT-BASED SOCIAL SIMULATION

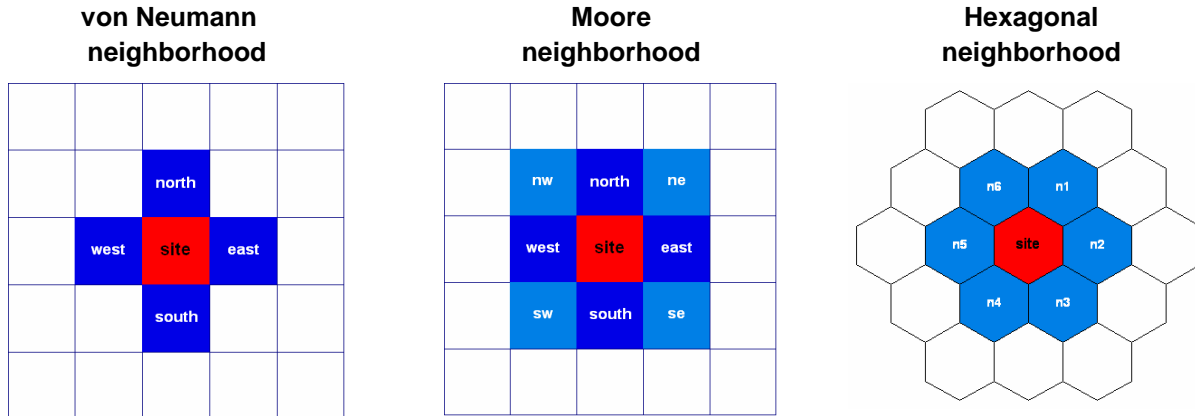
### Topologies for Agent-based Social Simulation

The three key representation issues relative to agent-based social simulation are:

- How to represent an agent,
- How to construct and represent the neighborhood surrounding an agent, and
- How to represent the population of agents and the society as a whole.

The foundation of agent-based simulation is the assumption that agents have access to only local information — that they are constrained effectively to the information available within an agent's neighborhood. Several neighborhoods are typically used in grid-type agent-based simulation (Figure 3), but the representation issues are exactly the same for any neighborhood. The representation issues are different in network-type agent simulation, as discussed below.

When we examine a computational system, software toolkit, or language, the key question is what the system allows or constrains in terms of the representation of an agent,



**FIGURE 3** Typical neighborhood topologies for grid-based agent simulation. For agent-based simulations that define agent relationships based on a grid, neighborhoods define the scope of agent interaction and locally available information.

neighborhood, and society. We examine these representations in MATLAB and *Mathematica* in the remainder of the paper. We consider two types of underlying topologies for social agent-based simulations: the grid model and the network model. For a typical grid model, we would construct an agent-based simulation in the following steps:

1. Begin with a representation of a matrix, which is a rectangular data structure in which each row is the same length and each column is the same length. The matrix represents the grid upon which the agents live.
2. Seed the matrix with agents and initialize the agent characteristics.
3. Define the structure of a neighborhood. Account for the boundary conditions when an agent reaches the edge of the grid. For example, boundary conditions may be warp-around or reflective.
4. Define an agent update rule on the basis of the local information available to an agent as it exists in its neighborhood. The rule is used to update the agent's position and status at each discrete time point in the simulation.

The update rules are applied to each agent in the matrix, usually at each point in time. The process of applying the agent update rule is effectively the agent interaction process, the process in which an agent interacts with all the other agents in its neighborhood. If the agent interaction is considered to be a process that operates over time, the process represents a dynamic simulation.

## Agent-based Social Simulation in MATLAB

We begin with a demonstration of a simple system that includes a fundamental aspect of agent-based social simulation. This is the MATLAB “Game of Life” (GOL) that comes in the standard MATLAB demonstration set. The GOL, developed by mathematician John Conway, is

a simple cellular automata that represents a problem of enormous complexity to analyze analytically (Gardner, 1970). The GOL has a long history of analysis (Poundstone, 1985; Sigmund, 1993) and is an excellent example of a highly complex system with a complexity that is built up from a number of relatively simple rules. The GOL is played on a two-dimensional rectangular grid consisting of a number of cells. The earliest agent-based social simulations were built in a form similar to the GOL (Epstein and Axtell, 1996; Schelling, 1971).

In the GOL, cells constitute the agents of the system. Cell behavior is governed by a set of rules based on the state of a cell's neighboring cells, or neighborhood, at any point in time. A cell has two possible states; it is either On or Off. The rules are as follows:

1. A cell will be On in the next generation if three of its neighbor cells are currently On.
2. A cell will retain its current state if two of its neighbors are currently On.
3. A cell will be Off otherwise.

In the following sections, we look at the underlying structure of the GOL simulation in MATLAB.

### *Agent Representation*

In the simple GOL example, agents are represented at fixed cell locations with binary status. A cell in the On position is represented as a 1, and a cell in the Off position is represented as a 0.

### *Grid Representation*

In MATLAB, the entire society is contained in a matrix representation. Here is typical MATLAB code for seeding the grid matrix, X, in the GOL (MATLAB built-in functions denoted in blue, comments in red):

```

m = 101 % set grid size at 101
X = sparse(m,m); % create 0 matrix of size m x m
p = -1:1; % create list [-1, 0, 1]

for count = 1:15, % generate 15 blocks of cells

    kx = floor(rand * (m-4)) + 2; % randomly select column
    ky = floor(rand * (m-4)) + 2; % randomly select row

    % using matrix addition, assign 1 to cell if random number
    % greater than 0.5, else set cell to 0

    X(kx+p, ky+p) = (rand(3) > 0.5);
end;
```

This code creates the underlying  $101 \times 101$  grid of cells, a matrix (double array) called  $X$  shown in Figure 4a. The entire matrix is first initialized at 0, then cells are selectively reinitialized to 1 to cells that are On initially. This code creates up to 15 sets of  $3 \times 3$  cell blocks, and it assigns 1's to randomly selected sites within each block to indicate the cell is On. The statement  $X(kx + p, ky + p) = (\text{rand}(3) > 0.5)$  assigns either a 1 or a 0 to a position in the array with probability 0.5, depending on the value for a random variable between 0 and 1. The initial cell configuration is displayed in Figure 4a, in which the locations of the 1's are shaded.

### Society Update

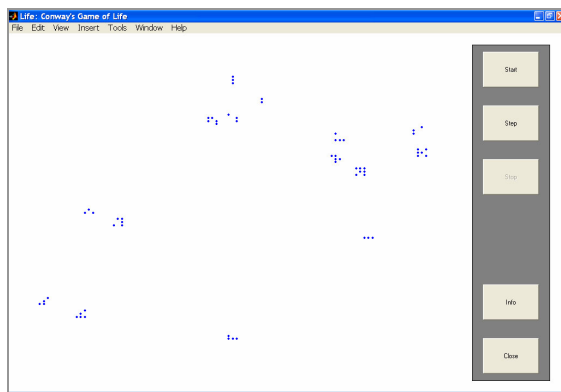
The next step is to update the cell at each time step according to three update rules. Here is the MATLAB code that does this:

```
% A live cell with 2 live neighbors, or any cell with 3  
neighbors, is alive at the next time step.
```

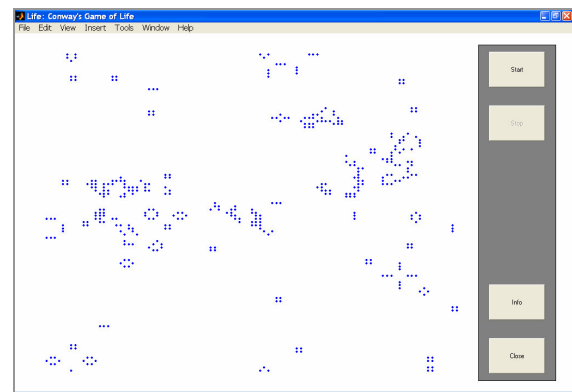
```
X = (X & (N == 2)) | (N == 3);
```

The updating rule for every cell of the simulation consists of this single line of code. Essentially it says that a value in the matrix  $X$  will retain its current value if the number of neighbors that are On (that is, have values of 1) is either 2 or 3. By default, the value of  $X$  is reset to 0 otherwise.

Figure 4b is a snapshot of the MATLAB GOL simulation after the update rules have been applied repeatedly to all cells. The figure illustrates one of the most striking aspects of the GOL. After the simulation begins with a randomly selected set of cells in the On state, patterns quickly emerge among the cells that are On. Some of these patterns can sustain themselves over long periods of time and maintain their integrity while they travel across the grid.



(a)



(b)

**FIGURE 4** “Game of Life” simulation in MATLAB (Starting from a set number of simple patterns (a), the GOL simulation proceeds by the repeated application of three simple rules applied to each cell. Complex patterns quickly develop (b), some of which are sustainable.)

Although the GOL example is simple, it illustrates the basic operations of grid-type, agent-based simulation and shows how the built-in matrix operations of MATLAB can handle a large number of operations in a remarkably small number of coding statements. (Somewhat more coding is required than shown here to specify the complete GOL model that includes the graphical user interface.) Development of more complex models with richer agent representations is then a matter of increasing the use of the data types representing the agents and the society as a whole. We now move on to *Mathematica* and show a more complex agent-based social simulation.

### Agent-based Social Simulation in *Mathematica*

We demonstrate social agent-based simulation in *Mathematica* with an example called “Mobile Heterogeneous Agents” (MHA). This simple agent simulation was originally published in a book on social simulation using *Mathematica* (Gaylord and D’Andria, 1998). The example, although rudimentary, has recognizable agents and behaviors specified by discrete decision rules. The example also illustrates the use of pattern matching for identifying the applicable agent and cell situation and the use of term replacement for implementing rules that update agent status and positions.

The mobile heterogeneous agents live on a two-dimensional grid, similar to the GOL, and their behavior consists of moving to their selected point on the grid. Each agent faces a particular direction, and the “nearest neighbor” site is defined as the cell that is immediately in front of the agent. An agent in any cell updates its position according to the following update rules:

1. If the nearest neighbor site is occupied by another individual, the individual remains in place and chooses a random direction to face.
2. If the site is empty but is faced by one or more individuals on its nearest neighbor’s sites, the individual remains in place and chooses a random direction to face.
3. Otherwise, if the nearest neighbor site that an agent faces is not occupied by another individual, the individual moves into that site.

In this simulation, the agents are very “polite,” moving only into uncontested sites and thereby avoiding conflict at every opportunity. Variations on these rules are easily implemented to reflect a wide range of alternative agent behaviors.

#### *Agent Representation*

In the MHA example, an agent is represented by a list and a set of attributes. Agents move to new cell locations as the simulation proceeds. An agent is represented as follows, by using the *Mathematica* brace notation for lists:

```
{direction agent is facing (integer between 1 and 4),
 unique agent identifier (an integer),
 agent type (0 or 1),
```



```

    list of 3 agent attributes (randomly selected values),
    agent's resources (a number between 1 and 4)
}

```

### Grid Representation

We construct the simulation for heterogeneous mobile agents as follows:

1. Create a society by seeding a matrix of 0's and 1's.
2. Create individuals by reassigning a list of agent attributes to each 1.
3. Create a set of update rules that operate on each cell of the society and update an agent and its neighborhood.
4. Nest the update process over the entire society.

First we create the agent society. Here is typical *Mathematica* code for creating a  $6 \times 6$  matrix and randomly seeding it with agents (*Mathematica* built-in functions denoted in blue, comments in red):

```

seedingDensity = 0.50 (* approximately 50% of the cells have agents *);
gridSize = 6 (* create 6 x 6 grid *);
grid = Table[Floor[seedingDensity + Random[]], {gridSize}, {gridSize}];

numAgents = Plus@@Flatten[grid] (* calculate number of 1's in grid *);
(* print the matrix and report number of agents *)
Print[MatrixForm[grid]];
Print["The society contains ", numAgents, " agents."];

```

Here is the result:

The society contains 21 agents.

$$\begin{pmatrix} 0 & 1 & 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 & 1 & 0 \\ 1 & 1 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

We next create the agent society by reassigning the 1 values of the matrix to lists representing agents and their attributes. We first set various parameters that indicate the variation in the randomly specified initial values for the agents, making use of various *Mathematica* built-in functions:

```

(* set parameters *)
seedingWell = g = 0.75 (* 75% of agents of type 1 *);

```

```

numAgentAtts = s = 3 (* each agents has 3 attributes *);
k=0 (* counter for agents initialized at 0 *);
RND:=Random[Integer,{1,4}] (* function to generate random number
between 1 and 4 *);

(* create agency society from initial grid using term replacement → *)
society = grid /. 1 → {RND, ++k, Floor[g + Random[[]],
Table[Random[Integer,{1,10}],{s}], Random[Integer,{1,4}]}];

```

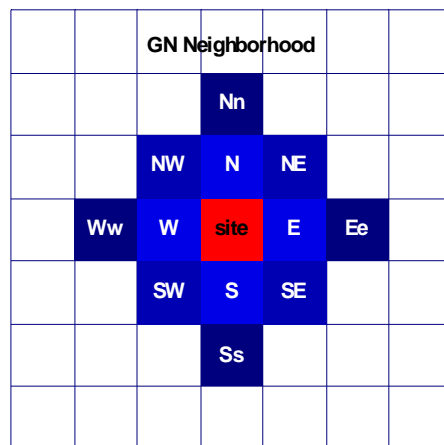
The key step is the substitution step in the last statement in which the all the 1's in the grid matrix are replaced with an agent representation, creating the agent society. Here is the result (each non-zero in the society matrix is an agent):

	0	(3, 1, 1, {6, 8, 7}, 2)	0	(1, 2, 1, {4, 5, 8}, 3)	(2, 3, 1, {5, 7, 10}, 1)	(4, 4, 1, {4, 1, 9}, 4)
{2, 5, 0, {8, 9, 8}, 1}	0		(4, 6, 1, {10, 10, 9}, 4)	(2, 7, 1, {3, 9, 4}, 1)	(1, 8, 1, {8, 7, 2}, 1)	0
{1, 9, 1, {3, 9, 7}, 3}	0		(2, 10, 1, {5, 4, 7}, 3)	(2, 11, 1, {1, 9, 6}, 2)	(4, 12, 1, {4, 7, 3}, 4)	(3, 13, 1, {3, 3, 3}, 1)
{1, 14, 0, {7, 2, 10}, 4}	{1, 15, 1, {5, 3, 8}, 2}		0	0	(3, 16, 1, {2, 1, 10}, 1)	0
{1, 17, 1, {4, 5, 7}, 3}	{1, 18, 1, {10, 7, 5}, 1}	{4, 19, 1, {3, 1, 9}, 4}	0	0	0	(3, 20, 1, {6, 8, 6}, 1)
{4, 21, 1, {2, 2, 2}, 3}	0	0	0	0	0	0

### Society Update

The main operation for grid-type, agent-based social simulation is to update the society through updating each agent's status and position on the basis of the state of the agent's neighborhood. To implement the update rules for the MHA simulation, following Gaylord and D'Andria (1998), we define an extended neighborhood, called the Gaylord-Nishidate neighborhood (Figure 5), that accounts for all the cells that need to be considered in updating a cell's contents.

We next define a set of rules that can be used to update any cell in the society. *Mathematica* allows one to define patterns within expressions. Patterns are uninstantiated placeholders or slots that allow the attachment of optional general constraints as to data type or



**FIGURE 5** Gaylord-Nishidate neighborhood for applying update rules



Otherwise, if a cell is unoccupied and a single agent is facing the cell, the agent moves into the cell, Rules 24 to 27.

```
walk[0, {3, a___}, __, __, __, __, __, __, __, __, __, __] := {RND, a}           Rule 24
```

Otherwise, if a cell is unoccupied, the cell remains unoccupied, Rule 28:

```
walk[0, __, __, __, __, __, __, __, __, __, __, __] := 0                       Rule 28
```

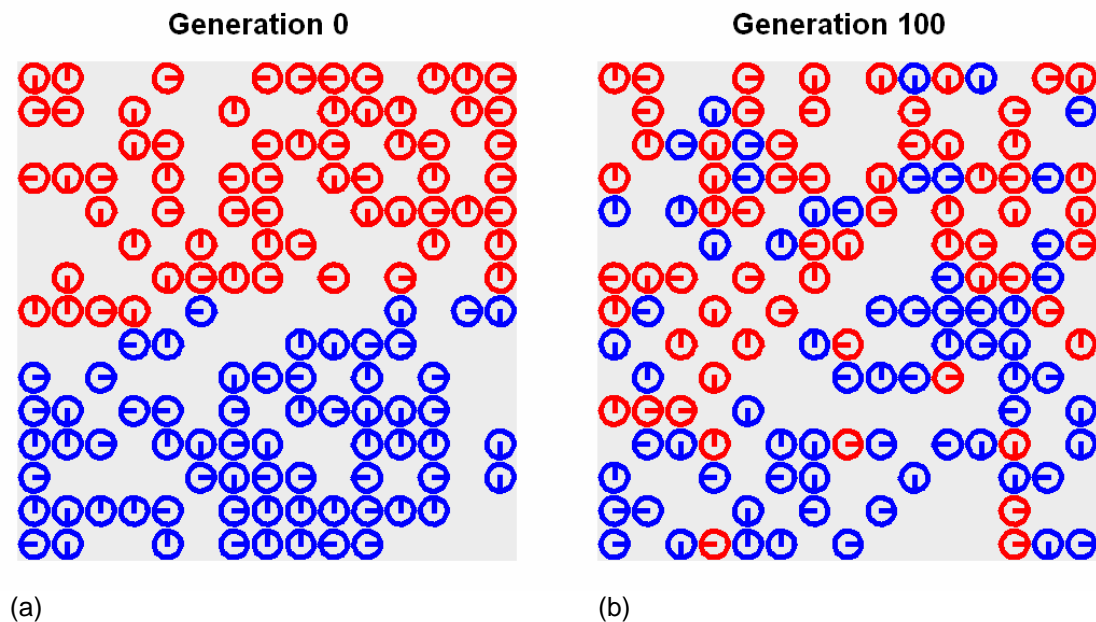
The update rules are applied to the entire society by defining a function called *GN*. *GN* takes each cell and creates a data structure called *walk* introduced above, consisting of the cell contents and the cell neighborhood. The update rules defined above are then automatically matched and applied to the cell, updating its contents. A time step consists of applying the function *GN* to all the cells in the society in a single statement:

```
newSociety = GN[walk, society];
```

A complete simulation consists of applying the *GN* function repeatedly for each simulation period. A simulation can be efficiently implemented by using *Mathematica*'s functional programming capabilities by recursively applying the *Nest* function:

```
simLength=50;
finalSociety = Nest[ GN[walk, #]&, society, simLength+1];
```

which simulates each cell being updated for each of 50 periods. Figure 6 shows the original society and the society after applying the update rules to all agents for 100 generations.



**FIGURE 6** Mobile heterogeneous agent society simulation — (a) initial distribution of agents, (b) simulation results after 100 generations

In principle, it should be possible to implement the MHA simulation in MATLAB. To do so would require defining data structures for agents and attributes, defining neighborhood update rules on the basis of the full set of neighborhood configuration possibilities, reasoning about numeric rather than symbolic variables, and using procedural programming constructs (for loops, etc.) instead of functional programming constructs. It is not clear how the symbolic programming constructs of SMT or Maple could be used to facilitate the agent-based simulation.

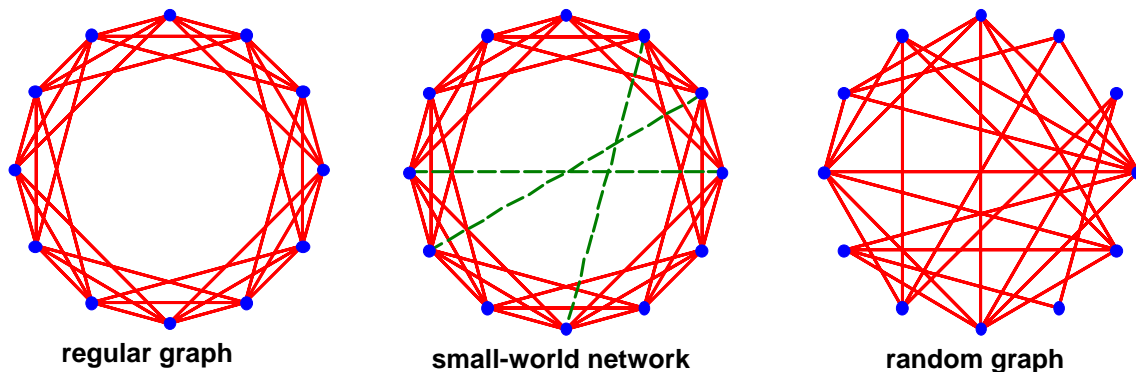
## Social Network Topology

The extensions from the grid topology to the network topology are straightforward in *Mathematica* (Gaylord and Davis, 1999) and similarly in MATLAB. Common network topologies used in agent-based simulation are shown in Figure 7. *Mathematica* has excellent built-in packages for graph generation and analysis. Extensions to modeling social networks require the use of more complex data structures than the matrix structure used for the grid representation.

In *Mathematica*, a network representation consists of combining lists of lists or, more generally, expressions of expressions, to various depths. In MATLAB, this involves combining cell arrays or structures in various ways. For example, in *Mathematica*, an agent would be represented explicitly as an expression that includes a head named agent, a sequence of agent attributes, and a list of the agent's socially connected neighbors:

```
agent[sequence of agent attributes, {neighbor 1,... neighbor i,... neighbor n}]
```

The list of neighbor references in the agent expression consists of pointers to the expressions for the agent's neighbors. Agent pointers could be numeric or strings in MATLAB and *Mathematica* or symbolic (functions) in *Mathematica*.



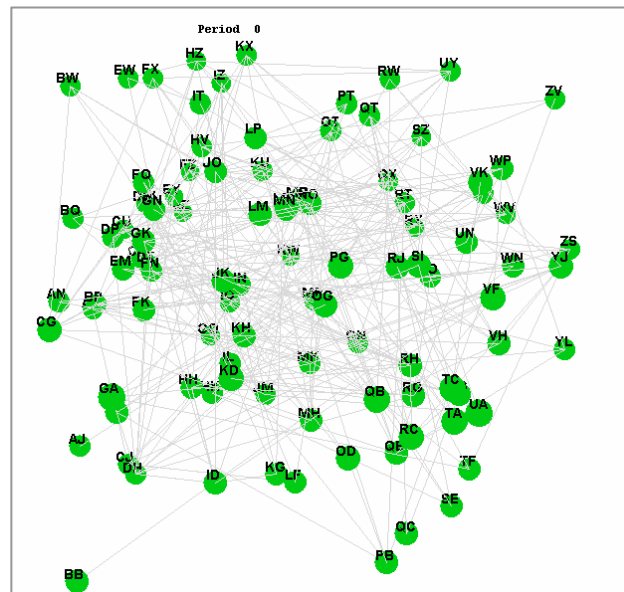
**FIGURE 7** Neighborhood topologies for network-based agent simulation (For agent-based simulations that define agent relationships on the basis of networks, connectivity defines the scope of agent interaction and locally available information.)

Social network interaction and social mechanisms between agents are defined to operate on the agent expression. Access to an agent's neighbors and attributes (including the neighbors of the neighbors) is provided by the list of pointers to the agent's neighbors. Dynamic social networks, which are networks that are formed and change during the simulation, would be implemented by manipulating the list of neighbors during the simulation on the basis of the current state of the agents and the simulation environment. Generating a neighbor list that consists of all agents with a particular attribute value determined dynamically during the simulation is an example.

Figure 8 shows an example of a dynamic network agent simulation using this technique and rendered in *Mathematica*. In this model, agents are represented as:

```
individual[
  name,
  coord[{x-coord, y-coord, z-coord}],
  resources,
  variable based on neighbor attributes,

  Neighbor list: {
    {neighbor 1, relationship attributes},
    {neighbor 2, relationship attributes}...,
    {neighbor N, relationship attributes}
  },
  other agent attributes and relationships ]
```



**FIGURE 8** Dynamic network agent simulation rendered in *Mathematica*

The society is defined as the list of *individual* expressions. Term replacement is used to update the entire society, as in the grid-type model. For example, an agent's attribute relating to its neighbors' attributes is updated with the mean value for all its neighbors as follows:

```
updatedSociety = society /.
  individual[individualID_, loc_, resources_, meanNeighbors_,
  neighborsL_]
  :> individual[individualID, loc, resources,
  Mean[neighborsL[[All,2]]], neighborsL]
```

This single *Mathematica* statement updates the entire society using the term replacement operator `:>`. This particular style of agent-based social simulation, which *Mathematica* allows, consists of a two-step process: (1) defining agents as abstract data types, independent of implementation, and (2) defining functions or methods that operate on the agents and any other data types in the model. This modeling approach is similar to that taken in object-oriented programming. Maeder (2000) provides an extensive discussion of agent data types and object-oriented programming in *Mathematica*. However the *Mathematica* implementation is structured; the same specification would result at the modeling level, through the Unified Modeling Language (UML) for example (Booch et al., 1998). This implementation-independent model description could be the basis for communicating and implementing the same model in a variety of object-oriented, large-scale toolkits, such as Repast (Collier and Sallach, 2001), MASON (GMU, 2003; Luke et al., 2003), or Swarm (Burkhart et al., 2000).

## SUMMARY AND CONCLUSIONS

Computational mathematics systems such as *Mathematica* and MATLAB can be alternatives or supplements to agent-based model development in the social sciences. These packages and others like them are fully integrated development environments offering numeric and symbolic computing capabilities. Their interpretative nature, ease of data import and export, and seamless integration of graphical capabilities provide immediate feedback to users during the model development process. This feature makes them particularly useful as learning tools as well as rapid prototype development tools. Besides the traditional form of social simulations based on differential or difference equations (as in Systems Dynamics), *Mathematica* and MATLAB facilitate the development of agent-based social simulations based on grid-type or social network topologies of agent interaction. Both *Mathematica* and MATLAB are continuing to rapidly develop. New releases with significantly improved capabilities occur, at the minimum, on an annual basis. The emphasis is on integration with other computing environments, ease of use for users, and expansion of technical capabilities.

## ACKNOWLEDGMENT

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## DATA FARMING REPAST MODELS

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### ABSTRACT

This paper briefly describes efforts to integrate Repast into the Project Albert data farming environment. The Marine Corps Warfighting Laboratory's Project Albert is a research and development effort with the goal of developing the process and capabilities of data farming — developing data sets through utilization of massive computation. Data farming is a decision support methodology that applies high-performance computing to modeling to examine and understand the landscape of potential simulated outcomes, enhance intuition, find surprises and outliers, and identify potential options. Data farming is made possible, in part, by the exploitation of high-performance computing assets and methods. To leverage these assets, we developed a suite of entity-based combat models for Project Albert that allow for rapid changes to entity characteristics and behaviors quite amenable to, and intentionally designed for, rapid, repeatable concept exploration. However, Project Albert does not currently possess a fully generalizable framework in its suite of models. Invariably during a modeling effort, interest in exploring a new phenomenon arises or in representing an additional behavior that has not previously been addressed — the very essence of an exploration. Repast, as a fully generalizable framework with its emphasis on agent-based modeling and simulation, affords Project Albert the flexibility that it currently lacks to explore new phenomena and problem spaces as they emerge.

**Keywords:** Data farming, Repast, high-performance computing, XML, XPath

### INTRODUCTION

This paper briefly describes initial efforts to integrate Repast — the REcursive Porous Agent Simulation Toolkit (North, 2002) — into the Project Albert data farming environment. The Marine Corps Warfighting Laboratory's Project Albert is a research and development effort with the goal of developing the process and capabilities of data farming — developing data sets through utilization of massive computation (Barry et al., 2004). A representative implementation of this process, namely, data farming the Repast demonstration, Heatbugs, is presented.

Data farming is a decision support methodology that applies high-performance computing to modeling to examine and understand the landscape of potential simulated outcomes, enhance intuition, find surprises and outliers, and identify potential options (Brandstein and Horne, 1998). Data farming is the method by which potentially millions of data points can be explored and captured. Akin to data mining, data farming incorporates feedback to inform the subsequent collection of more data points and a more comprehensive exploration of the parameter space. To glean insight from these potentially massive compilations of data,

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Project Albert is also developing and employing a wide range of data exploration and data visualization tools and methods.

## **DATA FARMING**

The metatechnique of data farming is made possible by recent technical advances in three areas (Horne, 2001): (1) complex adaptive systems models, which have the promise of capturing the aspects of adaptability, nonlinear interactions, feedback, and self-organization; (2) computing power, which enables us to generate the large volume of data needed to adequately represent vast spaces of possibilities; and (3) our ability to organize, synthesize, and visualize scientific data.

Data farming was first developed and used at the Marine Corps Combat Development Command in late 1997. It can be thought of as nothing more than putting the technical advances described above to work to engage the scientific method. The essence of data farming is to grow more data in particular, focused areas of interest. This growth within the specific definition of a particular model might be in the form of more runs or a different preparation of the sample space to include different parameters, finer gradations of parameter values, or greater ranges. After the execution of samples and analysis using data visualization and search methods, the data farmer is free to grow more data in interesting areas, integrate with information from other tools, prepare a different scenario using the same model, select another model, or any combination of these possibilities that he or she thinks might lead to enhanced decision support.

### **Tools of Data Farming**

Data farming is made possible, in part, by the exploitation of high-performance computing assets and methods. To leverage these high-performance computing assets, Project Albert developed a suite of entity-based, combat models that allow for rapid changes to entity characteristics and behaviors, quite amenable to, and intentionally designed for rapid, repeatable concept exploration. At this point, the reader might logically ask the question: “So, why Repast?”

### **Why Repast?**

To date, Project Albert does not possess a fully generalizable framework in its suite of models. Invariably during a modeling effort, interest in exploring a new phenomenon arises or in representing an additional behavior that has not previously been addressed — the very essence of an exploration. Repast, as a fully generalizable framework with its emphasis on agent-based modeling and simulation, will afford Project Albert the flexibility that it currently lacks to explore new phenomenon and problem spaces as they emerge. Our initial efforts to integrate Repast into the Project Albert data farming environment are described below in an example using the Repast demo, Heatbugs.

## IMPLEMENTING DATA FARMING IN REPAST

Our approach relies on two related technologies: XML and XPath. XML is the eXtensible Markup Language developed by the World Wide Web Consortium.<sup>1</sup> As the name implies, XML is a language where the user can define, within the rules of the specification, the naming, structure, and content of individual entities within that language, thus making it extensible. XPath is the XML Path Language.<sup>2</sup> Basically, an XPath is structured like file paths in the Windows or Unix operating systems. We give more details on the use of XPath in the Heatbugs example below.

Our approach works by constructing two XML-structured files: a model “scenario” file and a study file. The scenario file contains all of the parameters that the model developer decides are appropriate inputs for his or her model and acts as a template or specification of allowable parameter changes. An instance of a scenario file is called an “excursion,” with specific values for each parameter in the file. The excursion file is then passed to the model as input, along with a random seed, and an individual replicate, an excursion file with a specific random seed, is executed by invoking a command line call (no GUI). In Repast terminology, we have divided the Repast parameter file into two separate files: an excursion file, which indicates parameter settings for an individual run, and a study file, which indicates how the parameters are changed for separate runs (i.e., determining the batch operations).

The study file is a structured XML file that contains information about the user; the model; lists of random seeds to use; computing environment (e.g., local or distributed); and the specific data farming experiment, including number of replications, parameter bounds, and the desired data farming algorithm. The entries in the study file can be broken down into two classes: those for documentation purposes, like user and model used, and those that specify the conditions for the computer experiment, such as the data farming algorithm and the parameter bounds. We give an example of how to specify the parameter bounds below.

The software we developed currently implements four types of data farming algorithms: (1) gridded data farming, or simple parameter sweeps using a min/max/delta specification; (2) Cartesian product generation, which is a parameter sweep wherein the user indicates the specific values to use for each parameter; (3) specification runs desired in a comma-separated file, with each row indicating a setting of all the parameters for an excursion and each column indicating the individual parameter values; and (4) an evolutionary programming algorithm. The user can also group variables such that all the variables in the group take on the same values for a specific excursion (also called lock-stepping), in effect treating the group as one variable. These four types cover a broad range of experiments; however, users can also write and use their own data farming algorithm (e.g., a different evolutionary or search algorithm than the one currently implemented).

Our data farming software takes as input these two files, the excursion file and the study file, and conducts the batch runs, which can be run either on a single machine or over a cluster of machines. When using a cluster of machines, the software generates individual excursion files and then distributes the individual runs over the machines in the cluster. We have used Condor

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<sup>1</sup> The current official XML specification can be found at <http://www.w3.org/XML/>.

<sup>2</sup> The specification for XPath can be found at <http://www.w3.org/TR/xpath>.

(<http://www.cs.wisc.edu/condor/>) as our distributed computing mechanism. When using a single machine, the software generates individual excursion files and then sequentially executes the individual runs.

## DEMONSTRATION WITH HEATBUGS

To illustrate the approach, we use as an example a conversion of the Repast Heatbugs parameter file, depicted in the XML file in Figure 1. More complicated XML structures are possible, but this simple example serves our purpose.

An XML format is composed of a number of elements, where each element has a name and can have optional attributes. Each element has element start tags and corresponding element end tags; the start tags are structured in the form `<TagName...>`, where the ellipsis indicates an optional listing of attribute-value pairs, and the end tags are in the form `</TagName>`, with a backslash before the TagName and no attributes. Although it is a very basic XML-formatted file, it is sufficient for our purposes. Element tags are also nested; there must be a complete start-end set of tags nested inside another set of start-end tags, as shown in Figure 1 by the EvapRate tag, which is nested within, or surrounded by, the Heatbugs tags. The first line, `<?xml version="1.0" encoding="UTF-8"?>`, indicates that this is an XML file and uses a special format for that line indicated by the `<?xml ... ?>` pairing of character sequences. The next line, `<Heatbugs version="1.0">`, is the root element of the XML input file. "Heatbugs" is the name of this element, and it has an attribute called "version," with the value of this attribute set to "1.0." We envision using this structure for all Repast model input files.

This simple example has only nine elements. The name of each element reflects the name of an associated model input parameter and has a value associated with it, the float or integer value to use for that parameter at model initialization (the terminology used here is a simplification of the actual XML structure but suffices for our use). This example would constitute an entire Heatbugs scenario file. More type checking could be added, such as adding a parameter "type" (e.g., integer or float, by inserting a type attribute with the Element name, for example, `<EvapRate type='float'>`, so that error checking could be done on reading the file).

```

<?xml version="1.0" encoding="UTF-8"?>
<Heatbugs version="1.0" >
  <DiffusionConstant>1.0</DiffusionConstant>
  <EvapRate>1.0</EvapRate >
  <MaxIdealTemp>31000</MaxIdealTemp>
  <MaxOutputHeat>1000</MaxOutputHeat>
  <MinIdealTemp>17000</MinIdealTemp>
  <MinOutputHeat>3000</MinOutputHeat>
  <NumBugs>100</NumBugs>
  <WorldXSize>100</WorldXSize>
  <WorldYSize>80</WorldYSize>
</Heatbugs>

```

**FIGURE 17** Heatbugs XML scenario file

We could also develop an XML Schema for the scenario file to provide additional validation of the input file, but that is beyond our current discussion and implementation.

Now that we have defined the scenario file, we need to construct our experiment using the study file. As an example, we use a gridded or parameter sweep algorithm to illustrate how the parameters and the bounds on those parameters are specified in the study file.

Figure 2 shows an XML snippet from the study file detailing the dimensions, that is, the set of parameters that define the farming region. For a parameter sweep, this set is just a list of the parameters along with their associated upper (MaximumValue) and lower (MinimumValue) bounds and a step size (Delta value). For this example, the six runs listed in Table 1 would be conducted, with the number of replications indicated in the study file.

The type and name attributes, along with the XPath element, are the same for all types of data farming algorithms. These indicate the specific parameters to be modified. The other items in this example are specific to the type of algorithm, that is, (<MaximumValue>, <MinimumValue>, and <Delta>). The type attribute can be either “float,” “integer,” or “string,”

```

<Dimensions>
  <Variable type="float" name="EvapRate" >
    <XPath>/Heatbugs/EvapRate</XPath>
    <MaximumValue>2.0</MaximumValue>
    <MinimumValue>1.0</MinimumValue>
    <Delta>1.0/Delta>
  </Variable>
  <Variable type="integer" name="NumBugs">
    <XPath>/Heatbugs/NumBugs</XPath>
    <MaximumValue>200</MaximumValue>
    <MinimumValue>100</MinimumValue>
    <Delta>50</Delta>
  </Variable>
</Dimensions>

```

**FIGURE 18** Dimensions specification

**TABLE 1** Parameter levels for the six runs

Excursion Number	EvapRate	NumBugs
1	1.0	100
2	1.0	150
3	1.0	200
4	2.0	100
5	2.0	150
6	2.0	200

depending on the type of parameter in the scenario file. The string type can be used to define categorical parameters. The name attribute is specified by the user and is just a short name that is used in the header of the output file. There are no restrictions for composing this string. The user can either place “:” between strings to make it easier to read or use spaces. Thus, ‘name=“Heatbugs:EvapRate”’ is a legitimate name.

The remaining step is to construct the XPath for each of the parameters. The XPath is very easy to determine for our purposes, as the scenario files are reasonably structured. The XPath is a string that, when evaluated, actually points to a section of text in the scenario file. In our case, it is a particular value that we want the software to modify. Using the Heatbugs example above, the XPath for the EvapRate parameter is simply “/HeatBugs/EvapRate.” Each “/” indicates a drop in the tree hierarchy of the XML input file, with the last node pointing to the location of the value indicated by the XPath. Other XPath functions are also allowed, further increasing the flexibility in uniquely specifying the set of parameters.

In summary, the data farming software takes as input the scenario file and the study file. The software then constructs an excursion file for each combination of parameter settings as indicated by the algorithm and the dimensions specification. It does this by taking the scenario file, making a copy, modifying the parameters indicated by the XPath in that file, and writing out a new excursion file. For our example above, we would have six files created, where the EvapRate and the NumBugs parameters would be as shown, and the remaining parameters would be set at the values indicated in the original scenario file (they do not get modified). The software then constructs command line calls for each of the six runs and either distributes the runs over a cluster or conducts the runs sequentially on a single machine.

## SUMMARY

This paper briefly describes our first efforts at integrating Repast into the Project Albert data farming framework with an example using the Repast demo, Heatbugs. The Marine Corps Warfighting Laboratory’s Project Albert is a research and development effort with the goal of developing the process and capabilities of data farming — developing data sets through utilization of massive computation. Data farming is made possible, in part, by the exploitation of high-performance computing assets and methods. However, Project Albert does not currently possess a fully generalizable framework in its suite of models. Repast, as a fully generalizable framework with its emphasis on agent-based modeling and simulation, affords Project Albert the flexibility that it currently lacks to explore new phenomena and problem spaces as they emerge. The Repast community can also benefit by exploiting the capabilities of the Project Albert data farming environment.

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**DISCUSSION:****TOOLKITS****(Thursday, October 7, 2004, 3:15 to 4:45 p.m.)**Chair and Discussant: *Michael J. North, Argonne National Laboratory***NetLogo: Design and Implementation of a Multi-agent Modeling Environment**

**Michael North:** In this session on toolkits, Seth Tisue will talk about NetLogo. Following that talk, Seth and Chick Macal will discuss mathematics and MATLAB. Finally, Steve Upton will talk about data-farming Repast models. First, I'd like to introduce Seth Tisue. I've known him for many years. He is the lead developer of NetLogo at Northwestern University.

**Seth Tisue:** Thanks, Michael. I'm Seth Tisue. The inventor and author of NetLogo is Uri Wilensky. He may be coming to some talks tomorrow, so if you're hoping to check in with him, he may be here tomorrow. I work in Uri's research group at Northwestern University, which is called the Center for Connected Learning and Computer-based Modeling. We're jointly based in two departments: at the School of Education and Social Policy and at the Department of Computer Science. We're also associated with Northwestern's new institute, NICO, the Northwestern Institution for Complexity, which has just started up. It was publicly announced for the first time a couple weeks ago.

The name of my talk is "NetLogo: New Developments," but I'm mindful that some of you may not know about NetLogo. So in the first part of the talk, I'll fairly quickly cover the basics of NetLogo. I'll then talk about work that we've recently completed and released; I'll also explain what we're working on now and what we expect to be working on soon. I'll be trying to convey where NetLogo is positioned in the design base of possible tools for computer-based modeling and why we think that's a good place for us to be. I'll talk about what we're doing to try to spread out in that design space, so to speak, to make NetLogo a good choice in a wider range of situations.

[Presentation]

All of our papers are online. We have two papers about NetLogo as a research tool. The first is more introductory, less technical; the second is more technical. We also have lots of papers available about our work on NetLogo in schools.

**North:** Thank you, Seth. I have two quick questions, and then we'll open the discussion for questions from the audience. First, you mentioned for the license that there are no restrictions on use. I remember reading a license a couple of weeks ago. Is that true for noncommercial and commercial use or ....

**Tisue:** Yes. The wording on the current license is confusing. The intent is definitely to have no restriction on use, either commercial or noncommercial. That's not as clear from the wording as it should be.

**North:** Right. Here's the reason why. I don't want to embarrass you, but I'll take the opportunity anyway. The licenses I read, at least a few weeks ago, said that commercial users should contact Uri Wilensky for licensing terms.

**Tisue:** That's for redistribution of NetLogo itself or for distribution of the modified version. But if you're using NetLogo — building models with it — there are no restrictions. Actually, you should let everybody know that. I know how the license sounds, and it's not how it was intended to sound, so you should let everybody know that you interpreted it in the way that I've always interpreted it.

**North:** Exactly, that's right. I'll let him know that. My second question is how extensive is the GIS support? I thought that was a very interesting feature. In other words, is it built in where you point it at a file and it'll load it, or do you need to do other things to add to the system?

**Tisue:** There's no GIS support per se built in. What's new in the last year is that the fundamental capabilities are now there so that users can build GIS support themselves.

**Craig Stephan:** Craig Stephan, Ford Motor Company. Not to embarrass you further, but I'll take the opportunity, too. Strictly from the standpoint of the user, can you compare how NetLogo is with respect to something like Repast, in terms of both its strengths and its weaknesses? And as long as Michael [North] is standing right behind me, I'll ask him if he wants to chime in.

**Tisue:** Okay. Let's see, that's a big question. NetLogo's biggest strength is that you can write models and you can understand models without learning Java. You do have to learn NetLogo, but learning NetLogo's a much smaller pill to swallow than learning Java. So that's really the biggest advantage. Of course, Repast can also do things that NetLogo can't do yet. It's more flexible in many ways, and it also has specific support for doing network modeling, which, again, is something that's now possible by using our basic capabilities, but we haven't yet added capabilities that specifically help you with it.

**North:** We have time for one more question...

**Matthew Koehler:** Matt Koehler from MITRE. I'm curious about the controlling API. Does that allow NetLogo to run as a batch, in batch mode?

**Tisue:** You can run it in batch amount if you use X-11 with a virtual frame buffer. Do you know what that is, or should I translate that?

**Unidentified Speaker:** But it's easy. Don't worry.

**Tisue:** Yes, so you can run it from the command lines. The graphical user interface actually must be present, but you can use X-11 to fool it into thinking there's a GUI there. And I know that's possible because people are doing it.

**North:** I'd like to thank Seth again.

## Agent-based Modeling and Social Simulation with *Mathematica* and MATLAB

**Charles Macal:** When we began the process of putting together this conference — Dave Sallach, Michael North, and I — we had the notion that theory can work together with toolkits and methods, and that those, in turn, can work together closely with applications, and further that these three areas can benefit in a dynamic way from progress in each area. We're now turning to the applications part, and some of the issues that I'm going to discuss — just to put down some framework for discussion or ways of thinking about applications that we'll be seeing in the rest of the conference — are very similar to or at least overlap with some of the issues we've already discussed in the theory areas and in the methods and toolkit areas, as well.

[Presentation]

**Unidentified Speaker:** These are really big issues to think about. The other issue is that some of these models can be appreciated at multiple levels of granularity. So one has to decide, for example, what level of granularity you want to start on and which to finish on.

**Macal:** Thank you for your comments. The problem's even worse than I thought, based on what you've said. Not only that, what you're suggesting is that the trajectory is path dependent; it depends on where you start. I'm astounded by the complexity of it. In all seriousness, these are good things to sort out and get on the table. That's all we can do right now: attain consciousness.

**Unidentified Speaker:** Some models are set up to be added to incrementally, just like the others. You can't add big clumps, and therefore things are going to be much harder.

**Macal:** Right. What you're suggesting is there's a discreteness to going through the trajectory. And, yes, that's unfortunate, too. It's almost a model design issue. The question is a natural one. Where do you take that? Is there a notion of where you go with it? Does it make sense to go anywhere, or is it an end in itself? With regard to a lot of questions about applications, they come from different directions, and at some level, they aren't relevant from one type of model to another. If we have a better idea, I think it will be constructive.

**Unidentified Speaker:** Is it possible we could think about this a'la Karl Popper? Is your model falsifiable at some point? Could you pile on a whole preponderance of evidence that would say it's working, but then throw in a couple of wrenches and show that it's not working and there's something severely wrong with your model?

**Macal:** We could do that. That sounds pretty good — to develop some framework or structure for doing that. But I'd like to make another point. Suppose we have a model. Traditionally, we've always done a few discrete runs with the model. But now we have computational power to essentially search through all parameter spaces of important assumptions that are in the model and create what I guess Steve Banks would call landscapes produced by the behaviors of your model. What are all the behaviors? What are all the kinds of results your model can produce? Then the question is whether we have all the mechanisms in the model to represent reality. I think we still don't understand, for our models in general, all the behaviors they're capable of producing. We just play around with them and discover interesting things, some of which may be falsifiable simulation runs or something like that.

**David Sallach:** I'm David Sallach from Argonne National Laboratory. What you are showing is that however much we would like to bracket or hold off the complexity of the world that we live in, the closer that we get to applications, the harder that is to do. And, as we have found throughout this conference, however much we might like to debate the simplicity-complexity discussion, it keeps catching up with us and inveigling us in it again. I would like to relate that to the earlier discussion between BDI [Beliefs, Desires, and Intentions] and DBO [Desires, Beliefs, and Opportunities] that was going on.

I think that the idea of opportunities strengthens some of that basic mechanism. But one of the things that we can see from adding opportunities is that they are inherently linked with the larger world. It's some kind of opportunity that presents itself for a time period that requires certain prerequisites and so forth. There's a relationship between what we presume about the world and the opportunity structure that's inherent in it. What we can also see is that this is true about beliefs and desires and intentions as well. There are beliefs about the world, and they can exist at various levels of abstraction. There are desires for something in the world that may be more or less specific. They may be quite general: for success, honor, food, or whatever. So it seems to me that what you're suggesting is that we must, in some way, address the knowledge representation issue of the nature of the larger reality in which we're enmeshed. It brings us back to Herbert Simon — that perhaps our decisional processes are simple, but we live in a complex environment. Therefore, one of the issues that is always implicitly on the table is how we control the representation of the complexity in which we're embedded.

**Macal:** That point is well taken, David. We should think about these things in an explicit and in a conscious way and see if these two extremes that I've created, or taken positions on, have a lot more in common than I've suggested.

**Kostas Alexandridis:** I'm Kostas Alexandridis from Purdue. There is something I would like to propose. It's not enough to just think about the structural complexity of our models because we understand that complexity. However, there is another process going on: how people outside our own understanding as researchers conceive of those models. There was a very characteristic example, which I would call a very complex model but with a simply understood representation, a year ago in an experiment where people produced a highly complex model, but it was very easily understood by their own people, by the communities. There are other models that are relatively simple in terms of assumptions but that end up not being very well understood by the broader user community. That kind of complexity has to be taken into account at some point.

**Macal:** I would agree. I think that one of the promises of agent modeling is that it's easy to understand the agent behaviors that we include because they could be simple rules or whatever. The complexity comes necessarily as a mechanical process, just from the computer applying these simple rules in agent relationships over and over again. So there's really almost nothing left to explain when the complex results come out. If you agree with the simple rules that are included for the agents, you get complex behaviors. The other situation — of complex models producing simple results — is interesting, but I'm not sure how that relates to agent modeling in particular, unless we have complex agents in complex models and somehow the answer is the same all the time. But that sounds like an equilibrium model as opposed to one that's rich in its dynamics of interaction.

**John Sullivan:** I'm John Sullivan from Ford Motor. It seems to me the whole objective here is to build a model that gets at the essence of the question at hand. And presumably the model is being built to address a particular question and not to describe the world. I would like to ask Mike Macy (because he made a remark earlier this morning that you can prove right models wrong and wrong models right) to elaborate on what he meant by that, in the context of where we are with these models in describing the question at hand.

**Macal:** I would just like to add a note to what you said. You described the second way of using models. It's perfectly legitimate, valid, and of great interest to use a model strictly to create an insight with which you could do anything you'd like, such as designing a laboratory experiment to see if that effect is observed in the real world. It's knowledge for the sake of knowledge, which could ultimately lead to an application. But is that a question that Michael [Macy] should answer.

**Michael Macy:** Well, it turns out that the question I was going to ask was exactly on that point. Suppose that I'm being consulted by the Department of Education about what we should put into kids' textbooks. I have to choose between a group that's advocating multiculturalism and a group that's advocating sort of an older 1950s, 1960s, early 1970s approach that focuses on color blindness or ethnic blindness. I look at the Schelling model, and it tells me I should not use multiculturalism because that promotes ethnic awareness, which will get you segregation, whereas if I promote color or ethnic blindness, you won't get segregation. That's what the model predicts. So the model gives me a policy recommendation, even without any specificity in terms of trying to match it with real-world data.

I might go into the lab and design an experiment in which we test people. We give people a stimulus. In one case, we promote multiculturalism, and we give them a multicultural message. In the other case, we give them a liberal, ethnic blindness message, which makes them think about some attribute other than ethnicity. We prime them to get them to not think about it. Then we put them into a checkerboard and let them move around, and we see which one produces the segregation. It seems that this approach would inform policy in a way that I would perhaps trust more than I would an agent model that was extremely complex that I didn't really understand. Moreover — here's the thing I really worry about — what do we do about unobservable behavioral parameters? The key one to look at very carefully is that a lot of our stochastic models use a cumulative logistic function: one over one plus  $e$  to the minus  $x$ ,  $m$ , where  $x$  is a propensity that comes out of the model. It doesn't matter what it is;  $x$  is a propensity. And  $m$  is the slope parameter of the function, of the sigmoid.

We can find  $x$ ; we can measure the propensities. We can even get pretty good information about the distribution, so we can know what the variance is and so on. It's really hard to measure people's  $m$ 's. It's hard to know whether they're using the hard limiter function or whether it's linear. And even if we could find that for the mean of a population, good luck trying to find what the distribution of that looks like across the agents. I don't think you'll find either one. Moreover, we don't know anything about the correlation between  $x$  and  $m$ . We just aren't going to know that. Yet it doesn't do you any good to know  $x$  if you don't know  $m$ . Trying to get these agents to look like real people is a tough assignment. I would love to do it, but I just despair.

**Macal:** Well, I'm in your camp, Michael. I'm despairing, but I'm pressing on anyway.

**Macy:** I still think we could do the policy recommendations.

**Macal:** But how? How can we do that if the model's no good?

**Macy:** Somebody should do this.

**Macal:** That's the good use for essentially an insight coming out of a model. The model may not be ready for prime time. That's not your fault. It could be that the model's just getting skyrocketed into the policy domain. That's a very natural process because the policymakers want the answer today.

**Nick Gotts:** I'm Nick Gotts of Macaulay Institute. On your diagram and in a number of the questions, there's been an assumption that you start with a simple model and make it more complicated. That's not always the way it should go. You should be prepared to move up and down the scale of complexity. When you find some interesting phenomenon, one of the first things you should do is start taking things out of the model and see how long it survives because it may just be a bug.

**Macal:** Exactly. That's a very good point — a constructive way to do modeling, in the sense that in fact, it's a natural thing, too. Once you've got the observed effects in a very complicated model, the question occurs: "Can I throw out these assumptions and this module and find this didn't matter much? And can I even mechanically identify those factors that don't count much? It's the scaffolding of the model.

**Claudio Cioffi-Revilla:** I'm Claudio Cioffi-Revilla from George Mason University. I've got 5 minutes of notes, but I'll just pick the 15 seconds that I wanted to introduce them with. I hope I'm attributing this right. George Box, statistician, said this in the context of statistical models, but I think it applies here: All models are wrong, but some are useful.

**Macal:** John Sterman has a quote like that, too. I think he just says all models are wrong, period. There's a paper on that.

**Cioffi-Revilla:** Thirty years ago, when I was starting out in my career, I did the following exercise. I was deeply interested in mathematical models in international relations. There were no agent-based models at that time, unfortunately. But I did a huge survey of the literature in the whole field, going back to Day 1 — to Richardson and even earlier work that I was able to track down. I came up with a few hundred models that spanned everything — from set theoretic models to games, decisions, differential equations, stochastic processes, and the full panoply of mathematical structures. I had a matrix with all kinds of mathematical structures in rows, and it had different topics or behaviors — from arms races to international organizations, foreign policy cognitions, all kinds of things like that, and substantive domains — in columns.

Today, I would say the number of practitioners in this field is between about 500 and 1,000 globally. I think we'll cross the 1,000 threshold in a few years, but now we're probably just below it. So one day this type of inventory will be impossible to carry out. It might be possible because of co-authorships. Also, the actual number of individual, distinct models out there is probably on the order of 100 or in the low hundreds, perhaps. I did it 30 years ago, and I'm not going to do it again, but it is worthwhile because it gives the topology of applications and uses of different kinds of models where it's very easy to discover areas that, unless you do this systematically, we might miss in what we're actually doing and accomplishing collectively.



And it might be something worthwhile to look at. It would be, in fact, a way to populate that two-dimensional diagram.

**Macal:** Yes, I think that would be useful and possible, especially now with the automated information Webs that are out there, to just grab all those, whether they're historic or current.

**Spiro Maroulis:** I'm Spiro Maroulis from Northwestern University. When you had the graph up about the detail versus behavior at the end, I was thinking that there are two types of detail — detail in factors and detail in actors — and that their implications with regard to validity or credibility in the policy world may be different. Maybe they actually go in different directions, so if I have detailed factors and I can map them to empirical results, I get more credible. But the more complicated my explanation about the heuristics people use becomes, I may lose credibility or the model may become less powerful. I just wanted your comments on that.

**Macal:** You have to have a story as to how the model maps into the world — whether a model models the agents or the process or models or the whole model in general — whatever is needed to establish credibility. It's usually discrete elements at which credibility is in question. And if credibility can be established, they just say that your model's fine. But there are a few different things to focus on. You have to articulate and have a story; that's just part of the art of modeling. Plus, we have developed computers that some day can generate stories. Maybe that's something we should work on: generate! Here's the model, and out comes a story, instead of a Java dock or something (i.e., here's the story you should use to explain what's in my model).

**Unidentified Speaker:** That's sort of the ultimate in the narrative simulation I talked about. That's actually a technique in semiautomatic versions that we've used to convince people that certain things are working properly.

**Luis Antunes:** I'm Luis Antunes of the University of Lisbon. I just want to make a small comment along the lines of Michael's comment. I think it gets even worse because your vertical line in the axis isn't really there. It's kind of fuzzy because the real world is not available to us. So your observations depend on models, also. Many times, it would be useful to consider those models explicitly (e.g., when you have what you call raw data that are not raw data; they depend on someone measuring). All information, of course, is mediated, and mediated through something we can call a model, as well.

**Macal:** Yes. The real picture would be the real world — something we don't know and cannot attain. And even if we did, in our model, we wouldn't even know it. It would be like simulating the universe with a universal computer.

Why don't we continue the discussion about applications in light of some of these ideas? Please be kind to the developers of the applications. When you develop an application, you are open to an enormous amount of blind sides, weaknesses, what-ifs, and things like that.

**Unidentified Speaker:** And plead for understanding.

## Data Farming Repast Models

**Keven Ruby:** Thank you. Steve Upton has a very interesting project that, as I understand, is with the Marine Corps using Marine Corps data in a military environment.

**Steve Upton:** I'm giving this brief for Matt Koehler, so I'm not actually working on this project. If you have any detailed questions about what's going on, you'll have to wait for the paper or send an e-mail to Matt.

As Keven mentioned, we're doing this work for the First Marine Expeditionary Forces, or 1MEF, which is in Fallujah. Colonel Stanley is the G2 or the intel individual at 1MEF. A small cadre of 1MEF folks resides at Camp Pendleton, and Matt is trying to continue this work going while the main force is in Fallujah. We're trying to look at a particular application. Gary Horn, Phil Barry, and Matt are all with the MITRE Corporation. Brian's actually with Widdowsons at the Maui High Performance Computing Center; like myself, Adam Forsyth is with Referentia Systems. Adam is from Australia and has worked with the Australian army. So we have lots of military experience. I'm a retired Marine, so that helps. I know a little bit of something about the domain, not necessarily about the model.

First, I'll give short introduction about 'Albert' and then get into the SASO model, which stands for Stability and Support Operations. It's basically the winning-the-peace part. We did all the war; now we're trying to win the peace in Iraq. That's just one application. Some work occurred before the Iraqi War, so you can see that this has actually been of interest to all the military for some time. In fact, some of the work that we mentioned on Thursday (i.e., with the Germans) talked about the many peacekeeping operations, specifically at the elections in Kosovo. They developed a model called Pax to look at that. It's the same kind of interesting arena.

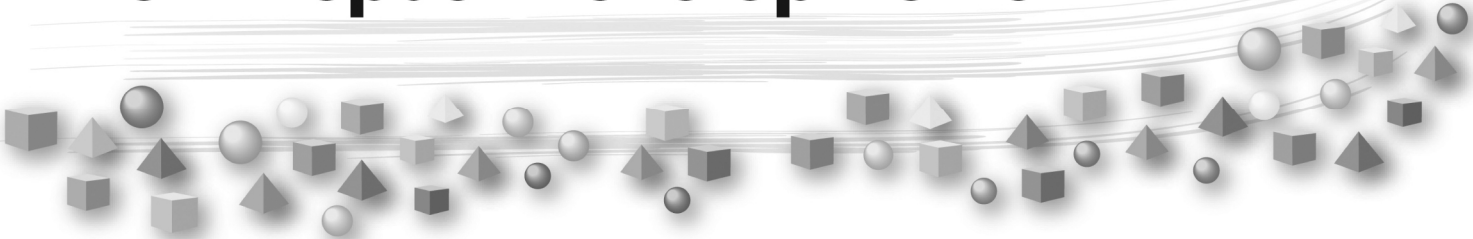
[Presentation]

**Ruby:** As we transition to the next speaker, let's take a question.

**Scott Christley:** Scott Christley from University of Notre Dame. This comment might be more relevant to your earlier talk with the data farming, but one of the purposes you're doing that is to find outliers — those special scenarios that occur. If you're generating lots of data, how are you actually finding those outliers without brute force? What are you using as a trigger to find those things?

**Upton:** Yes. A lot of data farming involves the use of different algorithms. As I mentioned, we have Design of Experiments to find those evolutionary algorithms, and a lot of it is just brute force. So there is a low base-rate problem. We normally do a set of replications on that because there's a lot of stochasticity. Even though you did 1,000 replications, there's one out of 1,000 that was of interest: how do you find that? So, yes, those are some of the ideas we're looking at now.

# New Repast Developments





## REPAST REVOLUTION: AN OVERVIEW OF NEW REPAST DEVELOPMENTS

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### ABSTRACT

Repast is a widely used framework for developing agent-based models. Repast includes components for developing agents and creating agent environments, as well as initiating, executing, and tracking simulations. Recently, several new enhancements have been added to the Repast system: multilingual model development, greatly expanded built-in features, and full geographical information systems (GISs) support. Historically, Repast has used the Java environment, but now Repast has been ported to the Microsoft.NET framework. This complete conversion, called Repast .NET, contains virtually all of the functionality of Repast for Java (Repast J) and is written in pure Microsoft C#. True to the Microsoft.NET approach, complete Repast .NET models can now be written in the user's choice of C#, Managed C++, or Visual Basic. Repast .NET is fully integrated with Microsoft Visual Studio and includes Enterprise Templates and examples for C#, Managed C++, and Visual Basic. Continuing this multilingual theme outside of the Microsoft.NET framework, Repast for Python (Repast Py) is a newly rebuilt visual model construction environment that uses Python scripting to define agent behaviors and environmental responses. Repast Py users can work with a point-and-click interface along with Python coding to create complete cross-platform models on any operating system, including Microsoft Windows, Mac OS, and Linux. Furthermore, Repast Py models can be automatically exported to Repast J models with a few mouse clicks. Repast also includes enhanced functionality, such as fully integrated systems dynamics modeling, linear programming, neural networks, and genetic algorithms. These powerful functions can be used for complete models or for individual agent behaviors. Repast has a new visual point-and-click framework to execute Monte Carlo simulations. The Repast family also now has full integration with ESRI ArcGIS and open source GIS. The new Repast GIS feature allows agents to be automatically created from, to be immediately displayed on, and to directly interact with real GIS maps as easily as standard grids. These and other new Repast developments are discussed.

**Keywords:** Agent-based modeling and simulation, toolkit, library, Repast

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## INTRODUCTION

The Recursive Porous Agent Simulation Toolkit (Repast) is one of several agent modeling toolkits that are available. Repast borrows many concepts from the Swarm agent-based modeling toolkit (SDG, 2004). Repast is differentiated from Swarm since Repast has multiple pure implementations in several languages and built-in adaptive features, such as genetic algorithms and regression. For reviews of Swarm, Repast, and other agent-modeling toolkits, see the surveys by Serenko and Detlor (2002) and Gilbert and Bankes (2002). Also, see the toolkit review by Tobias and Hofmann (2003), who reviewed 16 agent modeling toolkits and found that “we can conclude with great certainty that according to the available information, Repast is at the moment the most suitable simulation framework for the applied modeling of social interventions based on theories and data.”

Repast is a free open source toolkit that was originally developed by Sallach, Collier, Howe, North, and others (Collier et al., 2003). Repast was created at The University of Chicago. Subsequently, it has been maintained by organizations such as Argonne National Laboratory. Repast is now managed by the nonprofit volunteer Repast Organization for Architecture and Development (ROAD, 2003). ROAD is led by a board of directors that includes members from a wide range of government, academic, and industrial organizations. The Repast system, including the source code, is available directly from the Internet.

## GOALS

Repast seeks to support the development of extremely flexible models of living social agents, but it is not limited to modeling living social entities alone. From the ROAD home page:

Our goal with Repast is to move beyond the representation of agents as discrete, self-contained entities in favor of a view of social actors as permeable, interleaved, and mutually defining; with cascading and recombinant motives. We intend to support the modeling of belief systems, agents, organizations, and institutions as recursive social constructions.

At its heart, Repast toolkit version 3.0 can be thought of as a specification for agent-based modeling services or functions. There are three concrete implementations of this conceptual specification. Naturally, all of these versions have the same core services that constitute the Repast system. The implementations differ in their underlying platform and model development languages. The three implementations are Repast for Java (Repast J), Repast for the Microsoft.NET framework (Repast .NET), and Repast for Python Scripting (Repast Py). Repast J is the reference implementation that defines the core services. In general, it is recommended that basic models can be written in Python using Repast Py due to its visual interface and that advanced models be written in Java with Repast J or in C# with Repast .NET.

## REPAST'S ROOTS

Repast 3.0 is based on Repast 2.X. Repast 2.0 included a variety of features:

- Fully object-oriented
- Fully concurrent discrete event scheduler that supports both sequential and parallel discrete event operations
- Built-in simulation results logging and graphing tools
- Range of two-dimensional agent environments and visualizations
- Dynamic access for users to modify agent and model properties at run time
- Social network modeling support tools
- Available on virtually all modern computing platforms, including Windows, Mac OS, and Linux
- Various agent templates and examples; however, the toolkit gives users complete flexibility as to how they specify the properties and behaviors of agents

## REPAST 3.0 OVERVIEW

Repast 3.0 builds on earlier releases and has a variety of features:

- Various agent templates and examples; however, the toolkit gives users complete flexibility as to how they specify the properties and behaviors of agents
- Fully object-oriented
- Fully concurrent discrete event scheduler that supports both sequential and parallel discrete event operations
- Built-in simulation results logging and graphing tools
- Automated Monte Carlo simulation framework
- Range of two-dimensional agent environments and visualizations
- Dynamic access for users to modify agent properties, agent behavioral equations, and model properties at run time

- Libraries for genetic algorithms, neural networks, random number generation, and specialized mathematics
- Built-in systems dynamics modeling
- Social network modeling support tools
- Integrated geographic information systems (GISs) support
- Fully implemented in a variety of languages, including Java and C#
- Able to be developed in many languages, including Java, C#, Managed C++, Visual Basic.Net, Managed Lisp, Managed Prolog, and Python scripting
- Available on virtually all modern computing platforms, including Windows, Mac OS, and Linux (platform support includes both personal computers and large-scale scientific computing clusters)

### **SELECTED HIGHLIGHTS OF REPAST 3.0**

The Repast system has two layers. The core layer runs general-purpose simulation code written in Java. This component handles most of the “behind-the-scenes” details. Repast users do not normally need to work with this layer directly. The external layer runs user-specific simulation code written in one of several languages. This component handles most of the “center-stage” work, and Repast users work with this layer. Basic models can be written in Python, and basic or advanced models can be written in Java with Repast for Java or any Microsoft.NET language.

Repast 3.0 introduces many new capabilities beyond those in Repast 2.X. In particular, Repast 3.0 is multilingual.

Repast Py is useful for learning Repast and for rapidly prototyping models. Repast Py models can be automatically exported to Repast J with a few mouse clicks. Repast Py is shown in Figure 1.

Repast J is useful for experienced modelers. Repast J produces cross-platform models. Repast J is shown in Figure 2.

Like Repast J, Repast .NET is useful for experienced modelers. Repast .NET allows models to be developed in many languages. Repast .NET is shown in Figure 3.

Repast 3.0 integrates GIS modeling with agent-based simulation. Repast 3.0 works with ESRI ArcGIS and the free and open source Open Map system. The Repast GIS tools make it as easy to create GIS models as it is to create grid models.



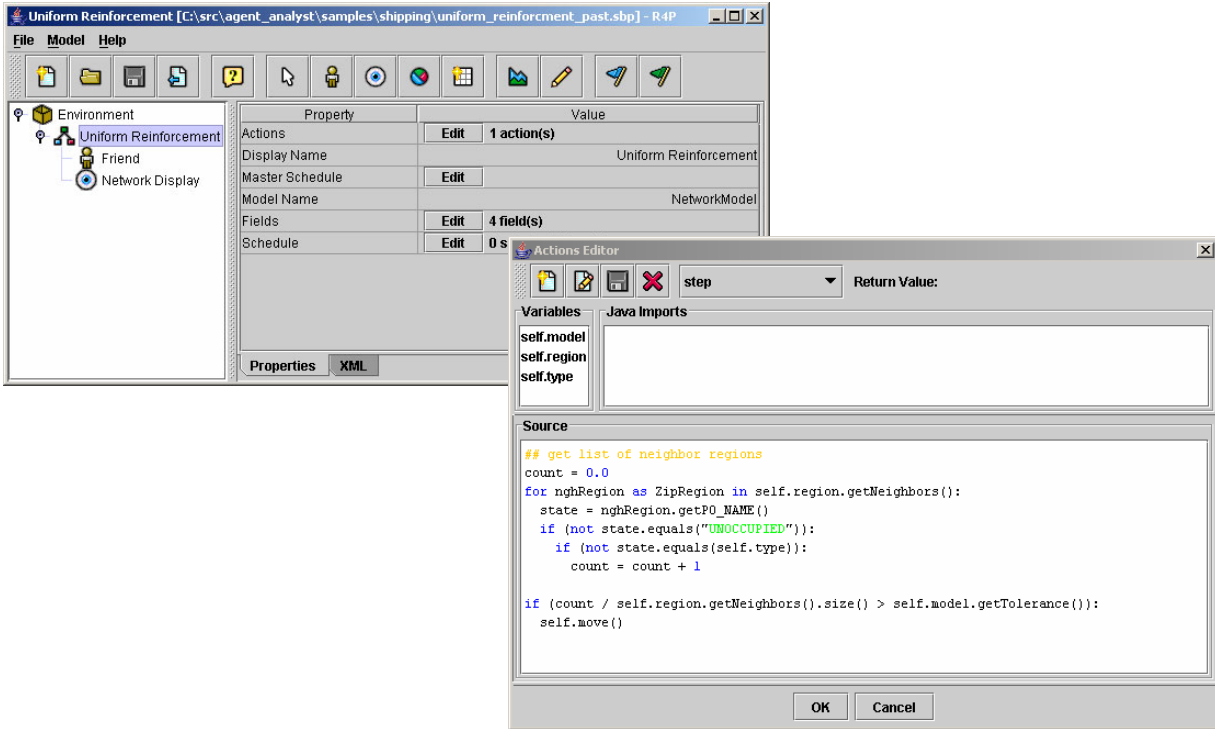


FIGURE 1 Repast Py

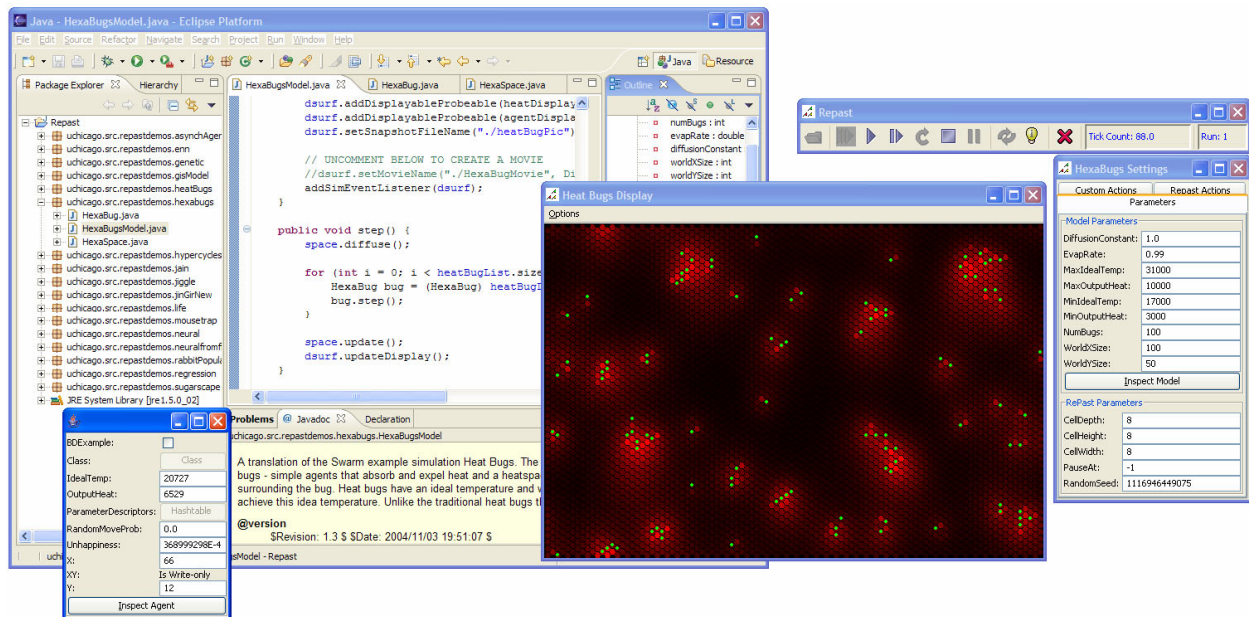
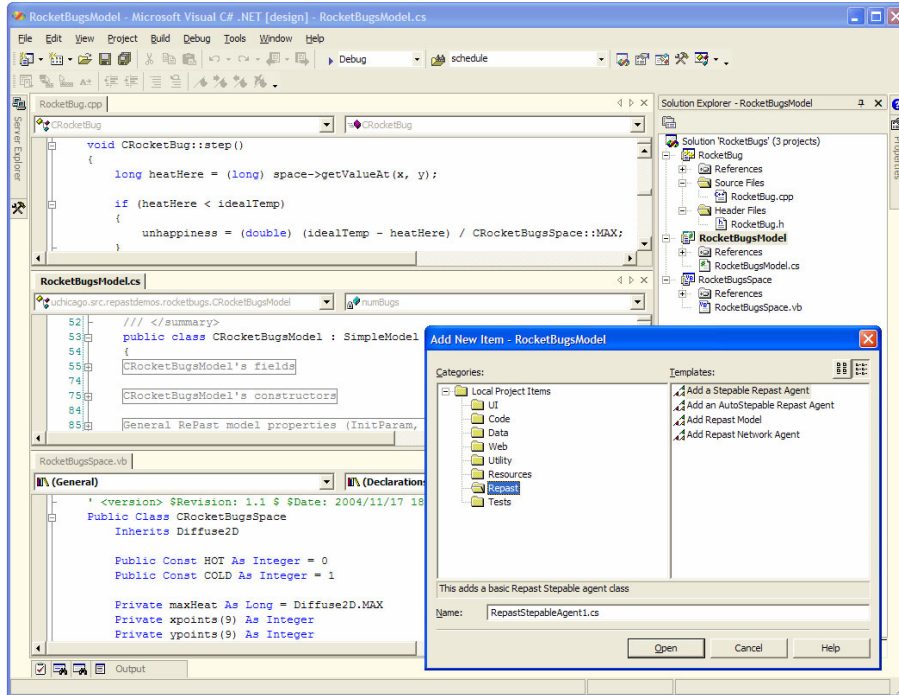


FIGURE 2 Repast J within the free and open source Eclipse development environment

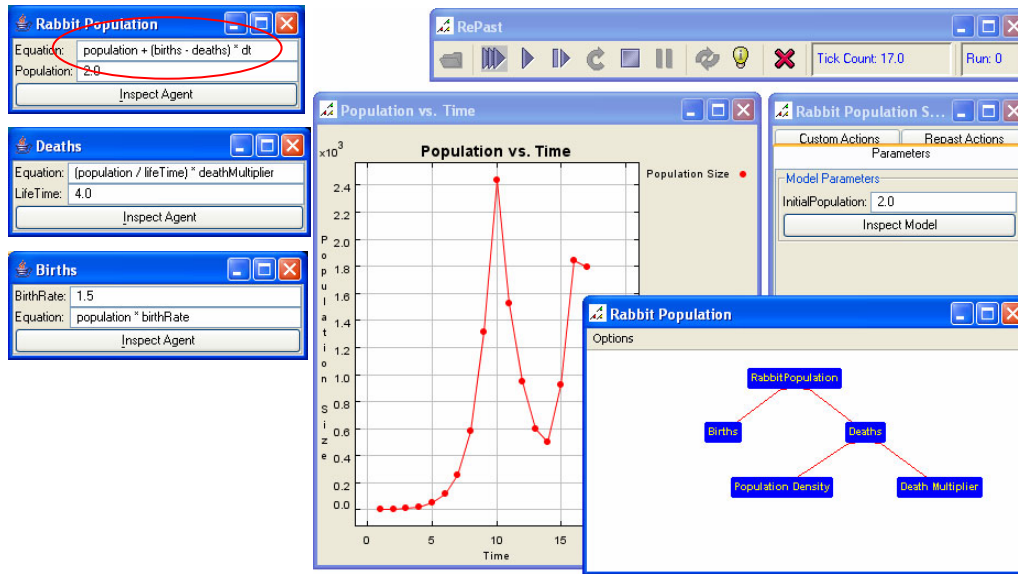


**FIGURE 3** Repast .NET within the Microsoft Visual Studio .NET development environment

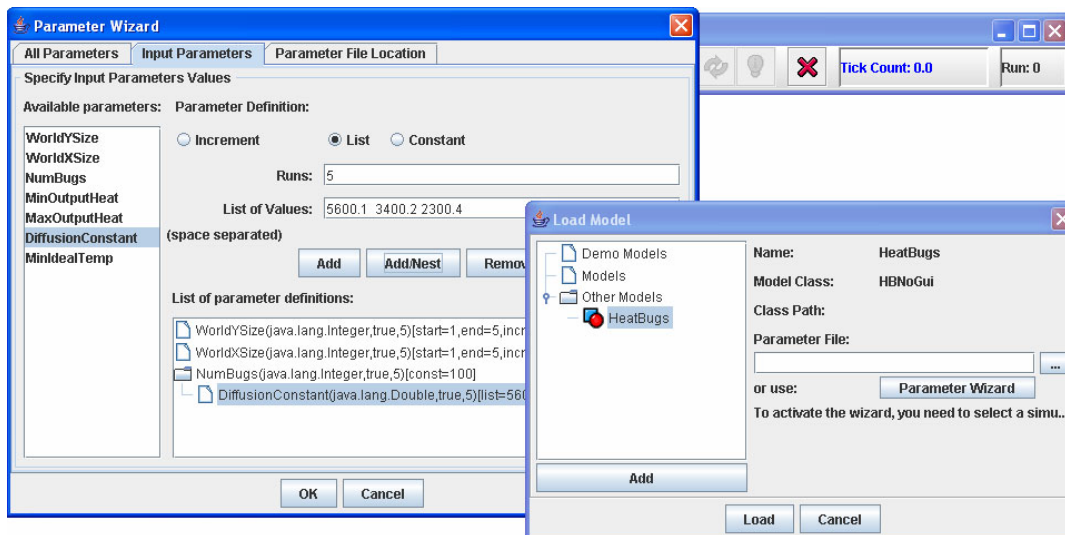
Repast 3.0 integrates Systems Dynamics modeling with agent-based simulation. Repast Systems Dynamics equations are specified using simple strings such as those shown in Figure 4. Equations can be updated dynamically at run time.

Repast 3.0 includes a point-and-click Monte Carlo simulation framework. The interface is shown in Figure 5. This framework automates the execution of parameter sweeps and stochastic replications.

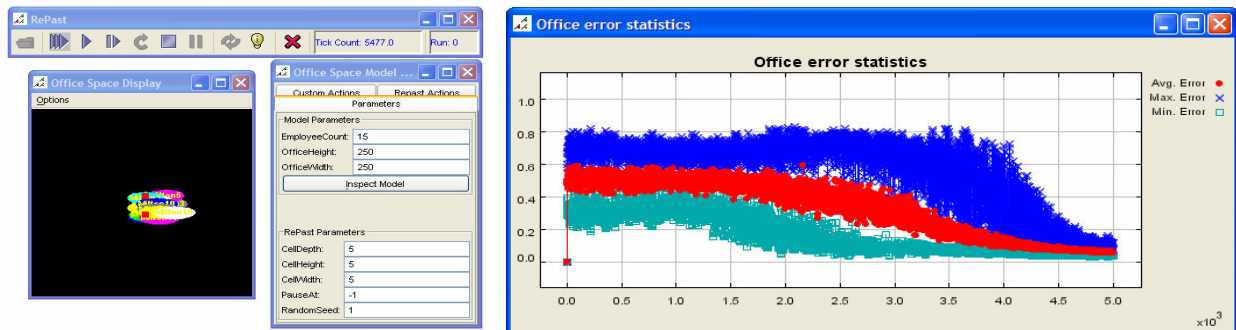
Repast 3.0 integrates several adaptation tools. Genetic algorithms are available in all Repast languages by using a special edition of Java Genetic Algorithms Package (JGAP). Automated regression tools are available in all Repast languages Neural networks are available in Repast J only using the Java Object Oriented Neural Engine (Joone). An example model showing the use of Repast 3.0's adaptation tools is shown in Figure 6.



**FIGURE 4** Repast 3.0 systems dynamics model with an equation highlighted in the upper left



**FIGURE 5** Repast 3.0 Monte Carlo simulation framework



**FIGURE 6** An example model showing the use of Repast’s adaptation tools

## SUMMARY

Repast 3.0 builds upon earlier releases. Repast 3.0 has all of the features of the earlier releases to make upgrading easy. Repast 3.0 offers many exciting new capabilities, including multilingual support; integrated GIS support; integrated Systems Dynamics modeling; automated, point-and-click Monte Carlo simulation; and libraries for genetic algorithms, neural networks, and regression.

## ACKNOWLEDGMENT

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## REPAST FOR PYTHON SCRIPTING

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### ABSTRACT

Repast for Python Scripting (Repast Py) is a rapid application development tool for producing Repast simulations. By using a point-and-click, component-based interface, users can easily construct a model and then use Python scripting to define model-specific agent behaviors. Repast Py is the next generation of Repast visual development tools, incorporating a streamlined user interface, improved Python language support, and the latest improvements to Repast. In particular, Repast Py can produce GIS-based models, and it integrates well with the new System Dynamics equation support. Finally, Repast Py now provides the ability to export Repast Py models to Java, allowing users to then work in the traditional Repast for Java environment. An overview of the tool and these new features is presented.

**Keywords:** Agent-based modeling and simulation, Repast, rapid application development, Python

### INTRODUCTION

Repast for Python Scripting (Repast Py) is a rapid application development (RAD) tool for producing Repast simulations. Repast Py provides the ability to create three different model types: a GIS (geographic information system)-based model in which agents can be generated from GIS features and can interact with a GIS-based landscape and topology; a network-based model in which agents are typically nodes in a network and can manipulate the network topology; and a grid-based model in which agents reside in and interact with a grid topology. In addition, it is possible to create and use a generic-type agent in each of the three model types. These model components are manipulated via a point-and-click user interface. The actual user-specific agent behavior is written in a special subset of the Python language,<sup>1</sup> allowing for full access to the various extensions and packages of the Java language and, more important, to the full Repast framework. The end result of this model specification and Python Scripting is a fully executable Repast model that behaves on the byte-code level just as a traditional Repast model written in Java. This paper is an overview of Repast Py, focusing on its use of a component model to produce a Repast simulation, on how agent behavior is defined in Python scripts, and on some of the new features added in this version.

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<sup>1</sup> For further information on Python, see the Python Software Foundation Web site. “An Introduction to Python” can be found at [www.python.org/doc/Introduction.html](http://www.python.org/doc/Introduction.html).

## COMPONENT MODEL

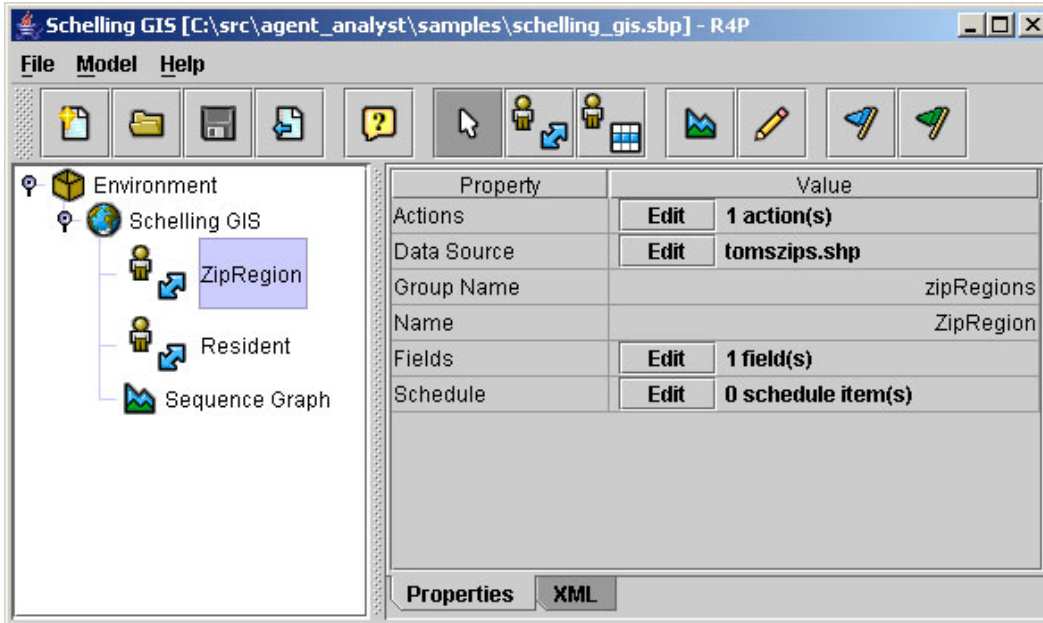
As mentioned above, Repast Py produces a Repast simulation; that is, it produces a simulation that follows the Repast notion of how to organize a software-based agent simulation. Typically, the so-called model part of the simulation is responsible for initializing the agents and any other required elements and defining what should occur every time step of the simulation. The agents themselves then perform the actual behavior that drives the simulation. For example, a GIS model would be responsible for creating various agents from a shapefile specification, associating those agents with the topology in which they operate, and defining what agent behaviors should occur each time step of the simulation. The agents then would perhaps forage the landscape looking for food.

Repast Py produces this type of simulation by building a description of the model and agents out of various components. The resulting composite description produced by these components is rich enough to compile into the actual compiled Repast simulation.<sup>2</sup> Each component can be thought of as providing a generic description of some piece of the final product. Repast Py contains three different types of components, each corresponding to what piece of the compiled simulation they produce. Model producers are responsible for producing the description of the compiled model; agent producers are responsible for producing the description of the compiled agents; and the last type of producer is responsible for producing additional Repast objects, such as charts and data recorders. These generic descriptions provided by each of the producer components are then specialized to the current task by setting the value of one or more of the component's properties. A trivial example of this task is the "display name" property that is common to all the model-producing components. The value of this property determines the simulation name that is displayed when the compiled model is executed.

Figure 1 illustrates what these components and their properties look like in Repast Py. The left side of the screen below the toolbar is the component tree, and the table on the right side is a list of the currently selected component's properties and their values. The environment component sits at the top of tree, and its properties are primarily concerned with the global compilation environment. The next component in the tree is the model producer. There is one of these for each type of model (GIS, network, and grid). As mentioned above, a Repast model is responsible for initializing agents and constructing the schedule for what happens each time step of the simulation. The model producer component's properties are thus concerned with those responsibilities. Below the model producer component are two agent producer components. The top one, "ZipRegion," is selected and its properties are shown on the right. Notable in its properties is the "Data Source." Here, the user can specify a shapefile whose features will become agents with the appropriate attributes. In addition, the agent producer components (as well as the model producer components) have an actions property in which behavior can be defined with a Python script. (For more on this subject, see the next section.) The last component in the tree is a producer for a sequence graph. This producer describes a chart that plots some user-specifiable value versus simulation time.

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<sup>2</sup> It is important to note that the user constructs a description of a Repast simulation and not of the compiled output. The user does not need to know that she is creating the byte-code representation of a Java class.



**FIGURE 1** Components and properties in Repast Py

In sum, Repast Py produces a compiled Repast simulation consisting of a model and one or more types of agents. It does this by allowing the user to create an abstract composite description of such a Repast simulation. The components of this description are each responsible for producing a description of a piece of the Repast simulation — the model, the agents, charts, and so on. The description that each component produces is specialized by setting the values of that component’s properties. The end result is a composite description that can be compiled into an executable Repast simulation.

## AGENT BEHAVIOR

In Repast Py, agent behavior (as well as model behavior) is defined by using a special subset of the Python language. A subset is used because the entire Python language is not necessary for specifying agent behavior. For example, such things as class and function declarations or the dynamic manipulation of a class structure are not necessary when defining an agent’s behavior. This subset is “special” because it integrates well with Java, and thus with the Repast framework as a whole.<sup>3</sup> As a result, it is easy to use pieces from the Repast framework when scripting agent behaviors and to compile these Python scripts into Java byte-code when producing the compiled simulation.

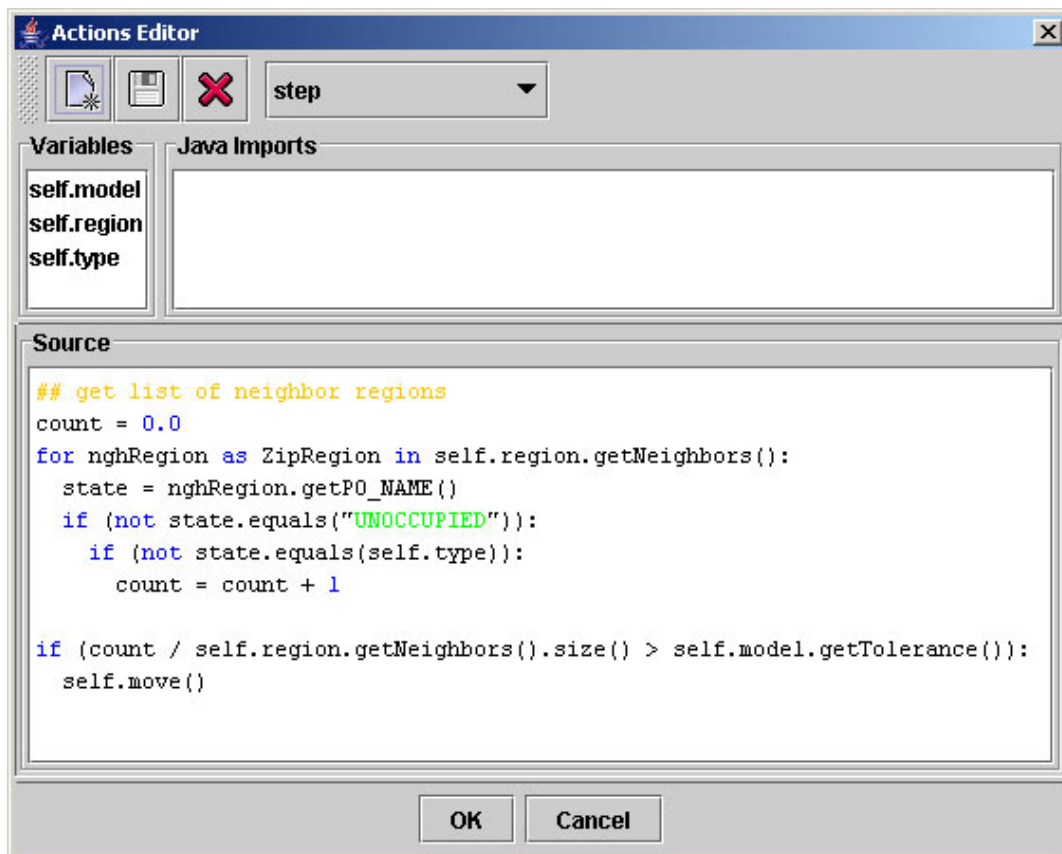
These agent behavior scripts are defined through an agent producer component’s action property (Figure 1). This property is essentially a list of the actions (Python scripts) that the produced agent can perform. For example, one of these actions may define a “look for food in

<sup>3</sup> Note that this “special subset” is not Jython, the Java port of Python, which achieves excellent integration between Python and Java (integrating Java into Python) but not between Java and Python (integrating Python into Java). Repast Py, unfortunately, requires both.

the immediate area and eat it” behavior. The agent producer defines the action for all the agents of the type described by the agent producer. However, each agent once created and running inside the simulation has its own copy of the action; thus, the actual performance of the action, the actual behavior of the agent, depends on the state of that particular agent. For example, if the action branches on location, it is the current location of the individual agent executing the action that makes the difference.

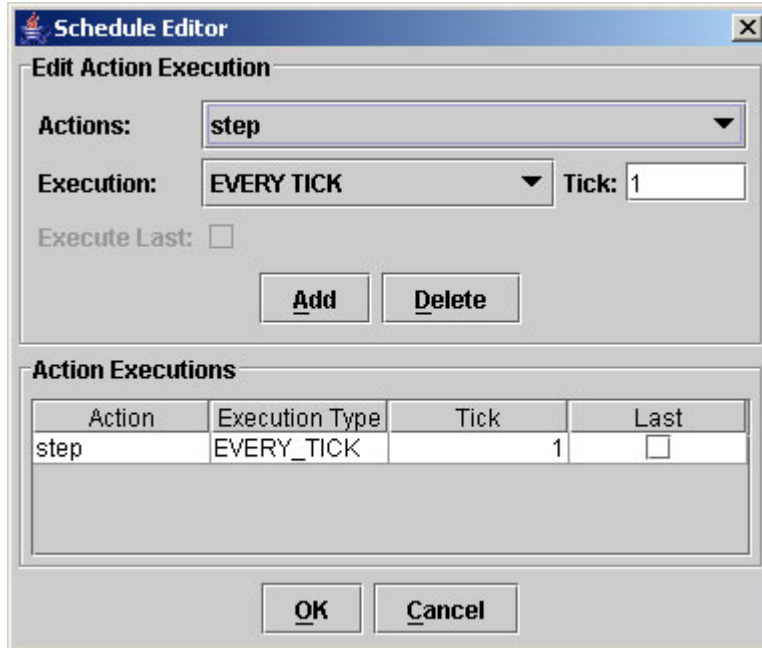
Actions are edited in the actions editor shown in Figure 2. This “step” action defines the main behavior for an agent in a GIS-based, Schelling-type simulation, where the agent will move to some unoccupied region if some fraction of agents in neighboring regions are not of its type. The Java integration is exemplified here in the “self.region.getNeighbors().size()” call, which returns a Java List and then the size() method is called on that List. Calls to Java objects are seamless in this way. It is also possible to iterate over Java collections in a Python style, as seen in the “for” loop above. Finally, an agent’s action may call other actions defined in that agent. The “self.move()” call in the above is just such a call in that it executes the move action defined in this agent.

The user has full control over the time step at which these actions will execute and the order in which they execute relative to other actions scheduled for the same time step. The time step at which an action can execute is specified in the Schedule property of a component, as seen in Figure 3.



**FIGURE 2** Repast Py Actions Editor





**FIGURE 3** Schedule Editor

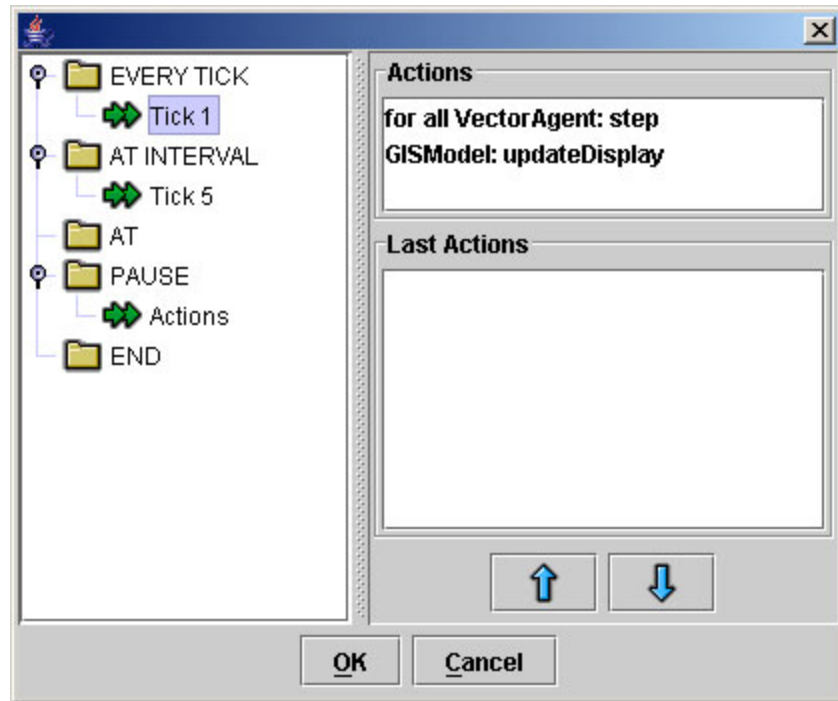
The user has full access to the features of the traditional Repast scheduler and is able to specify the tick (the time step) at which an action should be executed; the interval of execution (every tick, at an specific interval, at a single tick, and so on); and whether the action should execute after (i.e., last) all other actions not scheduled to execute “last.” As a convenience, some actions are scheduled automatically, although the user has the opportunity to override this automatic scheduling. The step action above, for example, is automatically scheduled to execute every tick. This ensures that when the simulation is run each agent executes its primary behavior.

The full view of what actions are scheduled when and how they are scheduled relative to each other is provided by the master schedule property in the model producer component (Figure 4).

Here we see that at every tick beginning at tick one every VectorAgent will execute its “step” action and the GISModel will execute its “updateDisplay” action. The order in which these execute relative to each other can be changed by selecting one of the individual actions and moving it up or down with the blue arrows. By using these two properties, the schedule and the master schedule, the full richness of the traditional Repast scheduler is available in Repast Py.

## NEW FEATURES

Repast Py is a significant upgrade to its ancestor application, SimBuilder. Among the new features added to Repast Py is support for GIS-based models. This support mainly consists of integration with popular GIS packages, such as ArcGIS and OpenMap. By using this new support, it is possible to create an agent description from a shapefile such that features specified in the shapefile become fields and accessor methods in the produced agent. For example, if the

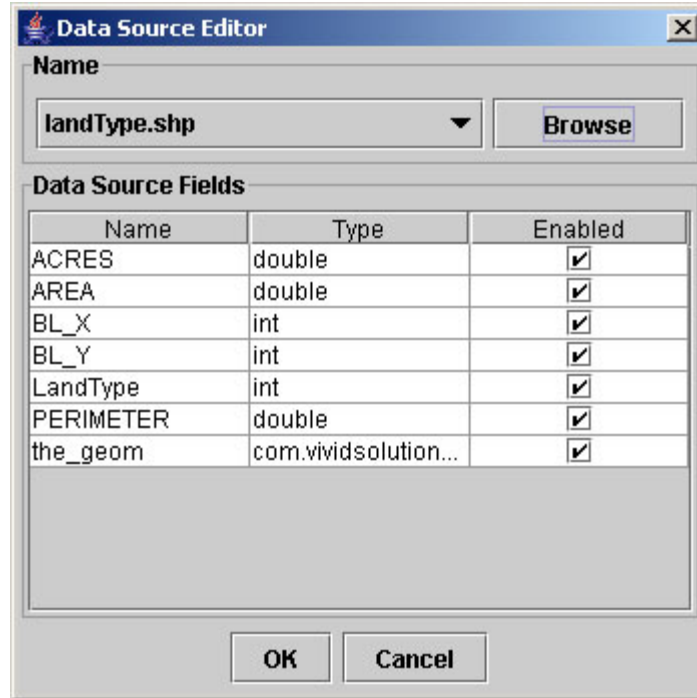


**FIGURE 4** Master Schedule Editor

shapefile contains a feature called LandType, the produced agent will have a LandType field together with getLandType and setLandType methods. When the simulation is run and the actual agents are created, each record in the shapefile provides the data for an agent. So, if the shapefile has 600 records, then 600 agents are created. The selection of a shapefile is accomplished via the vector agent producer component's data source property (see Figure 1). When a shapefile is selected, it is immediately interrogated and its features are displayed as shown in Figure 5.

Integration with the various GIS packages is accomplished either directly through API (application programming interface) calls or through shared files. For example, in the case of ArcMap, both ArcMap and the Repast simulation produced by Repast Py will share the same shapefile. As the simulation progresses, the current values of the agents will be written back to that shapefile, and ArcMap will be updated. Provided that the shapefile has been loaded into ArcMap, the current state of the simulation, that is, the current state of the agents, will then be visible in the ArcMap display. Direct integration via API works much the same way, but the data are shared and updated through a direct call to the GIS package (e.g., OpenMap) rather than mediated through a shared file.

Although GIS support is certainly the most significant new feature added to Repast Py, other new features have been added as well. It is now possible to work with multiple agent producers in a single Repast Py project and thus create a simulation with multiple different types of agents. An export to Java is now supported such that the description of the simulation created by Repast Py can be exported to Java and then worked on from there as a traditional Repast programming project. Finally, the old SimBuilder interface has been vastly improved in Repast Py.



**FIGURE 5** Data Source Editor

## CONCLUSION

Repast Py is a component-based RAD environment for producing Repast simulations. It produces a composite description of a Repast simulation, and this description is then compiled into a traditional Repast simulation. Repast Py components are specialized by setting the values of their properties. Where generic behavior is not sufficient, new behavior can be scripted by using a special subset of the Python computer language. These scripts are defined in a components “actions” property and have access to the Repast framework and to the myriad of Java packages. In addition, these actions can be easily scheduled to execute in a variety of ways in accordance with the Repast scheduling paradigm. Finally, many new features, such as GIS integration, have been added to Repast Py, making it a vast improvement on its predecessor, SimBuilder.

## ACKNOWLEDGMENT

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## REPAST .NET

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### ABSTRACT

The advent of the Microsoft.NET framework has signaled the beginning of a new era of language interoperability. By using any language targeted at Microsoft's Common Language Infrastructure (CLI), developers are assured that they can execute their software anywhere that Microsoft.NET is available. Individual project components can now be developed in the language most fitting the component's design, without requiring extra work to interface with the rest of the project. Through this capability comes the additional advantage of ability leveraging skills and libraries that in the past may have been tied to specific languages. It is the combination of these features that make .NET business cases attractive. This naturally brought Repast into the .NET world through the production of Repast .NET. Repast .NET is a port of Repast for Java (Repast J) to the C# language and therefore the .NET framework. Repast .NET allows agent-based models to be developed in any .NET compatible language, including Managed C++, Visual Basic, C#, Lisp, Prolog, and Smalltalk, by using Repast J's familiar application programming interface and functionality. Along with these features, Repast .NET provides integration into the main .NET development environment, Microsoft Visual Studio.NET, including complete Visual Studio templates. Finally, Repast .NET includes demonstration models written in C#, Visual Basic.NET, and Managed C++, illustrating the language interoperability of Repast .NET.

**Keywords:** Agent-based modeling and simulation, Repast, .NET framework, toolkit, library

### INTRODUCTION

Since its initial release in 2001, Repast has been used by numerous research projects, from geopolitical boundaries (Cederman, 2002) to electrical markets (North et al., 2002) to artificial stock markets (Ehrentreich, 2002), and by numerous types of groups, including academic, commercial, and governmental. While these projects followed different development models, in the end their models have been implemented in Java since Repast itself was a Java library. In many cases, Java is a suitable development language; however, not everyone is capable of using Java, whether it is from a lack of Java programming skills or licensing issues or for other unknown reasons. For the former group, using Repast would require an investment of resources into developing Java capabilities, while the latter group may not have been able to use Repast at all. With the development of the non-profit Repast Organization for Architecture and Design (ROAD), however, comes the generalization of Repast from the Java implementation to the simulation framework. Through this comes the expansion of Repast from the Java world (Repast for Java, Repast J), into the .NET world with Repast .NET.

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Repast .NET is an implementation of Repast in the .NET environment and as such, any model using Repast .NET has full access to all the .NET capabilities, including a variety of programming languages to work with (particularly Managed C++, C#, and Visual Basic), full language interoperability (allowing use of any .NET components in any .NET language), a full set of framework classes (from collections to XML handlers), and a managed runtime (with features such as garbage collection, interpretation, and security measures). Repast .NET originated as a port of Repast J, containing virtually all of Repast J's functionality (with an emphasis on the core functionality), written in C#. Repast .NET closely follows Repast J, keeping uniformity whenever possible.

This paper introduces Repast .NET, beginning with a brief history of the .NET framework, along with details on some of its benefits and a more thorough explanation of Repast's expansion to the .NET world. Next is a description of the goals of the Repast .NET project and a summary of the current state of Repast .NET. The paper concludes with a set of examples illustrating the use of Repast .Net.

## THE .NET FRAMEWORK

### .NET History

.NET<sup>1</sup> originated as a commercial development by Microsoft. When Sun introduced Java in 1995, Microsoft did not have an equivalent product. Java had (and still has) a wealth of features that have led to its strong presence, especially in the enterprise Web sphere and Internet in general. At the time, Microsoft recognized this and initially worked with Sun and Java, reaching an agreement to build their own Java runtimes, compilers, and class libraries and to distribute Sun's. However, in this agreement Microsoft's Java was to keep compatibility with Sun's Java; initially it was compatible, but over time the two diverged. In the end, there was a series of legal suits that the companies settled in 2001. This resulted in a financial settlement for Sun and technology sharing agreements between the two companies (Gilbert, 2003). During the litigation, Microsoft was not complacent, and it developed another managed environment, the .NET environment.

In June 2000, Microsoft announced its .NET framework. This was to provide integrated networking, a managed runtime environment, and a hierarchical set of framework classes, along with a new programming language, C#, that closely mirrors Java. While initially .NET was to be a commercial product, Microsoft chose to open the framework and the C# language's standards, submitting them in conjunction with Hewlett Packard and Intel to the Ecma International standards organization. The components of the .NET runtime were ratified in December 2001 as ECMA 335 (ECMA, 2002a) and the C# language as ECMA 334 (ECMA, 2002b). After this, the standards were submitted to the ISO/EIC group and were ratified in 2003 as ISO/EIC 23271 (the runtime) and ISO/EIC 23270 (C#). The first actual implementations of these standards were released by Microsoft in 2002. Today the second generation of the standards is under development, updating both the runtime and C#.

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<sup>1</sup> While the .NET term itself refers to any member of a set of Microsoft software, in this paper it refers specifically to the .NET framework (generally the .NET runtime environment).

## .NET Description

There are a few key concepts related to the .NET runtime environment; the first is the Common Language Infrastructure (CLI). The CLI is the runtime specification describing the main parts of the .NET environment: the format of the .NET assemblies (the compiled code and metadata, equivalent to a Java jar); the functions of the .NET virtual machine; and the virtual machine's instruction set, called the Common Intermediary Language (CIL).<sup>2</sup>

Unlike Java's bytecode, the CLI instruction set was developed to be independent of the high-level languages reduced to it. While C# was the primary language explicitly designed for the .NET environment, it is not in any way *uniquely* set up to work in the .NET environment. Any language with a compiler that generates CIL code can both run under the .NET runtime and interoperate with any other .NET-compatible language. Since all the languages and data types in the end are reduced to the same intermediary language, data and functionality are automatically exchangeable among the different .NET languages, without additional work being done by the developers.<sup>3</sup>

The intermediate language was developed to be generic enough to work with multiple programming paradigms. Its foundation is an object-oriented architecture (as is Java), but it is built with generic typing and supports such features as tail-recursion. Another large difference between this intermediary language and Java's bytecode is the ability to perform true memory manipulation (including true pointers) through regions of *unsafe* code.<sup>4</sup> The combination of these features allows for a variety of languages to be implemented for this runtime, including the current Microsoft .NET languages — C#, Managed C++, and Visual Basic.NET — along with the non-Microsoft implementations, including Smalltalk (S#), Prolog (P#), and Lisp (DotLisp).<sup>5</sup>

## CLI Implementations

Currently, the main CLI implementation is Microsoft's .NET runtime. This is Microsoft's core .NET environment and is the most complete implementation so far. However, an important point is that Microsoft's .NET only runs under Windows (specifically Windows 98+). There are other CLI implementations, however, including two from Microsoft.

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<sup>2</sup> At one point, the intermediate language was called Microsoft Intermediary Language (MSIL, pronounced "missil"), but for standardization reasons this was changed to CIL; therefore, MSIL is synonymous with CIL.

<sup>3</sup> A good example of this is the ability to create a base class in Managed C++, subclass it under C#, and instantiate it under Visual Basic.NET.

<sup>4</sup> This may be viewed as a security risk; however, applications or code marked as unsafe will run under a different set of configurable rights than normal managed code, allowing for minimization or elimination of these risks.

<sup>5</sup> While it is possible to implement non-Java languages on the Java virtual machine, the Java virtual machine is not built for this, complicating the development and integration. For more information, see [sourceforge.net/projects/dotlisp](http://sourceforge.net/projects/dotlisp), [www.dcs.ed.ac.uk/home/stg/Psharp](http://www.dcs.ed.ac.uk/home/stg/Psharp), and [www.smallscript.com](http://www.smallscript.com).

Microsoft's other runtime implementations are the .NET Compact Framework built for Windows CE and the shared-source<sup>6</sup> Rotor implementation. Rotor was developed by Corel for Microsoft and runs under Windows XP, FreeBSD, and Mac OS X. This implementation includes a full implementation of the runtime and C# specifications but does not include extensions such as Windows Forms, thereby preventing graphical user interface (GUI) development in it. Outside of Microsoft, there are some open-source implementations of the specifications, including Ximian/Novell's Mono and the GNU foundation's dotGNU. Mono is the more developed of the two, having a majority of the core features already implemented (including most of the runtime specifications and a working C# compiler); however, the .NET compatible GUI application aspects are still lacking. The good news is that one of Mono's goals is to be compatible with the .NET implementation and therefore the .NET windowing framework; therefore, .NET applications are expected to be truly portable in time.

## REPAST .NET

### Repast .NET Goals

Repast.NET is meant to replicate the functionality of RepastJ under the .NET framework. Repast.NET is not a replacement for RepastJ; it is a new member of the Repast family and a parallel development to RepastJ. Providing the Repast library under the .NET framework allows agent-based models to be developed under a variety of languages by using the Repast application programming interface (API) and functionality and provides a different environment for agent-based model production outside of Java. The .NET environment's managed runtime, class library, portability,<sup>7</sup> language interoperability, support,<sup>8</sup> and standardization made it a good choice for a Repast implementation.

### Technical Description

Repast.NET was developed as a port of Repast J's Java sources to C#. Choosing C# as the .NET destination language provided many benefits to the porting effort. C# shares a similar syntax as Java, allowing the Repast.NET code base to stay similar to its Repast J origins. This also allowed the use of Microsoft's Java Language Conversion Assistant (JLCA), which helped to handle the rudimentary aspects of the Java to C# conversion.<sup>9</sup> After the initial conversion with the JLCA, manual intervention was required for the more advanced features and code verification.

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<sup>6</sup> Microsoft's *Shared Source* license releases the source code but does not allow for commercial products to be developed based on it, or redistribution of the source. See <http://msdn.microsoft.com/library/default.asp?url=/library/en-us/Dndotnet/html/mssharsourcecli2.asp>.

<sup>7</sup> As mentioned previously, this portability is not yet fully developed.

<sup>8</sup> This includes its strong backing by Microsoft, its user base, and large amount of documentation, including Web sites, such as The Code Project (<http://www.codeproject.com>).

<sup>9</sup> <http://msdn.microsoft.com/vstudio/downloads/tools/jlca/>.



During the port, care was taken to keep Repast .NET as similar to Repast J as reasonably possible. Repast .NET generally keeps the Repast J class hierarchy, field names, method names, constant locations, etc., only diverging when a compelling need arose, including incompatibilities with .NET or C#, or Java and .NET/C# inconsistencies. An example of a C# incompatibility would be method names that are the same as field names (valid in Java but not C#); in these cases, the field would be renamed. An example of an inconsistency is .NET using properties<sup>10</sup> in place of getters and setters. Because care was taken to keep Repast .NET similar to Repast J, building a Repast .NET model is nearly identical to building a Repast J model; in fact, converting a Repast J model to Repast .NET generally only requires running the JLCA on the Java sources and minor changes to method names or method modifiers.<sup>11</sup> This is illustrated later in this paper with Repast .NET examples.

## Repast .NET Functionality

Repast .NET currently supports all the core features of Repast J, including:

- A fully functional multi-threaded scheduler;
- The Repast base models, agent classes, and spaces;
- GUI model manipulation and simulation control; and
- Batch functionality.

Repast .NET also includes noncore features, such as:

- Repast charting capabilities (including snapshot output);
- Data recording; and
- Visual displays of agents, models, and spaces.

Finally, Repast .NET includes a port of the Colt random number generation library used by Repast J. It is important, however, to note that the random number sequence generated by Colt is not the same in the .NET environment as in the Java environment. This arises from mathematical differences between the two environments (see the appendix).

Together, these features allow for full agent-based models to be built under Repast .NET. There are, however, some features that are not present in Repast .NET that are present in Repast J, particularly geographic information system (GIS) capabilities. Because Repast's GIS was developed concurrently with Repast .NET, the functionality port was not done, since the code base was not stable enough to convert. Future Repast .NET and Repast J development features will be synchronized.

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<sup>10</sup> Properties are a .NET feature pairing together a getter and setter into one logical unit. For more information, see <http://msdn.microsoft.com/library/default.asp?url=/library/en-us/csref/html/vcwlkSimplePropertiesTutorial.asp>.

<sup>11</sup> For instance, marking a method as *overriding* a parent class's methods.

## Visual Studio Integration

Repast .NET is also fully integrated into the standard .NET development environment, Visual Studio.NET, through Visual Studio templates. These templates range from single agent and model classes to full Repast modeling projects, complete with documentation and notes on where to implement an agent's logic. By using these templates, modelers can automate the generation of boilerplate model and agent code and concentrate on implementing agent logic. Templates are available for the main .NET languages: C#, Managed C++, and Visual Basic.NET.

Finally, Repast .NET includes example models written in C#, Managed C++, and Visual Basic. Repast .NET also includes an example called RocketBugs that illustrates the integration of those same three languages all in the same model.

## REPAST .NET EXAMPLES

### HeatBugs

It is fitting to introduce Repast .NET through the canonical HeatBugs agent-based simulation. The Repast .NET implementation of HeatBugs is merely a port of the Repast J HeatBugs model (which is a port of the Swarm HeatBugs Model). HeatBugs involves a group of agents (HeatBugs) that generate heat into a space (HeatSpace). The HeatBugs have an output heat and an ideal heat, and they move about the HeatSpace attempting to reach their ideal temperature, while their heat is diffused through the HeatSpace. Repast .NET contains multiple implementations of the HeatBugs model, with different versions being written in C#, Managed C++ (CPPBugs), and Visual Basic (VBBugs). Of course, each of these languages uses a different syntax in its implementations; however, the way each language interfaces with Repast and its functionality is identical to each other and to Repast J.

As Figures 1 and 2 show, the implementations under Repast .NET and Repast J are virtually identical, outside of some syntactical differences. Both sets of code are shown in

```
public void step() {
    // Diffuse the heat
    space.diffuse();
    // Iterate through the agents
    for (int i = 0; i < heatBugList.size(); i++) {
        HeatBug bug = (HeatBug) heatBugList.get(i);
        bug.step();
    }
    // Update the displays
    space.update();
    dsurf.updateDisplay();
}
```

**FIGURE 1** Selection of HeatBugs model code from Repast J

<b>C#</b>
<pre> public virtual void step() {     // Diffuse the heat     space.diffuse();     // Iterate through the bugs (agents)     foreach (HeatBug bug in heatBugList)     {         bug.step();     }     // Update the displays     space.update();     dsurf.updateDisplay(); } </pre>
<b>Managed C++</b>
<pre> void CCPPBugsModel::step() {     // Diffuse the heat     space-&gt;diffuse();     // Iterate through the bugs (agents)     for (int i = 0; i &lt; heatBugList-&gt;Count; i++)     {         CHeatBug *bug = dynamic_cast&lt;CHeatBug *&gt;(heatBugList-&gt;Item[i]);         bug-&gt;step();     }     // Update the displays     space-&gt;update();     dsurf-&gt;updateDisplay(); } </pre>
<b>Visual Basic.NET</b>
<pre> Public Overridable Sub steppingFunction()     ' Diffuse the heat     space.diffuse()     ' Iterate through the bugs (agents)     For Each bug As VBBug In heatBugList         bug.steppingFunction()     Next bug     ' Update the displays     space.update()     dsurf.updateDisplay() End Sub </pre>

**FIGURE 2** Selection of HeatBugs model code from Repast .NET

compatible development environments. This *step* method is called each simulation step and both updates the simulation's displays and causes the agents to act. The similarities continue when displaying HeatBugs. Figure 3 illustrates the similarities between the Repast J and Repast .NET user interfaces.

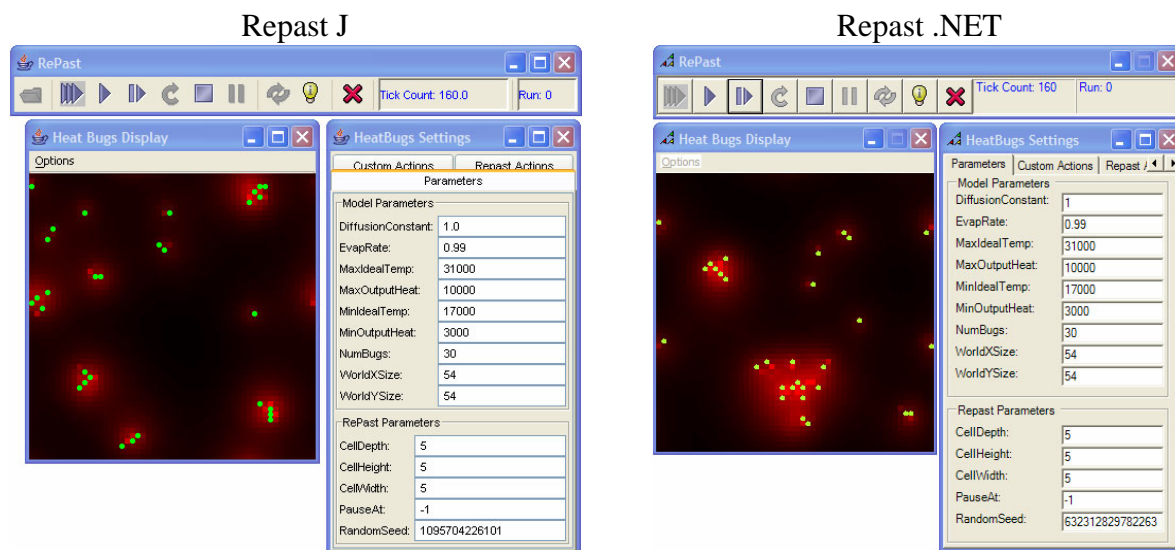
## Mousetrap

The next illustration of Repast .NET's features is in the Mousetrap model. The Mousetrap model is meant to illustrate nuclear fission by having each mouse trap represent a radioactive atom. When each atom is hit by a neutron (ping-pong ball), a fission reaction occurs releasing two more neutrons. The model itself is built to execute each ping-pong ball, hitting a mouse trap as a new event in the schedule. Therefore, each time a ping-pong ball hits a mouse trap two more events are scheduled. Repast .NET handles this without a problem, illustrating the fully functional scheduler. Figure 4 illustrates the similarities between the Repast .NET and Repast J scheduling mechanisms.

This example only shows one of the possible ways of scheduling an action. Repast .NET supports all the Repast J scheduling options. This example shows a given event class instance scheduled at a specific time with a specific order, but the other scheduling methods, such as scheduling an event based on an agent and a method name,<sup>12</sup> may also be used.

## Sugarscape

The final ported Repast J example model in this paper is an implementation of Axtell and Epstein's Sugarscape (Epstein and Axtell, 1996). This model simulates tribes of agents moving



**FIGURE 3** Repast J and Repast .NET HeatBugs model

<sup>12</sup> For instance, `schedule.scheduleActionAt(12.0, agentN, "actionMethod")`.

Repast J	Repast .NET
<pre>public void scheduleTrigger(double time,                            MouseTrap mt) {     TriggerAction ta = new TriggerAction(mt);      <b>schedule.scheduleActionAt(time,</b>                              <b>ta,</b>                              <b>Schedule.LAST);</b> }</pre>	<pre>public virtual void scheduleTrigger(double time,                                    MouseTrap mt) {     TriggerAction ta = new TriggerAction(this, mt);      <b>schedule.scheduleActionAt(time,</b>                              <b>ta,</b>                              <b>Schedule.LAST);</b> }</pre>

**FIGURE 4** Repast J and Repast .NET Mousetrap scheduling

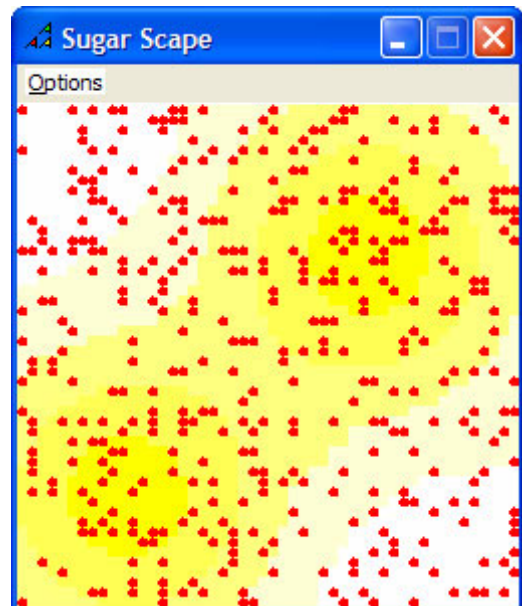
about on a (as the authors term it) “bagel-shaped” (toroidal) planet collecting resources (sugar). Compared with the previous two models, this model is unique for two reasons: (1) the Sugarscape model loads the contents of its space from a file and (2) because it uses two forms of graphs supported by Repast. Figure 5 illustrates the sugar space as implemented in Repast .NET.

Repast .NET is capable of producing all of the graphs produced in Repast J through the use of the ZedGraph library ([zedgraph.sourceforge.net](http://zedgraph.sourceforge.net)). With this library, Repast .NET can generate sequence graphs (graphs displaying linear data), plot graphs (graphs displaying specific points), histograms (with modeler-specified or dynamic bins), and network graphs (displaying statistics about a network). The Sugarscape model uses both a sequence graph and a histogram (Figure 6).

## RocketBugs

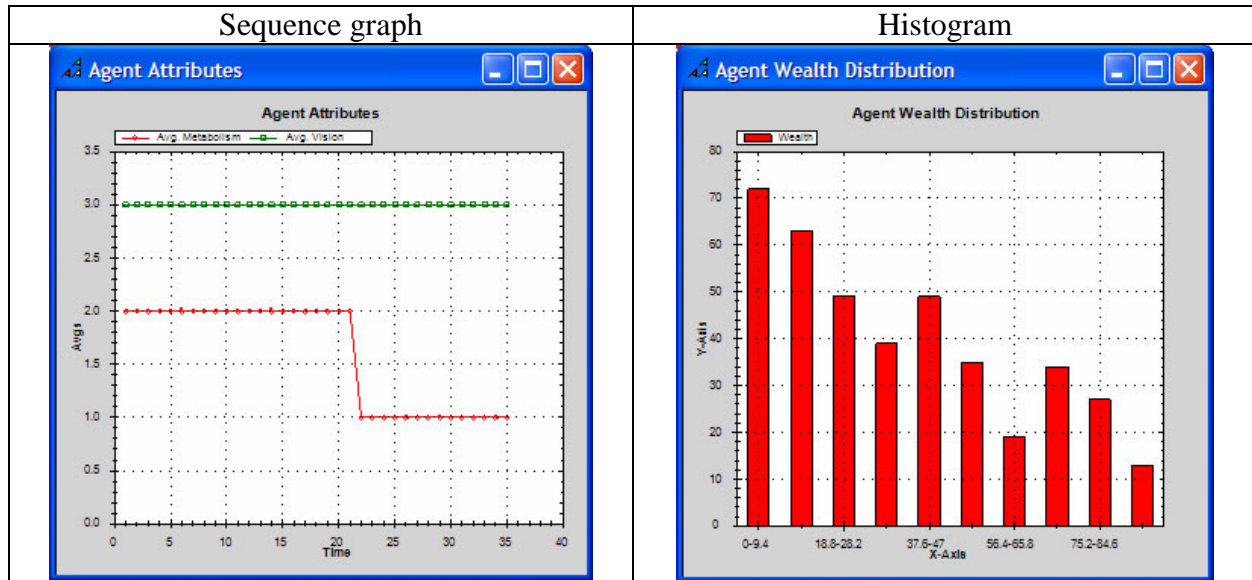
RocketBugs, the final example, is unique from the other demos in that each of the key components of the model is implemented in a separate programming language. The model itself is a special case of the HeatBugs model, in that the agents initially are not allowed to travel down or to the right, and the agents have a low output heat and a low input heat. This causes the bugs to all head in a nearly linear northeast pattern until a “RocketBug” is added to the simulation.

A RocketBug is an agent that has either an extremely high output heat and an extremely low (negative) ideal temperature<sup>13</sup> (a fire bug), or an extremely low output heat (negative) and an



**FIGURE 5** Repast .NET sugar space

<sup>13</sup> The temperature the bug is attempting to reach.



**FIGURE 6** Repast .NET Sugarscape graph examples

extremely high ideal temperature, creating bugs that are hot or cold addicts. This causes the RocketBug to move at a high (relative) speed, leaving a tail of hot or cold behind it (hence the term RocketBug).

The RocketBugs model was developed in Microsoft's three primary .NET languages, Managed C++, C#, and Visual Basic. The space that the agents travel in was written in Visual Basic, the RocketBug agent written in C++, and the RocketBugs model class written in C#. By merely adding a reference to the other projects in the development environment (done in the same way as referencing any other .NET assembly), the languages automatically interoperate with one another. This does not impose any extra performance penalty since each language in the end is reduced to the same intermediary language.

The three classes used by this example model are the CRocketBugsSpace, CRocketBug, and CRocketBugsModel.<sup>14</sup> Figure 7 shows the code from the CRocketBugsModel class that sets up the model by creating the space and the agents.

This method uses both the RocketBugs' space and the RocketBugs' agent, again, showing that they are used just as though they would have been written in C#.

Figure 8 shows the method that adds heat to the CRocketBugsSpace. As previously mentioned, and as the syntax shows, this method was written in Visual Basic.

The final excerpt from the RocketBugs model is from the CRocketBug class. This class was written in Managed C++, which is C++, but runs under the managed .NET environment. This allows use of the full functionality of C++, but with the addition of a few extra

<sup>14</sup> C is a class prefix.

```

/// <summary>
/// Builds the space/world and the agents (bugs)
/// </summary>
public override void buildModel()
{
    base.buildModel();

    space =
        new CRocketBugsSpace(diffusionConstant,
                             evapRate, worldXSize, worldYSize);
    world =
        new Object2DTorus(space.SizeX, space.SizeY);

    for (int i = 0; i < numBugs; i++)
    {
        int idealTemp =
            Uniform.staticNextIntFromTo(
                minIdealTemp, maxIdealTemp);
        int outputHeat =
            Uniform.staticNextIntFromTo(
                minOutputHeat, maxOutputHeat);
        int x, y;

        do
        {
            x = Uniform.staticNextIntFromTo(0, space.SizeX - 1);
            y = Uniform.staticNextIntFromTo(0, space.SizeY - 1);
        }
        while (world.getObjectAt(x, y) != null);

        CRocketBug bug =
            new CRocketBug(space, world, x,
                           y, idealTemp,
                           outputHeat, randomMoveProbability);

        world.putObjectAt(x, y, bug);
        base.agentList.Add(bug);
    }
}

```

**FIGURE 7** The RocketBugs model building method, written in C#

```

Public Sub addHeat(ByVal x As Integer,
    ByVal y As Integer, ByVal heat As Integer)
    Dim heatHere As Long = Convert.ToInt64(Me.GetValueAt(x, y))

    If (heatHere + heat <= maxHeat) Then
        heatHere += heat
    Else
        heatHere = maxHeat
    End If

    If heatHere < -maxHeat Then
        heatHere = -maxHeat
    End If

    Me.putValueAt(x, y, heatHere)
End Sub

```

**FIGURE 8** The method to increase the heat in the RocketBugs space, written in Visual Basic.NET

keywords that can create garbage-collected, bounds-checked code. The excerpt in Figure 9 shows the setXY method and an excerpt from the agent's step method; both using normal C++ syntax.

## CONCLUSIONS

The development of Repast .NET, along with Repast for Java and Repast for Python (Repast Py), presents modelers with a variety of environments and languages with which to implement their models. Repast .NET allows agent-based models to be built and run entirely outside of the Java environment,<sup>15</sup> thus lessening Java requirements from agent-based modeling.

Repast .NET in its current state supports the development of full agent-based models. This support includes a fully implemented multithreaded scheduler, basic agents and spaces for them to occupy, runtime manipulation of agents and models, graphical data display, automated data recording, and batch run capabilities based on parameter files. Each of these components is developed using the preexisting interfaces and methodologies implemented under Repast for Java, allowing anyone to apply Repast J knowledge directly under Repast .NET.

In the future, the Repast .NET project will implement the full functionality of Repast J, including GIS support. Repast .NET will continue to include the new features of Repast J, but it has the capability to expand outside of what is possible under the Java environment.

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<sup>15</sup> Albeit, replacing them with CLI requirements.



```

void CRocketBug::setXY(int x, int y)
{
    this->x = x;
    this->y = y;
    world->putObjectAt(x, y, this);
}

void CRocketBug::step()
{
    long heatHere = (long) space->getValueAt(x, y);

    if (heatHere < idealTemp)
    {
        unhappiness = (double) (idealTemp - heatHere) / CRocketBugsSpace::MAX;
    }
    else
    {
        unhappiness = (double) (heatHere - idealTemp) / CRocketBugsSpace::MAX;
    }

    int type = (heatHere < idealTemp) ? CRocketBugsSpace::HOT : CRocketBugsSpace::COLD;
    System::Drawing::Point p = space->findExtreme(type, x, y);

    if (Uniform::staticNextFloatFromTo(0.0f, 1.0f) < randomMoveProb)
    {
        p.X = x + Uniform::staticNextIntFromTo(- 1, 1);
        p.Y = y + Uniform::staticNextIntFromTo(- 1, 1);
    }

    if (unhappiness == 0)
    {
        space->addHeat(x, y, outputHeat);
    }
    else
    {
        int tries = 0;

        if (p.X != x || p.Y != y)
        {
            // get the neighbors
            int prevX = SimUtilities::norm(x - 1, xSize);
            int nextX = SimUtilities::norm(x + 1, xSize);
            int prevY = SimUtilities::norm(y - 1, ySize);
            int nextY = SimUtilities::norm(y + 1, ySize);

            while ((world->getObjectAt(p.X, p.Y) != NULL) && tries < 10)
            {
                int location = Uniform::staticNextIntFromTo(1, 8);

                switch (location)
                {
                    ...

```

**FIGURE 9** An excerpt from the RocketBug agent class, written in C++

## APPENDIX:

### MATHEMATICAL DIFFERENCES BETWEEN JAVA AND .NET

While testing the .NET port of the Colt library, we found differences in the handling of floating point numbers. Under multiple iterations, the numbers produced under the .NET environment and the Java environment will differ. As such, it may not be possible to directly compare results obtained in a Repast J model with a Repast .NET model. As an illustration of this, we present the programs in Figure A.1, which perform the same sequence of iterated mathematical operations in C# and in Java, but produce different results, as shown in Table A.1.

C#	Java
<pre> static void Main(string[] args) {     double d = -9877654028.9998812381111;      for (int i = 0; i &lt; 178; i++)     {         d /= 7.65E-3;         d /= 8713E6;         d *= 1.29E-3;         d *= 9.21E10;         d = Math.Sin(d) / Math.Cos(d);         d = d + 1.99E-3;         d = d - 7.34123E4;          d = d = d;          Console.WriteLine(d);     } } </pre>	<pre> public static void main(String[] args) {     double d = -9877654028.9998812381111;      for (int i = 0; i &lt; 178; i++)     {         d /= 7.65E-3;         d /= 8713E6;         d *= 1.29E-3;         d *= 9.21E10;         d = Math.sin(d) / Math.cos(d);         d = d + 1.99E-3;         d = d - 7.34123E4;          d = d = d;          System.out.println(d);     }     System.exit(0); } </pre>

**FIGURE A.1** Java and C# mathematical comparison programs

**TABLE A.1** Mathematical discrepancies between Java and C#

Iteration	C# Numbers	Java Numbers	Difference
1	-73412.972620	-73412.972620	0.000000
...			
4	-73386.507620	-73386.507520	-0.000103
...			
9	-73414.186190	-73413.585040	-0.601150
10	-73414.961470	-73412.439040	-2.522433
11	-73411.687570	-73415.200370	3.512797
12	-73412.197200	-73412.175170	-0.022033
...			
34	-73413.049490	-73412.628820	-0.420674
35	-73411.238070	-73257.794460	-153.443608
36	-73411.033460	-73410.378680	-0.654776
37	-73409.114890	-73413.154200	4.039305

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## REPAST FOR GIS

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### ABSTRACT

A wide range of spatial applications require geographic information system (GIS) functionality, such as natural resource management, social interactions, communication networks, and public infrastructure. As such, GIS functionality must be available to Repast users. The latest version of Repast allows users to work directly with GIS in their models. The overall goal is to make maps as easy to use as grids; the new integration of GIS into Repast achieves this goal. The implementation focuses on allowing users to access and display GIS maps and data. Users now have access to GIS programming interfaces that allow them to perform GIS queries, such as finding relative object locations and distances. This capability allows users to develop agent behaviors based on the spatial relationships among agents. Users can automatically create agents by using GIS data and by updating GIS data based on attributes from agents, including updating agent locations. Furthermore, Repast has the ability to display GIS data by using both open source software and ESRI ArcGIS via the new Repast Agent Analyst extension. Our implementation strategy involves separating the file input and output concerns from display operations. GIS data are handled through a GIS file handling system, while display is handled through rendering systems associated with each GIS.

**Keywords:** Agent-based modeling and simulation, Repast, GIS, geographic information systems

### INTRODUCTION

There is a great deal of interest in the integration of geographic information systems (GISs) and agent-based modeling systems (ABMSs) (Brown et al., 2005; Parker, 2004; Torrens and Benenson, 2004; Gimblett, 2002; Parker et al., 2002; Westervelt, 2002). Potential applications for such integrated models include land use models, natural resource management, social interactions, communication networks, and public infrastructure. For agent-based modelers, this means adding the ability to have agents that are related to actual geographic locations. For GIS users, this means adding the ability to model the emergence of phenomena through individual interactions of features on or related to a GIS over time and space.

A range of software applications are often described as GIS. Some, such as ESRI ArcGIS ([www.esri.com](http://www.esri.com)) and TNT products from MicroImages ([www.microimages.com](http://www.microimages.com)), provide a great deal of analytical capability in addition to the ability to view and edit geographic data. Others, such as OpenMap ([www.openmap.bbn.com](http://www.openmap.bbn.com)), GeoTools ([www.geotools.org](http://www.geotools.org)), and JUMP ([www.vividsolutions.com/jump](http://www.vividsolutions.com/jump)), are essentially map viewers with limited analytical capabilities. They can display data and work with information about area, extents, and relationships among geographical objects.

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The current implementation of GIS in Repast is focused on two systems: ESRI ArcGIS and OpenMap. The type of integration between Repast and these two systems is different. Repast has shapefile integration with ArcGIS and native Java integration with OpenMap. Shapefile integration is similarly a looser coupling based on sharing of files, with Repast having the ability to tell the GIS to update data based on the files that Repast has written out. Native Java integration is a tighter coupling, with both systems being written in Java, and the source code has been integrated, so there is full access to the GIS code from within Repast. These two approaches will be elucidated further in later sections.

## DATA REPRESENTATIONS

A GIS contains multiple layers of data. A layer is made up a number of elements. For example, a layer might contain a number of trees that represents a part of a landscape (Figure 1). Each tree in the layer would be a GIS feature. Each feature in the layer has two aspects to it, its geographical coordinates and the data associated with it. A common format for storing this information is the shapefile. A number of files are associated with the shapefile format: (1) the shapefile (.shp), which stores the geographical information needed to display the feature (x,y,z coordinates of vertexes and edges of the geometric shapes); (2) the database file (.dbf), which stores the data records for the feature; and (3) the index file (.shx).

GIS store data about layers in data base files, with each record in the file referring to a feature in the GIS. ABMSs handle data differently. While a GIS is layer centric, an ABMS is agent centric. Thus, each agent stores data about itself individually. However, there is in fact a large amount of overlap. For instance, each agent type has the same types of data, just as each layer type in a GIS has the same types of data. Thus, an agent type in ABMS can be seen as similar to a layer in a GIS, and each agent in ABMS is similar to a feature in GIS.

GIS data can be translated directly into agents or into other data objects that the agents use or know about. For example, given a model where agents are landowners, the GIS data might relate to the land parcels that the agents own. Land parcel data would then be read into ABMS for use by landowners.

Trees layer				
FeatureID	Geometry	Height	Type	Age
1	270,134	51	Coniferous	70
2	255, 120	63	Coniferous	100
3	263, 129	30	Deciduous	50

**FIGURE 1** Sample of GIS type data, representing a layer of data in the GIS. Other layers might include data on soil type and other environmental factors. Together, these layers could be used to model an environmental system.

An ABMS updates one agent at a time. In one time step, some or all of the agents might be updated. A GIS display, on the other hand, updates a whole layer at a time. Even though not all of the features may have changed, generally the whole layer will be redrawn. This means that although only some agents of a given type may have been updated in the ABMS, in order to update the GIS, all agents of that type have to be sent to the GIS so that the GIS can properly update itself.

## OVERVIEW OF USE

There are two general classes of tasks that need to be handled for Repast to work with a GIS. One is reading and writing data. The other is working with the GIS to coordinate the display of the GIS with updates to ABMS data. In the Repast-GIS integration, these tasks are generally broken up into two different classes, a data class and a display class.

The data class allows data to be read into Repast from the GIS and written out from Repast into a GIS format. Agents can easily be created from GIS data by specifying functions in the agent class that correspond to the fields in the GIS data. Similarly, in order to update the GIS data based on the agents, a corresponding function has to be specified in the agent class. For example, if there is a field in the GIS data called Landuse, the agent would need functions called `setLanduse()` and `getLanduse()` in order to read and write this data field. The `setLanduse()` function allows the data from the GIS file to be set in the agent, and the `getLanduse()` function allows the data from the agent to be used in updating the GIS data file (Figure 2).

Display classes vary with the GIS being used. Nonetheless, they all allow Repast to update the GIS display so that the display of the GIS can correspond to the data of the ABMS.

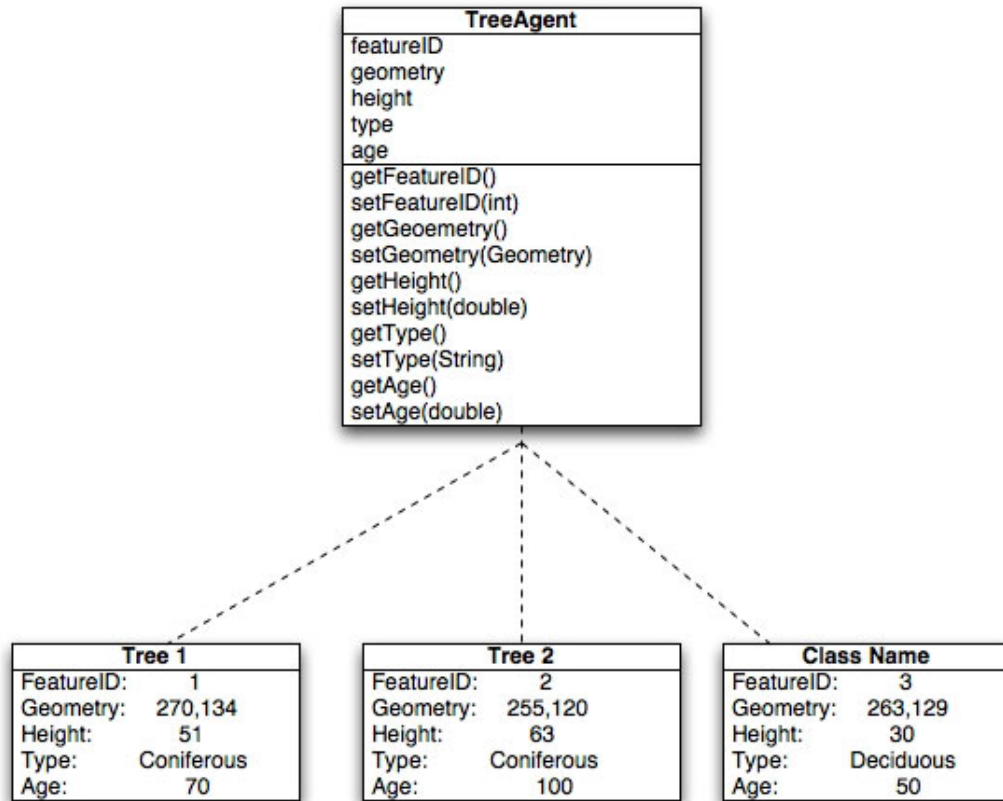
## SHAPEFILE INTEGRATION

Shapefile integration means that while Repast and the GIS use the same shapefile, they have very limited interaction with each other. The shapefile is loaded into the GIS, and Repast is used to read the shapefile data. Agents are created using these data, and the data are updated from the agents, as described above. In order to update the GIS display, the data must first be written out to file, and then the GIS can be notified to update its display by reading the newly written (updated) shapefile data. Repast's integration with ESRI ArcGIS via the Agent Analyst extension is an example of this. With shapefile integration, the display class only allows for the display to be updated. It does not provide a means for Repast to interact with the application programming interface of the GIS being used for display.

### Java Integration

Java integration means that a Repast program can have full interaction with the GIS:

- The shapefile is loaded into Repast.
- The GIS is launched from within Repast.



**FIGURE 2** GIS data in ABMS (TreeAgent is the agent type and is akin to a layer in GIS.)

- Shapefiles are added to the GIS from Repast.
- Layers are added to the GIS based on agent definitions.
- Updating of layers is also based on agent definitions.
- Agents are created from and written to shapefiles in the same manner as with shapefile integration.

Of course, layers can also be added and based on the shapefile as well, and in this way be used in the same manner as shapefile integration. Thus, while the data integration remains the same, there is a much tighter integration on the display end. Repast users can have full access to the GIS being used for display, thus allowing them to get information about agents on the map, such as location, distance from other geographic objects (including geographically represented agents), and more.



## CONCLUSION

There are two levels of integration of Repast and GIS, and there are different types of GISs available. The choice of integration type and GIS to use depends on the needs of the project. For example, if the project requires analysis on data during the run of the model, it might be appropriate to use ArcGIS. In this case, the data would be loaded into ArcGIS and run in the model. The model could be paused, and ArcGIS could be used to analyze the data as needed. On the other hand, if what is needed is the ability to update data quickly, query the GIS about agent spatial characteristics during the run of the model, and use that information from within the model itself, then it might be more appropriate to choose Java integration, such as that of Repast and OpenMap.

## ACKNOWLEDGMENT

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**DISCUSSION:****NEW REPAST DEVELOPMENTS****(Thursday, October 7, 2004, 5:00 to 7:00 p.m.)**Chair and Discussant: *T. Howe, The University of Chicago***Repast for Python Scripting**

**Tom Howe:** Our next speaker is Nick Collier who's going to talk about Repast for Python scripting.

**Nick Collier:** I'm going to talk about Repast.Py, which is Repast for Python scripting. First, I want to apologize because my slides are not very colorful, but mostly, I just want to introduce you to the tool, show a few demos, answer your questions about it, and talk about its architecture. There's not time to go into the internal details. I would really like feedback on it after you use it — either good or bad. So I encourage you to download it when it becomes available next week.

[Presentation]

**Steven Upton:** On the Python you're using, is it Python as the language? Are you not doing any compiling into Python or any of that kind of stuff? Is it just the subset of the language that you're using and then interpreting within Repast?

**Collier:** No. It compiles the Python into Java byte code and creates Java classes eventually.

**Upton:** That leads me to the second question. When you write/generate Repast.Py and you convert that to Repast.Java with all the code in Java, can I go in there and manipulate the Java code?

**Collier:** No. Well, if you did the export, it decompiles the byte code into Java. That's the idea. So the end result of a RepastPy compilation is typically a model class that is just like a Repast as if you'd written one in Java, but it's a model dot class, and an agent class, and it's in a byte code. That's the class representation.

**Upton:** I don't get any source code in Java.

**Collier:** If you do, the compile doesn't produce that. But if you export to Java, it compiles it and then decompiles the byte code back into Java source code. That works, actually, surprisingly well. Sometimes you may look at it and say that you know a machine generated that Java, but almost always you look at it and see what it's doing. That's not a problem.

**Unidentified Speaker:** Basically, what you do to export is get Java. Your source file has more complicated behavior.

**Collier:** Right.

**Greg Madey:** So RepastPy is a Java program?

**Collier:** Yes.

**Madey:** So it also is compatible on all Java.

**Collier:** Yes, it'll run anywhere Java runs.

**Unidentified Speaker:** I have a brief question about the size of a GIS file. Sometimes you get a GIS file and it's very, very large in terms of bytes or megabytes. When we saw that example, everything seemed to be one SBP file that you clicked that opened everything. So I was wondering, does your GIS file get ported into that SBP?

**Collier:** No. The SBP file just contains a description of the data source property, and that part of that description is the file name and path of where to find the GIS file.

**Unidentified Speaker:** Oh, so you do still keep your ...

**Collier:** Yes. If you work on your GIS model, you'd have to give someone all the GIS ...

**Steven Guerin:** ESRI now has Python in our GIS. Any ideas of using Repast further out and making it more embedded into GIS tools?

**Collier:** We've been working very closely with ESRI. It's very interesting to get agent modeling embedded into the ArcGIS product and the good number of people who are familiar with RGIS. It's basically what we call an enterprise geographical information system. We've developed a tool called Agent Analyst, which is a model tool for ESRI. It's a point-and-click tool that's actually inside the ESRI environment.

I don't know how many people have heard of model tools inside of ESRI. It's a brand new thing for ArcGIS, Version 9. Yes, you have suffered at the hands of the model tool — getting this, helping develop it. I was one of the coders.

Can you show the model tool? Yes. This is actually some of my code in the model tool, so we'll find out if it works. I'm on the hook if it doesn't work. You'd better click it right, Bob. I'm kidding. Bob has done a great job and put in a lot of extra effort to get this done. It's integrated on a point-and-click basis in ESRI now, so if you do a couple of clicks, it will create a Repast model and run it in ArcGIS. Bob can also show that in a few minutes.

I'll just show this quickly. This is the exported code. There are a few strange things, but it's no big deal. It's a comment. You can get rid of it. But for the most part, it looks clear enough, and it's formatted and looks like a Java file. You could work with it.

**Claudio Cioffi-Revilla:** It crossed my mind as I was looking at what you're doing here that we've got a couple of clients in Houston who have fallen in love with a graphical representation tool called Spotfire. It's a high-end, pretty expensive, very sophisticated tool for

graphical representation of large volumes of data. The lights are dimming in Houston as they load everything they've got into Spotfire and run around and build models. Any thoughts about extending beyond Repast in terms of hooking up with representation tools?

**Collier:** I'll just give a short answer. That's very interesting to us. I have not heard of that specific product, but that overall process is something that we're involved in. We should probably talk off line about that, but we're very open to these things. Fundamentally, Repast is a free, open-source environment. Everything we do, we set up so that it can be done free. For instance, obviously ArcGIS is a high-priced commercial product. I think it's worth the money because it's a very, very high quality system. At the same time, I can say that everything is OpenMap here as well, and so that's all free, open source — actually part of the Repast download next week. Yes, thanks, Claudio. But in any case, we always make sure that we make it available for the free and open-source community. That's a big part, but we are willing. We also, for instance, work with ESRI. We have equivalent functionality available, so we'd be interested in this type of thing for other tools as well.

**Howe:** Thank you, Nick.

## Repast .NET

**Tom Howe:** Our next talk will be entitled Repast.NET and the presenter will be Richie Vos.

**Jerry Vos:** I'm Jerry Vos, otherwise known as Richie Vos. I'll be going over the Repast .NET today.

[Presentation]

**Unidentified Speaker:** I hope this isn't a totally naïve question. Is it possible to start out with something in Repast.Py and then later try to bring maybe some C++ code, Legacy code, from some other thing, into the model? Can that be done in .NET? Can you take Repast code into .NET?

**Vos:** As in Repast.Java?

**Unidentified Speaker:** Yes.

**Vos:** The direct answer is no; however, the nice thing is that there's this thing called the Microsoft Java Language Conversion Assistant. That was a big thing used in the actual .NET port. If you do have Java code, this converter allows you to go from Java to C#. It actually does a pretty good job. It converts most of the rudimentary stuff. Microsoft did not make a C#-to-Java converter if you're looking for that. But if you do generate, and you build the model in RepastPy, and you output it in Java, you technically can then run it through the Java converter and have a .NET model pretty well set up.

**Guerin:** Is Python in .NET as well? Some people have been messing with that; is that also an option?

**Collier:** There's a new port of Python called Iron Python done by Jim Hugunin. He originally wrote Jython, and there was an original port of Python to .NET that was basically a disaster. They didn't do it correctly, so this guy said that he wanted to do it to show that you can't do it — to show that .NET is terrible for scripted languages, and he did it. It turned out great. That's at point 6 or something now, but supposedly it's going to make it to point 1. Now he's working for Microsoft, so hopefully, it'll keep going.

**Vos:** Yes, and if you look on Google for .NET languages, you'll get a whole list of them. It includes some of the Python stuff and some of the other languages also that we had listed.

**Unidentified Speaker:** Virtually every language that's ever been used.

## Repat for GIS

**Howe:** I want to thank everybody who's here for staying for this marathon session to see what new capabilities the Repast library has. We're going to finish up this evening's discussion with a talk by Robert Najlis about the GIS — or geographic information system — capabilities that have been added to Repast.

**Robert Najlis:** Repast for GIS: First, who here is familiar with GIS, has used one? Or who hasn't — maybe I should ask that. Oh, you have not. Okay. I was just wondering how much time to spend on the differences in data representation between GIS and ABM. They're a little different. Then we'll get into how to use it and the couple of different types of integration later.

[Presentation]

**Unidentified Speaker:** Do you have a pop-up model?

**Najlis:** Do we have time for that? Okay. Which is that, in the model?

**Unidentified Speaker:** This is brand new in the ArcGIS, the same product. We basically can click and drag model construction, or we can use Repast to build it. We can throw out the Repast model and let them work together on a visual basis. So that's how it builds into an Agent Analyst system. Agent Analyst is a specialization of Repast3. It's the system you see here that allows us to just integrate not only with several Repast models but with other ArcGIS tools as well.

**Najlis:** This actually is already ready.

**Unidentified Speaker:** Yes, it was released on Friday.

**Unidentified Speaker:** Which company is able to link agent properties with GIS? Can you do that?

**Najlis:** Yes. Are you saying that if I have some agents made from a shape file, can I ...? Yes, let me talk about that.

**Unidentified Speaker:** ... that you get not from the GIS, but to the agent classes.

**Najlis:** Yes.

**Unidentified Speaker:** If you could, in fact, have them mixing properties, like GIS with additional properties in other places, they could play with agents that didn't come from the GIS at all.

**Unidentified Speaker:** So the agent knows where, in fact, to reference to others' echelon.

**Unidentified Speaker:** Yes.

**Najlis:** Once Eclipse [referring to problems with laptop] comes back I'll show you. While we're waiting, let me talk about something else. One nice thing about using ArcMap is that as you're running the model, at any point during the model run, you can stop and do some analysis, and then you can go back and continue the model run.

**Unidentified Speaker:** ArcGIS is a powerful tool, but it is resource-intensive.

**Najlis:** Yes. Now, let me show you this same model using OpenMap. One problem we had with OpenMap (Nick pointed this out) is that it tends to open the data in this map, the world map. And you just wonder where are my data. So, yes, it has a little feature now.

[Presentation Continues]

**Unidentified Speaker:** Briefly, you can work in multiple shape files simultaneously, you can layer, and you can also change GISs. You have one line of code, so you could build a model with OpenMap. If you have ArcMap and change one line of code, it will run ArcMap instead.

**Najlis:** Yes, that's right. And, in fact, you could use both at the same time, if you want. I'm not going to try that right now, but you could do that.

[Presentation Continues]

**Brian Pijanowski:** I've been working in GIS for a long, long time. As a matter of fact, when I was here last year during the toolkit session, we were brainstorming, and I had a wish list, and GIS, neural nets, and ... that caliber that was wrong. This is phenomenal. So I'm really excited.

I have a question about functionality. A true GIS is not about spatial data; it's about functionality; that is, what you did with it. It's the analytical capabilities. This is where you could really move agent-based modeling forward, in my opinion, because you could have behaviors change as they move across the landscape. As they become closer to something, they have another set of actions. Is it possible to do that now?

**Najlis:** Well, you can get the distance from another object, for example. Even with OpenMap, I can get the distance from another object on the landscape, even within a different layer. So as you're getting closer, I can find the closest agent to me. I can find one within a certain distance. I can do all of that. So you have a lot of that capability. I think that you have

most of the capability that you will need for an ABM. There's some. You don't have the analytical capability on a GIS scale, where you can say that we have these data and we want to analyze this. But that's usually something you would do off line. For almost everything you do on line, I think we have the capability to do that.

**Unidentified Speaker:** The best way to put it is that the new system you see here provides you with the tools to build those behaviors. An agent could find out how close it is to things, what's nearby, whether it is approaching something, or whether something is approaching it.

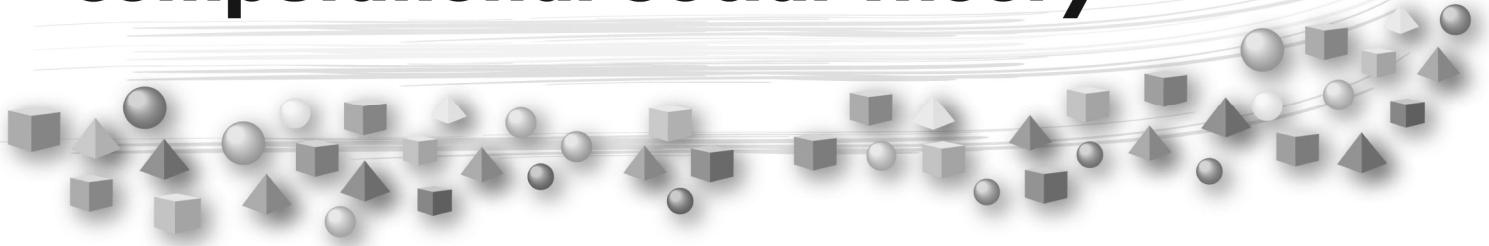
**Najlis:** Yes.

**Unidentified Speaker:** And then at that point, those would become triggers for behaviors that you would code because that's all here.



Friday, October 8, 2004

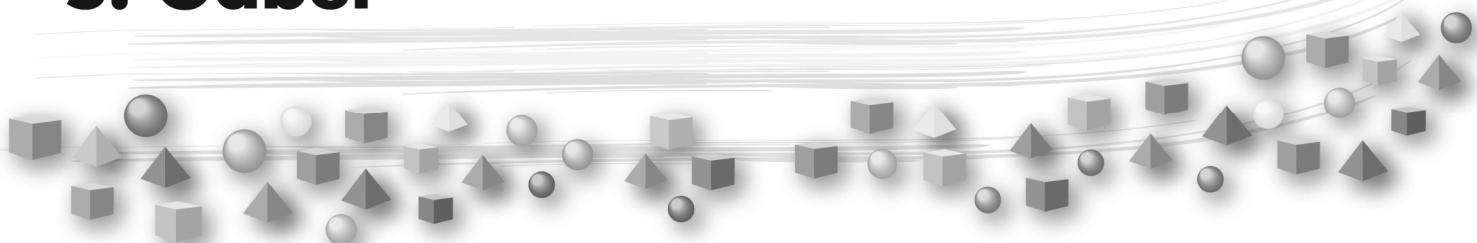
# Computational Social Theory





Welcome

**S. Gabel**





## WELCOME

S. GABEL, The University of Chicago

On behalf of The University of Chicago, welcome to the Computational Social Theory session of the Agent 2004 conference entitled, Social Dynamics: Interaction, Reflexivity and Emergence.

I would like to thank the organizers for inviting me again to introduce a session. It is a great pleasure to be here and to see first hand how the Agent conference is flourishing.

As I said last year, my academic training is in literature and is entirely nontechnical, and since I teach subjects like Homer and Aristotle, my presence here then and today may require a bit of explanation. Over the last two years and more, I have been working with old colleagues in the university and new colleagues at Argonne National Laboratory — Tom Wolsko, Chick Macal, Mike North, David Sallach, and others — to help build new collaborations and foster new exchanges among social scientists on campus and between them and the scientists at Argonne who are active in computational social science. In the process, I have had to try to understand what a complex adaptive system is and what in the world folks mean by agent-based simulations. I can only repeat what I said last year: I am getting there slowly.

Last year I spoke very briefly about how Aristotle's 2,000-year-old analysis of the distinctive properties of good drama shone some light into my own murky understanding of what a simulation is. I was charmed when I realized that, since antiquity, simulations have been thought to be a mode of investigating reality. But I was even more surprised that many of the scientists present were also charmed by the thought. Now that Chick has asked me to come back and open a session, I have to assume he was wondering whether I had the nerve to claim that Aristotle has anything to teach us about computational social theory.

Well, perhaps, but I cannot judge. Let me share a few new thoughts about some other work by Aristotle in the hope something emerges.

First, a brief bit of background. Aristotle's two most widely read treatises are entitled *Politics* and *Nicomachean Ethics*. The first investigates the nature, origin, and evolution of human communities; the second investigates agents, their goals, and their interrelationships. The two treatises each reference the other, but neither comes first. If politics is the "chicken," ethics is the "egg." Communities emerge from aggregated households (the "oikos" from which the word economics comes), grow, and take on the characteristics of the people who make them up. Conversely, communities have a decisive role in constructing value, socializing individuals, and instilling good habits in the young so that they can become self-directing, free agents. This may seem trite to us now, but centuries passed before anyone treated these subjects with comparable rigor.

One of the things that makes Aristotle's *Ethics* rewarding to study — and perhaps relevant to computational social science — is that it works on two levels that are in tension with one another. One level investigates the ideal society's socially constructed goals and what is meant by the idea of a person who has learned to become a fully realized, ideal human agent. Aristotle's notion of character is famously expressed in terms of virtues — which are conceived

as states intermediate between extremes. So, courage is a virtue — a component of being an agent who is free to make good choices. Courage is between reckless indifference to pain and death and paralyzing fear of them. Courage can be and, indeed, must be learned, which implies there must be teachers and social support for the learning of courage. If someone has courage, he or she will infallibly have the correct attitude and feelings when faced with threats. That is what it means to HAVE courage or to be a courageous character. And so on for other virtues.

But midway in the treatise, Aristotle completes that investigation of virtues and begins to look at the different reasons in the real world that human agents fail to be ideal — fail to make the choices that will allow them to achieve even their own modest goals, much less those goals that are most admirable or valued by others (one of which is to educate others and improve community). The world is not perfect, and neither are human agents, and Aristotle understands well the challenge of constructing theories that, as he says, “save the appearances,” that is, don’t treat the messy facts as inconvenient exceptions safely ignored.

A second thing that makes Aristotle rewarding is that he is NOT a moralist: there are no laws in his book, no rules to follow (for example, you will find in Aristotle very few statements such as “never tell a lie”). But without hard and fast rules, it turns out to be extraordinarily difficult for an agent to do the “correct” or right thing under any give circumstance. Everything — everything — depends on the unique situation, and the ability to perceive what its salient features are.

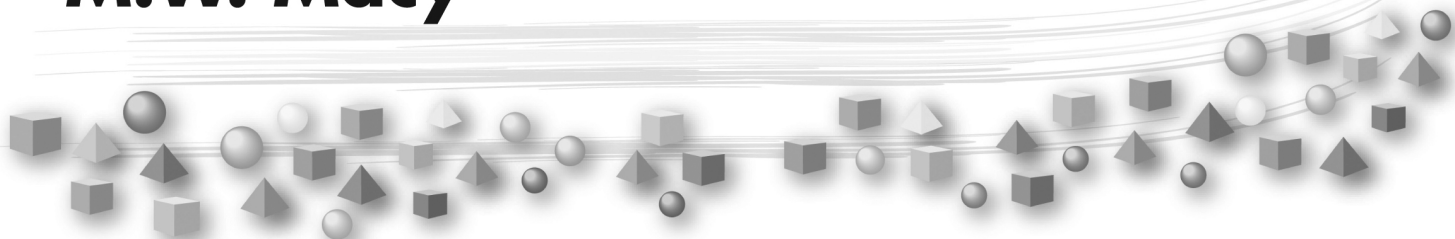
What I mean to suggest by these very, very brief comments is that Aristotle, to a remarkable degree, noticed and embraced the deep complexity of the world he observed. In this way, he broke with his teacher, Plato, who insisted that reality should cohere in internally consistent ways and was best understood in terms of eternal ideas, roughly analogous to mathematical entities. Aristotle, I am suggesting, absorbed what he learned from his teacher — the interest in ideal cases; then, without rejecting what he had learned, he transformed it by turning his attention to the complexities and gradations he found in the observable world.

My real reason for drawing on Aristotle this morning is twofold. First, it seems to me that it’s a good thing for all of us to remain aware of the intellectual genealogies of our disciplines. Today’s science and scholarship — even cutting-edge science — represent a branch of a tree that is very old, with deep roots. And some of the problems we try to understand today are problems humans have been thinking about for a long time. Second, it seems to me quite likely that the tools you work with in your field will have a great deal of resonance and utility for scholars in fields other than those represented here today. For example, I think it would be fascinating to re-read Aristotle alongside someone who was attempting to schematize and code his account of an agent in a Greek city-state. So, I would like to encourage you to get ready to encounter other visitors like me, aliens from the library who are intrigued by the work you are doing. Be patient with us: I think we may have more in common than we know.

I wish you all a stimulating and productive day.

Invited Speaker

**M.W. Macy**







## SOCIAL LIFE FROM THE BOTTOM UP: AGENT MODELING AND THE NEW SOCIOLOGY\*

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M.W. MACY, Cornell University, Ithaca, NY

### ABSTRACT

In the social sciences, agent-based computer modeling is a new approach that aims to model theoretically how complex social macrodynamics emerge from the interactions of autonomous, yet interdependent individual actors (“agents”). We describe the main principles of agent-based computer modeling as applied to social sciences and discuss its relationship to the theory building strategy of methodological individualism. We argue that agent-based computer modeling offers to methodological individualists a tool that allows combining the rigor of formal modeling with more freedom in the choice of behavioral assumptions than previous elaborations of methodological individualism do, in particular formal game theory. We illustrate this with a comparison of game theoretical and agent-based models of emergent social order. We review, in particular, contributions that address the effect of relational stability, network structure, and network dynamics on spontaneous social order. We also address models that explore variations in behavioral assumptions, such as effects of different specifications of learning behavior, or effects of individual altruism on social outcomes. We conclude with a set of methodological principles that agent-based modelers should adhere to in order to fully exploit the potential of this method for social theory.

**Keywords:** Agent-based modeling, computational modeling, social order, game theory, methodological individualism

### 1 INTRODUCTION

What do flocks of birds, traffic jams, fads, forest fires, riots, Internet search engines, and residential segregation have in common? The answer is self-organization. There is no leader bird who choreographs the dancelike movement of a flock of geese. There is no supervisor in charge of a riot. There is no librarian in a back room at Google headquarters who is busily classifying all of the Internet Web sites in a digital version of the Dewey decimal system. There is no conspiracy of bankers and realtors who are assigning people to ethnically homogenous neighborhoods.

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Traditionally, sociologists have tried to understand social life as a structured system of institutions and norms that shape individual behavior from the top down. In contrast, a new breed of social modelers suspect that much of social life emerges from the bottom up, more like improvisational jazz than a symphony orchestra. People do not simply play parts written by elites and directed by managers. They make up their parts on the fly. But if all the people are flying by the seats of their pants, how is social order possible?

New and compelling answers to this question are being uncovered by social theorists using an innovative modeling tool developed in computer science and applied with impressive success in disciplines ranging from biology to physics: agent-based computational modeling (ABCM). It is *agent-based* because it takes a model of the autonomous yet interdependent units (the “agents”) that constitute the social system as a theoretical starting point. It is *computational* because it formally represents and encodes the individual agents and their behavioral rules in a computer program so that the model dynamics can be deduced by step-by-step computations from given starting conditions.

ABCM was originally developed in computer science and artificial intelligence as a technology to solve complex information processing problems on the basis of autonomous software units. Each of these units can perform its own computations and have its own local knowledge, but the units exchange information with each other and react to input from other agents.

The approach was soon applied to problems involving the complex social dynamics that are of key interest to sociologists: notably emergent social norms, social structure, and social change. Norms emerge in ABC models without central coordination from individual actors (e.g., organizational elites). In fact, compliant individuals may not even need to be aware of the norm. Every individual appears to adhere to a global “consensus” on how to behave — a consensus that a Parsonian functionalist might regard as the basis of the orderly behavior of the individuals. Yet this consensus is entirely an emergent property of the population, and it does not exist at the level of individuals, who may not even be aware that the population exists. They are aware only of their immediate neighbors.

Can social scientists learn something from models of self-organized behavior developed for understanding computer networks, bird flocks, or chemical oscillators? We believe they can for several reasons. First, agent-based computational (ABC) models show how very simple rules of local interaction can generate highly complex population dynamics that would be extremely difficult (if not impossible) to model by using traditional methods. Second, these models show how Durkheimian “social facts” can emerge *sui generis* at the population level, even when these properties do not exist at the individual level. Third, these models can be used as virtual laboratories, to reveal the micro mechanisms responsible for highly complex social phenomena.

Agents have four defining characteristics: autonomy, reactivity, proactivity, and social ability (Gilbert and Troitzsch, 1999; Wooldridge and Jennings, 1995). Autonomous agents have control over their own goals, behaviors, and internal states. Reactive agents perceive and adapt to their environment. Proactive agents have the heuristic ability to solve problems in order to attain individual goals. Finally, agents with social ability have the capacity to influence other interdependent agents in response to the influences that are received.

Long before the advent of ABCM in the 1990s, the central ideas that underlie its theory-building strategy were introduced in sociology by methodological individualism. (See Udehn [2002] for a recent review article.) According to methodological individualism, the phenomena that sociologists study (e.g., norms, social or cultural differentiation, social networks, income inequality) can be explained as the macro consequences of the actions of autonomous but interdependent, purposively acting individuals (cf., Wippler and Lindenberg, 1987) who are, in turn, restricted in their actions by the macro conditions they collectively create (e.g., Coleman, 1990). The modelers' characterization of agents as autonomous, reactive, and proactive is clearly consistent with the individual-level models advocated by adherents of methodological individualism (e.g., Lindenberg, 2001). Until recently, however, the analytical complexity of modeling numerous interdependent individuals led adherents of methodological individualism to adopt highly stylized models of individual behavior that allow the application of standard mathematical solution methods. Most prominently, utility maximization was used as a basis for neoclassical equilibrium analysis in the rational choice approach (cf., Voss and Abraham, 2000). These rational choice models are clearly agent based, but they do not need to be computational. What, then, can ABCM contribute to methodological individualism?

The answer is that computational modeling uses numerical integration to relax the mathematical restrictions that are needed to guarantee analytical solutions. At the same time, ABCM is a formal method that deduces, in a systematic and rigorous way, macro-level implications from assumptions about micro-level behavior.

ABC models are increasingly used to address some of the most compelling questions in sociology, such as the emergence and dynamics of cultural differentiation (e.g., Mark, 2003; Axelrod, 1997), social network structures (e.g., Klüver and Stoica, 2003; Stokman and Zeggelink, 1996), cooperation in terms of norm compliance and collective action (Mosler and Brucks, 2003; Macy, 1990), fairness norms in bargaining (Vetschera, 2003), and cooperation in dyadic social exchange (Macy and Flache, 2002).

The rise of ABCM in sociology reflects the increasing demand for such an approach. The reason is that many sociologists share the individualistic perspective that social phenomena can be properly understood as a (possibly unintended) consequence of the purposive behavior of individual social actors. At the same time, there is an increasing awareness that the apparatus of analytical equilibrium solutions imposes restrictions in the theoretical formulation of agent behavior that are not justified substantively, or are at least questionable, in light of recent advances in experimental work, mainly in behavioral game theory (Camerer, 2003) and contemporary theories of "social rationality" (Lindenberg, 2001; Boudon, 1996). These studies contradict utility maximization by pointing to nonlinearities and discontinuities in choice behavior (e.g., frame switching) that make it very difficult, if not impossible, to straightforwardly derive analytical equilibrium solutions from corresponding models of individual decision making. These developments suggest that human social decision making may be best described by a set of behavioral heuristics that do not necessarily maximize individual decision outcomes (e.g., Fehr and Gächter, 2000), may change across decision contexts (e.g., Todd and Gigerenzer, 2003; Vanberg, 2002), or are sensitive to "irrelevant" social cues that affect how a particular situation is framed or perceived (e.g., Lindenberg, 2001).

Recent advances in evolutionary game theory (e.g., Bendor and Swistak, 2001), formal theories of learning in strategic interaction (e.g., Fudenberg and Levine, 1998), and socio-physics (e.g., Helbing and Huberman, 1998) have successfully incorporated individual decision

heuristics into equilibrium analysis. However, to make analytical treatment possible, these approaches still need to impose strong restrictions on network structures. Almost all game theoretic applications need to assume either a complete graph or a random graph (actors interact with randomly chosen partners) to keep models tractable.

ABC models provide a way out of the dilemma by relaxing the heroic assumptions of rational choice theory while preserving the power to model social life as it emerges out of a multitude of local interactions, embedded in highly structured networks, with clustering, bridge ties, etc. The steep decline in the cost of powerful desktop computers has made this technique more accessible to many sociologists than the analytical mathematical models based on traditional rational choice theory.

Paradoxically, the enormous speed and power of these computers also pose a danger. Effectively unlimited computational power removes physical constraints on the elaboration of the models, allowing researchers to write “realistic” models of enormous complexity. It is relatively easy to write a program that includes a long list of plausible elaborations, such as Younger’s models of hunter-gatherer societies, which include intricacies such as when agents fall asleep and what is needed to wake them (Younger, 2004). It is far more difficult to analyze results in order to understand the mechanisms that generated them and their relevance when questions are theoretical. Without a proper methodology of systematic experimentation and model analysis, ABCM-based sociological theorizing may end up losing all deductive power, because model creators may not be able to develop any solid intuition or explain their models’ behavior independently from the details of a particular implementation and execution on a computer. Without systematic knowledge about the underlying causal mechanisms, one cannot rule out the possibility that the results are nothing more than artifacts of particular modeling technologies or even bugs in the source code. Accordingly, this paper concludes with recommendations for a rigorous methodology of agent-based theoretical research in the social sciences.

ABCM in sociology is a rapidly progressing field. It is impossible to consider all of its contributions adequately in one overview article, so this paper focuses on documents that address a fundamental sociological problem: emergent social order and its micro-level foundations. The following recent overviews of this field complement this paper: Gotts et al. (2003); Sawyer (2003); Macy and Willer (2002); and Moretti (2002).

The discussion here proceeds as follows. Section 2 addresses the relationship between ABCM and methodological individualism. Section 3 discusses ABCM in the theoretical research of emergent social order. Section 4 focuses on methodological issues. Finally, Section 5 concludes with an outlook on future research directions and possible contributions of ABCM to sociological research.

## **2 ABC MODELS AND METHODOLOGICAL INDIVIDUALISM IN SOCIOLOGY**

The paradigm of methodological individualism can be traced back to classical social thinkers like David Hume, Adam Smith, and, later, Schumpeter and Hayek (cf., Udehn, 2002; Voss and Abraham, 2000). Homans (1974) introduced methodological individualism into sociology. He argued that while social facts (i.e., regularities on the macro level) can change across situational and historical conditions, their explanations can be systematically derived from

an invariant (“sub-institutional”) common core based on the behavior of individual actors. Many sociologists followed Homans’ proposal for basing the theoretical analyses of macro phenomena on a model of individual behavior. However, it was soon argued that descriptively realistic psychological theories of action are too complex to use for analyzing collective phenomena (Coleman, 1990; Wippler and Lindenberg, 1987, pp. 13–21).

Despite this argument, social scientists were reluctant to abandon the individualist principle. They recognized that assumptions about individual interests cannot readily be transformed into social outcomes without a detailed analysis of the interaction between individual members (Coleman, 1990, p. 22). This is illustrated by a wide range of paradoxical phenomena for which individual intentions produce unexpected results, such as these:

- The “bystander problem,” in which everyone observing or hearing the cries for help of a crime victim assumes that someone else will come to his or her rescue.
- “Rational herding,” in which everyone crowds into an inferior restaurant because each person assumes that the food must be great if so many people want to be there.
- The “free rider problem” in which a collective action fails when everyone prefers to “let George do it.”
- Overcrowding, caused by subjectively higher chances of being successful in the competition for scarce resources.

Not being discouraged, adherents of the individualistic approach found a solution for the complexity problem in the method of neoclassical economics: utility maximizing (Coleman, 1990, p. 14). In Coleman’s orthodox version of the “rational choice” perspective, analytic tractability is obtained through the explicit introduction of the notion of *goal maximization* in combination with the heuristic principle of a uniform human nature in terms of universal ultimate social goals that all individual actors aim to maximize (Voss and Abraham, 2000). These assumptions give the theory its deductive power, because when an individual’s goals are known, the actions taken are those that are most efficient in terms of achieving the goals from the individual’s perspective. In this way, the model allows deduction even when individual interdependence and micro-macro relationships are taken into account. Individual decision making can be represented in terms of mathematically tractable maximization problems, because the theory implies that individual actions eventually lead to equilibrium outcomes, in which all individuals maximize their utility given the rational (i.e., utility maximizing) behavior of all other individuals. General statements about the properties and conditions of such equilibrium outcomes can then often be derived with standard mathematical methods without the need to compute step-by-step the actual dynamics through which the equilibrium arises. Formal game theory allows the pure model to be elaborated so as to address decision making under uncertainty and strategic behavior (Fudenberg and Tirole, 1991).

Until recently, rational choice theorists have tended to downplay concerns about the cognitive plausibility of utility maximization. Researchers readily admitted that “real” individual decision making can be described better by a set of “boundedly rational” or “intendedly rational” heuristics than by perfect rationality (Coleman, 1990, pp. 14–15). At the same time, it was

argued that this did not compromise the analysis of regularities at the aggregate level (Hechter, 1988, pp. 31–33; Coleman, 1987, p. 184; Wippler and Lindenberg, 1987). These authors stressed that micro deviations from rational behavior fail to affect macro regularities, because deviations may be unsystematic “random errors.” Moreover, theorists referred to “backward-looking” mechanisms supposedly underlying real decision making (e.g., learning, imitation, and selection pressures in the competition to reproduce and propagate). They argued that these adaptive mechanisms and environmental constraints compel actors to behave as if they were fully rational decision makers with unlimited calculating power and perfect information.

This confidence is now being shaken by repeated demonstrations that global properties that emerge from local interaction can be highly sensitive to details in the specification of the micro model of goal-directed decision making (e.g., Flache and Hegselmann, 1999a,b).

Concerns about the robustness of rational choice explanations with regard to variations in behavioral plausibility have been behind efforts to develop more cognitively realistic models of the actors (Lindenberg, 2001; Boudon, 1996). However, by abandoning the deductive precision of utility maximizing behavior, these efforts faced the same dilemma as the one that was behind orthodox rational choice models in the first place. On one side, more sophisticated micro-level models prevent the possibility of modeling the complexity of the emergent system. On the other side, models of heuristic decisions by adaptive actors cannot be implemented by using the analytical tools imported from economics and classical game theory. The need for a new tool was growing at the same time that advances in computational technology were making one widely available.

### 3 EMERGENT SOCIAL ORDER

One of the first questions that agent modelers attacked was the old problem of social order. In individualistic theorizing, the classic problem of social order is represented as the questions of how and under what conditions cooperation can be attained in a social dilemma. A social dilemma (Dawes, 1980) arises when cooperation is Pareto efficient but may nevertheless fail because individuals fear being “suckered” or are tempted to exploit the willingness of others to cooperate.<sup>1</sup> Societal problems that have been described as social dilemmas include lack of trust in business transactions, the free-rider problem in work groups, failure of collective action, and declining social solidarity in societies undergoing modernization.

Traditionally, sociologists have explained social order as the result of top-down enforcement of norms and laws by formal institutions (cf., Gouldner, 1960; Hechter, 1988). However, choice theorists noted the circularity of this explanation: norms, laws, and institutions of social control presume the very social order that they are supposed to explain (e.g., Oliver, 1980). The challenge is to explain the emergence of cooperation and social norms from the bottom up, through self-organizing individual interactions.

Rational choice theory has explanations of successful cooperation without either altruism or global (top-down) imposition of control (for a recent overview, see Voss, 2001). Orthodox game theoretical approaches based on rational choice assumptions emphasize two key

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<sup>1</sup> See Raub (1988) for a more precise game theoretical definition on the basis of what Harsanyi (1977) calls “problematic social situations.”

conditions: relational stability and network structure, particularly the clustering of social networks (more precisely, the proportion of closed triads). According to game theoretical analyses, the mechanism that makes relational stability important is conditional cooperation in repeated interactions (Friedman, 1971). Intuitively, if there is sufficient interest in the long-term gains derived from ongoing cooperation, then rational participants may refrain from the temptation to choose a “hit-and-run” strategy because it may disrupt relationships with other conditional cooperators. Analyses of the effects of network structure also rest on the logic of conditional cooperation, but they extend it to reputation mechanisms (Raub and Weesie, 1990; Buskens, 2002). Here, conditional cooperation extends to the universal strategy to cooperate only with other players as long as one has not received third-party information that indicates past uncooperative behavior. Given sufficiently clustered communication networks, the expectation that others will adopt such a strategy deters players from building up a bad reputation. Further elaborations showed that the individual rationality of conditional cooperation generalizes to collective action problems with a large number of participants (e.g., Taylor, 1987; Raub, 1988), and to games with imperfect information, where agents may have only distorted information about others’ past behavior (e.g., Bendor and Mookherjee, 1987; Flache, 2002) or may lack knowledge about their preferences (e.g., Buskens, 2003). However, as group size and noise increase, conditional cooperation tends to become less viable.

Criticism of game theoretical explanations of emergent order has focused on three related issues: implausible behavioral assumptions, indeterminacy, and coordination complexity. Although behavioral implausibility can be troublesome in some applications, it has proven very useful in the study of social order. The reason is not the “as if” principle (i.e., people behave as if they were rational). It is rather the “what if” principle, or perhaps one might call it the “even if” principle. Even if individuals were perfectly rational, and even if social order was in everyone’s rational self interest, there is no guarantee that it would be obtained. If mechanisms that might allow perfectly rational maximizers to escape the social trap could be identified, we could then test them to see whether they were also effective with actors whose rationality was constrained by cognitive limitations.

Ironically, the weakness with analytical game theory is the inability to identify those mechanisms. The central solution concept of game theory, Nash equilibrium analysis, tells us if there are any strategic configurations that are stable, and if so, how they are characterized. Knowing that a configuration is a Nash equilibrium means that if this state is obtained, the system will remain there forever, even in the absence of an enforceable contract. However, even when Nash can identify a unique equilibrium, this does not tell us whether this state will ever be reached, or with what probability, or what will happen if the equilibrium should be perturbed. Nor does the Nash equilibrium explain social stability among interacting agents who are changing strategies individually, yet for whom the population distribution remains constant, as in a homeostatic equilibrium. Put differently, the Nash equilibrium explains social stability as the absence of individual change, not as a dynamic balance in a self-correcting distribution of evanescent individual strategies, each of which influences others in response to the influence that it receives.

Moreover, in most games, Nash cannot identify a unique solution. Some social dilemma games, such as Chicken or Stag Hunt, have three equilibria, and game theory cannot tell us which one will be obtained. Worse yet, if these games are repeated by players who care about future payoffs in an ongoing relation, the number of Nash equilibria becomes indefinitely large (even in Prisoner’s Dilemma, which has a unique equilibrium in one-shot play). This problem of

indeterminacy is known as the “folk theorem” of the theory of repeated games. The theorem asserts that “if the players are sufficiently patient then any feasible, individually rational payoffs can be enforced by an equilibrium” (Fudenberg and Tirole, 1991, p. 51) in an indefinitely repeated social dilemma game. When games have multiple equilibria, Nash equilibrium analysis cannot tell us which will be obtained or with what relative probability. Nor can it tell us much about the dynamics by which a population of players can move from one equilibrium to another.

Game theorists have responded to the problem by proposing procedures that can winnow down the set of possible equilibria. For example, the solution set can be narrowed by identifying equilibria that are risk dominant (every player follows a conservative strategy that earns the best payoff that he or she can guarantee for himself/herself), payoff dominant (no other equilibrium has a higher aggregate payoff over all players), Pareto dominant (every other equilibrium is less preferred by at least one player), trembling-hand perfect (strategies remain in equilibrium even if one player should accidentally deviate from equilibrium behavior), and subgame perfect (the strategy profile constitutes a Nash equilibrium in every subgame). However, these equilibrium selection methods are theoretically arbitrary (e.g., there is no *a priori* basis for payoff-dominant or risk-dominant behavior), and they often disagree about which equilibrium should be selected (e.g., in Stag Hunt, payoff dominance and subgame perfection identify mutual cooperation, while risk dominance points to mutual defection).

In sum, although in principle, it can be rational to cooperate in an ongoing social dilemma based on reciprocity, the choice between many possible equilibrium solutions makes coordination on one of them too complex to be attained. So how can cooperative solutions ever emerge from the interactions of autonomous social agents? This question has inspired a range of ACBM studies that explore the structural conditions in which adaptive actors might find their way out of social traps. Not surprisingly, these studies often focus on the two conditions identified by analytical game theory: relational stability and network clustering.

### 3.1 Relational Stability

The classic study of emergent order without rational actors is Axelrod’s (1984) evolution of cooperation. Axelrod tested whether relational stability can foster cooperation based on reciprocity, even when individual agents lack the capability to make strategic choices. He assumed a population in which individual agents represent “hardwired” behavioral strategies that interact with each other. The strategies were designed by game theorists for winning a tournament in which every agent had to play repeated rounds of a dyadic Prisoner’s Dilemma game with each of the other members of the population. At each round, each player knew the moves of the partner in all of the previous rounds. The winner was one of the simplest strategies submitted, “tit for tat” (TFT), which cooperated on the first move and thereafter copied the partner’s previous move.

Rather than assuming that individuals rationally calculate the optimal strategy, Axelrod modeled the selection of strategies on the basis of competitive pressures operating at the population level, a principle imported from evolutionary biology. These pressures favor survival and physical replication of strategies that are successful across all games in which they are played in comparison with the population average. In human social life, Axelrod argued, such pressures may arise when learning individuals imitate strategies they have observed being used by successful role models.



Axelrod's computational experiments showed that the game theoretic solution of conditional cooperation is highly robust, even for players who expend minimal cognitive resources in making decisions. Moreover, consistent with game theoretical analysis, the experiments showed that conditional cooperation flourishes only if there is an opportunity for repeated interaction, so reciprocators can benefit from the cumulative payoffs for mutual cooperation, while more aggressive strategies gain only a "quick hit" that cannot offset the long-term losses caused by the disruption of the exchange relationships with conditional cooperators. However, the evolutionary findings contradict the game theoretic prediction that conditional cooperation requires an indefinite endpoint, or else players will arrive at defection through a process of backward induction.<sup>2</sup> Laboratory experiments show that human behavior does not confirm the game theoretic prediction of backward induction; instead, defection becomes more frequent as the end approaches. That pattern is also consistent with Axelrod's model, which predicts greater cooperation the longer "the shadow of the future."

In sum, ACBM has played a key role in demonstrating that relational stability promotes emergent social order. These studies have extended analytical game theory by showing that (1) social order based on conditional cooperation can arise in a lay population that lacks the cognitive sophistication of highly trained game theorists and (2) conditional cooperation tends to decline as the end game approaches, a pattern observed in games played in lay populations but not in games played by game theorists. Axelrod's study showed that cooperation based on reciprocity can thrive even in a highly competitive world. His work was highly influential far beyond the game theory community (Etzioni, 2001). It has triggered a number of follow-up studies that have supported and extended his findings (cf., Gotts et al., 2003).

At the same time, Axelrod's work has also motivated rejoinders by game theorists, such as Binmore (1998), who have identified two serious limitations in his original tournament: the dependence of his results on an arbitrary strategy set and the assumption of perfect information. Each of these limitations is examined here.

### 3.1.1 *The Strategy Set*

Axelrod attributed the remarkable success of TFT to three principles: being nice (never defect without provocation), being provokable (never let defection go unpunished), and being forgiving (always return to cooperation when the partner does so). Critics (e.g., Binmore, 1998) pointed out that the performance of any strategy in Axelrod's tournament was an artifact of an arbitrary population of contestants. For example, if all of the other strategies played All-D, TFT would not have won.

Recognizing this limitation, Axelrod used a genetic algorithm (GA) in a follow-up study to see if TFT would emerge in an open-ended population in which strategies could evolve from a random start (Axelrod, 1997, pp. 14–29). The GA opens up the set of strategies that are allowed to compete by allowing "nature" to generate entirely new strategies, including some that might never have occurred to any game theorist. Genetic algorithms are strings of computer code that can mate with other strings to produce entirely new and superior programs by building on partial

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<sup>2</sup> Rational players will defect on their final move, since there is no fear of retaliation. Knowing the partner is certain to defect on the last move, there is no incentive to cooperate on the next-to-last, and so on, back to the first move of the game.

solutions. Each strategy in a population consists of a string of symbols that code behavioral instructions, analogous to a chromosome containing multiple genes. A set of one or more bits that contains a specific instruction is analogous to a single gene. The values of the bits and bit-combinations are analogous to the alleles of the gene. A gene's instructions, when followed, produce an outcome (or payoff) that affects the agent's reproductive fitness relative to other players in the computational ecology. Relative fitness determines the probability that each strategy will propagate. Propagation occurs when two mated strategies recombine. If two different rules are both effective, but in different ways, recombination will allow them to create an entirely new strategy that may integrate the best abilities of each "parent," making the new strategy superior to either contributing strategy. If so, then the new rule may eventually displace both parent rules in the population of strategies. In addition, the new strings may contain random copying errors. These mutations restore the heterogeneity of the population, counteracting selection pressures that tend to reduce it.

Working with computer scientist John Holland, Axelrod found several strategies similar to TFT that proved to be highly robust. These strategies resembled TFT in being provokable and forgiving, but they were also more predatory when paired with naïve partners. Other studies using GAs (Linster, 1992) and self-programmable Moore Machines (Probst, 1996) obtained very similar results. In Probst's model, an agent could have up to 25 internal states, which represent the behaviors of cooperation and defection, respectively. Depending on the behavior of the opponent (cooperation or defection), the agent switches its internal state. Probst found that TFT was initially successful, but that in the course of evolution, a punctuated equilibrium arose in which cooperation collapsed for some periods, only to revive in others. Moreover, the experiments showed that an evolutionary "arms race" unfolded, in which the complexity of machines gradually increased in the course of evolution and TFT was eventually displaced by more aggressive, conditionally cooperative strategies. Like TFT, these strategies were able to build up cooperative relationships with partners found to be not easily exploitable. But unlike TFT, they had no qualms about exploiting naïve cooperators.

### *3.1.2 Uncertainty and Tolerance*

While Axelrod's original study assumed that players are perfectly informed about each others' behavior throughout the history of their relationship, game theoretic analyses have suggested that uncertainty caused by imperfect information may jeopardize the viability of strategies based on reciprocity (e.g., Bendor and Mookherjee, 1987; Flache, 2002). For example, Bendor and Mookherjee (1987) looked for analytical solutions for repeated Prisoner's Dilemma games in which players occasionally defect involuntarily, but their interaction partners do not know whether the defection was intended or not. The strategically rational response to such a "disturbance" is to become more tolerant of occasional defection in order to avoid a tragic cycle of mutual recrimination that no one wanted or intended. At the same time, rational players should not become too tolerant in order to credibly deter free riders. The dilemma over how much defection to tolerate becomes especially acute as the number of partners increases. In an  $n$ -way interaction, it becomes impossible to distinguish between predatory defection and retaliation against predators. Bendor and Mookherjee (1987) show that as the group size exceeds a critical threshold given by the payoffs, top-down sanctions against defectors become more efficient than bottom-up sanctions based on retaliation.

Game theoretic analyses of conditional cooperation under uncertainty suffer even more from the problem of theoretical indeterminacy than studies that assume perfect information. Tolerant and forgiving reciprocity requires that players coordinate on compatible levels of tolerance and forgiveness. For example, when one player, after an accidental shock, returns to cooperation after three rounds of punishment, but the other player adopts the rule to impose four rounds of punishment, then cooperation can never be restored again because players continue to punish each other for punishment. Nash equilibrium solutions fail to explain how rational players can solve this problem of coordination on compatible norms.

Meanwhile, computational studies have tested whether this coordination can evolve under selection pressures in a competitive environment among players whose decisions are hardwired rather than rationally deliberated (e.g., Kollock, 1993; Nowak and Sigmund, 1993; Lomborg, 1996). Broadly, these experiments confirmed the hypothesis that uncertainty favors “tolerant,” conditionally cooperative strategies that do not always retaliate after defection of an opponent. For example, Kollock (1993) found that in “noisy” environments (with mistakes and miscues), strict reciprocity is prone to needless recrimination that can be avoided by looser accounting systems.

An interesting variation in this line of work showed that backward-looking strategies like Win-Stay, Lose-Shift (WSLS) are particularly effective in coping with noise (Nowak and Sigmund, 1993; Macy, 1996). With WSLS, behavior changes only if the partner defects. In contrast to TFT, where the partner is taught a lesson, with WSLS, lessons are learned from the partner. In a repeated Prisoner’s Dilemma under noise, the strength of these learning strategies is that they can avoid endless cycles of mutual punishment and find a way back to mutual cooperation after the relationship with a friendly opponent has been disturbed by a random shock. The reason is that dissatisfaction with the social costs of mutual defection leads backward-looking players to eventually offer an “olive branch” that allows them to break out of the cycle.

More recently, researchers have explored variations of TFT that combine looser accounting under uncertainty with selective partner choice. These studies relax a restriction adopted by most earlier work on emergent reciprocity: the absence of exit possibilities (i.e., possibilities to voluntarily leave the relationship). Computational analyses of exit effects (Schüssler, 1989; Vanberg and Congleton, 1992; Schüssler and Sandten, 2000) put the role of relational stability for emergent cooperation into perspective. The route to emergent order that these studies uncover is exclusion of defectors from relationships with cooperative partners, based on the principle “be cooperative, but leave any partner who defects.” When enough members of a population adopt this strategy, cooperative players stay in stable relationships, leaving defectors with no one but other defectors to have as partners. As a consequence, defectors perform poorly, and conditional cooperation thrives even under conditions of anonymity where unfriendly players can hide in a “sea of anonymous others” (Axelrod, 1984, p. 100) after they “hit and run.” Considering more complex agent architectures, Schüssler and Sandten (2000) — similar to Probst (1996) and Axelrod (1997) discussed above — show that under exit possibilities, more sophisticated and not necessarily strictly friendly strategies may survive under evolutionary pressure. In this study, the unfriendly players are successful when they cooperate if partners are found to not be exploitable but hit and run if a growing search pool suggests that new exploitable victims can be easily found. In further computational studies, researchers began to introduce uncertainty into the study of effects of exit mechanisms (Zeggelink et al., 2000; De Vos et al., 2001). Future work may use GAs to explore whether

complex exit strategies like the ones identified by Schuessler and Sandten can emerge from a random start.

### 3.2 Social Structure and Emergent Order

From a rational choice perspective, a central mechanism through which social networks affect emergent order is the diffusion of reputations (Coleman, 1990). Game theoretic elaborations predict that cooperation among rational actors increases with the number of potential partners who might hear about their reputation and with the decrease in the time it takes for this information to spread through the network (Raub and Weesie, 1990; Buskens, 2002). This implies that there is more cooperation in densely clustered networks and by incumbents with more central positions in a network. However, empirical tests of predicted effects of network characteristics on cooperative behavior in business relationships have only been moderately successful (Buskens, 2002).

These game theoretic studies employ implausibly extreme assumptions about information and cognitive capacities. In particular, they assume that actors can anticipate perfectly how information about their present behavior spreads through the entire network on the basis of full knowledge of all relationships in the network, even those at a great distance from one's own network position. A further problem is the standard assumption of fixed network structures. This assumption seems inconsistent with a rational actor perspective that implies that people break and make new ties to optimize their positions in the network. Despite the burgeoning literature on models of network dynamics in economics (e.g., Jackson, 2004), game theorists have been reluctant to tackle analytically the complex dynamics in which agents change both their behavior and their relationships simultaneously.

#### 3.2.1 Reputation and Network Clustering

ABCM has been used to study reputation systems while addressing two problems: the need for more plausible behavioral assumptions and the need to model dynamic networks in which agents can change their relations as well as their strategies.

Takahashi (2000) uses an evolutionary model to study the emergence of generalized exchange, in which agents give and receive help but not to and from one another directly. Takahashi challenges previous studies that assumed either altruism or centralized enforcement of the rules of exchange. He then uses an evolutionary model to show that exchange systems can self-organize on the basis of norms of generalized reciprocity (giving selectively to those who give to third parties). This approach is similar to reputation-based strategies in that players base their decision to cooperate on what they know about the target's previous behavior with regard to third parties. However, the approach is different in that this knowledge is based on direct observation rather than diffusion of information in a network.

Takahashi programs agents with two genes. The first gene controls the amount the agent gives to others. The second gene controls reciprocity and is based on the recipient's reputation for giving to others. The net benefits from giving and receiving determine each agent's chances for reproduction. Reproduction copies the agent's genes with a small probability of mutation. However, with only two genes, there is no need for recombination, so Takahashi does not use a

genetic algorithm. He found that a system of generalized exchange can evolve in a population that is initially not generous, when it is assumed that agents have perfect information about the past behavior of other agents. Takahashi then relaxes this assumption by positioning agents on a two-dimensional grid, restricting their knowledge, interaction, and reproductive competition to their close neighborhood. Takahashi uses a so-called Moore neighborhood, in which each agent has perfect information about eight potential exchange partners (instead of 19 as in the original experiment). Generalized exchange emerges within each of the overlapping neighborhoods, but Takahashi did not test to see if generalized exchange could evolve between members of different neighborhoods when reputational knowledge remains local.

Castelfranchi et al. (1998) (see also Conte and Castelfranchi, 1995) examine the effect of reputations on the deterrence of aggressive behavior on a two-dimensional grid where agents compete locally for scarce resources and adaptation operates through evolutionary selection. They find that a cooperative strategy can thrive in a homogeneous population but suffers as contact with aggressors is increased. However, the aggressor's advantage is diminished if agents can exchange information on the reputations of others. Saam and Harrer (1999) used the same model to explore the interaction between normative control and power. They find that systems of informal social control can tip toward either greater equality or inequality, depending on the extent of inequality at the outset.

More recently, Younger (2004) comes to similar conclusions by using a model that aims to mimic food sharing in hunter-gatherer societies. Younger simulates societies that contain both sharing (normative) and stealing (aggressive) agents. The author compares regimes with and without communication of "normative reputation" in the group. Only sharing agents exchanged information on others' behavior. Younger concludes that communication of reputations increased the viability of normative behavior because it enabled potential victims of theft to avoid predators and to exclude aggressive agents from sharing networks. While this result is generally in line with previous work, the complexity of Younger's model makes it difficult to assess how much it depends on particular combinations of assumptions.

### *3.2.2 Homophily and Social Order*

Homophily refers to the tendency for people to interact with similar others, expressed by the aphorism "birds of a feather flock together" (McPherson et al., 2001). Homophily increases the probability that agents interact with partners who use similar strategies (Cohen et al., 2001). This, in turn, promotes the evolution of strategies like TFT that do well when interacting with copies of themselves.

Nowak and May (1992, 1993) illustrated in a series of papers how spatial clustering of cooperative players can make cooperation viable in a Prisoner's Dilemma game even when interaction is not repeated. In these models, every agent is located in a cell on a two-dimensional grid and is either a cooperator or a defector. Agents play one round of Prisoner's Dilemma with one of their neighbors, then they replace their strategy with that of the neighbor that earned the highest payoff in their neighborhood. The authors show that spatial clustering of cooperators causes defectors to perform poorly because they mostly interact with defectors, while cooperators are better off because they interact primarily with cooperative neighbors. The analyses also show that cooperation and defection can co-exist permanently in the spatial structure. The balance is maintained by the self-limiting logic of both strategies. If too many

players cooperate, remaining defectors increasingly benefit from exploitation of their cooperative neighbors and begin to replicate more quickly. Conversely, when defection spreads, cooperative agents in remaining clusters outperform the defectors in their neighborhood, because the latter suffer from mutual punishment with other defectors. This analysis of homophily effects has been further extended and confirmed in follow-up studies in which the level of homophilous clustering in spatial networks was directly manipulated (Eshel et al., 2000).

Several recent studies also suggest that the viability of cooperation is greatly improved when populations can self-organize into locally homogeneous clusters. A series of papers elaborates a cultural similarity mechanism that is based on so-called “tag” mechanisms (Holland, 1993; Hales, 2000; Riolo et al., 2001). Tags are initially arbitrary but observable cues or markings, like clothing or ethnic markers. This work studies how tags can sustain cooperation between self-interested agents on the basis of the willingness to transfer resources to those with a similar tag. As a consequence, the entire group benefits more than nonmembers and thus gets reproduced preferentially. While studies of tag-based cooperation suggest an explanation of norms of in-group altruism, robustness tests also demonstrate that this result may sensitively depend on a combination of very specific details of the replication mechanism and the mechanism through which targets of donations are selected (Edmonds and Hales, 2003).

### 3.2.3 *Emergent Order in Dynamic Networks*

Hegselmann (1996) (cf., Flache and Hegselmann, 1999a,b) addressed cooperation problems that occur in dynamic exchange networks, in which actors may change interaction partners and in which potential partners differ in their attractiveness as a result of variations in their material resource endowments (such as the tendency for firms to establish cooperative relationships with partners whose attractiveness reflects their technological resources and status within the industry, as observed by Podolny and Page [1998]). On the basis of standard game theoretic rationality, Hegselmann assumed that players cooperate conditionally in ongoing exchanges if they expect a relationship to last for a sufficient duration and if their partner is sufficiently attractive. Hegselmann then used cellular automata to model partner selection. In this framework, actors maintain a number of exchange relations simultaneously and can change all or at least some of their partners by migration to a new location on the cellular grid. Partner search is based on boundedly rational heuristics of myopic optimization, because of the great complexity of the decision problem actors face in searching for a partner in a continuously evolving network. Under a large range of conditions, a dense network of exchanges with a distinct segregation pattern arises, in which actors favor exchange with those who are similar in attractiveness. Actors who are most attractive form the core of the network, whereas the least attractive individuals are driven to the margin, where they find mainly unattractive members of their own kind to exchange with. Broadly, this onionlike pattern resembles the “Matthew principle” found in empirical research (Komter, 1996): “The less needy you are, the more likely you are to have an attractive exchange partner.”

In a similar vein, Smith and Stevens (1999) model the formation of psychological support networks in which agents seek out relationships with others that will help them manage anxiety. In their model, agents decide with whom to form relationships through a process of assortative mating. The authors find that agents form relationships with partners who are similar to themselves in their ability to manage stress, creating homophilous clusters. In needy populations,

the support networks that form have stronger attachments but lower transitivity than they do in populations with less need for social support.

### 3.3 Emergent Order and Micro-level Assumptions

The previous section surveyed research on the effects of structural conditions on emergent cooperation. This section discusses studies that manipulate micro-level behavioral assumptions about how agents optimize outcomes (e.g., how agents learn) and the outcomes that agents aim to optimize (e.g., whether they optimize payoffs to self or others).

#### 3.3.1 *Social Learning*

In the wake of Axelrod's seminal study (1984), evolutionary game theory proposed an explanation of emergent social order without the need to assume sophisticated cognitive abilities. However, critics of evolutionary explanations have pointed out that genetic replication and selection may be an equally misleading template for models of adaptation at the cognitive level. For example, Chattoe (1998) has raised probing questions about modeling cultural evolution as a genetic analog. What is the mechanism that eliminates poor performers from the population and allows others to propagate? "Imitation of the fittest" may be more applicable than starvation and reproduction, but, unlike survival of the fittest, mimetic selection replicates only observed behavior and does not copy the underlying (unobservable) rules. Biological metaphors cover the importance of this distinction.

Concerns about the looseness of the evolutionary metaphor have prompted growing interest in relocating the evolutionary selection mechanism from the population level to the cognitive level. Reinforcement learning assumes that actors tend to repeat successful actions and avoid those that were not. This behaviorist principle was proposed by early adherents of methodological individualism (Homans, 1974). Hence, the more successful the strategy, the more likely it will be used in the future. This closely parallels the logic of evolutionary selection at the population level, in which successful strategies are more likely to be replicated (as a result of higher chances to survive and reproduce or greater social influence as a role model). And like evolutionary approaches, learning theories also avoid the criticism directed against game theoretic solutions based on perfect rationality. However, evolutionary models explore changes in the global frequency distribution of strategies across a population. In contrast, learning models operate on the local probability distribution of strategies within the repertoire of each individual member.

Macy (1996) used genetic algorithms and artificial neural networks to compare the two levels of adaptation: individual-level learning and population-level evolution. Like a GA, an artificial neural network is a self-programmable device, but instead of using recombinant reproduction, it strengthens and weakens neural pathways to discover, through reinforcement learning, the optimal response to a given configuration of inputs (like the previous course of the game). Consistent with previous findings of Nowak and Sigmund (1993), Macy found that evolutionary selection favors, in the long run, backward-looking strategies similar to Win-Stay, Lose-Change. However, these strategies fail to emerge when agents have to discover them through experience; that is, when selection takes place at the agent level (based on learning) rather than the population level (based on evolutionary selection). Even cognitively sophisticated

agents have difficulty self-organizing backward-looking cooperation, because the complexity of coordination on the right strategy increases exponentially with the size of the strategy space.

Agent models with simple reinforcement learning rules have been used in sociology and economics to identify conditions in which cooperation can emerge in social dilemmas (Roth and Erev, 1995; Erev and Roth, 1998; Flache and Macy, 2002; Macy and Flache, 2002). Following Rapoport and Chammah (1965), Macy (1989, 1990) used a Bush-Mosteller stochastic learning model of cooperation in Prisoner's Dilemma based on reinforcement learning. Macy identified how reinforcement learning can lead agents into a self-reinforcing equilibrium of mutual cooperation. This equilibrium results when a combination of strategies yields payoffs that, for all participants, at least match their aspirations. This includes the possibility that both players receive less than their optimal payoff (such as the payoff for mutual cooperation in the Prisoner's Dilemma game). Suppose two players in Prisoner's Dilemma are each satisfied only when the partner cooperates, and each starts out with zero probability of cooperation. They are both certain to defect, which then causes both probabilities to increase (as an avoidance response). Computational experiments showed how this allows the players to escape the social trap through a chance sequence of bilateral moves. Macy (1990) showed that this principle of "stochastic collusion" generalizes from repeated dyadic to  $N$ -person Prisoner's Dilemma games. These extensions also reveal that stochastic collusion depends on conditions that limit the complexity of the coordination problem. These conditions include (1) a high learning rate that limits the number of coordinated bilateral moves needed for players to "lock in" mutual cooperation, (2) a relatively small number of partners whose moves need to be coordinated (Macy, 1990), and (3) small-world networks (Watts, 1999) that minimize the average number of partners for each player yet still permit locally successful strategies to propagate.

Subsequent studies showed that Macy's findings for Prisoner's Dilemma generalize to a larger class of social dilemma games (Macy and Flache, 2002). These studies also highlighted actors' aspiration levels as a decisive condition for self-reinforcing cooperation. With a low aspiration level, learning actors settle too readily for outcomes with a low level of cooperation. If aspirations are too high, the reward for mutual cooperation may be too weak to sustain a self-reinforcing equilibrium. In further research, Flache and Macy (2002) integrated two different specifications of the basic model of reinforcement learning: the Bush-Mosteller stochastic learning algorithm and the payoff-matching model of Roth and Erev (1995) that has recently received considerable attention in economics and game theory (cf., Erev and Roth, 1998). Computational experiments indicated that both specifications of reinforcement learning can generate cooperation through stochastic collusion. However, in the Roth-Erev mechanism, cooperation does not suffer nearly as much from high aspirations as it does in the Bush-Mosteller mechanism, but it suffers from low aspirations much more.

### 3.3.2 *Individual Preferences*

ABCM has revealed a possible flaw in the conventional wisdom inherited from classical authors, from Durkheim to Adam Smith, that altruistic moral sentiments entail higher levels of cooperation. Following Taylor (1987), altruism is specified as a utility function that takes into account the payoffs to oneself as well as those that accrue to one's exchange partners. The Flache and Hegselmann (1999a) model of social support in an evolving network (see above) confirmed the conventional wisdom, but only to a point.



Consistent with previous studies, Flache and Hegselmann found that mutual support can arise on the basis of reciprocity between pure egoists. Also unsurprisingly, the experiments suggest that higher levels of altruism foster cooperation in social support relationships, because moderate altruistic sentiments increase the subjective gains that agents attain from mutual cooperation, and thus they compensate for the instrumental costs of support by altruistic benefits. However, the surprising result was that too much altruism can also reduce social support, when it pushes highly compassionate but needy members into mutual support relationships that would be avoided by their more egoistic counterparts. Given constraints on the number of simultaneous exchange relationships, these needy altruists crowd out stronger partners whose resources for providing support are then not optimally allocated to those who need them most.

Jaffe (2002) likewise uses ABCM to test explanations of social order based on altruism. He asks whether and under what conditions society would be better off in aggregate economic terms, if altruism were more widely practiced among its members. Jaffe builds an agent-based model of a simple agricultural society. His model explores different types of conflicts between individual members and the group, by varying the degree to which altruistic acts benefit the recipient and harm the altruist. In computational experiments, the possible benefit of altruism on the aggregate wealth of society was assessed by comparing the overall efficiency of the system in accumulating aggregate utility in populations of altruistic agents, and with equivalent systems where no altruistic acts were allowed. The author concludes that there is no simple situation where altruistic behavior is beneficial to the group, and that in pure economic terms, altruism can even lower society's level of aggregate wealth. Altruism was only efficient in terms of aggregate utility when altruistic acts were "synergistic" (i.e., increased the economic utility received by the beneficiary and thus his ability to make donations to himself in the future).

In sum, agent-based models are a useful tool with which to explore the sensitivity of macrosocial outcomes to behavioral assumptions, such as bounded rationality or individual risk preferences (Flache, 2001). They can also be used to demonstrate robustness. A prominent example is Olson's (1965) prediction that collective action declines with group size. Computational models showed that this effect of group size also holds for backward-looking learning actors (Macy, 1990) and for the forward-looking actors assumed in orthodox game theoretic analyses (Raub, 1988).

#### **4 METHODOLOGICAL PRINCIPLES**

ABCM searches for microsocial causal mechanisms that may underlie macro regularities. One advantage of this approach is that model specification is not restricted by the requirements of analytical solutions for system dynamics. At the same time, this is also a potential weakness, because researchers may be tempted to create models that are too complex to be understood independently from their particular implementation. Nothing is gained by modeling when explaining the dynamics of the model is as difficult as explaining the empirical phenomena addressed. The following set of methodological principles should avoid this problem.

Start from a well-specified problem and theory. Computational experiments in virtual worlds provide a rigorous methodology for studying the effects of different micro foundations on macro dynamics. Following Coleman's (1990) advice, agent modeling should be guided by the goal of predicting or explaining observable relationships between well-specified macro phenomena, such as the relationship between relational stability and cooperation in exchange

relationships. With such an approach, the research problem is clearly defined, and a natural link to empirical applications is given. However, the main task is theoretical: to find out how predictions may change across different sets of assumptions. Sawyers' advice (Conte et al., 2001) that prior sociological theorizing on empirical relationships serves as a useful starting point is good, because it provides observations and substantive ideas about underlying social mechanisms. The more clearly specified these ideas are, the more useful they can be as a guideline for subsequent ABC model building.

The prescription to start from existing sociological theory contrasts with the method advocated by some agent modelers who start not from theory but from detailed, formalized descriptions of an observed phenomenon (cf., Conte et al., 2001) and then search for a model that can generate this empirical pattern. Such an approach is misguided for two reasons. First, there is likely to be an indefinitely large number of models that can generate any given set of observational data. "Growing" the pattern shows that an explanation is possible but does not tell much more than that. Second, even if only one model can generate the empirical pattern, the mechanism that is responsible is still unknown. This problem becomes especially acute as the complexity of the model increases. And the model is likely to become complex as new assumptions are added to allow the model to better fit the empirical data.

Start it simple. Some agent modelers might regard the models reviewed here as being overly simplistic in their micro-level assumptions and prefer instead much more elaborate models of human cognitive processes (Conte et al., 2001), with situationally changing modes of cognition, such as repetition, imitation, deliberation, and social comparison (Jager et al., 2000). Pressure to make models more realistic (and agents more cognitively sophisticated) is misguided if models become so complex that they are as difficult to interpret as natural phenomena. When researchers must resort to higher order statistical methods to tease apart the underlying causal processes, the value of the experimental methods is largely undermined. Analysis of very simple and unrealistic models can reveal new theoretical ideas that have broad applicability, beyond the stylized models that produced them. Models should start out simple, and complications should be added one at a time, making sure that the dynamics are fully understood before proceeding.

Experiment, don't just explore. Agent-based modeling is an experimental tool for theoretical research. While important discoveries can be made by open-ended exploration of theoretical possibilities, researchers need to resist the temptation to become freewheeling adventurers in artificial worlds. Careful, systematic mapping of a parameter space may be less engaging, but it makes for better science. This requires theoretically motivated manipulation of parameters, based on careful review of current theoretical and empirical knowledge, and a clear statement of the hypotheses that guided the experimental design.

Test robustness. Although simulation designs should use experimental rather than *post hoc* statistical controls to identify underlying causal processes, that does not mean researchers should avoid statistical analysis of the results. On the contrary, agent-based models, especially those that include stochastic algorithms, require replications that demonstrate the stability of the results. Where possible, replications should include variation in parameters that are theoretically arbitrary or of secondary interest. Researchers should then be careful to distinguish between experimental manipulations, where results are expected to change with the parameters, and robustness tests (or sensitivity analyses), where they are not (cf., Saam, 1999; Chattoe et al., 2000).

Replicate results independently. Testing model implications empirically is only meaningful when modelers are reasonably certain that they validated the model (i.e., they know that they have implemented the theoretical assumptions that were intended). Edmonds and Hales (2003) point to a fundamental problem for the validation of computational models that can be implemented in different ways. The authors propose to replicate models by at least two independent implementations. In an instructive example, they show that their re-implementations of the Riolo et al. (2001) model of tag-based cooperation first revealed subtle differences between their results and those originally published. Subsequently, they could show how these differences could be explained by using a specific version of a reproduction mechanism that was consistent with the published original model description. However, it turned out that in this new version of the model, the conditions under which tag-based cooperation was viable were much more restrictive than claimed by Riolo and his coauthors.

Compare and align models theoretically. Model replication helps to validate that an implementation represents the intended model. Model alignment (Axtell et al., 1996) aims at close comparison of different competing models of the same phenomenon. In model alignment, the goal is to identify the assumptions that cause differences in model behavior and separate them from model differences that are inessential for the results. Ideally, model alignment can lead to theoretical integration of competing designs as special cases of a more general model. For example, we showed above how Flache and Macy (2002) aligned and integrated the Bush-Mosteller and the Roth-Erev implementations of stochastic learning. Clearly, for models of multi-agent dynamics, such analytical model alignment may not always be feasible. However, we argue that nevertheless, different conceptual models of the same phenomenon should be carefully compared with computational experiments to assess model robustness and identify the model features that are most important for differences in model results. Once these are found, researchers can abstract with more confidence from model details that have little effect on results.

Test external validity. Virtual experiments test the internal validity of a theory, without which there is no need to test the external validity. However, this does not mean there is never such a need. ABCM is often used to grow familiar macrosocial patterns, as a way of identifying possible causal mechanisms (Epstein and Axtell, 1996). When this succeeds, researchers need to think about ways these mechanisms can be operationalized and tested in the laboratory or in natural conditions. An instructive example for such an approach can be found in a study by Mosler and Brucks (2003), which proposes a model of cooperative behavior in the exploitation of limited environmental resources. The authors move beyond previous work by integrating, in their individual-level model, cost-benefit-driven considerations of the ecological consequences of harvesting decisions with social-comparison-based normative evaluations of decision consequences. The authors then systematically match the parameters of their model to conditions manipulated in previous laboratory experiments with commons dilemmas. They argue that their model can replicate a large number of known empirical relationships.

## 5 CONCLUSION

This survey of ABCM compared analytical and computational studies of emergent social order. This focus entailed neglecting other applications that are equally important and compelling, and these oversights should not be taken to suggest otherwise. In particular, modeling tools for the support of policy design were neglected. Examples include agent-based

computational models that predict large-scale traffic dynamics (Balmer et al., 2004) and the dynamics of natural resource utilization and conversation in a riverbed (Doran, 2001). These models resemble “microsimulations” that emerged in the 1970s (cf., Orcutt et al., 1986) in their use of observational data about individuals to forecast the state of the population. However, these studies move beyond traditional microsimulation by explicitly modeling individual decision makers as autonomous agents who actively pursue their own agendas and react to changes in their environment brought about by other agents. While this work can eventually be very useful for informing policy decisions, there is a concern (Doran, 2001) that the great complexity of these models makes it hard to appropriately test and verify them.

ABCM is a powerful new technique for theory development guided by methodological individualism. The technique combines the rigor of formal model building with behavioral complexity that would not be possible with orthodox rational choice theory or game theory. Agent-based computational models provide an ideal testbed for deriving testable implications for macrosocial dynamics of behavioral principles, such as social rationality (Lindenberg, 2001) and “fast and frugal” decision heuristics (Todd and Gigerenzer, 2003). At the same time, these tools can also be used to perform computational experiments that test the effects of structural conditions, such as network structure. With the adoption of a standard methodology, ABCM will lead to significant advances in the bottom-up approach to the study of social life.

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**DISCUSSION:****COMPUTATIONAL SOCIAL THEORY****(Invited Speaker, Friday, October 8, 2004 - 8:45 to 9:45 a.m.)**Chair and Discussant: *D. Zhao, The University of Chicago***Social Life from the Bottom Up: Agent Modeling and the New Sociology**

**Charles Macal:** Our next invited speaker, Michael Macy, is from Cornell University. He's particularly well known in the fields of social simulation, social networks, social processes, modeling, and similar subjects. Our chair and discussant for this session is D. Zhao. Here's Michael.

**Michael Macy:** Thank you very much. It's a pleasure to be here. I want to thank the people who put this conference together and created this opportunity.

Let me ask you to consider a flock of birds — of geese, perhaps — flying in tight formation. Collectively, they form the image of a single delta-shaped bird that moves as purposely as if it were a single organism. This idea of a flock and the motion of a flock may give us some insight into group processes among humans.

[Presentation]

**D. Zhao:** It's a very nice talk, but, I must say, the paper is even better. I was invited by David [Sallach] to discuss this paper. The first time I heard about agent-based models, I was introduced to them by David, but I never had a chance to read what exactly they are. After reading Macy's paper and listening to his talk, I feel I know what they are. My understanding may be wrong, so I really want to discuss these models — to view them from all sides and see their extent.

In my misunderstanding last year, I believed an agent-based model was something between an analytical model and a simulation model. An analytical model is really an analytic simulation model that simulates reality. Now I understand that the agent-based model is a type of analytical model.

Before I listened to the talks, I struggled to determine the difference between an agent-based model and a game theoretical model. Now I see that the agent-based model originates from the game theoretical model. It still is, by and large, a game theoretical model, but it is different in that it loosens the assumption about human models. The game theoretical model assumes humans make rational choices.

So game theoretical models can play around with structures, where the information may or may not be perfect, or the chain of interaction may last so that cooperation becomes possible, or the number of people may be large so that cooperation becomes less likely, and so on. But they are not able to play around with the assumption about human beings. The agent-based models are much more flexible; human behavioral mechanisms and decision-making

mechanisms are all embedded into the models. These models are much more complex and can explore many more things. They are still analytical models and because they are, I agree with Macy's comments, suggestions, and recommendations on the heart test model, bone test model, empirical cases, especially the cases where there was reformation — that '98 movement, the rise of the French Revolution, and so on. You test by conducting an experiment in nature, a test in a laboratory experiment, or a test by the logic itself.

When you test in a laboratory experiment, it is hard to judge the importance of this model. There are so many different and interesting models like it, and some models are better than others. How do you judge which is the better model?

I think that you should judge by using examples to see how the model's base logic can capture the wide spectrum. Nevertheless, the real world does not actually work that way. That's why I think Michael's model and "tit-for-tat" models and past models, such as "free ride," are interesting. Our society has so many mechanisms that work against getting a free ride. Any complex mechanism would fully expose itself. On the other hand, if you design a society in a certain way, like communism, and if everybody is paid less, it works. On the other hand, the entire evolution of protest in human society is that you're always against the free ride — different organizational mechanisms. So the importance of the free ride province is that it captures so many things; nevertheless, it predicts nothing. So it's important like the emperor's new clothes. I think it's an excellent model; it captures so many different things. It's a crucially important model. But once you use this model to predict, actually, what ... the clash of communism ... it is the earth ... it is because of the emperor's new clothes. That's completely wrong. I know there are some people who do it. The Marxism movement in China is because of the emperor's new clothes. Suddenly people just have opinions, not choice.

On the other hand, did this mechanism somehow work there? And where did this mechanism work, such as in a particular case, like working is more important in Germany than in China. Maybe it is. So the importance is that it gives illustrative examples that provide insight, but it should never be used to predict a new situation. Once you predict a new situation, many go to one problem. For example, I do most of the ethnographics, but there are so many people built around different game theoretical models and different agent-based models to try to predict movement.

I tried different scenarios to predict why the Chinese student and the Chinese government eventually crashed into each other. They had different information, or they could not come close or did not have trust (even though the information comes close), or two sides had different behavior patterns. So it is important for the test to use a good example. The model should be judged not by how well it can predict empirical reality but by the importance of its assumption — by how much this assumption can capture a wide spectrum of phenomena so that you can use a wide spectrum of illustrative examples.

So what is the biggest challenge? I think it is — because Macy claims this kind of competition — macro-sociology. Also, it's a real approach from methodological individualism.

So if you really want to use this approach of individualism, you should be looking at the hard chance of a human agent with behavior that can change the outcome. But with the emperor's new clothes model, in the end you can change networks. You change it once you have

a particular kind of phenomenon. Then what you really proved is that its structure worked. You should really work harder, which I think you can. That's the first thing I would suggest to you.

Another thing on which to base the largest challenge is that to be in competition with macro-sociology, which is, not like what I see, competition of micro- and the meso-sociology, is to extend the model to predict the rise of stratification and rise of the state. That's crucial because my understanding of human evolution is that it is not only evolution but also devolution. That's why society can last so long: all people want the collective power that is produced by society, but no people like distributed power. Once you have a society, you have a stratification system: some people get more, some people less — so people get a free ride. That's why it lasts so long; it's devolution.

So, the key in most models, in essentially all models, is that you have rise orders: rise of cooperation, rise of what I call the rank society, not a stratified society. So also, of course, it's still useful to predict, analyze, simulate, stratify society. You presume that the other stratified society ... [inaudible]. What's going on? Actually, there's no rupture that I can see. The rupture [comes from] the rise of stratification, of civilization, of states, and the rise of more complex problems. So that is a way to work: basically make the model and make the human agents more evenly flexible to make sure it's more like individualism. Another is that to simulate this, it took not just the rise or the rank of societies, but the stratification of societies, the rise of stratified society. Those are my two recommendations.

It's excellent work. I'm not completely without any background on simulation and modeling. When I was an entomologist (not a sociologist at that time), I did some simulation modeling, but all on differential models — completely different. So I have experience. Thanks for giving me this opportunity.

**Macal:** Thank you very much. It's our tradition to open the floor up for discussion and questions. We'll have about 15 minutes for that.

**John Sullivan:** John Sullivan, Ford Motor Company. By way of comment, you were expressing the desire to see more work in which you compare modeling results with laboratory experiments. As a matter of fact, that's already started. Economists Duffy and Brown have looked at the emergence of fiat currencies. Prior to their work came that of Keshi and Wright. So at least that work was starting.

**Elenna Dugundji:** Elenna Dugundji from the University of Amsterdam. I have what may be a controversial or devil's advocate point. It's about your eighth commandment, which was about truth and simplicity. In my opinion, it would be better to modify this slightly, and rather than saying that there's truth in simplicity, if it's in commandment form, you should begin with simplicity and not end with simplicity. The reason for this is that if you just say just truth and simplicity and leave it at that, it can be misinterpreted if it's in commandment form because, for example, deterministic behavior by itself is simplicity, and it's adding stochasticity that gives interesting results.

Simplicity could be seen as global interaction structure, yet it's the local interaction structure that gives interesting results. These cases of going from global to local and from deterministic to stochastic are actually not simplistic. Instead, the cases are becoming more complicated but interesting.

To continue a bit more, if you stay with very simple cases, you can get equilibria that do not exist in real society. So you think that you found a great result, but since this simplistic thing never really exists in real society, of what use is it? It's the same kind of thing that was mentioned in the general game theory discussion, where you might get an equilibrium that is predicted, but you don't know how often it occurs, or how long it takes to get there, or this kind of thing. So that's why if I were to restate this, I would say begin with simplicity, so that you have a guideline, but then ask (I think this is what the commenter said) how much can assumptions capture. I think that's a very good thought because if you begin with simplicity and then think you have some robust truth, it's very important to make small modifications to that in different directions to see how robust that truth is. You do not want to promote a "great simplistic truth" that's just meaningless for real life. So my point is to begin with simplicity and then test it.

**Macy:** I agree entirely with what you said, and I admire how much better you said it than I could have. Indeed, I was thinking precisely those thoughts as I was planning the slides and realizing I wasn't capturing the nuance that you did — and I guessed that somebody would point this out to me. How can you say simplicity and stochasticity in the same set of commandments? You're absolutely right.

In the paper, we actually modified the military KISS principle, which says, "Keep it simple, son," or "Keep it simple, stupid." We changed it to the SIS principle, which is "Start it simple." Then you add complications only as you fully understand the model that you have so far. And you add only those complications that are theoretically motivated. You resist the urge to be realistic just for realism's sake. That's really the spirit of that eighth commandment, and it's always dangerous to write these things as commandments because it does obscure the very important point that you're raising.

**Kostas Alexandridis:** Kostas Alexandridis, Purdue University. I'm not a social scientist. I think that many of us are involved in the natural sciences and are looking at cognitive domains, since we appreciate a little bit more the complexity that is associated with real-world phenomena. I'd like to think that starting from the complexity of the real world and trying to have simplicity emerge has value in itself. So, if we take the opposite direction to agent-based modeling, how do you propose that we bridge the gap with scientists who are involved in agent-based modeling?

**Macy:** Well, I don't know that I have any of those ultimate epistemological answers. At some point, the results of the computational laboratory experiments need to somehow be articulated along with what we observe in the world.

The approach that I've taken is to start with empirically established global patterns that are well established and well documented but poorly understood or puzzling, then try to understand them and identify the mechanisms that might produce them. We may not necessarily have the right ones, but I don't have a program for ultimately integrating with natural science, any more than game theorists do. I think in 40 years of game theory, there's no real clear program for how you then take the theory and use it to make real-world predictions in a way that really tests the games. People do it all the time, but I haven't seen it systematically established at the level of a rigorous epistemology.



**Peter Hedstrom:** Peter Hedstrom, Nuffield College, Oxford. In anticipation of one of my main points in my talk tomorrow morning, I must say that I'm not entirely convinced about your argument that we should avoid entering this — I don't remember how you expressed it — "confusion" of the real world. I think that [it involves] making a distinction between two different types of tests. I mean, on the one hand, we want to test whether a specific mechanism operates as we assume that it does. In most of these cases, of course, the laboratory experiment is the preferred strategy, but there is another and equally important test. There are two types of test. One is a test of whether a mechanism that we are using operates as it should. A laboratory experiment seems to be the choice of method. The other type of test is to see whether the proposed mechanism actually contributes to explaining the specific empirical pattern that we wish to explain. That is where I have difficulty in seeing how one could avoid the confusion of empirical reality. Somehow, we must be able to demonstrate the relevance and importance of our preferred mechanism for the specific thing that we want to explain. Somehow, we must also take alternative explanations into account because, for example, there are lots of different models that can generate exactly the same aggregate patterns. So the fact that our preferred model generates the pattern that we want to explain is not necessarily, in and of itself, such a strong argument in its support.

**Macy:** Computational experiments are very similar to mathematical proofs. Such mathematical proofs are extremely useful, yet you do not have to immediately test them in the empirical world in order to recognize the knowledge that's generated by that deductive process. These are not deductive proofs, and they lack generalizability, but they nevertheless allow us to investigate dynamics that we couldn't necessarily do by using deductive methods.

That's why I see the need for controlled experiments. I'll certainly grant you this: any time I can do a controlled experiment in the field, I would always prefer that over doing it in the laboratory. There are tremendous advantages to doing controlled experiments in the field, but they're very hard to do. There are also situations where using data collected from the field is absolutely in order. What I worry about, though, is a kind of fetish that says that we have to show that our model explains a particular historical occurrence. If we don't do that, then there's no value in it. I'm suggesting that we adopt the empirical orientation that has developed and served game theory very well. The approach that game theorists have taken to the relationship between theory and testing is an appropriate model for agent modeling.

**Claudio Cioffi-Revilla:** Claudio Cioffi, George Mason. Michael, I thank you for a really stimulating presentation, and I hope the 10 commandments are published in AJS.

**Macy:** Maybe someday.

**Cioffi-Revilla:** I wanted to ask you about that very important distinction that you drew in computational social science between demonstration and experimentation in the use of agent models. It's a very important and very insightful distinction. The question is this. What thought have you given to the problem that arises in the context of experimentation with agent models? We want to have a minimally complex model in which to conduct experiments, manipulate conditions, and so forth. We don't want to make it too complicated because reality will begin to obfuscate the matters that we're looking at. You mention the Schelling check port city model. You don't want the roads, pollution, and all that other stuff because they're perhaps irrelevant to study in the segregation dynamics. On the other hand, the model can't be too simple because it won't produce sufficiently rich behavior.

Clearly, there is a spectrum of complexity for the experimental model, and the criteria for designing the model at the proper level are tricky, unclear, and sometimes very difficult to find out. Have you given some thought to this? For example, in your model of the emperor's dilemma, what made you stop at that level of construction as opposed to proceeding on to implement multiplexes and other features of that artificial world that you could have thrown in, but didn't? You left out those other features — lots of them, infinitely many, perhaps. Can you say something? You must have thought about this.

**Macy:** The person from University of Amsterdam — what is your name?

**Dugundji:** Elenna Dugundji.

**Macy:** We actually used the method that Elenna was articulating. We started out with regular grids and only later added irregular ones. We started out deterministically and added stochasticity. So the model actually did become more complicated, not necessarily more complex, but more complicated as we understood it.

I have nothing against enriching the models. I don't mean to suggest that. There are two points I want to make. We should not suppose that we cannot find enormously important explanations — indeed, perhaps even lawful regularities of social life — that will be breathtakingly simple. We should not rule that possibility out. Such explanations are all over the place. I'm just urging that we resist the pressure from people to make these very complicated models.

I get very frustrated when I find agent models in which they have thrown in everything because some colleague said that you need to add this or you need to add that. Then I examine the thing and I can't make heads or tails of it. That's all I mean to say; I don't mean to endorse not adding complications through a systematic program.

I think we should really study the history of game theory and examine how that body of work has unfolded. We can learn a lot from what is a very successful program. It's now very well integrated with laboratory experiments. Wonderful breakthroughs are happening now by people who are having games played in the lab, people have been doing this for 40 years. Agent modelers need to take a very careful look at that progress and see what we can learn from them.

**Robert Reynolds:** Bob Reynolds, Wayne State University, Computer Science, and Museum of Anthropology, University of Michigan. I was thinking of another commandment. Models can also be viewed as learning devices or vehicles, and you could treat them as you would a student. For example, in education, they have a philosophy called scaffolding, where you touch the student in deterministic or controlled situations, then you gradually relax those controls and let the models sort of organize themselves. That systematic approach you talked about might, in fact, relate to this notion of gradually relaxing constraints. For instance, consider the example of the emperor's new clothes, where the agents were allowed to rethink their own diagrams and to adjust the grid on their own to perhaps get a closer approximation to equilibrium — to a network that would allow equilibrium to be reached and kept. This notion of viewing the agents as learning devices and treating them almost as students, allowing them to go on their own gradually, is certainly a way I do things.

**Macy:** Yes, I think that's a great idea. I'd love to see a special issue of JASSS. Maybe there already has been one on agent modeling in the classroom and ways of teaching. Does anybody know? Has Nigel [Gilbert] done this? I think we need to pay careful attention to them, because they are marvelous teaching tools, and I use them in undergraduate courses.

**William Lawless:** Bill Lawless, Paine College. First of all, I admire how quickly you went through all that material. I hope that I can do that as quickly in my paper. But it left some questions. First, you said imitation of the fittest is false. Is that correct? There's an article in *Science* this year on public information that seems to contradict that. You might want to follow up on that. I think overall it's a nice demonstration of flock behavior. I agree with you about lab experiments very strongly. I disagreed when you said you don't need field experiments, but then you seemed to correct that. I think you do need to have field experiments. But, more important, I think the field of agent-based modeling will suffer until we can actually solve a problem that has not been solved. Although it's nice to be able to show how norms (even bad norms) flow or stay, we've got to do more than that. At this stage, it's really good, but we've got to go beyond that.

**Macy:** I agree, and thank you for the citation. I'll look that up. I've actually challenged my graduate students to find a way to solve this problem of imitation of the fittest. I haven't seen anybody do it, so I look forward to looking at that.

**Macal:** Thank you for the questions. Thanks very much to Michael Macy for an extremely stimulating thought, and thank you very much. And thanks to our chair and discussant for some valuable insights and comments. We're going to take a 15-minute break. Then David Sallach will give an overview of computational social theory, which will be followed by the various sessions of the day.



# Challenges in Computational Social Theory





## CHALLENGES IN COMPUTATIONAL SOCIAL THEORY

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### ABSTRACT

To fulfill their potential, the computational and social sciences need to work together to create heretofore unprecedented types of models. This paper outlines current challenges and suggests ways that computational models can become more effective in modeling social interactions.

**Keywords:** Abstraction, ontology, generative models, meaning orientation, situated agents

### INTRODUCTION

By way of introducing the Computational Social Theory track at Agent 2004, I would like to discuss seven challenges facing computational social science (CSS). They represent issues facing the subdiscipline that must be addressed in order for CSS to realize its potential:

- Navigation of strong policy trade-offs;
- Generation of patterns from abstraction;
- Construction of formal organization;
- Prospective ontologies;
- Orientation by endogenous meaning;
- Social entities: contingent, contested, and emergent; and
- Critical social tests.

Each of these issues and their interactions are discussed below.

### NAVIGATION OF STRONG POLICY TRADE-OFFS

Societal priorities in an area of research create scientific opportunities. Where society and its primary institutions have an interest, concern, and, therefore, funding, an opportunity for progress is created. Areas that exemplify such concerns to varying extents are health, war and

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peace, ecological sustainability, homeland security, and the possible emergence of an integrated global civilization.

Such issues, however, may not yet be well-framed from a (social) scientific perspective. In this situation, societal interest may also create a demand for early solutions, while the models' prerequisites for understanding and addressing the issues have yet to emerge. Under such circumstances, the opportunities arising from institutional priorities may be offset by unrealistic expectations. The potential for putative near-term solutions may be exaggerated. When such projects disappoint, the entire field may suffer, including potentially more realistic strategies that seek to establish a foundation in basic (social) science.

Naturally occurring social issues are inherently complex. Demographic, economic, political, cultural, and microsocial interaction interleave, making it difficult to control the richness of particular phenomena by using a strategy of isolation from remote or extraneous sources of complexity. Thus, all situated social issues are inescapably high-dimensional. Simple models can be helpful in producing insight, but the study of actual problems must confront the interaction of complexities.

At this point, it would seem the strategy most likely to be effective in modeling the interaction of complex processes is through identifying relevant and effective abstractions, from which complexity and complex interactions can be *generated*.<sup>1</sup> The underlying process can be understood through the abstractions (i.e., theory), and the effectiveness of the abstractions can be assessed relative to the complex patterns that they generate. When abstraction is effective, theory can drive and focus experimentation.

How can such abstractions be best identified? Computational modeling has a critical role to play, one previously unavailable to the social sciences, by providing a means of complexity generation through social simulation. Compelling insight into the nature of social theory will doubtlessly contribute to the process, but it seems clear that computational experiments will play a vital role in identifying and comprehending the sources of social dynamics.

Addressing strong policy concerns will necessarily require advances in the social (and/or complexity) sciences. Simple models can provide valuable insights, but policy-relevant models will require effective abstractions from which to generate patterns of social complexity. Strong social interests may result in the provision of resources that can support advances in the computational social processes, but they may also result in demands for near-term but ultimately ineffective strategies. Assuming the present interpretation is accurate, clarity concerning the need to generate social complexity from effective abstractions is the best protection against unrealistic shortcuts.

## **GENERATION OF PATTERNS FROM ABSTRACTION**

The generation of social dynamics has the potential to provide a wealth of empirical detail. As a result, abstraction can be a key path to theoretical progress. Generative models, however, require that effective abstractions be identified. Progress in the complex sciences is likely to require a reconceptualization of underlying ontologies.

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<sup>1</sup> For a line of technical research that might support this substantive effort, see Czarnecki and Eisenecker (2000).



Several natural sciences in the twentieth century provide dramatic examples of such ontological reorganization, specifically around the concepts of *quantum*, *gene*, and *tectonic plate* and the process by which they came into being. The implication for CSS is that social theory is currently fragmented and may be organized around various folk concepts that have yet to be identified as such. It is also possible that methodological individualism has tended to limit the nature and types of social interaction within models. These and related topics are naturally the focus of computational experimentation.

To frame the issue of complexity generation from theoretical abstraction more concretely, consider the role of networks in social phenomena. In recent years, this has been an area of active and productive research that has helped frame processes like infection, imitation, and diffusion. The network structures and patterns under investigation are generated by mathematical models and algorithms. However, the mapping to social networks is, as yet, limited.

Algorithmically generated networks are determinate and/or structural in nature. However, social categories with a particular name or structure (e.g., between cousins or neighbors) do not necessarily manifest the same effects. Cousins may be the same gender or not, age-near or age-far, raised in close or remote contact, raised as friends or not, and so on; the details of variegated human relationships are endless. A reified network structure, however generated, cannot capture the richness and variability of human social relationships. Thus, despite all the recent progress in modeling social networks, it also appears to remain an area where experimentation in alternate abstractions has the potential to make important conceptual contributions.

## **CONSTRUCTION OF FORMAL ORGANIZATION**

The problem of moving beyond reified organizational structures is compellingly addressed by Stinchcombe (2001). Specifically, he explores how formal organizations form and operate *within* fields of informal social interaction. He documents this process in a range of diverse domains, including:

- Construction blueprints,
- Civil law and procedures,
- Commodification and liquidification of residential mortgage pools,
- Classification of aliens at border crossings, and
- Stratification of scientific knowledge.

Formalisms applicable in each domain give rise to distinct abstractions. The application of formalisms requires officials, agencies, and other participants to distinguish, reason, and negotiate about the pertinence of situations and rules.

The construction of formal organization involves participants in a process of defining, invoking, and using selected abstractions. While formality is a structured arrangement of discourse that preserves essential informal accomplishments, the functioning of formal

organization inevitably goes behind the formalities, where informality serves, *inter alia*, as loose joints among various types of formality.

Participants continually define, utilize, mediate, challenge, accept, modify, and/or reject formalities that they, and others, introduce. Each such negotiation is open-ended and occurs through direct social interaction. Alternately stated, unmediated social interaction provides the enveloping context in, by, and for which formality is created, invoked, focused, and employed.

This interpretive process applies not only to the process of creating and using formal organizations, it permeates all social life. From the modeling perspective, however, a key issue remains: what theories and/or ontological structures will best help us handle the dynamic processes that Stinchcombe describes? It is to this question that we now turn.

### PROSPECTIVE ONTOLOGIES

It is beyond the scope of the present paper to fully consider and assess prospective theoretical frameworks, and how they may be applicable, at various orders of abstraction. It is sufficient to suggest a range of possible theories with the potential to play a generative role. A sample list of such theories is named below:

- Cultural evolution,
- Recognition theory,
- Exchange theory,
- Polarity dynamics,
- Interaction order,
- Situation theory,
- Social fields, and
- Attractor systems.

As one example, in-group versus out-group dynamics is a well-studied social model that has the potential to provide the basis for a computational polarity mechanism in which in-group solidarity and out-group solidarity are counterposed and sometimes lead toward group conflict. At the same time, however, cross-cutting interests pull the two groups toward integration as well.

While this model has been applied extensively in social psychological settings, CSS will support the exploration of in-group and out-group dynamics on multiple scales. Similar possibilities are likely to apply to the competing theories listed above.

## ORIENTATION BY ENDOGENOUS MEANING

Situated agents are arguably constrained by:

- Physiology and ecology;
- Social and institutional structures;
- Presentational self, intelligibility, and interaction order; and
- Intentionality: orientations, expectations, and purposes.

Let us look more closely at what any such models will need to generate. As discussed above, the models that advance the social sciences will need to generate the production, invocation, challenging, and negotiation of meaning. More specifically, to capture the textured and situated nature of human action, models will need to be based on abstract ontologies that can generate indexical methods and responses.

Indexical representations are tied, in epistemological and causal terms, to the agent's immediate circumstances<sup>2</sup> and are thus more fully endogenous to both model and agent. As Agre (1996, p. 12) writes, "Perception and action, after all, are inherently indexical in character."

There are many exogenous models, but meaning-oriented architectures are rare. As work moves forward, designs based on exogenous rules will increasingly need to document that their rules successfully define that determinate regularities have been identified under appropriate sets of circumstances.<sup>3</sup> Arguably, when pushed to the limits of modeling assumptions, action is controlled *either* by meaning *or* by exogenous factors. The substantive significance of this choice will surely be explored in the decade to come.

## SOCIAL ENTITIES: CONTINGENT, CONTESTED, AND EMERGENT

Unlike many natural kinds of entities considered by philosophers and physical theorists, social entities are often contingent, emergent, and/or contested. This is particularly obvious with regard to small-scale social groups. The political process has given rise to the examples of blue-collar workers, teenagers, yuppies, soccer moms, NASCAR dads, security moms, and so forth, *ad infinitum*.

Individuals are frequently referenced in partial and/or stylized ways as well, as when a waitress says, using metonymy, "The chicken salad is ready for his check." Nonoverlapping entity definition can become a source of misunderstanding and contention. Models that focus exclusively on exogenously discretized entities ignore important sources of social nonlinearity.

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<sup>2</sup> Indexical representations may not, however, be as well-suited for other purposes, such as distributing knowledge about spaces and times to agents at distant or unknown locations.

<sup>3</sup> Along a parallel line, probabilistic approximations are unlikely to generate nonlinear or innovative agent responses.

## **CRITICAL SOCIAL TESTS**

No scientific breakthroughs have been more compelling than those that have emerged from critical tests. When two (or more) scientific theories with conflicting predictions are counterposed and assessed, the very focality of the investigation can create dramatic clarity. No critical test provides a clearer example than the investigation(s) that used light data collected during a solar eclipse to test the theory of relativity. The result was made more dramatic by the difficulties in carrying out the test, which only heightened anticipation and interest in the result. When relevant data were ultimately recorded and analyzed in 1919, the result was proclaimed “one of the highest achievements of human thought.”

The greater complexity of social dynamics, and the comparatively less mature nature of the social scientific disciplines, have combined to obscure the potential role of critical tests. Indeed, at this point, it is not clear that unique and effective critical tests can be identified.

However, one area in which critical tests have been explored within the social sciences concerns international conflict, more specifically, democratic peace theory (the thesis that democracies rarely go to war with each other). Consider, for example, that the sources of conflict may be attributed to either divergent interests or incompatible governing structures. Maoz (1997) counterposes the two potential sources of conflict as a critical test and finds that, even when democracies not strategically aligned, they remain unlikely to fight each other. If the comparison is with nondemocratic governments that share strategic interests, the contrast is even more striking.

Cederman (2001) shows how agent modeling can help tease out and explore the complexities inherent in a theory of democratic peace. He constructs a model based on three interacting mechanisms (strategic identification, ideological alliances, and collective security) and demonstrates how these mechanisms might generate the empirical social patterns of democratic peace as an emergent macropattern.

## **CONCLUSION**

To fulfill their potential, both the computational and social sciences will need to work together to create heretofore unprecedented types of models. Necessary mechanisms will be more endogenous, reflexive, and deeply interactive than any yet developed by the computational sciences. In the substantive social sciences, existing concepts and theories will need to be integrated across a range of domains and scales, and at a higher level of abstraction. The result, in both cases, will be forms of innovation and experimentation that open up new analytical horizons. If time, resources, and scientific progress coincide, it is possible that important social priorities can be addressed in increasingly effective ways.

## **ACKNOWLEDGMENT**

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**DISCUSSION:****CHALLENGES IN COMPUTATIONAL SOCIAL THEORY****(Friday, October 8, 2004, 9:45 to 10:00 a.m.)***D. Sallach, Argonne National Laboratory and The University of Chicago***Challenges in Computational Social Theory****Michael North:** Here is an overview of computational social theory.

**David Sallach:** Good morning. It's nice to see you all here today. When this particular session was conceived, it was conceived as being somewhat longer than 15 minutes. As the schedule evolved, it shrunk. I do not think that in 15 minutes I can actually do an overview of computational social theory, so instead I will try to comment on challenges in computational social theory. Happily, some of the issues that I'd like to raise are in the arena of simplicity versus complexity. Thanks to previous presentations and subsequent discussions, we seem to be already immersed in that discussion. Now, some will say that this was a sneaky plan to get us to this point. It's not true. I deny it.

I want to be quick and just raise a few issues pertaining to computational social theory and how it may have the potential to contribute to advances in the social sciences. I'm not bold enough to issue commandments yet, so I would say that there are seven considerations. This is the substance of all my comments on the kinds of policy concerns that influence the emergence of computational social science, on the kinds of effects that they might have, on a strategy that involves generation from abstraction, on the idea of conceptual or ontological experimentation, and on the issue of endogenous meaning, which will be quite short because I always talk about it and most of you have already heard it or versions of it. I want to raise the issues of viewing entities in social simulations as being contingent, contested, and emergent; understanding how the above might contribute to theory-driven computational models and tools; and identifying critical social science tests and complexity science tests. That's my talk. As is said in more religious contexts, the rest is commentary, but I will do just a little bit of commentary too before I sit down.

[Presentation]

**Sallach:** There's always a commercial after the message. The commercial here is to encourage you to consider becoming active in the North American Association of Computational, Social, and Organizational Science (NAACSOS) or, if they're more relevant to you, the European Social Simulation Association or the Pacific Association for Agent Modeling. They provide a professional context in which issues like those we're discussing can be explored. Indeed, Agent 2004 is held in association with NAACSOS. The next NAACSOS conference will be held at Notre Dame in June 2005. Thank you very much.

**North:** Thank you, David. We have time for a few questions while the next speaker sets up.

**William Lawless:** Bill Lawless, Paine College. Excellent talk. You've given a very nice overview, but there are a couple of areas where I'd like to push you a little bit. First, you talked about the importance of effective theory driving experiment and sometimes what occurs. There's a recent article in *Physics Today* on astronomy. Sometimes advances in technology lead to discoveries; theory is way behind that and then catches up. Sometimes theory leads, and sometimes it follows. The only objection I have is the importance you've placed on meaning. I think meaning is quite important, but sometimes it is a distraction or leads us astray because humans justify their actions a lot. I'd point out that Tversky in economics, Edgley in social psychology, and Kelly in game theory have not found a good relationship between explanation, meaning, or justification and actual behaviors — the choices that are actually made in situations.

**Sallach:** I would like to say a couple of things. One is that I totally agree with the emphasis on technology. I think that the reason for the advances in a lot of the microsociological things, particularly ethnomethodology (of which I'm a fan, even though I don't do anything that they would like), is the advent of video recording and the ability to microanalyze interactions at that level. I think that what we're looking at here is exactly that the new technologies are making new possibilities available.

As for my interest in meaning, I'm most interested in scale-free meanings (that is, processes that can happen at multiple scales). So, for example, the things that happen between states might happen in time units of a year, a decade, or something along that line, but you can still ask if it represents a threat. And the thing I would caution you about with regard to studies that say whether meaning is useful or not, is that meaning itself is a very fluid phenomenon. If you try to view it statically, you're going to, as the ethnomethodologists say, lose the phenomena.

**Claudio Cioffi-Revilla:** Claudio Cioffi, George Mason. You brought up a very important point just now that ties in closely to something that Michael Macy mentioned earlier with regard to the experimental use of agent-based models: the scale-free or the scaling variance of social laws or patterns. This is really important because experimentation in physics really hinges on the fact that if you conduct an experiment in a lab on the laws of physics are preserved under a vast reduction in scale. We don't seem to think about this often enough in the social sciences. For example, one reason why I've always objected to using people to simulate international systems is because people are not countries, and countries make decisions and have expectations in a very different way than people do. This means that there's a preservation of interaction patterns that is not invariant to scale in many social systems. How do you think about this problem in the agent-based context?

**Sallach:** We have a nice exemplar here in Schelling's example. Think of the strategy of conflict, where he talks about what could reasonably be called meanings. In the game of chicken, for example, it applies to when you're cutting into merging traffic but refusing to look at the other drivers. So the other driver has no choice but to back off. And it happens in international arms races. He's clearly identifying scale-free phenomena that have scale-free meaning associated with them, so that's very nice.

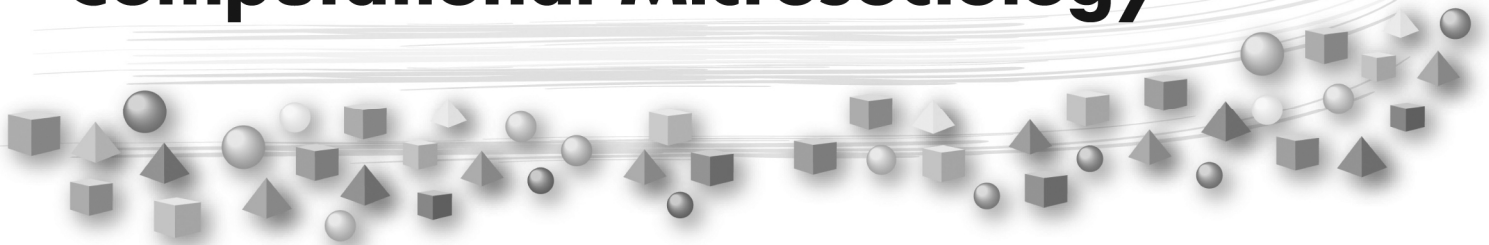
In terms of your idea, I have no problem at all with modeling states as actors. You'll get a certain level of purchase from doing that. In other words, there may be times at which knowing the kinds of micro-identifications that the human actors in the state process have (whether



they're via corruption, partisan commitment, electoral constituencies, military reliability) — there may be times when pushing it down and including more of the micro may be beneficial. But I think it's a strategic focus as to how much of the micro that you want to include, and that however much you want to include, it may be useful to try to identify meaning-oriented responses.



# Computational Microsociology





## SIMDYAD: AN AGENT-BASED MODEL OF INTERACTION BETWEEN INTIMATES

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### ABSTRACT

The agent-based model SimDyad was used to examine the possibility that system dynamics and the subsequent emergence of phenomena typically generated by hundreds or thousands of independent agents can be modeled by using only a few agents (i.e., behavior is a matter of agent impact rather than agent quantity). Constructed to simulate the interactional and affective patterns observed in married couples, SimDyad uses eight verbal and nonverbal behaviors as agents that interact, exchange information, and modify subsequent behavior. SimDyad uses estimates of relationship satisfaction, relationship goals, and perceived alternatives to modify algorithms that determine how the information exchanged between agents is used to alter the likelihood of an agent's presence or absence later on. Although the model is in the early stages of development, initial results indicate that SimDyad can approximate affective patterns seen in real couples whose members have similar relationship satisfaction levels.

**Keywords:** Agent-based model, emotion, affect, married couples, ABM

### INTRODUCTION

With the improved ability to videotape and electronically capture the intricacies of micro-social signaling, scholars across a range of scientific disciplines are increasingly examining the dynamics in these ubiquitous processes. Working on diverse subjects ranging from ants to antelopes and porcupines to people, scientists ask the same basic questions: How is social information exchanged, how does it modify structure, and what is its function? Germane to these questions is the notion of decision making: specifically, what behavioral and cognitive processes generate micro-social signaling? Numerous quantitative methods for exploring the nuances of group-level or individual-level behaviors exist, but there are few techniques for elucidating the minutiae associated with the social complexity that results from the simultaneous decisions made by multiple interactants.

To appreciate micro-level behavior, analytic methods must be able to capture the discrete nuances of patterns within social exchanges. Moreover, they must be able to identify the macro-level mechanisms that spawn these patterns. A recently developed approach to computer simulation, the agent-based model (ABM) is an analytic tool that can accomplish these goals. Agent-based simulations, which are viewed as generators of phenomena that demonstrate possible causal pathways (Kohler, 2000) and as tools to enrich our understanding of fundamental processes (Axelrod, 1997), allow for intuitive experiments on ways that the unique configurations of agents generate social processes (Axelrod, 1997; Hannon and Ruth, 1997).

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Previous ABM work focused on a surplus of independent agents to generate phenomena. Our work, however, focuses on understanding and modeling the reciprocal evolutionary dynamics ubiquitous at multiple scales across all social processes (Conte et al., 1998). As such, it must include agent pathways capable of explaining processes in smaller social units. Specifically, we examine the possibility that system dynamics and the subsequent emergence of phenomena, typically generated by hundreds or thousands of independent agents, can be modeled by using only a few agents as a matter of agent impact rather than agent quantity. In the proposed model of dyadic interaction, the agents, although few, contribute strongly to the simulated process. In other words, the impact per agent is greater in this small and dynamical process than is the impact typically ascribed to an agent in more traditional ABMs.

Focusing on small social systems allows us to identify a discrete social process at a specific level (i.e., dyadic interaction) while maintaining some ability to generalize to broader social processes. To address social processes germane to all human interactions involving micro-exchanges of social organization and structure, several related questions need to be answered. (1) How is the emergence of small cohesive social units evident? That is, how is a relationship knowable beyond merely examining two or more individuals interacting? (2) Does the emergent structure characterizing the dyad derive from a chain of extended interactions that become less stochastic? Stated differently, is reduced behavioral or affective stochasticity the quantitative definition of a dyad or a small group? (3) Given that relationships derive from multi-scale interactions (second to second, day to day, eventually extending into years), what is the morphological correspondence over these scales? This paper addresses the first question.

## **DEFINING AGENTS IN SMALL $N$ DYNAMICS**

Intuitively, defining agents in small social units would consist of assigning each individual within the unit to an agent class. Given that some units consist of only two people, however, this task becomes analytically challenging, as data points become too sparse for the simulations. Solving this problem requires several assumptions. First, we assume that social processes are complex, continuously evolving entities that adaptively configure themselves according to basic rules. These adaptive changes, in turn, modify the environment housing the agents that make up the entities (Axelrod, 1997; Casti, 1997). Thus, for simulation purposes, we assume that individuals are, in fact, the environment housing the agents. In our model, agents are the behaviors displayed by an individual. Second, under this assumption, we further assume that agents can then be defined as independent, heterogeneous elements within the individual that configure themselves in ways to communicate with complementary agents housed within the adjoining individual(s). Finally, as agents exchange information across individuals, we additionally postulate that sociality is created (i.e., emerges), adapts to intra-unit variation, and, in turn, modifies the system itself.

To maintain consistency with our approach for understanding general social processes, we must define agents as elements available to all individuals across various types of social exchanges. That is, irrespective of the particulars of a social exchange, we must identify behavioral features that are plausible, ubiquitous, and convey interpersonal information. Fortunately, there is literature suggesting that nonverbal behaviors and, to a lesser degree, verbal statements are the primary cueing features of human interaction (Mehrabian, 1971; Noller, 1984a,b). Moreover, there is evidence suggesting that behavioral manifestations (e.g., head nod) serve as a proxy for internal affective states and, as such, reflect the state of the relationship

(Gottman and Notarius, 2000). On the basis of these findings and the aforementioned assumptions, we postulate that behaviors, as proxies for latent cognitive and affective processes, evolve according to an indigenous algorithmic rule-set and that, over time, individuals are modified, as are their decision-making processes.

Thus far, we have not put forward our ideas about why we think that we can build ABMs with fewer than a dozen agents, whereas the general assumption is that this number should be increased by a factor of 10 before interesting dynamics can occur. Tentatively, we are proposing that with small  $n$  dynamical models, the agents, although few in number, contribute disproportionately more to the emergence of a general process than do the agents in models containing hundreds of agents. This proposition is not surprising or especially informative. However, it does imply a computational and pragmatic advantage: updates among agents (as well as their human analogs) are nearly instantaneous. In a recursive ABM model, reflecting the dynamical systems computational approach, this means that each agent has at least a moderate vision relative to the state of the system, is sensitive to the mean state of the system, and is responsive at each iteration. Agents with these attributes can populate a landscape that is mathematically tractable, permitting a calculus of social emergence and cohesion.

### **THE SMALL SOCIAL UNIT: MARITAL DYADS AS AN EXAMPLE OF SMALL $N$ DYNAMICS**

Although many dyadic or small  $n$  groupings exist naturally in the social world, empirical findings on the evolving micro-social processes of these entities are nearly nonexistent. To ensure validity in simulated models, real data are critical for comparison purposes. As a result, our work focuses on modeling the dynamics of the marital dyad for two reasons. First, it is possible to create salient indices of dyadic interaction that are indicative of differential patterns in married couples (Griffin, 2000, 2002). Second, we have immediate access to real-time observational interactions of couples over an extended period of time (Griffin, 1993). These assets afford us the benefit of extracting the behavioral and affective tendencies that are needed to regenerate dyadic processes in our simulations and a method for determining the validity of our model.

#### **Relationship Mechanisms**

We propose that three mechanisms influence moment-to-moment behavior in marital relationships: (1) relationship satisfaction; (2) relationship goal; and (3) potential alternatives. The first, and most central, is relationship satisfaction. Commonly defined as a global evaluation of the marriage, this mechanism is usually assessed by using self-report instruments that measure satisfaction across a range of areas (e.g., finances, parenting, in-laws) (Lock and Wallace, 1959; Crane et al., 1990). Abundant research shows that contextual factors (such as those noted above) strongly influence relationship satisfaction and, more important, that the satisfaction level is evident in the moment-to-moment behaviors of interactants (see Bradbury et al., 2000; Gottman and Notarius, 2000, for a review). Specifically, numerous observational studies have reported an inverse relationship between the presence of negative verbal behavior (e.g., put down, criticize, disagree), nonverbal expressions of negativity (e.g., eye rolls), and relationship quality (Gottman and Notarius, 2000).

A second mechanism contributing to the moment-to-moment behavior in married couples is the relationship goal, which is the commitment to the relationship. For the current model, this construct is defined as an individual's intention to continue or leave the relationship. The concept of relationship goal has been closely examined in the commitment literature and appears to be contingent on three factors: (1) the individuals' expectations of the relationship, (2) the amount of work they expect to do in order to achieve these expectations, and (3) the degree that these expectations are met (see Le and Agnew, 2003, for a review). The relationship satisfaction and the commitment literature agree that several contextual factors unique to the relationship influence an individual's intention to remain. These factors are referred to as investments and include such resources as the amount of time in the relationship, social status maintained as a result of the relationship, and material possessions accumulated in the relationship.

Finally, the perception of alternatives to the relationship has also been identified as modifying an individual's evaluation of the quality of his or her marriage. Although less is known about this particular construct, the commitment literature suggests that the perception of extra-relationship options is often related to levels of commitment (Le and Agnew, 2003). Specifically, it was found that an individual's decision to leave the relationship becomes stronger when he or she has more options outside the relationship. In addition, contextual factors (e.g., age, physical attractiveness, presence of children) may influence an individual's perception of alternatives.

Moreover, the influence of perceived alternatives on interactional behavior requires an additional assumption of utility. Specifically, if we assume that options vary in terms of viability, then the influence of perceived alternatives varies as a function of salience rather than simply the presence of options. Although the presence of options may co-vary with age or level of physical attractiveness, what an individual does with the knowledge of having options is likely to be determined by a cost-benefit analysis between the relationship and the alternative(s). It is plausible that the viability of extra-relationship options perceived by an individual is determined by relationship satisfaction. For example, an attractive female may have many potential partners outside her current marriage, but if she is highly satisfied with her relationship, the saliency of those alternatives is minimal. While the processes that account for the influence of perceived alternatives have not been established, we anticipate that perceived alternatives, in conjunction with overall satisfaction and goals, determine the moment-to-moment behaviors of married adults.

Although the current model introduces three putative mechanisms that influence behavior, we do not assume uniform influence during moment-to-moment behavior. Specifically, we posit that the level of satisfaction is the primary determinant of moment-to-moment interaction, with relationship goal and perceived alternatives having secondary and tertiary influences, respectively. This hierarchy is imbued in SimDyad and is discussed below in more detail.

### **DISAMBIGUATION: THE GENERATING MECHANISM**

Although the aforementioned micro-level behaviors and utility mechanisms provide a basis for understanding the evolving affective states of a marital dyad, they fail to articulate a macro-level generating mechanism that necessitates their invocation. We propose that a plausible mechanism might be disambiguation, or the reduction of uncertainty. Specifically, at each turn in



an interaction, the machinery invoking the behavior in the next small increment of time serves to reduce ambiguity surrounding the state of the relationship. Stated differently, we assume that behavioral nuances expressed during moment-to-moment exchanges simultaneously reflect and generate the dyadic state, and that each participant directs these features to minimize the ambiguity. In short, at each time step, overt behaviors simultaneously reflect, maintain, and modify the dyadic relationship.

## METHOD

At the Marital Interaction Lab at Arizona State University, we began collecting couple and family interactional data 15 years ago. Since that time, we have conducted numerous studies examining affective and behavioral expression in marital and post-marital interactions and the role of disease in interactions (e.g., Parkinson's disease in marital interactions and asthma in family interactions) (Griffin, 2002; see Griffin et al., 2004a, for an overview). Across studies, the general methodology for collecting adult dyadic data has remained the same. A brief overview is given here.

### Data Collection

Upon arrival at the Marital Interaction Lab, couples were greeted by a lab assistant and then seated in a room constructed to resemble a small living area containing prints, curtains, plants, and two chairs in the center of the room. Two unobtrusive, partially concealed, remotely controlled cameras were mounted on the walls at head level behind each chair. All audiovisual and mixing equipment was controlled from a room adjacent to the interaction. Video signals were combined, producing a split-screen image; audio was obtained from lavalier microphones worn by each spouse.

### Problem-solving Task

After completing informed consent forms, couples were given an areas of disagreement questionnaire (i.e., standard Strodbeck's revealed differences task; see Gottman, 1994). Each marital partner selected and ranked a list of potential disagreement areas typically associated with marital relationships, according to how much they disagreed and for how long they had disagreed. Couples were then instructed on how to use the affect generation computers in the lab (see below). After they became familiar with the procedure, they returned to their chairs. With the lab assistant's help, the couple selected the three most common topics from the list of problem areas and agreed to discuss them. The lab assistant then instructed the couple to engage in a 12-minute discussion and attempt to resolve the issues. This is a common task used to evoke interaction in married dyads (Gottman, 1994). Controlling the audio and video equipment from the adjacent room, the lab equipment operator recorded the couple's conversation.

### Affect Generation

After completing the conversation, lab assistants escorted the marital partners to their respective seats at the affect generation computers. The lab assistants left the room, and each

spouse then simultaneously reviewed and rated his or her own affect while watching a videotaped split-screen playback of the interaction. Separated by a partition and wearing audio headsets, husbands and wives could not see or hear their spouse while reviewing the videotaped interaction. A study using a similar methodology for recalled self-report of affect reported that the procedure was valid with respect to observational coding (Gottman and Levenson, 1985). The videotape was played back through a specially configured microcomputer by using software that overlays a nine-level, color-coded, vertical bar on each color video monitor. This overlay was positioned beside the face on the monitor of the spouse reviewing the tape. The affect rating ranges from extreme negative (red), through neutral (gray), to extreme positive (blue) and is controlled by a personal computer mouse. Extreme negative is at the monitor bottom, neutral is at mid-monitor, and extreme positive is at the top of the monitor. The width of the bar varies at each affect level (5-pixel increments) corresponding to the intensity of the affect; neutral is the thinnest. The widest affect level is 28 pixels wide (1.5 cm). As the reviewer moves the mouse, the affect bar corresponding to the degree and direction of the affect is highlighted. For example, as the individual's affect rating becomes more negative (positive), the mouse is pulled back (pushed forward), and the appropriate affect level becomes highlighted, and, as the highlighted area moves further from neutral, the width of the level expands to reflect intensity. During the review of the tape, and viewing only his or her own rating, each individual is asked to move the mouse to reflect affective experience during the interaction (i.e., "How were you feeling at each moment?"). In this context, affect refers to the speaker's assessment of an internal reference to the meaning of "feeling" (i.e., over a continuum from positive to negative). Software records the location of the bar position every second, providing a continuous measure of affect throughout the interaction. Average ratings are referenced to a reduced five-point scale: 1 and 2 = negative, 3 = neutral, and 4 and 5 = positive.

In this method of affect retrieval, each affect has a subjective reference that is unique to the rater, within the context of the interaction, given the dyad's history. For each individual, there is only an internal template referencing a positive, neutral, or negative affect state. In effect, an internal state that is pleasant to one individual may be only neutral to another. Moreover, because it is a self-report, it could be argued that such a recall procedure provides a good proxy of the true affect state and requires less inference than other data collection procedures that operate from an outsider's perspective (Griffin, 1993).

## **Behavioral Coding**

We initially code the "talk turn." Reliability is in the mid-0.9's (kappa). These codes delineate the conversational structure at each turn into the roles of speaker or listener. Nonverbal cues are then coded for each talk turn. "Nonverbals" is a listener category containing three positive attending behaviors (eye gaze, head nod, and back channel) and one negative contemptuous behavior (eye roll). We also code "gaze" for the speaker to examine if the speaker is looking when talking. Basically, we include this category to determine if the speaker has reason to perceive the listener is not listening, being disrespectful, or worse, being contemptuous. This impression of the speaker may or may not be evident by his or her actions, but it usually influences the affect rating, which then provides an opportunity to compare (e.g., ratio) the speaker's values versus the listener's values, either in real time or averaged across the talk turn.

Similarly, by using the "verbal" codes, we add more dimensionality by assessing whether the speaker is being generally helpful or facilitating (i.e., problem solution, agree) or destructive

(i.e., negative, such as making a hostile statement expressing unambiguous dislike or disapproval of a specific behavior engaged in by the partner or a comment intended to demean or embarrass the other person). These are also compared to the listener's attending behavior or examined for internal consistency with the self-reported affect. In effect, at each unitized time point (either a talk turn or in real time), we have information on how each person was feeling, the presence or absence of constructive or destructive statements, and attending behavior by the listener. In composite form, these coded behaviors form an index of the process at time  $t_x$  that permits the reconstruction, visualization, and pattern classification of dyadic interactions (see Griffin, 2000, 2002). See Griffin et al. (2004a) for an overview of the data collection and behavioral coding procedures.

### ABM ALGORITHM

By using the conceptualization of a dyadic process outlined above, we created a simple algorithm of agent interaction that consisted of three steps. In Step 1, an initial interactant matrix was populated with the probability of the appearance of each agent. These values were derived from best-guess estimates obtained from reviewing the literature and the data collected in our lab. There are eight agents per interactant; a randomly pulled value taken from a normal distribution with a specified mean and standard deviation was used to assign a likelihood of occurrence. The respective distributions for the four verbal agents were as follows: problem solve (0.5, 0.05); agree (0.5, 0.05); gaze while talking (0.65, 0.1); and negative female (0.35, 0.1) and male (0.25, 0.05). For the four nonverbal agents, the respective distributions were as follows: back channel (0.65, 0.05); head nod (0.65, 0.05); gaze (0.65, 0.10); eye roll female (0.20, 0.04) and male (0.10, 0.02). Consistent with the existing literature reviewing observational studies of marital interaction, females tend to be more negative and report higher levels of negative affect (Gottman and Notarius, 2000).

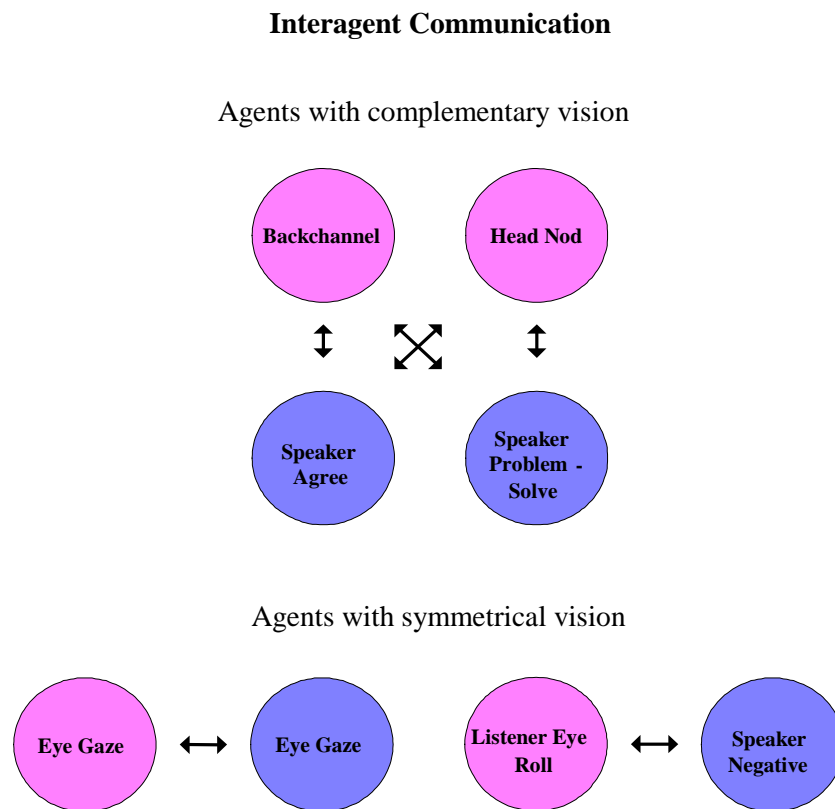
Step 2 consisted of creating an interaction scenario analogous to a 15-minute (900-second) discussion by a married couple. Similar to the interaction data obtained in our laboratory, a couple begins an interaction when one person speaks and the other listens. At each iteration, the respective agent groups (speaker [verbal] vs. listener [nonverbal]) are "displayed" by an interactant and evaluated by the other to determine similarity or "sameness." This evaluation method is discussed in more detail below. However, prior to the evaluation that occurs during each iteration, the value of each agent is examined and modified as a function of the expressed (1) relationship satisfaction, (2) relationship goal, and (3) perceived alternatives. More specifically, the probability value of the behavioral agent is modified as a function of relationship satisfaction (i.e., higher satisfaction increases the propensity for the agent [i.e., behavior] to appear). Next, the propensity to invoke relationship goal is inversely related to relationship satisfaction. Finally, the propensity to invoke perceived alternative is inversely related to relationship goal. In effect, as noted above, relationship satisfaction is the major factor determining moment-to-moment behaviors. Only when relationship satisfaction falls below a specified threshold does the influence of relationship goal contribute to behavior change; the situation is similar for perceived alternatives. (Additional details about threshold values and other aspects of code construction can be obtained from one of the authors of this paper, W.A. Griffin.)

Each agent (i.e., behavior) is modified at each iteration, and the collective agent grouping (i.e., verbal; nonverbal) is used to create the affect rating. Since the estimated affect rating,

analogous to the affect rating generated in the laboratory, is not observable, we construe it to be the emergent property of agent interaction. Each agent, although observable through either statements or behavior, contributes collectively to the nonobservable affective state. In the current model, affect is constructed as the sum of the inverse of the positive behaviors plus negative. For example, listener =  $[(1 - \text{head nod}) + (1 - \text{back channel}) + (1 - \text{gaze})] + (\text{eye roll}) \times (\text{scaling factor})$ . Calculated in this manner, a greater positive affect receives a lower score, whereas a higher score suggests greater negativity. This calculation method is similar to the one used in our laboratory studies and allows for easy comparison to our realized data.

Finally, in Step 3, the agent likelihood is again modified. As noted above, during each iteration, comparable agents assess whether or not the other agent is present. Comparable agents are defined as those agents that are complementary in their behavior. For example, listener head nod and back channel are complementary to speaker agree (see Figure 1 for a complete list). As noted in Figure 1, some behavioral agents have restricted vision (e.g., speaker gaze can only evaluate listener gaze), whereas others (e.g., head nod) can view multiple agents. This variable vision contributes to greater unpredictability in modifying the agent action.

Agent presence is assumed if the likelihood of the complementary agent exceeds a critical value, usually 0.5 at that particular iteration (i.e., talk turn). If each agent exceeds the necessary value, then at the end of the iteration, a slight modification in the dyad matrix occurs,



**FIGURE 1** Permissible communication links between agents

with the respective likelihood increasing for each agent. If either agent does not exceed the critical value during the window of examination (e.g., iteration  $t$ ), then the probability of being present is reduced in the next iteration. As expected, the joint presence of negative behaviors increases the probability of their subsequent presence in the next iteration.

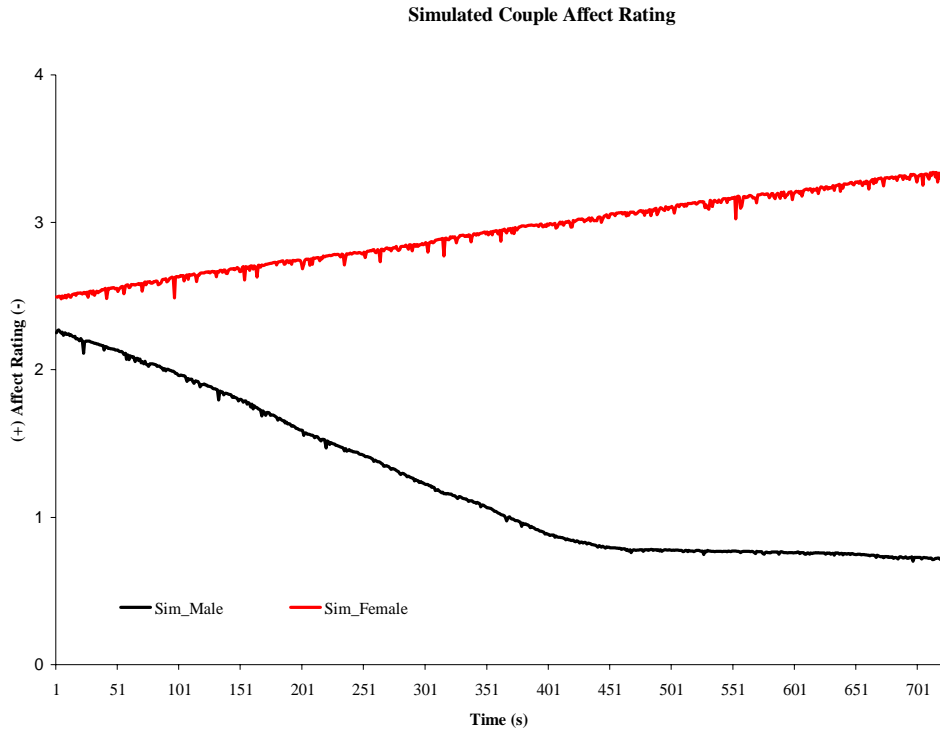
At this step, as the reader may have deduced, the computational attempt at disambiguation occurs. In effect, each person is cognizant of the behavior of the other person and responds in a manner that reduces the discrepancy. For example, an eye roll may or may not elicit a negative statement during iteration  $t_x$ , but the eye roll does increase the likelihood of a negative statement during iteration  $t_{x+1}$ . Similarly, when it is assumed that speaker agree co-occurs with listener head nod at  $t_x$ , the likelihood of their joint appearance at  $t_{x+1}$  increases. However, if only listener head nod occurs, hence creating a discrepancy, the chances of a head nod occurring at  $t_{x+1}$  decreases, thereby increasing the odds that neither will co-occur during subsequent iterations.

## RESULTS AND DISCUSSION

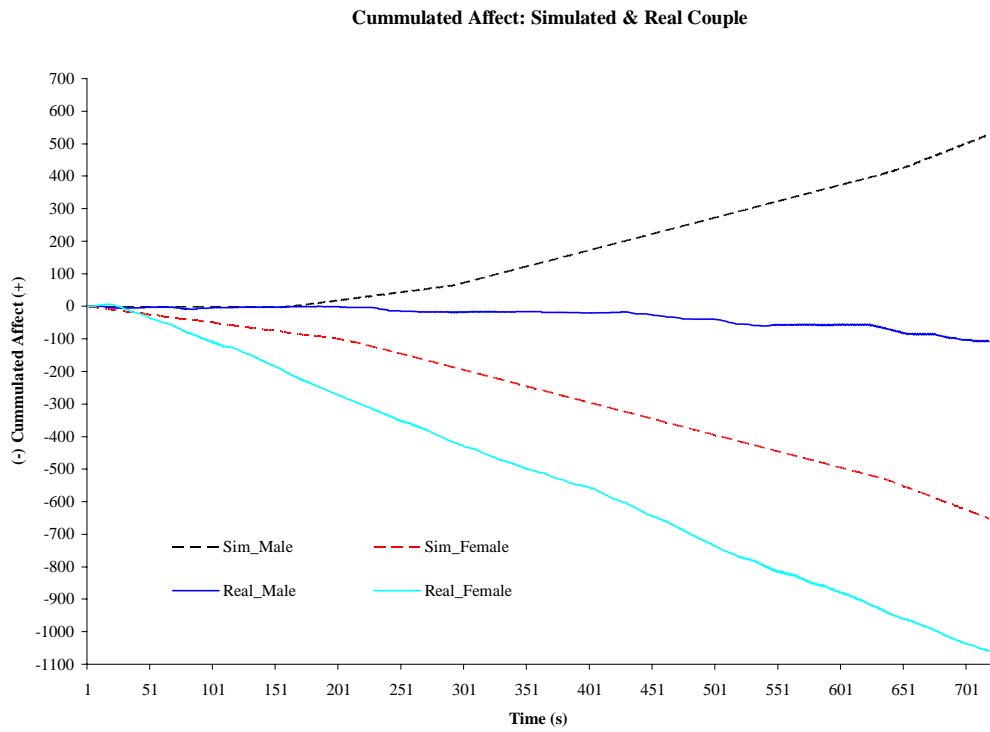
To assess the viability of SimDyad, we ran several hundred simulations by using various combinations of relationship satisfaction, relationship goal, and perceived alternatives. Because of the newness of SimDyad, simulation runs were used to modify codes until we were able to obtain output that was consistent with our expectations, given the input parameters. For example, if SimDyad, in its current configuration, is given an interaction between a moderately satisfied male (65/100) with moderate goals for the relationship (70/100) and minimal perceived alternatives (10/100) and a slightly dissatisfied wife (45/100) with low goals for the relationship (30/100) and minimal perceived alternatives (10/100), the model can produce output that looks similar, albeit less variable, to output by real couples with similar attributes (Figure 2). As evident by the path shown in Figure 2, as the interaction continues, the wife becomes more negative (i.e., the value increases), whereas the husband initially becomes more positive (i.e., the value drops), then maintains a lower level throughout the interaction.

This is very typical of a profile generated by actual couples in our laboratory. A couple with similar relationship scores was located, and their affects were plotted on a cumulative affect graph (Figure 3). For Figure 3, we reversed the affect direction and then plotted the cumulative values. When the values are plotted in this form, it is easier to see trends over time. Note that the simulated couple shadows the real couple; however, the male in the real couple reported lower relationship satisfaction (than the simulated male), owing to the lower cumulative trend.

Although SimDyad reproduces affect patterns that are consistent with expected and realized patterns, it still lacks several features that we consider essential for replicating dyadic interactions. First, the generated affect rating lacks the variability seen in realized data. Although we introduce stochasticity at several locations per iteration, it does not induce sufficient lability. It would be simple enough to increase variability by modifying code, but doing so without a strong rationale or theory would be antithetical to the empirically derived generating mechanisms used to construct the model.



**FIGURE 2** Simulated couple interaction



**FIGURE 3** Cumulative affect rating of simulated vs. real couple with comparable satisfaction levels

A second, and possibly somewhat more worrisome, problem is assessing the veridicality of the model (defined by Carley [2002] as model truthfulness). As discussed in Griffin et al. (2004b), it is possible that we can replicate realized data and still not be using the actual generating mechanisms. This problem, however, is beyond the scope of this discussion. Nonetheless, we are implementing several things in the revised SimDyad to assess model fit and veridicality. First, we are attempting to compare simulated outputs to realized data by using matched couples. Differences in the second-to-second affect rating are used to score the simulation. These scores are then used to modify parameters (e.g., role of relationship goal). The simulation is re-run, and assessments are made again. Note, however, that even real couples with very similar levels of satisfaction show moderate variability in their affect ratings.

Second, our objective is to eventually perform a sequential analysis of the behavioral agents generating the affect rating. Ample data have been generated in our lab that would permit the analyses. By comparing realized data and their associated affects to our simulated behaviors and their resulting affects, we can assess whether the two types of data have similar generating processes.

### ACKNOWLEDGMENT

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## PLAYMATE: NEW DATA, NEW RULES, AND MODEL VALIDITY

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### ABSTRACT

A paper presented at the Agent 2003 conference illustrated how PlayMate, a multi-threaded agent-based model, simulated the formation of playgroups in preschool children. Each child (agent) possessed rankings on multiple attributes. Homophily, sex, and memory were used as the other critical features of group emergence. In an attempt to reassess model fit, an additional year of data and an increased sample size were later added to the model. Also, to simplify the model, attribute variables were reduced to those that were initially found to predict group formation. An affect variable generated by and reflective of peer dynamics was also added. As speculated, the affect variable in the current version is a better predictor of model fit than the static variables used in the previous iterations of PlayMate. Moreover, preliminary evidence suggests that children use emotion to evaluate the utility of maintaining their relationships with other children and that relationships change in proportion to the amount of time spent in established groups. In PlayMate, it continues to be difficult to simulate high-density cells.

**Keywords:** Agent-based model, ABM, group process, preschool peer group

### INTRODUCTION

Ubiquitous self-organizing animal and human groups have increasingly become the focus of research by scientists interested in social dynamics. These groups range from married couples and co-workers to large crowds, with each type of group having a distinct structure and ontology. What is not clear, however, is how discrete entities, each with unique attributes and preferences, contribute to the formation of these groups. Even less is known about the socio-developmental processes involved in these groups or the influence that these processes may have on subsequent group evolution. One contributing factor to this shortcoming is the difficulty in capturing these dynamic social processes in their natural contexts. Most researchers do not have the opportunity to observe the formation of a couple or the development of a growing family. As a result, social scientists have resorted to explaining the process via static traits or individual characteristics. These methods may provide some preliminary insight into group formation, but they lack the dynamical process components that illustrate how complex socio-developmental contexts emerge and evolve.

Although natural environments that contain the possibility of group formation are difficult to find, the task is not impossible. Over the past few years, we have been collecting naturalistic observations of children in their preschool and kindergarten environments. In the fall

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of each year, new and returning children come together in our university child development lab. Eventually they settle into groups of semi-stable play partners. We can thus examine some of the intricacies of playgroup formation and stability in each year's cohort. When children play, they exhibit a huge range of behaviors, yet much of their behavior is also restricted and redundant. This odd mix of behavioral and affective novelty combined with redundancy and pattern provide a natural laboratory for studying the complex evolution of groups.

A focus on social processes requires the use of methodologies that account for the complexity of the differential systems housing the interactions. Recent advances in computer-based simulation, specifically agent-based models (ABMs), provide a tool to achieve this goal. ABMs allow us to simulate clustering based on agent attributes and to model how these groupings subsequently modify the environmental field that permits the expression of these attributes. We can also model the concurrent materialization of peer preferences. Finally, we assume the evolution of these preferences modifies the influence of child attributes and the co-existing environment.

From this primary assumption, secondary assumptions are made. First, we assume that the propensity to play is driven by ontological characteristics of the child and by the quality of the group interaction. Second, we assume that the quality of mutual dynamics is generated by reciprocal exchanges that predict the subsequent propensity to play. Finally, we assume that quality is a function of child-to-child homophily, or high levels of within-group similarity (Berndt, 1982). Therefore, we propose a model of dynamical influence that incorporates (1) the ontology of the individual child, (2) the influence of this ontology on the likelihood of group formation, and (3) the influence of relationship quality and the frequency of interaction on the social trajectory of the individual child and the group. Within the framework of these assumptions, we address two basic questions: What is the utility of group play? What mechanisms do young children use to evaluate the cost and benefits related to group play?

At the Agent 2003 conference, we illustrated how PlayMate, a multi-threaded ABM, simulates the formation of young children's playgroups based on the individual attribute rankings of each child (Griffin et al., 2004). Although the ABM adequately simulated real data, we have tried to improve the model by (1) simulating an additional year of data on a larger number of children (57 versus 18) across different classrooms and (2) developing an affect variable that is sensitive to inter-child dynamics within evolving groups.

## **PLAYGROUPS**

### **Peer Preferences and Socio-emotional Processes**

We assume that each child brings a unique set of behavioral and affective propensities to his or her interaction with another child and that consequently the group develops idiographic interaction rules. These rules, sensitive to environment change and intra-group variation, evolve as the group coalesces. Implicit in this description is the allowance for increased interactional flexibility and behavioral novelty with each moment-to-moment exchange. Quantifying such a process allows an investigator to answer the following two questions. How do moment-to-moment exchanges within the group serve as a mechanism to determine relationship quality? How does the relationship quality influence the subsequent propensity to play?

For preschoolers and kindergartners, the affect displayed during a typical play exchange is probably the best indicator of relationship quality for a stable or semi-stable group. These affective exchanges, in their simplest form (i.e., positive, negative, neutral), give each individual in the group an opportunity to convey his or her like, dislike, or neutrality about what is currently occurring in the interaction (Ekman and Friesen, 1969, 1978). Although, in general, all emotions are available during any given social exchange, scientists have focused primarily on two: positive and negative (Denham et al., 1990; Macguire and Dunn, 1997; Walter and LaFreniere, 2000). Unquestionably, positive and negative emotions play an important role in determining the propensity for children to play. However, neglecting neutral expressions predisposes the investigator to lose possible critical information about micro-social processes and eventually bias the interpretation of the process. To date, only Vaughn et al. (2001) have examined the role of neutral, as well as positive and negative, affects as being critical features used by children to initiate play. The findings were clear: initiations of peer interactions predominantly involve neutral affect.

If peer interactions are, in fact, characterized by disproportionate amounts of neutral emotion, we can consequently speculate that enduring peer groups (i.e., stable groups) contain either more or less neutral affect than is typical, or instead contain an additional emotional component — most likely positive emotion. The plausibility of this latter possibility (the addition of positive emotion in stable groups) is well supported in the literature (Newcomb and Brady, 1982; Denham et al., 1990; Newcomb and Bagwell, 1995). However, quantifying the ability of positive emotion to modify the subsequent propensity to increase play between peers is a difficult, although not impossible, task. Conceptually, this impact is measurable by using the basic tenet of information theory (Shannon and Weaver, 1949). Specifically, if we assume that neutral emotion is prevalent and essentially redundant, we can assume that the rare expression of positive emotion contributes unique information to the members of the group, and when positive emotion is present in amounts greater than expected, it increases the desire to subsequently play with a particular child.

Essentially, an affect expression can be viewed as the manifestation of the internal state of the relationship. Thus, we can assume that the affective environment, evident in moment-to-moment interactions, provides the milieu for extracting the information used to evaluate the utility of continuing to interact with a particular child. Preliminary work by Ladd (1999) supports the idea that young children have the ability to evaluate their relationships. If we assume that displayed affect provides the peer group with the necessary information needed for these evaluations, then as peers maximize positives within their interactions, an important objective is achieved: preservation of the group (Dishion et al., 1994; Ladd et al., 1996). We propose that as these evaluations accumulate over time, children use them to determine whether or not to play with their peers.

Although the addition of positive affect likely provides critical information for group formation and stability, the amount of positive affect that a young child exhibits is best understood as the proportion of positive relative to the overall affective expression. For example, from existing economic models, we can assume that if we are correct in identifying positive affect as the primary indicator of group stability, then a child will produce only the amount of positives necessary (relative to the entirety of their affective makeup) to achieve a desired benefit (Nass, 1996). This, of course, is plausible only if energy expenditure is higher for a positive affect than for either a neutral or possibly negative affect. It is currently unknown what benefit(s) is (are) specifically derived from play. Despite the lack of this knowledge, however, there is

strong evidence in the ethology literature to suggest that no organism, particularly large mammals, can afford to expend energy without producing some outcome that will promote its long-term success of survival (Altman, 1984, 1987; McNab, 1986). This suggests that positive affect expression is essential in establishing interactions, but because of the cost, the proportional use of positives will decrease over time as relationships become more stable.

## **Static Characteristics**

The concept of emotional expression as a determinant of a child's desire to play with another child has intuitive appeal as well as some empirical support. Emotional expression is, however, constructed as a dynamic modifier of that desire to play: its impact can change over time and with new circumstances, new peers, factors external to each child, and a host of other influencers, some known and others unknown. Consequently, to aid in interpreting its role in the stability of peer friends, we also need to examine the demographic characteristics that each child brings to the group interaction. Consistent across the peer literature and evident in our previous model, gender appears to be a determinant factor in the peer selection process (Maccoby, 1988, 1990, 1998; Serbin et al., 1994; Martin and Fabes, 2001). It is possible that the match in physical appearance provides some social signal of "sameness" to same-sex children, and that the idea of sameness somehow influences their belief that interaction would be enjoyable (Kohlberg and Ziegler, 1967). In effect, gender serves as a semaphore for activity preference in same-sex children, and thereby it increases a child's propensity to play via physical proximity to an activity.

While gender sameness may be one potential influence of who plays with whom, it does not provide micro-social process information. Yet, it could be speculated, for example, that sex sameness modifies emotional expression during group play, and that this modification, in turn, modifies the likelihood of additional play between the interactants. This is not an established fact, and any investigation of the socio-emotional process described above would need to account for the concurrent influence of these two salient features.

## **Behavioral Characteristics**

In addition to the influence of demographic characteristics, the quality of group relationships may also be modified by skill sets or behaviors that children bring to their interactions. Like affect, these behaviors are indicative of ways children attempt to engage peers in social contexts, and they likely provide cues about the state of the group relationship. While a range of unique behaviors has been noted in the peer literature, previous iterations of PlayMate indicate that prosocial and socially inhibited behaviors are the best indicators of play propensity. Like gender, it is possible that the presence of either prosocial or socially inhibited behavior has the bidirectional effect of modifying emotional expression and subsequent propensity for interaction. In fact, from previous observational literature, we know that behaviors are a proxy of displayed affect and provide information about the state of the relationship (Gottman and Notarius, 2000; Griffin, 2002). However, given that these variables were collected via static methods (i.e., one-time teacher or observer report), we have no accurate way of accounting for the interaction of behavior and emotion, nor for determining if behavior is likely to change over time as a function of group evolution. As a result, we attempt to increase the accuracy of the model by using emotion and comparing its fit to the realized data.

## Homophily

At the micro-level, displayed affect (as it is influenced by gender and possibly behavior) is a plausible predictor of play preference. However, to appreciate the general process of peer selection, a macro-level generating mechanism is also needed. Given that children's playgroups are characterized by homophily (Berndt, 1982), we can assume that homophily increases play propensity. Essentially, children seek out similarities in their peers, with gender and behavior providing a preliminary reference point to signal sameness. In turn, these dimensions modify the moment-to-moment affective exchange, thereby further altering the perception of sameness. As each child interprets emotion and behavior and evaluates the sameness of the other child, the value of continued play is assessed.

### SIMULATING PLAYGROUPS: PLAYMATE

By using static and dynamic child attributes to modify the likelihood of interacting with another child, PlayMate provides a representation of postulated developmental shifts in playgroup formation for children ages three to six years. Each child, represented as an agent, can be in one of four states: (1) playing with another child, (2) playing with an adult (a teacher), (3) playing alone after playing with another child, or (4) playing alone after playing with an adult. Two key components are used to model the shifts in play likelihoods between and among children across the four states. The first is play propensity, the likelihood that any specific pairing of children will occur. The second is arousal, a behavior proxy (of a child's internal configuration of cognitions, affects, and behavioral tendencies) that externally characterizes the propensity to shift states. Arousal does not imply a change in physiological systems (e.g., central nervous system); it is a descriptive term to indicate the current level of a child within each state as he or she moves toward shifting states.

The underlying mechanism PlayMate uses is briefly described as follows. At each observed epoch (analogous to a single real playground observation), a child is in one of four discrete states (noted above). Although the child is in a particular state, he or she has a cumulating value in each of the four states that is used to allow spontaneous state transitions (excluding those logically not permitted, such as solitary [3] following solitary [4]). In "round-robin" fashion, a child is selected to play with another child from the available pool (one is randomly removed to simulate a "sick" day). Upon pairing, child  $i$  assesses child  $j$  on several dimensions determined by the investigator; minimally, these include sex and the relevant attribute (e.g., emotion) being examined. Arousal, and thus the propensity to leave the child-playing state, increases in proportion to play partner dissimilarity. The greater the homophily, as assessed by closeness on the variables in the model, the less likely the child is to leave the child-playing state and continue playing with other children. This reduces the amount of solitary play and increases the likelihood of a child playing with other children as long as they are similar. After each play episode, the assessed attribute level difference is used and two things happen. First, the arousal level of each state is updated according to a set of transition rules and values associated with those rules. Second, the degree of similarity in attribute level, plus the assigned value for sex similarity, plus a memory value (higher value assigned to having played recently) are converted to an integer value associated with an investigator-determined curve (e.g., exponential). This value is then entered into an adjacency "tally" matrix. This matrix is a proxy to the observation matrix containing real data. After each run, the simulation tally matrix

is converted to a child-to-child play probability matrix and compared to a similar matrix derived from actual data. (Griffin et al., 2004, has additional details.)

Real data were collected via intensive 10-second observations of children's naturally occurring interactions at preschool and kindergarten. Real-time observations of emotions and play partners were recorded into handheld computers and repeated for a randomized list of children in each classroom. The data were collapsed into six time frames, each consisting of approximately 2,000 to 3,000 observations, with the reliability of each coder consistently found to be high (see Martin and Fabes, 2001, for an example).

To assess model fit, PlayMate generates numerous quantitative indicators of the structural and compositional differences between the simulated and real data. These indicators include difference measures of Euclidian distance, mean cell values, entropy, uncertainty reduction (a measure of mutual information), solitary play, and row (i.e., child) signal-to-noise ratios. Each measure is assumed to provide slightly different information about the characteristics of the matrix's structure.

## Data Simulation

Before the simulations were run, each child received a score based on three factors: gender, attribute level, and memory. For gender, each child received a binary number (e.g., 0, 1). Rank orders were given on the basis of a summary score for prosocial and socially inhibited behavior. Rankings for emotions were based on the ratio of positive to all affective occurrences. Finally, integers for memory rankings were based on a list of recent play pairings, with a current capacity of five possible pairings.

For the current iteration of PlayMate, simulation runs consisted of each child in the class playing 50 rounds in the round-robin fashion. Performing the routine 50 times allowed us to obtain approximately 75–120 play episodes, characteristic of the numbers obtained for each child in the real data within each time frame. State shift and play partner propensities were influenced by the three factors, with each variable weighted according to the theoretical justification that displayed affect and its proxy (i.e., behavior) being the strongest predictors of peer selection. Essentially, increased peer preferences were determined by the aggregate of the three factors, with an attribute level difference modifying the likelihood of being in a child play state.

## RESULTS

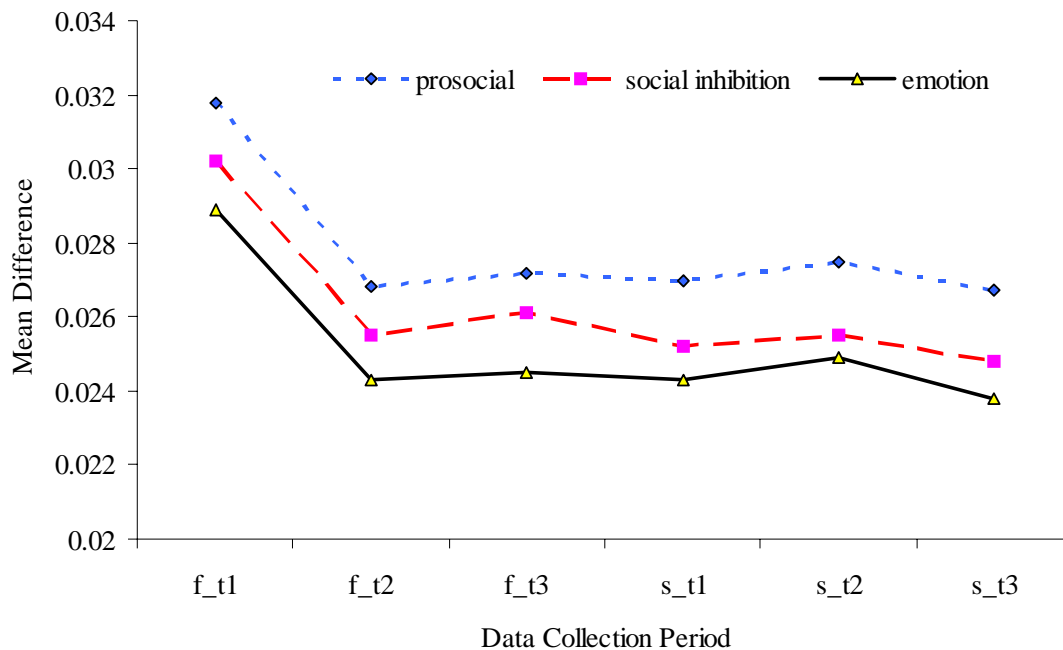
In an attempt to capture the natural dynamics of the population under study, we initially ran the model to produce simulated matrixes that included all possible combinations of pairings across the three classrooms. However, given the limited availability for contact between the preschoolers and the kindergartners in the actual data, the sparseness of the real matrix in conjunction with the round-robin method invoked in PlayMate was not an appropriate combination for the specification of the model. As a result, all subsequent simulations were run on two different groups — the kindergarten classroom alone and the two preschool classrooms combined. In addition, peer availability was restricted to within class selection for producing the realized and simulated tallies.

Consistent with previous iterations of the model, the two indexes most sensitive to children's attribute difference were Euclidean distance and mean cell difference. Figures 1 and 2, showing mean cell differences for preschool and kindergarten children, respectively, indicate that the affect variable had a better fit (i.e., a smaller difference) than either prosocial or social inhibition for 10 of the 12 data points.

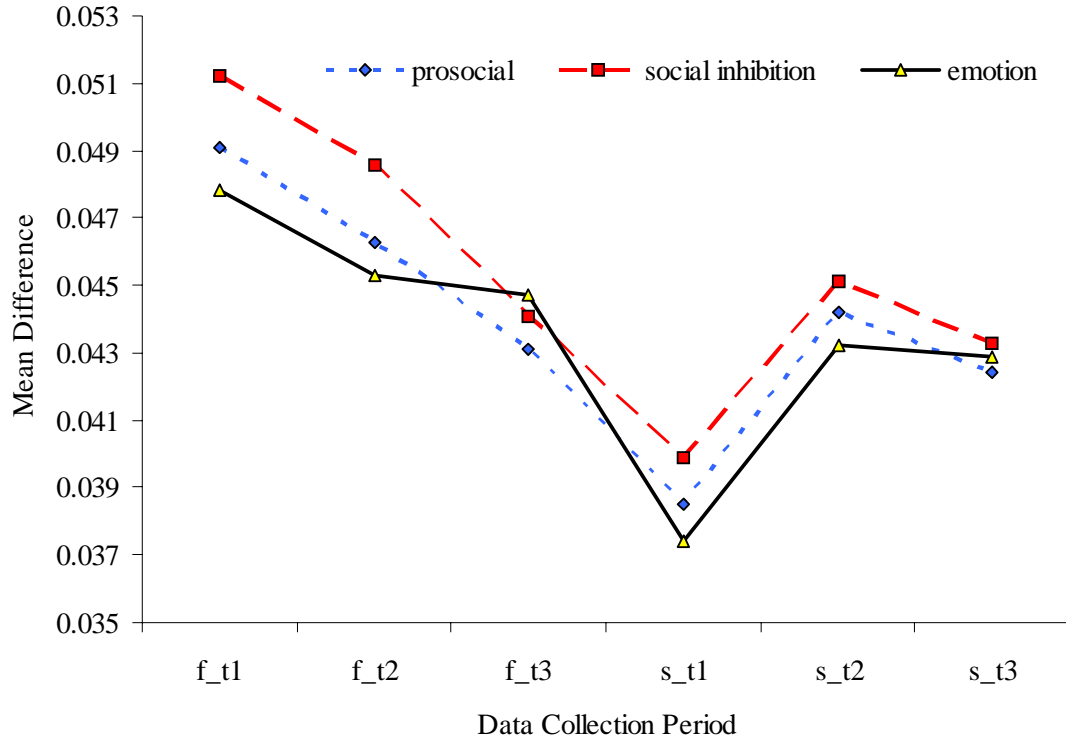
In addition, Mantel tests (Dietz, 1983) indicated that while the model fit well for preschoolers across each of the six time periods, significant correlations between the real and simulated matrixes deteriorated over time for kindergartners (Table 1). The scattergrams of the kindergarten data clearly suggest that most cells are characterized by no more than 10 observations per time period. Initially, this result appears promising, given that the simulated matrixes are producing these values the majority of the time.

However, two cells had extremes as high as 40 occurrences in the real data and only simulated values of 6 and 7. In summary, the observed affect manifested in the moment-to-moment interactions of young children was better associated with the matrix fit than with a static, one-time report of behavior by a teacher or observer. However, as children move away from solitary play over time and develop established play partners, the values in the matrix disperse out into the rows. Unfortunately, the current version of PlayMate lacks a mechanism to capture these changes.

In an attempt to test preliminary ideas related to the utility of emotion and its changing function over time, a repeated measures ANOVA was conducted. As hypothesized, a main effect for the decrease in the proportion of positive affect over time was found:  $F(1,43) = 317$ ,  $p < 0.001$ . In addition, the interactions of groupXemotion and between subjects tests were



**FIGURE 1** Mean cell difference between simulated and realized data for preschool children



**FIGURE 2** Mean cell difference between simulated and realized data for kindergarten children

**TABLE 1** Significance levels for simulated versus realized matrix fit from using Mantel test

Class <sup>a</sup>	Time	<i>p</i> Value
K	1	0.035 <sup>b</sup>
P	1	0.031 <sup>b</sup>
K	2	0.23
P	2	0.006 <sup>b</sup>
K	3	0.005 <sup>b</sup>
P	3	0.011 <sup>b</sup>
K	4	0.88
P	4	0.000 <sup>b</sup>
K	5	0.36
P	5	0.000 <sup>b</sup>
K	6	0.11
P	6	0.000 <sup>b</sup>

<sup>a</sup> K = kindergarten; P = preschool.

<sup>b</sup> Significant at  $p < 0.05$ .

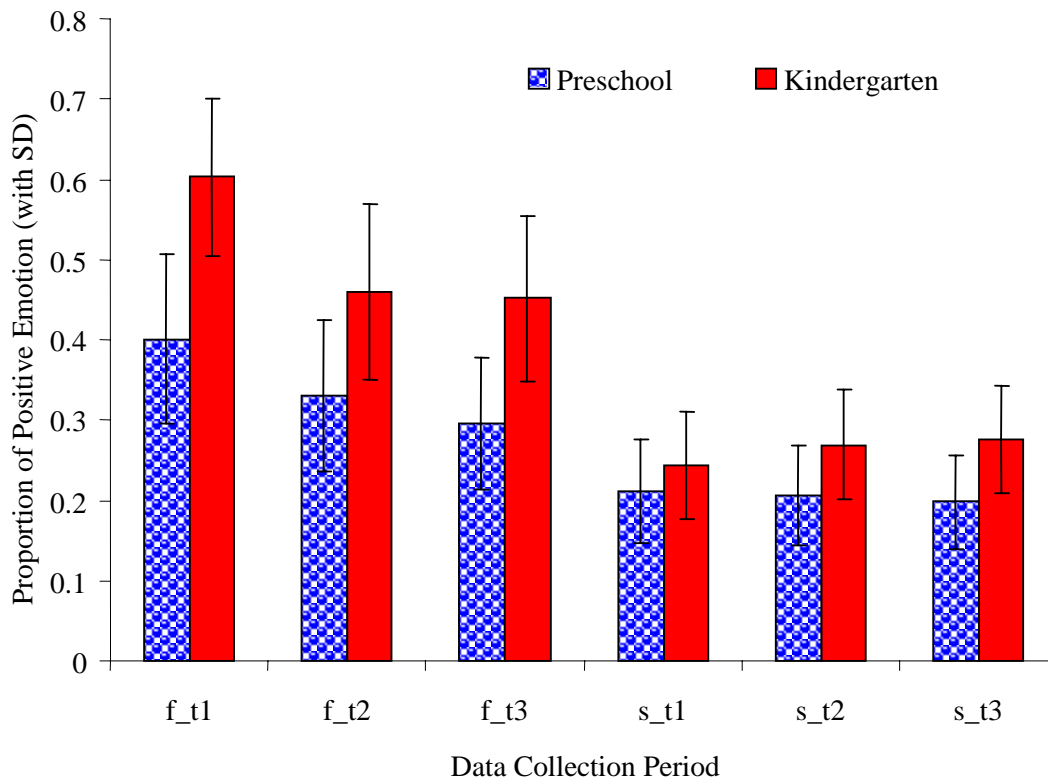


significant:  $F(1,43) = 19$ ,  $p < 0.001$ , and  $F(1,43) = 30$ ,  $p < 0.001$ , respectively. As seen in Figure 3, although both groups decreased their proportional use of positives over time, the kindergarten class decreased their use at a more rapid rate.

## DISCUSSION

Although improvements have been made to previous versions of PlayMate, two areas of concern should be noted. First, although the model did a fairly good job of mapping onto mean-level play propensities, it continues to have difficulty specifying high-density cells. In a real population of young children, or in any normally distributed population, extremes are expected. For example, in this particular year of real data, we encountered one autistic child who rarely played with other children and another child who spent more than 80% of his time in solitary play. In addition, a few children in the real data appeared to pair off early and show extreme exclusivity with one particular partner. While these extremes are somewhat expected in real data, we have yet to develop a method to effectively model them without inhibiting our ability to capture the general behavior of the classroom.

A second area of concern involves the static rule implementation in the current version of PlayMate. The programming code is written to allow homophily to generate the dynamics of who plays with whom. However, we have no mechanism for allowing rules to evolve over time as a function of the evolution of the group itself. While homophily may be a primary influence on initial group formation, it is likely that over time and with increased frequency of



**FIGURE 3** Observed emotion by class and time period

interactions, the social rules regulating group formation and maintenance change. These changes probably reflect the need for parsimonious energy expenditure during play and the concurrent reduction in variability among play partners. Theoretical and computational models that postulate the threshold levels of play frequency (and density) that induce these putative changes need to be developed. Such models should enable us to pick up the problematic high-density clusters and, as a result, produce stronger evidence of model validity.

Despite the aforementioned shortcomings of the current model, two important objectives were achieved. First, we replicated evidence that PlayMate maps onto real processes involved in group formation. Second, we developed a more sensitive measure (i.e., affect) that is capable of capturing the dynamics within and across groups as well as across time. The latter objective is critical for understanding the cohesion of social interaction and will become increasingly more important as future attempts are made to further determine the utility of play for children. Moreover, developing better measures will aid in formulating the function that affective exchange serves in the evaluation of that utility, and, finally, how similar processes translate into other types of social networks.

In its current form, PlayMate provides the preliminary foundation to suggest that the degree of friendliness is inversely related to the familiarity of the group over time. From a coupled economical and biological premise, this makes intuitive sense: the goal of any complex adaptive entity is likely to minimize the amount of energy expended or the cost required to achieve the intended benefit (e.g., see optimal foraging theory as discussed in Beauchamp, 2003, and Vucetich et al., 2004). If, in fact, positive affect requires energy expenditure and provides the milieu that children use to preserve the group, it could be that once the group exceeds a particular threshold (i.e., becomes a stable group), the members of the group no longer need to provide new information for the purpose of maintaining the already established group (i.e., the continued use of proportionally high positives would become redundant information and an unnecessary expenditure of energy). Given the difference in the rate that this effect is accomplished by the kindergarten and preschool groups, it could further be speculated that there is an advantage to achieving developmental maturity. Essentially, the older the child, the more social experience he or she is likely to have had. Older children are thus likely better at reading the requirements of social situations and, in turn, quicker at minimizing the required energy expenditure over time. Although it is yet to be determined whether this particular finding is a function of age or learning, it is likely that age and learning are correlated. If this is the case, we can assume that, on average, social acumen increases with developmental age.

Although the idea of behavior serving a utility function has been supported in various areas of the ethology literature (Real, 1991, 1996; Montague et al., 1995; Schank and Alberts, 2000; Deaner et al., 2005), the attempt to explain human behavior from this perspective remains speculative and untested. Examining human behavior, specifically children's social interactions, as phenomena from this particular framework first requires a more microscopic focus on the smallest social units possible (i.e., unique dyadic pairings). Doing so will aid in determining whether the phenomena occur only as a function of aggregation across the system or whether they occur in each stable pairing, and subsequently, in determining if the combination of dyadic pairings produces the effect at the group level. More important, adopting this type of framework requires theoretically and empirically answering a fundamental question that has been unexplained thus far in the child development literature: Why do children play? What do children get from interacting with other children that essentially promotes their adaptation and survival as a young member of a complex species? Obviously, children cavorting on a

playground appear to be enjoying the activity. This enjoyment requires energy, however, and no complex species can afford to engage in such energy expenditure without achieving some evolutionary gain. To assess this gain, we must pose questions and test models that attempt to define generating mechanisms for behavior. As determined by all iterations of PlayMate thus far, homophily is capable of explaining a fairly adequate proportion of play propensities. However, a large portion of the picture remains a mystery. Even though answering these types of questions is challenging, to truly understand the processes occurring within social interactions, we must first understand what drives individuals to engage in those interactions. Fortunately, computer simulations and ABMs are powerful tools for examining these questions from a framework consistent with the very dynamics that influence the emergence of the phenomena in question.

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## PROTOTYPE CONCEPTS AND SOCIAL INTERACTION

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### ABSTRACT

The modeling of human decision making will benefit from the use of interpretative agents that can assign meaning to situations. Meaning can be based on three interpretive mechanisms: prototype inference, situation definition, and orientation accounting. These mechanisms work together to create individual and collective interpretive responses to circumstances and events. This paper is a progress report on modeling with interpretive agents.

**Keywords:** Agent-based modeling, interpretive agents, social prototypes, prototype concepts

### INTRODUCTION

In communication and action, human actors are oriented by meaning and its attribution. In every situation, we consider, discern, define, attribute, convey, question, dispute, affirm, reconsider and evolve its meaning. Inevitably, the attribution of meaning is an indexical process: the meaning of referents is determined by interactive context. Participants may also view shared situations as having distinctive, or even conflicting, meanings.

Meaning attribution is dynamic, often shifting rapidly. Notwithstanding, it is actor interpretation and interaction that shape and inform the flow of communications and acts. An “interpretive agent” (IA) computational research strategy emphasizes the way that meaningful responses to circumstances are produced via social interaction. In the context of artificial society and multi-agent systems (MAS) strategies, interpretive agents themselves remain relatively simple, while their interaction process is comparatively rich.

### INTERPRETIVE AGENTS

Modeling social agents is a compelling area of research for a number of reasons, including the complexity of the domain, its applicability to a significant range of real-world situations, and the inherent challenge of IA design and modeling issues. Modeling the social interaction of agents has richer potential when the agents’ interpretive process is addressed. Designing such agents requires caution, since modeling even simple interpretive behaviors in agents can multiply computational complexity to exponential levels. The IA strategy developed in Sallach (2003) undertakes to capture domain complexity without confronting the limits of

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computational constraints. The approach emphasizes shared social prototypes and actions by using three mechanisms to simulate the meaning-oriented and nonlinear nature of social interaction.

In its current architecture, the IA strategy is based on three assumptions and three mechanisms. The three assumptions and their rationales are summarized in Table 1.

Cross-translation captures more of the complexity of human conceptualization and decision making than, for example, symbolic representation can. Fields of orientation combine both cognition and emotion. The modeling of orientation fields allows experimentation as to how natural agents reason about complex and diverse phenomena.

Situated reactions to events, and the ensuing shared discourse, establish the dynamic contours of culture. Agent simulation, however, has not yet incorporated this form of knowledge representation. It is a premise of the IA research program that the utilization of topological inference can help produce a second generation of social agent simulation (see, for example, Gardenfors 2000).

Three interpretive agent mechanisms and their associated dynamics are summarized in Table 2.

The three mechanisms work together to create individual and collective interpretive responses to changing circumstances and events. In aggregate, such mechanisms can also simulate the process of cultural construction and evolution. The present paper is an interim report on the IA research program.

## CONCEPTS WITH RADIAL STRUCTURES

Prototype concepts are an empirical discovery of cognitive science. Once recognized, they can be theorized or modeled, but their form was identified through experimentation. Prototype structure is multi-dimensional and radial, with a (possibly idealized) exemplar at the

**TABLE 1** Interpretive assumptions

Assumptions	Rationale
Agent experimentation	Agent simulation provides a productive domain for experimentation with models of interpretive agent interaction, allowing exploration of diverse ontological and epistemological assumptions.
Continuous/discrete cross-translation	Natural agents dynamically translate from continuous settings to discrete models, and back into nuanced communication and calibrated action. Social agent models will improve in responsiveness and sophistication by simulating this process.
Fields of orientation	Natural agents dynamically maintain an orientation field with an emotional valence maintained or derived for every relevant actor, situation, object, and resource. Changes in cognitive models and/or emotional valences cause a shift in the orientation.



**TABLE 2** Interpretive mechanisms

Mechanisms	Dynamics
Prototype inference	Human agents organize concepts into prototypes (i.e., radial structures oriented by exemplars) and draw inferences relative to those reference points.
Situation definition	Social actors maintain prototype concepts of situations and orient prospective actions relative to these concepts. Prototype situations are open-ended and evolve with each interaction.
Orientation accounting	Human agents are sensitive to the orientations of other actors, whether present or absent, living or historical, and even real or fictional. Anticipating such responses, their reactions are shaped accordingly.

core while more idiosyncratic representatives reside along the radians. Prototype concepts and reference point reasoning can be seen as defining the form that is taken by bounded rationality.

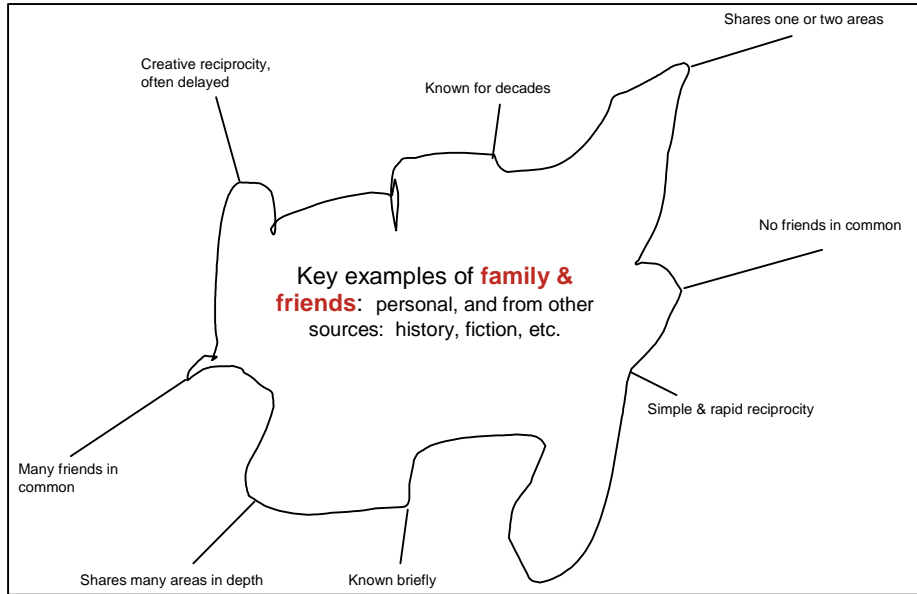
Prototype effects have been identified in concepts of many types (e.g., birds and animals, human emotions, and social relationships). Thus, robin, love, and friendship are clearly better exemplars of their categories than, for example, ostrich, ennui, and clerk, respectively. Even mathematical objects manifest prototype effects in ways that are highly revealing. For example, two and four are seen as prototypical even numbers as opposed to, say, 112 or 4,516.

A prototype concept is constructed from a set of (sometimes irregular) dimensions. As illustrated in Figure 1, a prototype concept of an affinity relationship might vary along axes of (1) the extent of relationship, (2) the number of common acquaintances, (3) the shared areas of interest, and (4) the immediacy and symmetry of reciprocity. As values vary along these (and potentially other) dimensions, the nature of the relationship will be considered more (or less) prototypical. In reasoning, concept exemplars form a *reference point* relative to which situations and actions can be assessed.

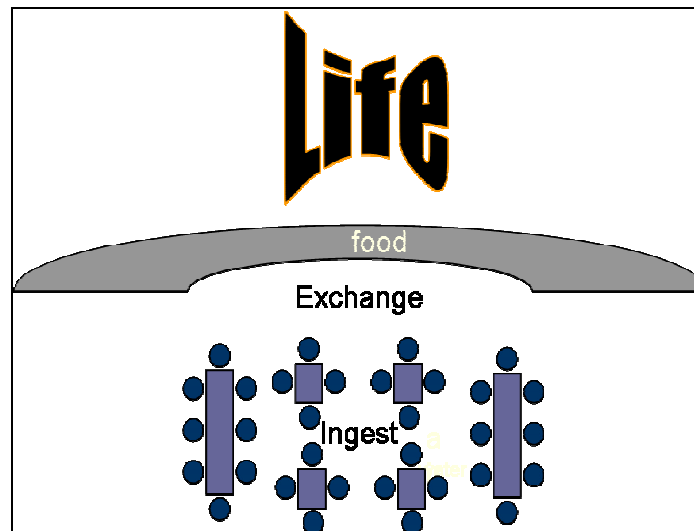
Prototypes are the form that concepts take under the limits of bounded rationality. Like other concept forms, prototypes are used in combination. Figure 2 shows a simple example in which life, food, exchange, and ingestion are combined within the integrating concept of restaurant.

Different actors typically combine concepts in somewhat different ways and to different extents. As a result, meanings are continuously negotiated among participants.

A sample restaurant discourse structure is depicted in Figure 3. The hypothetical conversational participant is prepared to discuss, with equivalent priority, politics, work issues, and rumors that capture his or her interests. In the absence of a specific topic, s/he will engage in casual sociality. When restaurant employees take orders, serve food, etc. (as illustrated in Figure 4), that activity takes priority over conversational threads (depicted as the blue line interleaving the service interruptions). Should adverse circumstances create an even higher priority, such as the emergence of a danger, that new priority, when recognized, will be given the highest salience.

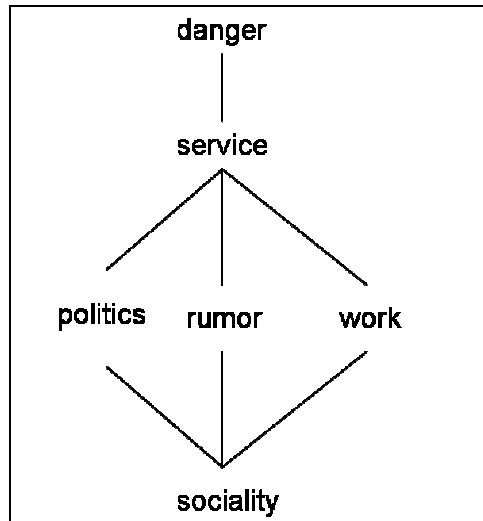


**FIGURE 1** Affinity prototype

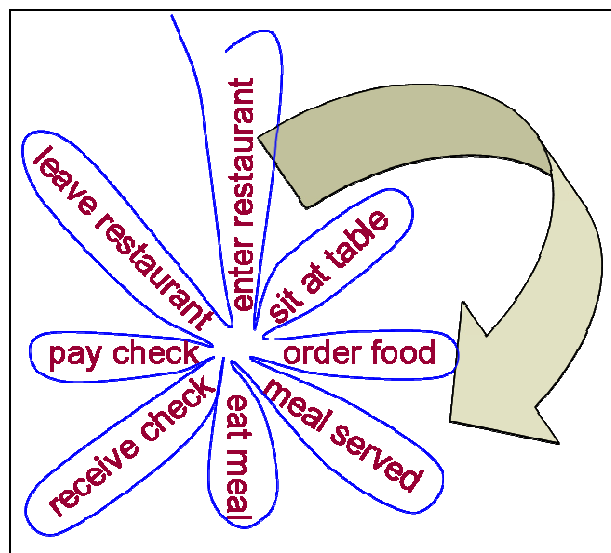


**FIGURE 2** "Restaurant" combines prototypes

The prototype concepts active in a restaurant overlap and intertwine with each other. When friends exchange gifts, or diners pay for the meal, there is an exchange. In the face of danger, whether an explosion in the kitchen, an armed robbery, or some other disruption, possible actions are considered relative to the constraints and affordances inherent in, for example, friendship relations and a restaurant setting (see Figure 5). These new prototypes (danger) blend in with the others (friendship, exchange, etc.) and form the definition for a new situation, in which the agent needs to interpret, decide, and perform actions.



**FIGURE 3** Restaurant discourse structure



**FIGURE 4** Contingent restaurant scenario

In an interaction setting, there is, of course, more than one actor and, as suggested above, their prototype concepts, even when similar, are not perfectly aligned. As Figure 6 depicts, while generally sharing overriding priorities, the participants will, or will not, also share topical interests. Subsequent interactions will invoke, refine, contest, and evolve shared prototype concepts, thereby creating an emergent interaction order (Rawls 1987; 1989).

The restaurant example is not just an arbitrary setting. Rather, it is a generic framework in which a wide variety of modeling problems can be explored (Figure 7). In the particular

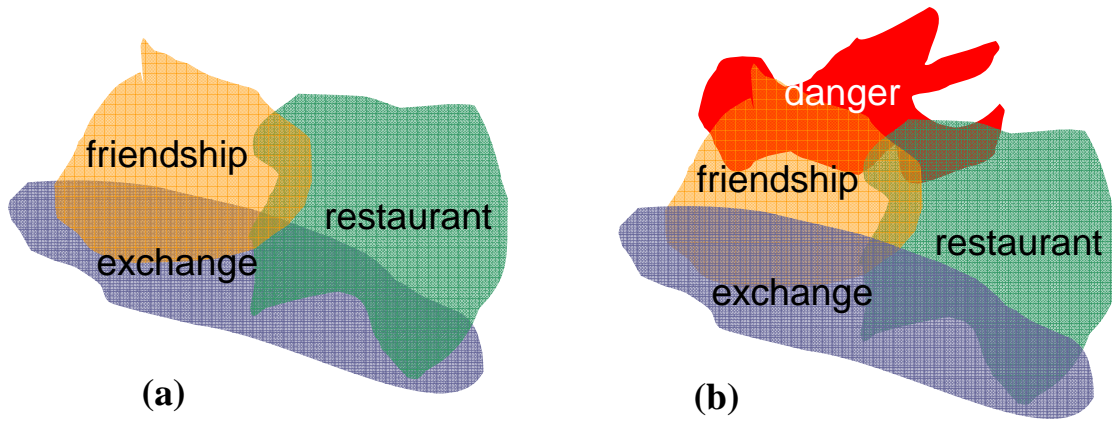


FIGURE 5 (a) Blended concepts evolve with (b) new developments

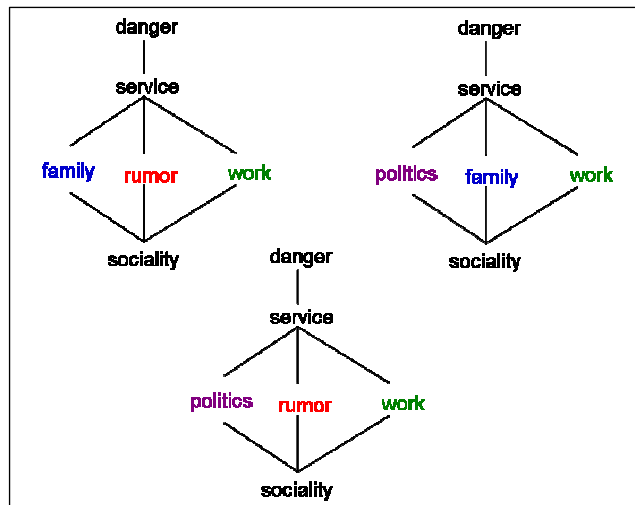


FIGURE 6 Overlapping discourse structures

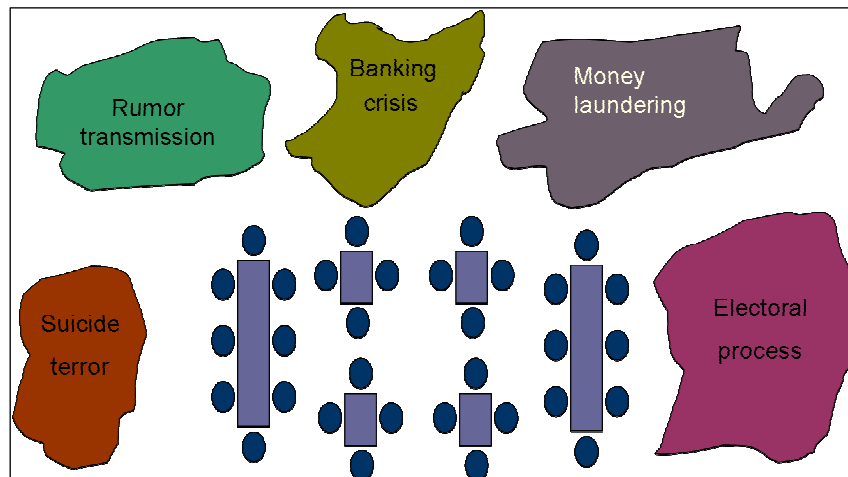


FIGURE 7 *Chez Argonne*

examples, and potentially many others, interaction orders of various structures give rise to a flow of deeply situated responses. The depth of these interaction-rich settings allow for more texture and nonlinear patterns than are normally feasible from using agent simulation models.

## MODELING PROTOTYPE CONCEPTS

To model prototype reasoning, it is important to design mechanisms of prototype invocation and topological inference (Gardenfors, 2000). As part of ontological experimentation, the cognitive part of an orientation field can be implemented, not as a set of facts, assertions, or beliefs, but as a prototype network or field. In other words, agent concepts, individual and collective, should manifest a core/periphery structure.

Concept exemplars, as well as departures from the conceptual prototype, vary radially along axes that together define the concept. Issues that need to be considered in designing such models concern, *inter alia*, the representation of the structure of basic/core prototypes as well as the dimensions (and domains) that define the relevant prototype concepts.

Ultimately, prototype concepts are employed in the action selection process (Bryson and Stein, 2001). In contrast to a restaurant discourse structure, the action hierarchy considers a broader set of possible priorities and actions. In Figure 8, action selection is conceived as an attractor system (Juarrero, 1999), in which compatible *intentions* are combined and integrated.

The IA action selection process is defined relative to a bio-social action hierarchy that integrates both social frames of reference and biological drives. Frames and drives are rooted in the social and biological orders, respectively, and can be seen as forming complementary poles with respect to each other. At the horizontal sides of Figure 8, there are exogenous

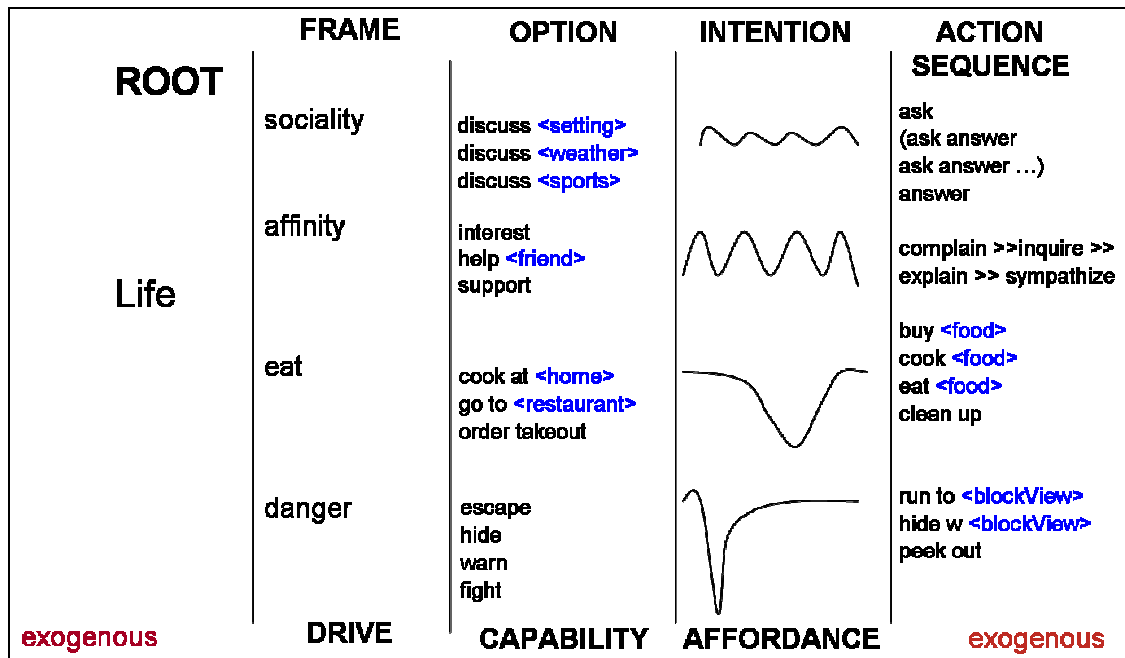


FIGURE 8 Bio-social action hierarchy

processes/actions that drive and constrain endogenous options. Several frames/drives are involved during interaction; these frames acquire or lose focus as agent requirements change. Sociality is a frame that is given the lowest priority and is used when there is no pressing need for other interactions or actions. The drive to eat is periodic, receiving higher priority when hunger increases and disappearing when the agent is satiated. Danger is given the highest priority in the system and, when perceived, the agent attends to it immediately in order to achieve safety. These frames give rise to multiple options, which are considered and assessed as the selection process moves toward the congruent satisfaction of a set of important goals.

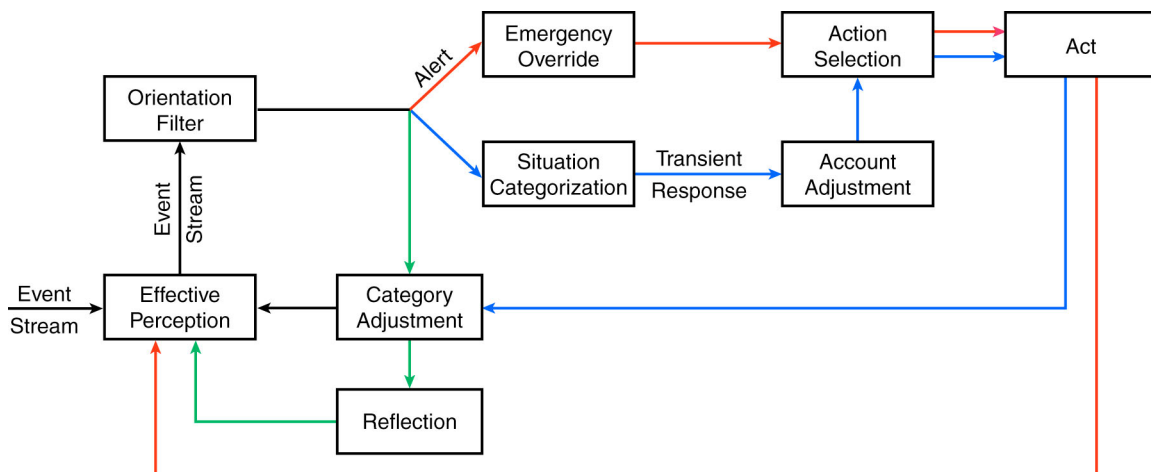
Prototype concept models draw upon a number of related formalisms: the relational data model, including its conceptual (RM/T) form (Codd, 1979); situation-theoretic “infos” (Devlin, 1991); and action selection “tuples” (Bryson and Stein, 2001). These formalisms are integrated into an intra-agent response cycle, in which the particular sequence is determined by the urgency and level of activity of the agent. On the basis of prior experience and orientation, current agent perceptions are categorized by using shallow and/or deep joins, as relative urgency permits. An overview is provided in Figure 9.

Since each agent is individually situated, and each has unique conceptual and action structures, patterns of responses and interactions are less likely to be redundant or reductionist.

## CONCLUSION

The present paper considers and applies the three mechanisms in the design and implementation of a general prototype model. While the latter is applied to multiple domains, the restaurant setting serves as a common focus. The dynamic evolution of interpretive processes of social interaction is explored. More concretely, a sociality laboratory is created in the form of a prototypical restaurant. The dynamics of interpretive social interaction, as manifested in a variety of simulation problems, are being investigated and modeled in the ambience of *Chez Argonne*.

Future topics will consider the method of drawing inferences from a network of prototypes, representation of orientation fields, definition of situations in prototypic terms, level



**FIGURE 9** Response cycle

of granularity in differentiating two situations, extraction of similarities from different situations, categorization of a new situation in the prototypic sense, and so forth.

### ACKNOWLEDGMENT

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**DISCUSSION:****COMPUTATIONAL MICROSOCIOLOGY****(Friday, October 8, 2004, 10:15 to 11:45 a.m.)**Chair and Discussant: *X. Zhong, The University of Chicago***SimDyad: An Agent-based Model of Interaction between Intimates**

**Michael North:** I'd like to move on to the Computational Microsociology session. I'll be hosting it instead of the previous host due to a last-minute change. I'd like to introduce Bill Griffin from Arizona State University (ASU). He'll be discussing "SimDyad: An Agent-based Model of Interaction between Intimates."

**William Griffin:** Good morning. Let me tell you what we're trying to do at the lab at ASU. This particular presentation and the one that follows cover a series of efforts we've been working on for a while. We've been trying to figure out, at a theoretical level and at an implementation level, how one can generate a reasonable agent-based model or models by using very small  $n$ . It's fairly easy to conceptualize how a mass (a very large number) of entities, collectively, with simple rules, can produce an emergent phenomenon. It's much more difficult to envision how this occurs with only a few entities interacting. We are accustomed to conceptualizing large quantities of interactants as being necessary for generating complex processes. But most of the important socialization processes that we know of and that we've all been a part of occur in very small groups or in intimate dyads, and they're very complex. Those of you who are old enough to have been in relationships long enough know that they get nasty and messy and everything else, and there're only two people. No, actually, there are not really two people; there are a lot of people. We don't know how the complexity of this runs its course, however, so that features of a dyad emerge. Features that characterize the dyad are small groups — groups of two and three people who have an intimate network. Thus far, theoretical agent-based modeling has stayed away from that. That's what we're trying to do.

We're also trying to look at phenomena for which we have empirical data. Thus, the talks this morning will cover our attempts to replicate or start simulating a proxy to what we have good data on, and what we've had enough good data on for years, and things like that. This morning, the first thing we'll talk about is dyads, specifically married couples, and we have some data on divorced couples. We're the only lab in the world right now that has interactional data on divorced couples. We want to see if we can simulate what they do by using an agent-based approach rather than just, say, an ordinary differential approach or differential equation approach.

[Presentation]

**Brian Pijanowski:** Brian Pijanowski from Purdue. Excellent work. I have a question that's actually not related to the work but is related to administrative red tape — to human subjects' research. I'm trying to get into this myself and finding that I spend a lot of time just filling out forms and attending workshops. I'm working in a social system in East Africa where if you walk into a room and say that you have a form for someone to sign, it affects the way in

which they'd like to participate in your overall process. Could you comment on that with respect to your work?

**Griffin:** Yes. I actually have a unique perspective on that because I started doing this work before there were human subjects, but it was typically very local in terms of the department. By the way, he's [referring to Pijanowski] right. If you started doing this, the human subjects would be all over you because one of the things that's assumed is that you will induce psychological distress, and you have to write in your human subject forms that there's a possibility of psychological distress. I used to say to the clinician that people will never talk about something that has not been talked about before a hundred to a thousand times. Nothing new will come out of it. Twenty years ago that was not a problem. Your colleagues would say that was okay. Since that time, I've been on the ASU Human Subjects Board. It's a very different story now. Not only is it much harder to get that, and my position is in the minority ... as if this is not going to induce distress in this form or in a lot of forms that the government is now trying to protect.

The only advice I have is to be very clear up front and say that there is a possibility of psychological distress. As I say (and I've been doing this for over two decades), it's never been a problem because there is a misunderstanding that you, as an experimenter, can induce psychological distress. You cannot. You will not — not if you're doing a task where you're asking a married couple to discuss problems that they are having in their relationship. These have all been discussed a lot. In fact, one of the nice things about doing this research is that it's so heavily patterned. In one of the experimental designs I had, we had a "positive interaction" and a "negative interaction." A positive interaction occurs, for example, when you pick from a list of ten things those three things that you like to do and that you can remember doing (e.g., first date, honeymoon, marriage, birth of a child). A highly distressed couple will fight about the first date. They'll fight about the honeymoon, who spent all the money, why didn't they go where they were supposed to go. I don't even have that in my protocol now because you generate the same data. The same thing happens. It is built in; it's a pattern, and this pattern of response is what we're actually using to develop the models.

What I was going to say about the human subjects is to make sure you say up front that there's a possibility of psychological distress and that you have an immediate debriefing protocol that they can use to get out of the distress. You will probably run into that same language.

**Pijanowski:** I have a couple of questions. I agree with you about the importance of validating what you've got with the agents. Can you talk about where you are in that and about whether or not you see that the agents might lead you in directions for dealing with interventions? I also have a more theoretical question. Why would people in distress express that distress more readily than persons who are doing well if they're put into a contentious situation? I would think that you might sometimes find the opposite if you're comfortable in your relationship. For example, I've observed Mormons in their 80s who seem to snipe at each other very quickly and very harshly but are not under any threat that they're going to break apart.

**Griffin:** Yes. Let me answer the latter question first. One thing that's difficult in this kind of work, which you just pointed out, is that every couple is unique. Every couple has a history, and the behaviors of any given couple that you see don't necessarily put them on a trajectory toward a dismal outcome, but they reflect the structure. There's an ideographic sort of nature about this. Sniping may simply reflect how their relationship was defined, and all the

sniping isn't the same. They know when it changes. They know the tone of voice. They'll know real quickly when it is not the same thing.

**William Lawless:** Do you pick that up?

**Griffin:** Yes. You have to. Depending on the protocol, you may have to see them more than once, or you'll notice that when a topic shifts, what verbally would sound the same comes across nonverbally very differently. Because you don't have access to that information, one of the ways you know it is to look at the shift in the probabilistic structure of the response.

**Lawless:** So you wait for the point to arise. You're not manipulating things.

**Griffin:** We ask couples to list things and areas in their relationship that they want to address. Again, it doesn't matter. You could talk about who's supposed to pay for car repairs. It doesn't matter. They'll drift there anyway. They will always drift there, and that's what you want them to do. What was the other question?

**Lawless:** The importance of the intervention. Based on what you've seen with the agents, does intervention happen too soon?

**Griffin:** Yes, it was way too soon. I'll go to the validation. We actually got a mathematician to do Monte Carlo calculations on this. We're trying to feed him enough data to look at the amount of variation. We're working on that. The critical thing is we're assuming that this is akin to the actual generating process, but we don't know that. We can reproduce a data set without knowing if it's valid, and that's going to take some time.

## **PlayMate: New Data, New Rules, and Model Validity**

**Michael North:** I'd like to introduce Shana Schmidt, also from Arizona State University, who will discuss "PlayMate: New Data, New Rules, and Model Validity."

**Shana Schmidt:** Last year, Bill [Griffin] developed a simulation to model children's play groups. When I started working for Bill, we talked about the full model, about the kids, and about how the model applies to them. One thing we talked about right away — even though there were a couple of variables (a couple of behaviors) that it mapped on very well — was that the method, that the data collected, was static. We started talking about how they're not actually the most adequate capturers of the social processes that are going on and about how that determines the group's evolution over time. We decided to go after what happens in kids' moment-to-moment interactions that would be a better indicator of how group processes in young children emerge and evolve over time.

[Presentation]

**Ebony Bridwell-Mitchell:** Ebony Bridwell-Mitchell, New York University. The question I have is probably more relevant with regard to older children. I'm thinking about your point that similarity and attraction drive the way we see these agents being connected. I imagine that for an older kid, as well as these kids, what people are attracted to is not the similarity they

perceive between themselves and a particular agent, but the similarity between that agent and some prototypical characteristics of an “in group.” I imagine that might be more true.

**Schmidt:** You’re talking about cliques and crowds, like “in” teenagers?

**Bridwell-Mitchell:** Yes, instead of necessarily being attracted to someone I perceive as being similar to myself, I’m more attracted to someone who’s similar to what I believe to be the prototypical member of some in group.

**Schmidt:** Sure, but I think you have to be careful, because with that, you have an awfully smart agent. It’s not just physical; you can’t miss physical similarity. It doesn’t take a lot of smarts to be able to do that. What you’re giving your agents is extreme cognition, and I think people do that. It’s just that I don’t know how we’re going to model that.

**Bridwell-Mitchell:** No, my question was regarding whether you anticipate that some of the things you found might have been different if you were looking at similarity based on similarity to some other set of agents versus similarity to my own personal characteristics?

**Schmidt:** Sure.

**Bridwell-Mitchell:** I think there would be a huge challenge with modeling that.

**Michael Macy:** This is really interesting work. I’d like to compare notes with you sometime because I have some grad students who are doing something very similar on clique structures among older kids, but one thing that’s different in the model — and I wanted to run this past you — is that homophiles can actually be decomposed into two forms: “likes attract” and “opposites repel.” What we found is that when you assign valence to homophiles, the dynamics really do change. Allowing for both “likes attract” and “opposites repel” gives very different dynamics than just having “likes attract.” I wondered if you explored some of that.

**Schmidt:** Not typically, but one thing is that we rank or order all of our attributes, so if they were opposites, they would repel. I do think it’s interesting that you say that. I think for this particular age group, it would be somewhat interesting. There’s actually a small group of people out there doing what’s called “mutual antipathy” research. They work with three- and four-year-old kids who have this mutual antipathy. They’re having a lot of negative interactions, but they’re completely opposite from each other, so it’s going to be a function of how your data are collected because there’s a difference between interaction and playing. I think that that would probably be a graduate student’s biggest challenge: modeling to accurately reflect whether it’s a positive play thing or an interaction. That’s something that we’ve bumped into more times than I care to count, but it’s actually a really good concept.

**Macy:** I didn’t quite get your last comment. I had one other question, but your last comment, was that about positive emotions?

**Schmidt:** Yes, it was about how the more familiar you are, the less friendly you need to be.

**William Lawless:** I think it might indicate a degree of comfort that you’re not under a threat that the relationship is going to break apart.

**Schmidt:** We kind of played around with it that, again, utility and what is the cost of play. What is the energy expenditure? Even though play is fun for most kids and they get something out of it, a substantial amount of energy goes into it. If you are comfortable with a kid and know that he's not going away because you've had enough exchanges together to tell you that he's not going to go away, then you don't need to expend that much energy anymore, but, again, this is all preliminary. I feel like we're jumping the gun even going there, but I'm a little excited about it.

**Lawless:** Maybe emotion is not necessarily a by-product. Maybe it represents a constraint, an internal constraint. You're bumping up against a constraint, and the kids don't have the skills to go past that.

**Schmidt:** Yes. Especially a three-year-old.

**William Bulleit:** Bill Bulleit, Michigan Tech. It's certainly beyond my area, but my limited interaction with kids would seem to indicate that the crossing you get between kindergartners down to three-year-olds is probably related to their size. Small kindergartners seem more likely to play with three-year-olds, and big three-year-olds tend to play with kindergartners.

**Schmidt:** In this new round of studies, because we have a new grant, we're collecting actual data on height and weight. One of the things that we're looking for with height and weight is the popularity feature — that bigger or older kids tend to be more popular within these little nested groups. We actually went after age with it. We went after discrepancies (kind of the other way around). There are a thousand different things that you could do with it. You could do cognitive ability, asking if they are academically even. If you've got a really astute three-year-old child playing with a five-year-old kid who's in kindergarten, but not quite on the same level as the other kindergartners, that makes sense. But having collected and knowing these data, I can tell you what's going on with that, although our population's probably not going to be applicable to others. Some of the kids have been there since they were three and have moved up, and they remember the kids who stayed back in preschool. They've moved on to kindergarten but are still bumping into them from time to time, so we don't really know enough.

One of the struggles that we've been having with modeling this is finding out what's really going on. In a new year of data, would the same things hold? We're not quite sure. Absolutely, it's one of the things you could look at.

**North:** I'd like to thank the speaker.

## Prototype Concepts and Social Interaction

**Michael North:** I'd like to reintroduce David Sallach and introduce Veena Mellarkod from Texas Tech. They're going to talk about prototype inference and social interaction.

**David Sallach:** Some themes in this presentation are similar to some that we were talking about. This is a joint work with Veena Mellarkod. I'm going to do the first half of the presentation, and she'll do the second half. The themes in common with what we were talking about earlier are the idea of using meaning-oriented agents to generate macro processes and the

emphasis on bounded rationality. In particular, this research takes a look at the potential importance of prototype concepts and the use of prototype concepts within agent simulation. You might view this as a continuation of a larger initiative that we call the interpretive agent initiative, which was discussed in a paper presented last year. It summarizes principles and is available in the proceedings, but I will very briefly summarize the dominant assumptions of this research initiative.

[Presentation]

**North:** We have time for a few questions.

**Claudio Cioffi-Revilla:** Claudio Cioffi, George Mason. I have two quick questions to see if I understood correctly. Could you back up to the diagram of the event stream? Is it appropriate to understand the event stream as situational changes?

**Veena Mellarkod:** The event streams have many different things, like the emotions and the prototypes. They might not be situations, but more than that.

**Cioffi-Revilla:** Not situations as such, but changes in a given situation?

**Mellarkod:** Yes.

**Cioffi-Revilla:** So the event streams prompt some responses, some problems to respond to or opportunities. My second question is where do prototypes fit in this general flow?

**Mellarkod:** They're everywhere. At the input level, there is mainly a quick join of the immediate situation and then act immediately, give a quick response. At this level, it's more a deep join as to what's happening, a detailed situational analysis that would be done in an off-line way. It might not be done during the interaction, but while the agent is sleeping, it would occur.

**Robert Reynolds:** Bob Reynolds of Wayne State University and the University of Michigan, Museum of Anthropology. A follow-up on the prototype question is that prototypes are like rules: they're meant to be broken. Any given situation may not fit the prototype exactly. For example, you order something on the menu and you want to substitute something. Negotiation always comes into play to different degrees to massage the prototype into something that fits the current situation. How do negotiation and tweaking the prototype to fit a given situation fit in terms of the process?

**Mellarkod:** At this level, they find comparisons where different prototypes are occurring, and at that place, the new situation evolves. It would be adapted to the current existing prototypes, or if new prototypes are emerging, they try to fit in the event stream to a particular prototype. Did that answer your question?

**Reynolds:** Yes. So, if this is an internal process, then these prototypes are constantly refined based on the actual flow of events. But you also raised the issue of negotiation, which would take place more at the table level. In other words, might this be one of the interaction structures that would be going on? There was an example that we gave, but there's also a negotiation example that could then be plugged into those situations where negotiation was the relevant interaction protocol.

**Dingxin Zhao:** I'm Dingxin Zhao from The University of Chicago, Department of Sociology. I have a question. You say that you can link from micro to macro. Can you give me an example of how it can be linked?

**Sallach:** What we're doing is using the restaurant as a metaphor. The point is that at each of these tables, micro-interactions are going on; however, there is a macro structure. Maybe we can see this most clearly in, for example, the occupation authority. Imagine that there is an occupation authority. (By the way, this idea of occupation authority is just a totally abstract example.) The occupation authority has a set of policies that can be implemented. They may be more concerned with ideological convincing or perhaps with the application of coercion; that is, there may be different structures of policy. There may be differences within the occupation authority in terms of relative priorities — a sense of what is effective strategy and so on. These differences can be the subject of negotiation. As a result, however, at the outset, a policy would be put in place. That policy would be transmitted to the troops, and the troops would try to carry it out. It's not that they would carry it out perfectly. In fact, there would be discussions about this: Does this policy make sense? What has our experience in the field been? And so on. So you have some slippage that a lot of times you don't get. But the point is that you have a sequence of interaction context manifests — certain kinds of decisions and actions and so forth — that then move (or are translated) into a macro framework.

**William Lawless:** I have a quick question. I like the notion of adjustments. You also talked about evolution. Are those two related, and, if so, how are they related?

**Sallach:** What do you mean by evolution?

**Lawless:** You talked about cultural evolution at the beginning of your portion of the talk.

**Sallach:** Yes. I mean that this contains within it the potential (depending on what simulation you're working with) or some mechanisms for what you might call micro-culture. In other words, culture presents resources that are then available in the interaction context and may be invoked in a variety of ways. These resources may include prototypes that are shared, but not completely shared. There has to be an alignment of the underlying concepts and so forth, but the culture is this kind of vast field of available symbolic, artifactual, and other types of resources.

**Lawless:** Then how would evolution occur? Is there a stress or strain on the prototypes?

**Sallach:** We don't have a model that specifically models evolution *per se*. Certainly situations evolve. We have micro-transitions that take place, but we do not, at this point, have macro ones.

**Xing Zhong:** I am just briefly commenting because a lot of discussion has already involved these issues. With regard to the first paper, we also constructed a dynamic model of diet interaction, and I would like to say that the author did a nice job of constructing a complex adaptive system in the way that the hierarchical influence mechanism worked as a positive feedback mechanism, whereas the inherent uncertainty in the system, what with encoding and decoding errors and attribute bias, etc., work as an active feedback in the system. The bias is an interesting process, and I wonder whether it is appealing to the author to construct an alternative bias that is an intrinsic parameter produced by an individual. I would argue that this so-called intrinsic bias can play a role in this agent process by modifying the capacity of reduction of

uncertainty in a situation. We can observe the robustness of the market that is of interest by introducing this noise into the system. In the meantime, I would encourage the authors to articulate the patterns observed within the small ... emerged from experimentation to shed light on the data mix of interest.

With regard to the second paper, I think that it raised a compelling question by asking how discrete entities emerge into self-organized groups. With PlayMate, the author's model to obtain information through peer preference by addressing both ontological-level and interrelational-level processes. I would like to suggest an extension to that site, if it has not yet been constructed, by allowing behavior attributes to interact with group-level characteristics. Although it may be marginal to the emergence of group permission, the interaction of behavior attributes with group dynamics can establish a feedback loop where growth dynamics and stability of the group are concerned.

With regard to the third paper, it presented a concrete design of an interpretive agent. The mechanism discussed here, prototype influence, has three advantages in simulating situated meaning in social interactions. First, the prototype concept with its radial structure allows malleability and interpretation of the capacity of agents, which endogenize the heterogeneity at the macro level. Second, by allowing interactions among prototypes, this design accommodates variety in social interactions. Third, the design of the general prototype domain reduces the computational complexity. As a result of these advantages, we can attain a higher level of accuracy and reliability with a more complicated agent. With these advantages in modeling, I would like to push the point further by asking the authors to speculate on, or even highlight the question of where and when, the modeling interpretative agents become substantive in the process of our theory building.

**Sallach:** Thank you. I hope we don't have to answer that question right away, but I agree with you. It's a major focus to determine when they have the potential to make the unique contribution and how best to link that up with the range of theories that I discussed earlier, the one we'd like to see experimentation with.

**North:** Are there any other questions or comments?

**Luis Antunes:** Luis Antunes from Portugal, University of Lisbon. I would like to ask the author of the second paper about the utility of considering utility in the relationships between very young infants. I would think that kids are not really energy savers or utility maximizers, and I wonder if that preconception about looking for the utility in your vision distorts the real motivation behind behaviors. I was worried about the results and the concept of utility.

**Schmidt:** I think from the utility, it's not ...

**Unidentified Speaker:** The proceedings are taped, and your comments will appear in the proceedings.

**Schmidt:** That's perfectly okay. I think it's a good question, and it's one we've been playing with. We're trying to define how this could even be working for these kids. In terms of utility, it's probably not the same way that an adult thinks of utility. A kid simply either likes something or doesn't like it. As far as the cost goes, there is a cost to them to stay in it if they don't like it, and it's overwhelming for them. So there *is* a utility function in defense of that. In



terms of a cost/benefit analysis or something like that, the kids probably don't do that. But there has been substantial literature saying that kids (even very young kids, I believe ...in a work by Gary Black) do evaluate the relationships in terms of utility. It's just probably not the same kind of utility that adults use.

**Unidentified Speaker:** They don't have the same relationships.

**Schmidt:** Yes. It's not that they don't engage. It's that they ....

**William Griffin:** I think you're asking whether our interpretation of utility is influencing our interpretation of the data. Yes. It doesn't affect me because I'm not a child developmentalist. That's just the Marva part of that.

One thing that's very clear from watching children play is that there is an energy cost and an emotional cost to engaging in behavior that they're not pleased with. You can watch them move quickly to solitary activity, or they will lessen the probability of playing with another child if there's a cost involved. You can watch this sequentially over time. That's a good question, though. I don't think it influences our interpretation of the data. We know the phenomena exist. How do you think it's influencing it? It's a good question.

**Antunes:** You try to say what's happening in terms of this region of study. I think ... can prevent you from ... this explanation, which says that they're saving energy here, so let's move on. Can you observe in detail what's happening and determine energy and utility?

**Sallach:** Well, there's more than just interpreting the data. We've gravitated toward that because there's some empirical support for it, but we also don't exclude other alternatives. One thing we're looking at, for example, determining the caring capacity of the group in a case where you have two kids playing. Does bringing a third person into that group modify the child's interpretation of how much fun it is to play with the initial person to begin with? We're looking at that. So it's not just being familiar with another child, or how close you are ... with an attribute as having a simple utility function and reducing energy costs or expenditures or something like that. There is more to it. We know that. So, yes, it's not limiting the lenses in any way. But what happened, just from what you said, is that it becomes much more complex very quickly, and we just keep gathering data.

**North:** Thanks to everyone. We need to cut off our discussion at this time.



# Structure and Emergence





## TOWARD A GENDERED-BASED AGENT MODEL

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### ABSTRACT

We propose an integrated approach for exploring gender differences by using models provided by multi-agent systems and psychology. First, we present some psychological theories that try to explain gender differences, focusing on both proximal and distal causes. We concentrate on the schema and role theories for proximal causes and the biosocial theory for ancient causes. We describe a general framework for gender differences that is not limited by the weight of utilitarian restrictions. Second, we apply our research ideas into that context by tackling the consequences of gender-differentiated decision, its social consequences, and agent adaptation. Finally, we put forward a simple model of an experimental setting to test both the framework and some common ideas about gender issues, and we present some preliminary results of our simulations.

**Keywords:** Gender differences, agent behavior, agent-based social simulation

### INTRODUCTION

Many artificial intelligence (AI) and computer science techniques and applications make use of sex-related concepts when they need to address topics such as evolution or reproduction. However, in most cases, the sex of an agent is used only as a group-distinctive feature, and the study cannot be limited merely to gender issues, from either a biological or social standpoint (e.g., Troitzsch, 2004). In this paper, we examine gender as a social/biological concept, not just sexed agents. In particular, we investigate the conditions under which the concept of gender arises as well as discover the features that are relevant for modeling gender-differentiated decision and its consequences at both the micro and the macro level.

Gender presents a new class of problems to AI researchers, since women as a class behave recognizably differently from men, and no one would deem either gender's behavior as being "more rational" than the other. The two genders just happen to have different rationalities (Antunes et al., 2001a). But why? Is this difference rooted in genetic dispositions or in social environment? In both cases, the questions are, "Are there mental structures supporting this difference?" and, if so, "What are they?" Only in this way can we justify the need for a gendered agent-based model — a need that arises in many fields (e.g., economics, social sciences, demographics). It is hard to address some social dynamics without taking into account the fact that social actors have a gender. For example, consider the differences in the salary that women and men receive for carrying out the same task (europa.eu.int, 2004). The differences in salary are bound to have an impact on the (perceived and real) utility that both genders take out of their labor, and this necessarily affects the overall dynamics of society.

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The research reported herein is being conducted by an AI research group, and it strongly emphasizes multi-agent systems. Knowledge about gender differences, however, comes mainly from psychology. To bridge this gap in notions, methodologies, and approaches, we must essentially build a common set of concepts and terms, reach an understanding about the topography and borders of both areas, and operationalize the psychological concepts into AI models that we can explore. Without this integrated approach, we risk obtaining inconsistent results, as demonstrated by the first attempts to introduce the concept of gender in economy and game theory studies. In particular, game theory focused on gender differences with regard to altruism, but results were mixed: some studies found women to be more cooperative or generous, while others found men to be more cooperative (Eckel and Grossman, 2001). This inconsistency can be ascribed to an ingenious use of the Prisoner's Dilemma game or its public good variants. Indeed, the risk component of this kind of game was not taken into account, even though it affects women's behavior. So, women are more likely to defect in a task that implies risk (Simpson, 2003).

This approach, like many others, found its agent modeling in a utilitarian view of rationality. While the empirical results are indeed interesting, this prevailing utilitarian view (or totalitarian view; see Kahneman and Tversky, 2000; Antunes et al., 2003) dramatically limits the complexity of the model and hence the realism of results. In particular, when all the motivations being considered amount to maximizing expected utility, the deep roots of gender (i.e., sex) are excluded. In this case, belonging to a given gender is, for all simulation purposes, equal to supporting a given football team or to arbitrarily being assigned some distinctive tag. This is a drastic methodological trap that we endeavor to avoid. In the following section, we give an overview on some theories about gender differences. Then we present our model.

## **GENDER STUDIES**

In the last century, many biological and social scientists have performed research on sex differences. The former used evolutionary theory to provide a coherent theoretical framework; the latter started from a completely different theoretical approach, using concepts from social psychology, such as schema and role. We briefly present these concepts, concluding with a theory that sums up the investigations made by biologists and social scientists.

### **Schema and Role Theory**

Various psychologists use the concept of schema to address sex differences. A schema is a cognitive structure — a network of associations that organizes and guides an individual's perceptions. It works as an anticipatory structure, encompassing a readiness to search for and to assimilate incoming information. In schema theory, what is perceived is a product of the interaction between the incoming information and the perceiver's pre-existing schema.

In particular, gender schema theory (Bem, 1981) asserts that the phenomenon of sex typing derives from gender-based schematic processing (i.e., a generalized readiness to process information on the basis of the sex-linked associations that constitute the gender schema). Sex typing, in turn, results from the fact that self-concept is assimilated into the gender schema. The activation and therefore the use of the gender schema depend on various factors: situation, availability of supplemental information, and personal inclination to use schemas

(Barberà, 2003). The content of the gender schema is related to the society in which the schema is developed.

At a social level, schemas or stereotypes are represented by gender roles. A role is a set of expectations about the ways in which people are expected to behave in different situations. Roles depend on many things, like the position a person holds, the person's culture, and, of course, the person's sex. Social role theory suggests that most of the behavioral differences between males and females that we know about are the result of cultural stereotypes about gender. In particular, because they perform different tasks, males and females may develop different skills and abilities, different expectations for their own behavior, and different beliefs about their own traits. This brings about the formation of gender roles, that is, shared expectations about behavior that are applied to the people on the basis of their identified sex. The contents of gender role are reproduced within a society through various socialization and social psychological processes (Bussey and Bandura, 1999).

## **Evolutionary Psychology**

Evolutionary psychologists state that the sex-specific psychological dispositions built into the human species through genetically mediated adaptation to primeval conditions are responsible for sex-differentiated social behavior (Wood and Eagly, 2002). In conformity with the principle of differential parental investment and the mechanism of sexual selection, males and females developed distinct strategies for solving the different reproductive challenges (Trivers, 1972). As a result, ancestral men competed with other men for sexual access to women, and men's evolved dispositions came to favor aggression, competition, and risk taking. Ancestral women developed a proclivity to choose mates who could provide resources to support them and their children. Furthermore, because of females' internal fertilization, males developed a disposition to control women's sexuality and to experience sexual jealousy in order to increase paternity certainty and gain fitness benefits from investing resources in their biological offspring. In summary, according to evolutionary psychologists, much of the sex-differentiated behavior that occurs in contemporary societies emerges from these evolved psychological dispositions.

## **Biosocial Theory**

Wood and Eagly (2002) proposed a new perspective called biosocial theory. It is a synthesis of the psychological and biological approaches. Biosocial theory takes into account both the sex-related biological differences and the social context (Eagly, 1987). In particular, Wood and Eagly claim that physical sex differences, interacting with social and ecological conditions, influence the tasks accomplished by men and women because certain activities are more efficiently performed by one sex. For instance, females, being characterized by pregnancy and childbearing, are less efficient in fulfilling tasks that require long amounts of time far from home and long periods of training, while men, being characterized by greater size and strength, are more efficient in performing hunting and warfare. Therefore, women and men allied in complementary relationships in societies, and the division of labor produced greater efficiency. The psychological attributes are seen as a result not only of the evolved characteristics of the sexes but also of developmental experiences and activities performed within a society.

Wood and Eagly studied numerous nonindustrial societies and focused on the different sex-typed social arrangements in each society. Their work underscored that the division of labor between men and women is an almost universal characteristic, which allows childbearing by women. However, the tasks performed by women and men depend on the local economy and environment. For instance, even if women usually do not hunt, they do hunt in some environments where hunting does not conflict with childbearing. Another variable that affects women's roles is the possibility of supplemental feeding of infants, which allows women to perform more productive tasks. The same result is obtained if other people are available to care for infants. In general, Wood and Eagly stated that in accordance with role theory, biological sex-related differences interacting with the environment determine the roles held by women and men, which, in turn, determine the psychological attributes, skills, and socialization of each sex (i.e., the gender of each sex).

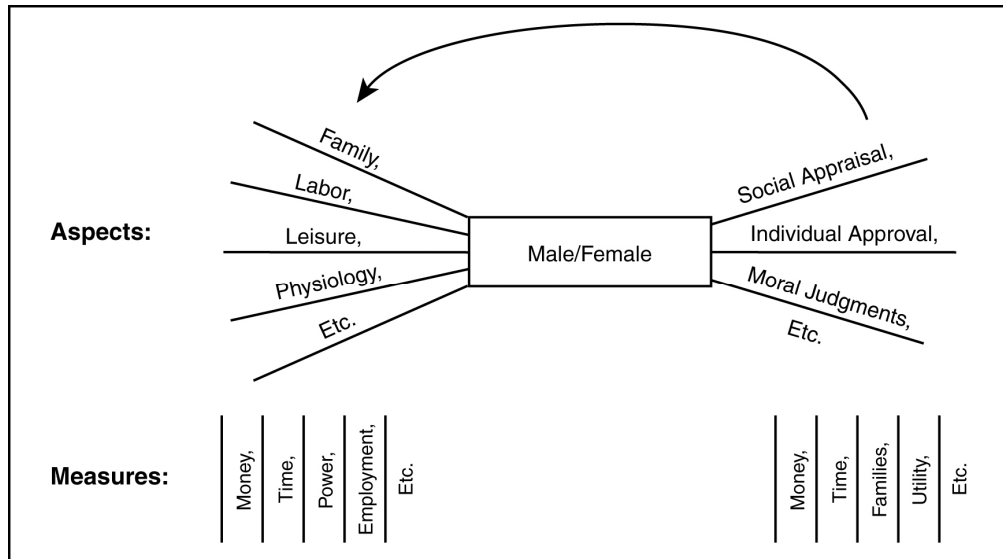
## METHODOLOGICAL CONTEXT

From the decision standpoint, we consider a setting where agents use a multi-varied, situated, evolving choice mechanism (Antunes et al., 2001a,b). A choice function is set up for each individual agent; it encompasses both the reasons for preferring different options and a mechanism for updating the choice parameters according to results of previous decisions. This complex choice framework makes it possible to generate realistic, nontrivial types of behavior. Hence, we can obtain behavior heterogeneity in an agent society that is fundamental to overcome the problems of the traditional approaches (based on utilities and probabilities) (Antunes et al., 2003).

In the interaction of gender-differentiated decision and societal consequences of gender differences lies a complex set of gender-relevant aspects, whose dynamics determine the very idea of gender (as opposed to simple sex of the individual). These aspects can be measured (or valued) against a set of dimensions, influencing the idea of gender in different manners. In previous work, we explored the idea of decisions being influenced by different dimensions (Antunes et al., 2001b; Antunes and Coelho, 2002). Basically, an agent has a choice function that uses multi-varied measures over the relevant dimensions (called five values), and the agent possesses mechanisms that evaluate the outcomes of decisions and “tune up” the machinery to choose differently (hopefully better) in the next situation. An example of the application of such a schema to gender-differentiated agents is shown in Figure 1.

The relevance of the aspects listed in the upper left of Figure 1 differs on the basis of the agent's gender. These aspects can influence a decision by being measured against various dimensions, such as those shown on the lower left. The outcome of a decision is then assessed in terms of aspects such as those shown on the upper right, again according to measures like those shown on the lower right. For instance, a male agent can decide to spend more time with his family and earn less money in his work, and he can evaluate this decision as being socially more fair while being individually bad for his finances. This kind of assessment will ultimately provide motives for change and evolution in the society that will “spin off” from each individual. Individual decisions will contribute to but not ultimately determine how the society will act as a whole.





**FIGURE 1** Dynamics of gender as a role: relevant influential aspects

## EXPERIMENTAL SETTING

We adopted the Wood-Eagly (2002) biosocial theory about gender differences, since it provides us with a link between the distal biological reasons that might have caused gender differences, while allowing the realization of gender-aware behavior as a social role that could, by itself, reinforce the difference in genders. We propose a simple model based on a cross-cultural study conducted by these two authors.

There are several interesting hypotheses we could explore. At this stage of our work, we concentrate on the relationship between labor and child nurturing, with the natural emphasis being on the role of women in these two activities. We hypothesize that different social organizations affect the contribution of women in productive activity — a contribution that is a cue of their power and status in the society (Schlegel and Barry, 1986).

For validation, we used data from cross-cultural anthropological research, particularly from the standard cross-cultural sample (SSCCS) (Murdock and White, 1969). The SSCCS is a database that contains information collected from about 186 nonindustrial societies. These societies are considered less complex than post-industrial society and more similar to the early human communities. They are not homogeneous, which reduces the presence of cultural biases.

In this experimental environment, we propose to conduct an exploratory simulation aimed at better understanding the problem. Even if our setting is too simplistic, we can address issues (e.g., the adequacy of the models of agents, their groups, their societies, and their interactions among these several entities), and we can evaluate the effectiveness of the societal and individual measures we use to test the results of the chosen models. In a more ambitious effort that is more realistic, we can compare our simulation results to the results and conclusions from anthropological models based on empirical experiments. The idea of exploratory simulation is to develop intuitions, conjectures, and preliminary results into better and better hypotheses and theories (Conte and Gilbert, 1995; Hales, 2001).

## THE MODEL

Our model attempts to replicate the conditions of a simple society. The world is represented by a grid ( $100 \times 100$ ) with random scattered food, regenerated periodically. Each agent cannot move diagonally, and opposite edges are connected (tours world). A central area ( $10 \times 10$ ) constitutes the village, to which the agents return after each cycle. There is no food in this area.

Each agent is characterized by a set of attributes:

- Sex (male or female),
- Speed (2–5),
- Current age,
- Death age (between 50 and 60), and
- Metabolism (4–8).

Agents are organized into nuclear families composed of only parents and children (at this stage). The main goal of an agent is to increase the amount of stored food, which determines the well-being of the family and the number of offspring. Thus, there are two main tasks: a productive task and a reproductive task that implies childbearing.

The capability of gathering food is based on agent speed. Speed measures the time and capacity that agents have to accomplish their tasks. In general, the value of the male agents' (M-agents) speed is higher than that of the female agents (F-agents). So this characteristic constitutes the physiological difference between the male and female agents. Furthermore, F-agents must care for their offspring until they are 2 years old.

In each turn, every agent leaves the village to look for food and carries out a number of steps equal to its speed. It then returns to the village, places the collected food in its family's food storage, and eats a quantity of food equal to its metabolism. The agents do this in order of age, so parents and older children take advantage of the food storage first. This mechanism follows a habit also observed in the animal realm, in which parents, in situations of necessity, favor the older children, in whom they have already invested a remarkable quantity of energy (Dawkins, 1976). At the end of a turn, the age of each agent is increased. Agents younger than 15 years old totally depend on their family and slow down the agent who cares for them. At the age of 15, agents start to contribute to the well-being of the family, and, at the age of 18, they can form an independent family by selecting a (random) mate.

When every member of the family has eaten, the family decides whether to have another child by considering the level of food in the food storage. The family then decides which member will be entrusted with the children. The parent who remains with the offspring is slowed down in its productive activity. The value of this penalization depends on the number of children, which is multiplied for a value between 0 and 1. This is done in order to simulate that some tasks clearly contrast with the care of offspring (1), while others do not at all (0).

We start with very simple-minded agents. Each agent embodies a fixed belief about the sex of the children's caretaker. Thus, agents have three possible characters: traditionalist, nontraditionalist, and utilitarian. The first always assigns the childbearing function to the female, the second assigns it to the male, and the third uses an algorithm to calculate the most profitable choice for the successive turn. These kinds of characters allow for three different social organizations.

In each simulation we measure:

- Number of agents,
- Life expectancy,
- Male contribution to subsistence, and
- Female contribution to subsistence.

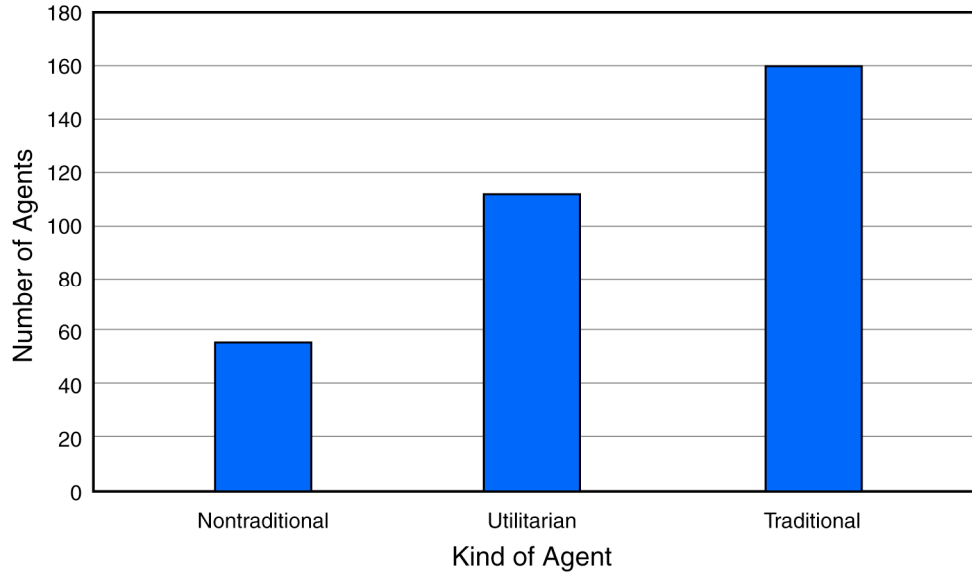
Societal measures of status are taken only directly (i.e., by observing the contributions of women to the family wealth). Also, the influence of women on the stereotypical female role is realized only through self decision. In a more realistic setup, women can do this by either setting an example for society members or directly influencing their children's education. Neither of these cases should be neglected. In fact, an equally interesting hypothesis to model would be to investigate the long-term effects of these socially influencing strategies on the gender equality of a society (see Conte and Castelfranchi [1995] on micro-macro link).

## **PRELIMINARY RESULTS AND PROSPECTS**

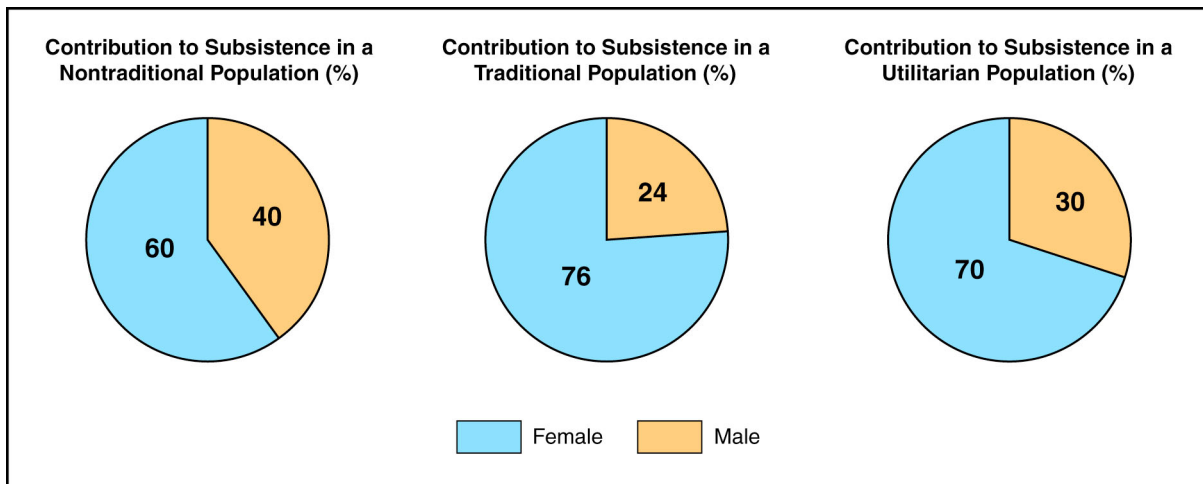
In our first simulations, we ranged the weight of interference between childbearing and the subsistence task over (0,1) and manipulated the speeds for females and males to simulate the existence of tasks that contrast more with child nurturing than others and that require a higher physical aptitude than do others. We started by observing populations composed of only one kind of agent (nontraditionalist, traditionalist, or utilitarian) in order to compare the performance of each one against the others.

Results show that in a very competitive environment (requiring physical capacity to collect food and incompatibility between child nurturing and productive tasks), populations composed entirely of traditionalist agents obtain a better result in terms of number of members (about double) than do populations composed only of nontraditionalist agents (see Figure 2). The utilitarian population presents similar results, because almost all the families decide to let female agents do the child nurturing.

We also tracked the contribution to subsistence in competitive environments. The female contribution to subsistence is about 25% in traditional populations and 40% in nontraditional populations (see Figure 3). In real populations, this figure is considered quite good in terms of women's productive contribution, and also in terms of the fairness of the distribution of domestic labor between sexes (Schlegel and Barry, 1986).

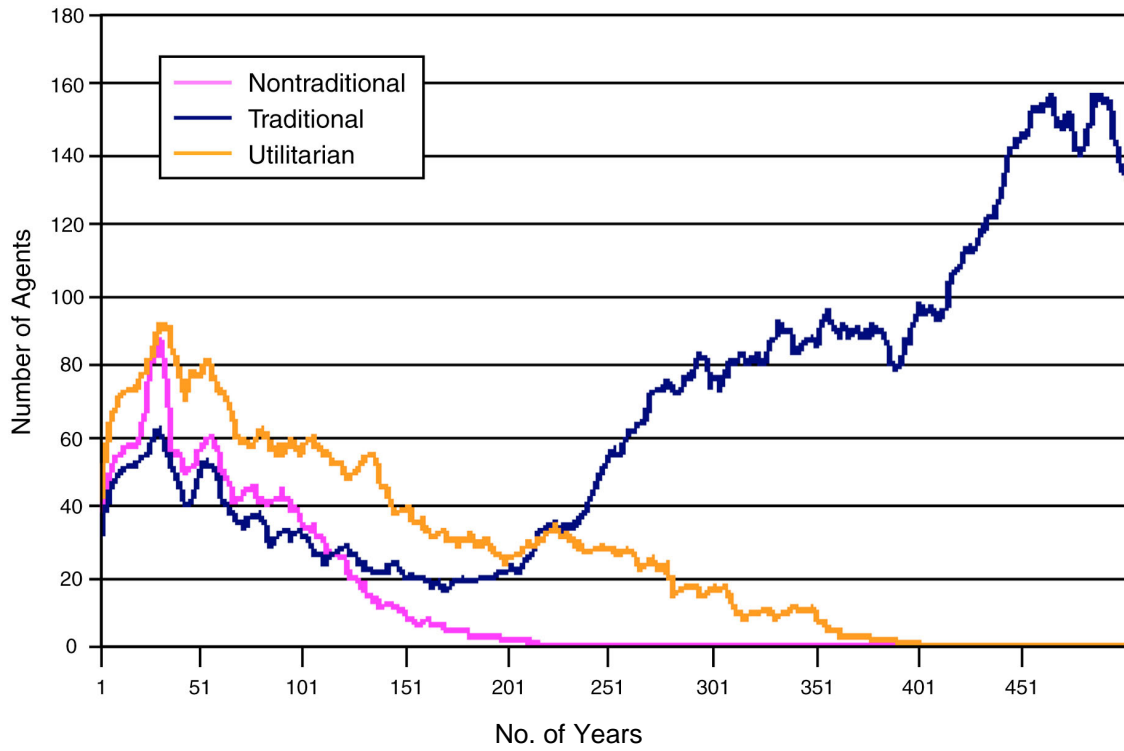


**FIGURE 2** Size of three populations at iteration 1,000

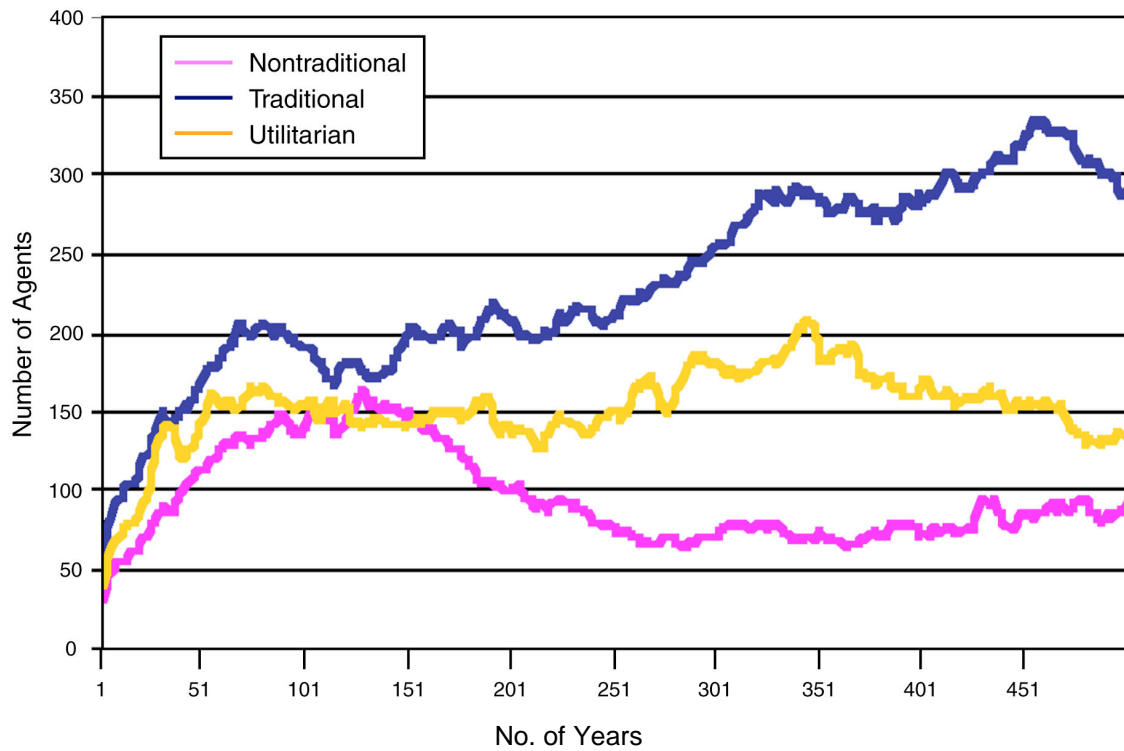


**FIGURE 3** Contribution to subsistence

We performed simulations with the three kinds of agents, starting with populations of 100 elements. In iterations of 1,000 cycles, we noted that the nontraditional agents disappeared quickly, while the utilitarian group remained a little longer. In the end, only traditionalists remained, with a good population growth (magnitude of 140 elements, in contrast with the original 35) (Figure 4). Our conclusion is that groups do not survive because they cannot originate enough wealth to ensure the support of their offspring. However, when we experimented with less competitive environmental conditions, we verified that the three kinds of agents can survive (Figure 5).



**FIGURE 4** Population with the three kinds of agents in a competitive environment



**FIGURE 5** Population with the three kinds of agents in a noncompetitive environment

To produce less competitive environments, we uniformly increased the agents' velocity. Other possibilities would be to change the rate of food supply or its total quantity. For experiments with more heterogeneous and ingenious agents, these alternatives would surely be more adequate. In our simulations, we ran the same 1,000-cycle iteration and observed that traditionalists prevail as the biggest population. The utilitarian and nontraditionalist groups survived as minorities, with the utilitarians being the larger group of the two. These final distributions were stable. When we performed additional cycles, we noted that the three groups remained. These results allow us to conclude that the three group strategies we programmed are not bad; given the right world circumstances, they allow for the group's survival. In future experiments, our goal is to provide further dynamics in these groups. On one hand, we want to allow individuals to change their group during their lifetime, either because of a change in opinion about the best way to optimize family life or because of the consequences of social contacts (weddings, education, etc.). On the other hand, we want individuals to observe and ponder the individual and societal measures that affect them and to dynamically adapt their behavior as a consequence of that assessment.

## CONCLUSIONS

This paper discusses preliminary work on the implications of considering gendered agents in a simulated experimental setting. We hope to gain insights into the anthropological problem itself, yet we also recognize the challenge that this work poses to current models of artificial agents' rationality. Our prospects include refining our model, gaining insights from it, and discovering regularities in the problem we are addressing (Gilbert and Doran, 1994; Conte and Gilbert, 1995). The overlapping of subjects from psychology and AI also must be checked for realism, relevance, and, especially, correspondence in complexity granularity. In future work, we intend to complete this set of experiments and proceed with data analysis. We then plan to refine our agent and society models. We also envision an application of these ideas to avoid certain learning problems in genetic algorithms.

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## OVERLOOKED IMPLICATIONS OF ETHNIC PREFERENCES FOR RESIDENTIAL SEGREGATION IN AGENT-BASED MODELS

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### ABSTRACT

The impact of preferences is investigated for co-ethnic contact on residential segregation, as supported by Schelling's hypothesis that modest preferences can have important consequences for segregation under certain conditions. The findings temper and, in some instances, contradict Laurie and Jaggi's claim that expanding "vision," the size of the immediate neighborhood used in evaluating ethnic mix, makes stable integration a likely outcome in Schelling-like models with weak or moderate preferences. Laurie and Jaggi's results have limited relevance for *residential* segregation for several reasons. Most important is that their study *underestimates* the segregation-producing potential of weak-to-moderate preferences because they overlook a powerful interaction between preferences and ethnic demography and perform their simulations by using the optimal ethnic mix for achieving integration. This paper shows that preferences described by Laurie and Jaggi as compatible with stable integration generate high levels of segregation in their model under settings for ethnic demography common in real cities.

**Keywords:** Ethnic demography, residential segregation, SimSeg model, agent-based modeling

### INTRODUCTION

Laurie and Jaggi (2003) reported that standard interpretations of Schelling's (1969, 1971, 1978) agent-based model of residential segregation should be reconsidered and revised. If correct, the implications of the Laurie-Jaggi study are significant, as the Schelling model is one of the most influential and celebrated of the agent-based models. It is a valuable tool for investigating how micro-level residential choice behavior can produce aggregate-level patterns of ethnic residential segregation. It is routinely cited as an exemplar of how relatively simple, micro-level behavior can produce unexpected emergent structure in spatial networks (Macy and Willer, 2002). Clark (1991), Epstein and Axtell (1996), Krugman (1996), Young (1998), and Wasserman and Yohe (2001) are among the many scholars and researchers who have explored different aspects of Schelling's model and endorsed his conclusions that integration tends to be an unstable condition in model systems and that high levels of segregation can occur even when no individual in the population wishes to reside in the type of ethnically homogeneous neighborhoods found in highly segregated cities.

Laurie and Jaggi extend Schelling's model by investigating how "vision," a parameter governing the size of the immediate "neighborhood" surrounding residential locations, affects segregation behavior. They report that vision interacts with preferences to produce "non-simple

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segregation behavior” that includes *stable integration* under model specifications they view as relevant for residential segregation in urban areas. Accordingly, Laurie and Jaggi contend that their study provides evidence against “claims of inevitability of segregation in Schelling-like models” (2003, p. 2689) and claim to have “discovered that there is a large region of the parameter space” for preferences and vision “where integrated communities remain stable for arbitrarily long times” (2003, p. 2690). They stress that this “stable regime does not correspond to some unrealistic, Gandhian levels of racial preferences/tolerances of the agents” but is consistent with “non-zero and quite substantive values” of preferences and can serve to generate “an optimistic outlook for the future of neighborhood integration” (2003, pp. 2690–2691). Thus, they assert that “contrary to popular belief, rather modest decreases in xenophobia and/or preferences for one’s own kind, *when coupled with increased vision*, can lead to stable and integrated neighborhoods,” and they suggest that “the education community and other social agents who work to lower preferences for one’s own kind and to increase tolerance for the ‘other’ can take strong encouragement from this study” (2003, p. 2703; emphasis in original).

We commend Laurie and Jaggi on a number of counts. First, unlike some critics of the Schelling model, they show great respect for his contributions and the depth of his original insights. Even as they question conventional assessments of Schelling’s theories, they note that he was careful to recognize the limits of his contributions and showed subtle understanding of the complexity of the issues. Thus, where many have studiously ignored Schelling’s work or dismissed it without engaging it in a direct way, Laurie and Jaggi take his model seriously; they seek to extend and refine it with the goal of better understanding the potential linkages between individual preferences and segregation.

Second, Laurie and Jaggi display a welcome appreciation for the value of developing theory from the ground up by exploring models purposefully kept simple, at least initially, to better understand the implications of the model. They resist the urge to introduce excessive realism in their model before the complex behaviors manifested in simpler versions of the model are well understood. Rather, they are guided by the view that theoretical development is served well by elaborating established models in incremental steps to minimize problems in establishing cause-and-effect relations.

Third, Laurie and Jaggi clearly describe how they implement and modify Schelling’s model. The broader literature on residential segregation is replete with discussions of the relationship between preferences and segregation that offer strong conclusions without outlining a model that supports them or providing a basis for evaluating the conclusions in a rigorous way. In contrast, Laurie and Jaggi are clear and explicit about the components of their model and the key mechanisms that drive their findings. They describe precisely how they implement preferences, urban structure, ethnic demography, and agent behavior involved in a housing search and residential choice. In short, they provide the essential ingredient for cumulative scientific inquiry — a clearly specified model that facilitates replication and extension.

Fourth, Laurie and Jaggi show a nuanced understanding of the fact that segregation in real urban systems is the product of many factors. They avoid contrived arguments pitting one factor against another when no basis is found for portraying them as mutually exclusive or competing explanations. Thus, while they recognize the role of factors such as economic inequality, housing discrimination, and institutional forces in segregation dynamics, they pursue an intentionally restricted analysis aimed at better understanding the linkages between preferences and segregation. This theory leads them to suggest policy options for reducing

segregation, namely, enhancing available information about neighborhood ethnic composition and promoting increased tolerance of residential contact with out-groups and reduced preferences for in-group contact, which would not necessarily be highlighted in analyses focusing on other factors contributing to segregation (e.g., mortgage loan discrimination, realtor steering, minority economic disadvantage).

We applaud the Laurie-Jaggi study for the reasons just enumerated and for the care of their analysis and the clarity of their exposition. We believe, however, that close scrutiny of their implementation of Schelling's model leads to the conclusion that their findings must be interpreted much more narrowly than their discussion suggests. Specifically, we conclude that, while the Laurie-Jaggi results are technically correct, the broad implications from their analyses are misdirected in two crucial respects:

- Their central findings are based on very low settings for vision, which have limited relevance for *residential* segregation.
- They adopt idiosyncratic model settings for ethnic demography and search that lead them to seriously *underestimate* the impact of preferences on segregation and the magnitude of the changes in preferences that may be needed to reduce segregation in real cities.

Our conclusions are derived from several observations. First, we introduce the simulation model, SimSeg, which we use to perform our analyses, and highlight points of similarities and differences between it and the Laurie-Jaggi model. Second, we replicate key findings from the Laurie-Jaggi study to show that the SimSeg model produces similar segregation behavior when implementing model specifications that correspond closely with those used by Laurie and Jaggi. Third, we introduce variations in the implementation of search and vision to show how they influence model-based findings. Finally, we introduce other variations in model specifications to document that preferences and ethnic demography interact in a complex way that is both central to determining segregation behavior in agent-based models *and* relevant to understanding *residential* segregation in real cities.

## THE SIMSEG MODEL

SimSeg is an agent-based model written by the first author of this paper for use in conducting simulation experiments to explore segregation dynamics (Fossett, 2003). The characteristics and capabilities of the SimSeg program have been outlined by Fossett (1998), but only a few are relevant to the analyses presented in this paper.<sup>1</sup> This section briefly reviews the key points of similarity and difference between the Laurie-Jaggi agent-based model and SimSeg. We then use the SimSeg model to replicate key findings from the Laurie-Jaggi study and show that our contradiction of their findings cannot be attributed to technical differences between the two models.

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<sup>1</sup> Information about the program can be obtained by going to the first author's Web site at <http://sociweb.tamu.edu/faculty/fossett/index.htm>. A version of the program geared to undergraduate teaching can be found on the Internet by going to the Web site for Amber Waves Software at <http://www.amberwaves.com>.

First, we consider the concept of “agent.” In both models, agents are virtual households with the ability to search in a virtual housing market and make residential choices. Households possess binary ethnic status. Following Laurie and Jaggi, they are labeled either White or Black; however, these labels are arbitrary. Households have preferences for co-ethnic contact specified in terms of the percentage of co-ethnic households found in the neighborhood in which the household lives or to which it is considering moving. In the Laurie-Jaggi model, ethnic preferences are homogeneous within and across groups. In the SimSeg model, preferences may vary by ethnic group — a feature we draw on in some of our extensions.

Households reside in housing units at fixed locations in a virtual city landscape. Housing units have no qualities other than occupancy status and neighborhood ethnic composition. Searching households can move only to unoccupied housing units. When they move, their original housing unit becomes unoccupied and “available.” Their destination housing unit becomes occupied and “unavailable.” In both models, housing units are arranged in a virtual city landscape. In the Laurie-Jaggi model, the landscape consists of a  $50 \times 50$  square grid with 2,500 housing units and no boundaries of any kind. The apparent east-west boundaries of the visual representation of the grid are analytically treated as “wrapping around” to meet each other. The same is true with regard to the apparent north-south boundaries. Thus, their landscape forms an “edgeless torus.” As is evident in figures presented later, the landscape in the SimSeg model consists of 5,488 housing units organized into a roughly circular city form. Housing units are grouped into 112 “bounded areas,” each of which is subdivided into a square  $7 \times 7$  housing grid. The SimSeg landscape has outer boundaries or “edges” analogous to those of real urban areas. Laurie and Jaggi describe their edgeless torus landscape as attractive because it suppresses “boundary effects.” However, we found no evidence that this matters for purposes investigated in this paper.<sup>2</sup>

In both models, the initial condition is one of random assignment of households to locations in the city landscape with 10% of housing units left vacant. By definition, residential location is not systematically linked with racial status, so the city landscape is “integrated” at initialization on the basis of “even” distribution. Laurie and Jaggi quantify segregation by using a measure  $S$ , which they describe as the “ensemble averaged, von Neumann segregation coefficient,” which generally varies between 0 and 1.<sup>3</sup> SimSeg computes a variety of segregation measures; we report the index of dissimilarity  $D$  computed by using data for the 112 bounded areas in the city landscape.<sup>4</sup> Laurie and Jaggi describe  $S$  as being normed against the expected value under random assignment. We draw on Winship (1977) to apply a transformation formula that norms  $D$  against its expected value under random assignment. Because of the norming procedures, both  $S$  and  $D$  can take on negative values, meaning that the city is *more* integrated than would be expected under random assignment.

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<sup>2</sup> Laurie and Jaggi do not suggest that the substance of their findings depends in any important way on using the edgeless torus urban form. If this were the case, we would wonder why an edgeless form would be favored over the urban form implemented in SimSeg because real urban systems have boundaries.

<sup>3</sup> The computing formula is given in Laurie and Jaggi (2003, p. 2693).

<sup>4</sup> Laurie and Jaggi describe  $S$  as “closely related to the dissimilarity index” (2003, p. 2693) but do not support this assertion. We examined values of  $D$  obtained by using an individual-level computing formula found in Winship (1977) that can be used with immediate neighborhoods. We found that these values correlated more closely with  $D$  (computed from data for bounded areas) than with  $S$ .

In both studies, the focal variables in the analyses are the ethnic composition  $C$  of the city, the range of vision  $R$  defining the size of immediate neighborhoods, and preferences for co-ethnic contact  $P$ . Laurie and Jaggi characterize these as “the interesting, essential, and dominant independent variables in this model” (2003, p. 2703, note 6). Laurie and Jaggi set the city ethnic composition  $C$  to 50% Black ( $C = 50$ ) in all of their analyses<sup>5</sup> for several reasons. They state that “the model has been intentionally kept symmetrical between the two races” to further the study’s goal of understanding the effect of vision (2002, p. 2692) and “because it is the prototypical case and has been the focus of much earlier work (2003, p. 2693). Finally, they suggest that they chose this value “to concentrate on the *worst-case* scenario” (2003, p. 2969; emphasis added). For purposes of replicating Laurie and Jaggi, we also set the city ethnic mix to 50/50. In later analyses, however, we varied ethnic mix for three reasons:

- To highlight the fact that it is a crucial factor conditioning the impact that preferences for co-ethnic contact have on segregation outcomes;
- To show that imbalanced ethnic ratios are typical in real cities; and
- To show that the 50/50 ethnic mix, far from being the worst-case scenario, is *optimal* for obtaining stable integration.

Laurie and Jaggi specify immediate neighborhoods on the basis of the value of  $R$ .  $R$  neighborhoods are site-centered regions consisting of the housing units that can be reached by traveling  $R$  spaces by cardinal moves from a chosen point. These neighborhoods assume the form of diamond-shaped areas where the vertices of the diamonds extend out  $R$  units from the focal housing unit on the points of the compass. For this paper, we also implement immediate neighborhoods in this way.<sup>6</sup> The approach yields neighborhoods that are very small when  $R = 1$  and that rapidly increase in size as  $R$  increases. We also implement vision by using bounded areas (i.e., neighborhoods with fixed boundaries) and find that results obtained by using this specification are similar to those obtained by using large  $R$  immediate neighborhoods.

Laurie and Jaggi specify an agent’s preference for co-ethnic contact  $P$  as the minimum percentage of same-race agents it must find among the residents of its immediate neighborhood to be “satisfied.” In their simulations, preferences are homogeneous and symmetric; that is, the value of  $P$  is constant within and across ethnic groups. They vary the value of  $P$  from a minimum of 20% to a maximum of 50%. In our initial simulations replicating those of Laurie and Jaggi, the SimSeg model is set to implement ethnic preferences as they do. In later analyses, we vary the implementation of preferences in two ways: (1) we allow it to vary over a much wider range, and (2) we allow it to take different values across groups.

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<sup>5</sup> While Laurie and Jaggi state that  $C$  is restricted to the range  $0.0 < C \leq 0.5$  (2003, p. 2692),  $C$  does not take any value other than 0.5 in their analyses.

<sup>6</sup> SimSeg also can implement immediate neighborhoods based on all sites that fall within a circle of radius  $R$  extending out from the relevant housing unit. If a substantive basis exists for choosing between the two approaches, it is not known to us. Cardinal traversing rules may be more efficient from the perspective of computational burden, but they are curious in that they produce vision patterns where households see “farther” by a factor equal to  $\sqrt{2}$  on the north-south and east-west compass points than on the diagonal points of the compass.

Laurie and Jaggi specify a search process in which an agent is selected at random to evaluate the ethnic mix in its immediate neighborhood  $C_N$ . If the agent is satisfied (if  $C_N \geq P$ ), it does nothing. If the agent is not satisfied, it attempts to move by randomly selecting available housing units and evaluating them in the same manner. If the agent discovers an available unit with an immediate neighborhood that would allow it to improve its satisfaction, it moves, thus creating a vacancy at its origin location. This process continues until a static “equilibrium” is reached, that is, until movement ceases because no household is able to improve its satisfaction by moving. This specification has two characteristics that we consider in more depth later in the paper. One is that it has no mechanism of population turnover; households are immortal and a satisfied household can reside in the same location *forever*. The other is that households move only to improve satisfaction and, in a given simulation, *may never move from their initially assigned locations*.

To replicate Laurie and Jaggi, we specify a similar search process by using the SimSeg model. During a period of activity termed a “cycle,” households are selected at random and given the opportunity to evaluate their immediate neighborhood and compare it with the immediate neighborhoods for a set of a dozen vacant housing units selected at random. The household will move if it discovers a vacant housing unit that is more satisfying. If more than one of the evaluated units is more satisfying, the household will move to the one that is “most” satisfying. The evaluation process continues until a number equaling 25% of all households have been given the opportunity to move. This ends the cycle. The process is repeated for a sufficient number of cycles to establish a static equilibrium.<sup>7</sup>

In the analyses featured in this study, we use a modified version of this search process in which households are required to move the first time they are selected for search. Significantly, they must move even if the housing options they encounter are less satisfying than their initially assigned location. This rule assures that every household will move at least once during the simulation experiment, and at the end of the simulation, they will reside in a location they identified and selected through search.<sup>8</sup> The modification is simple but has important consequences for segregation outcomes. Later, we show that our modified search process produces substantively sensible results under conditions where the original Laurie-Jaggi search process produces pathological results.

## REPLICATION OF THE LAURIE-JAGGI STUDY

In the previous section, we noted many points of similarity and several differences between the Laurie-Jaggi model and the SimSeg model. The measurement of segregation in SimSeg follows conventions in the demographic research literature on residential segregation, whereas Laurie and Jaggi use the less well known  $S$ . Likewise, SimSeg’s implementation of the city landscape corresponds closer to real urban form, while the Laurie-Jaggi landscape conforms closely to stylized forms used in agent-based modeling. In this section, we demonstrate that these

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<sup>7</sup> We run our simulations for 30 cycles. This is an arbitrary number, but it is sufficiently high to ensure that segregation patterns have converged on an equilibrium. In most cases, the number of moves in a cycle will fall to zero or near zero well before cycle 30 because no households can improve their situation by moving.

<sup>8</sup> Under the Laurie-Jaggi search specification, households can remain in their originally assigned location as long as they remain satisfied. Thus, at the end of the simulation, they do not necessarily reside in a location that they choose through search.

differences do not appear to be consequential with regard to our ability to replicate Laurie and Jaggi's central findings by using the SimSeg model.

Figure 1 presents the results of three representative simulation experiments that replicate the first set of results in the Laurie-Jaggi study. Panel 1 shows the unsurprising result that when households have no preferences for co-ethnic contact, segregation does not emerge.<sup>9</sup> Panel 2 shows that when households seek 50% co-ethnic contact and vision is specified to the very low value of  $R = 1$ , the experiment produces what Laurie and Jaggi term "small-domain" segregation characterized by dendritic regions of ethnic homogeneity. Panel 3 shows that if vision is increased to  $R = 5$ , it produces a much higher level of segregation with expansive "ghettos" (a term they use). These results correspond closely with results presented in Laurie and Jaggi's Figure 3. There is no indication here that our representation of the city landscape or our use of a modified search process causes the results generated by the SimSeg model to differ in any important way from those reported in the Laurie-Jaggi study.

Figure 2 presents final landscapes from representative simulation experiments replicating the analyses that Laurie and Jaggi present in their Figure 4. These analyses explore how preferences for co-ethnic contact interact with vision in their model. In all simulations, the initial landscape (not shown here) is characterized by segregation near 0.0. The results in column 1 show that when households have low preferences for co-ethnic contact ( $P = 30$ ), the level of segregation in the ending landscape *declines* as vision increases from  $R = 1$  to  $R = 3$  to  $R = 5$ . Furthermore, when vision reaches  $R = 5$ , the ending landscape has extremely low segregation. In contrast, the results in column 2 show that when preferences for co-ethnic contact are set at a moderate level ( $P = 50$ ), the level of segregation in the ending landscape *increases* as vision increases and stands at a very high level when vision reaches  $R = 5$ .

Note that the simulations presented in Figures 1 and 2 use our modification of the Laurie-Jaggi search process. In Appendix A, Figure A.1 shows the results of comparable replications from using Laurie and Jaggi's original search process. We can also replicate other findings presented in the Laurie-Jaggi study.<sup>10</sup> We limit our discussion to these results, which we view as central to their conclusions.

Laurie and Jaggi interpret their finding of an interaction between vision results and preferences results as lending "theoretical support to two specific policy initiatives" for reducing segregation: (1) to increase vision by improving "the availability and flow of housing market information" and (2) to encourage reductions in preferences for co-ethnic contact that would make home seekers more willing to "consider alternative neighborhoods where their own race is not concentrated" (2003, pp. 2697–2698). We do not strictly disagree with these findings or with Laurie and Jaggi's general policy recommendations. However, we argue that both findings must be qualified and placed in realistic context.

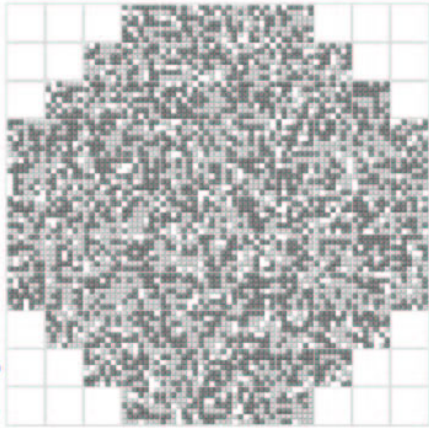
We conclude that the first policy recommendation is largely moot, as households routinely use nonminimal vision when they evaluate neighborhood ethnic mix in subdivisions,

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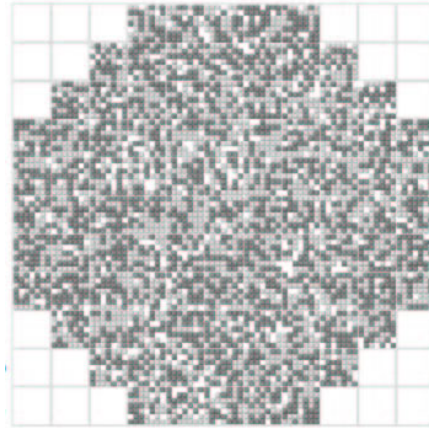
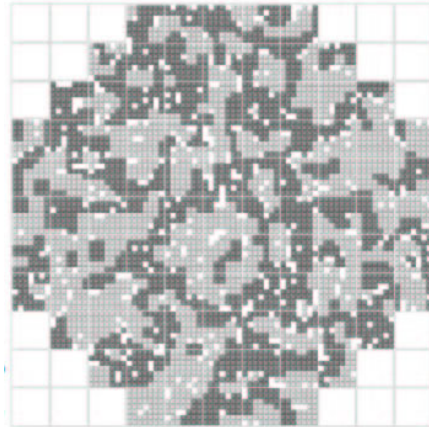
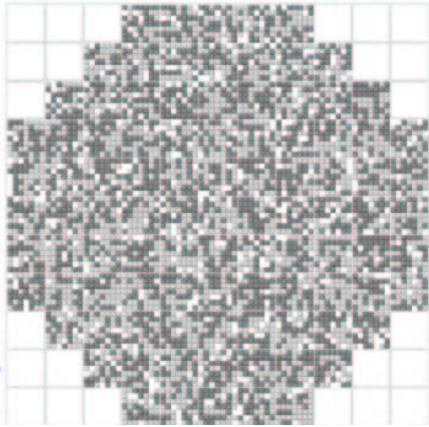
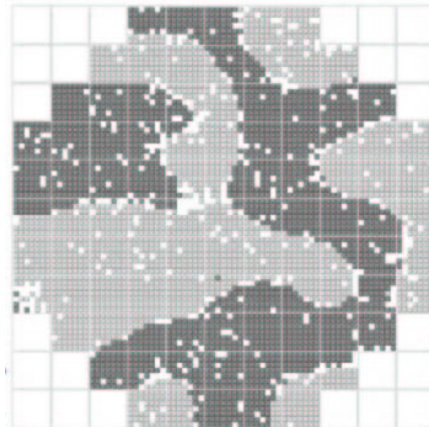
<sup>9</sup> Laurie and Jaggi do not present a similar result because under their search process, no households would move in this simulation. In our search process, each household moves on the first search.

<sup>10</sup> Table A.1 and Figure A.2 in the appendix reproduce the Laurie-Jaggi results (shown in their Figures 5 and 7).

Initial Landscape

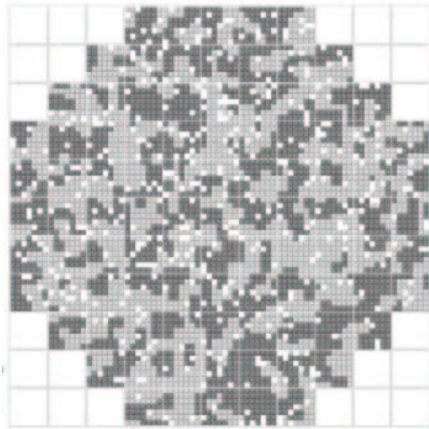


Ending Landscape

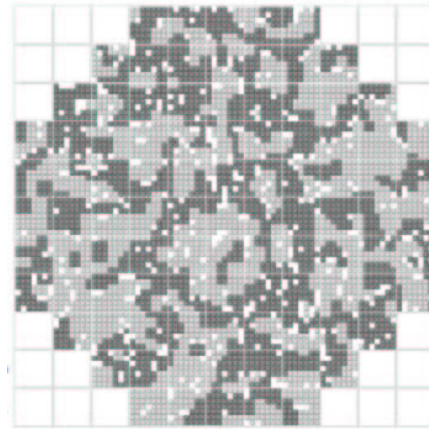
Panel 1: No Preferences for Co-ethnic Contact;  $D = 0.02$  and  $0.00$ Panel 2: Preference for 50% Co-ethnic Contact, Vision = 1;  $D = 0.02$  and  $0.26$ Panel 3: Preference for 50% Co-ethnic Contact, Vision = 5;  $D = 0.02$  and  $0.79$ 

**FIGURE 1** Initial (left) and final landscapes from simulations replicating the Laurie-Jaggi analyses investigating how vision conditions the impact of preferences under 50/50 ethnic mix

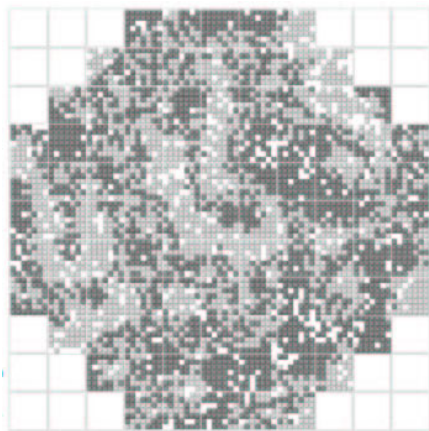




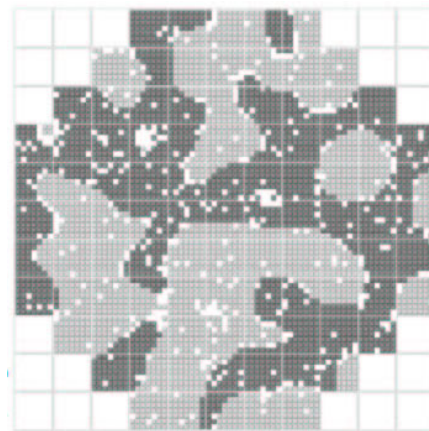
$P = 30$ ; Vision = 1;  $D = 0.20$



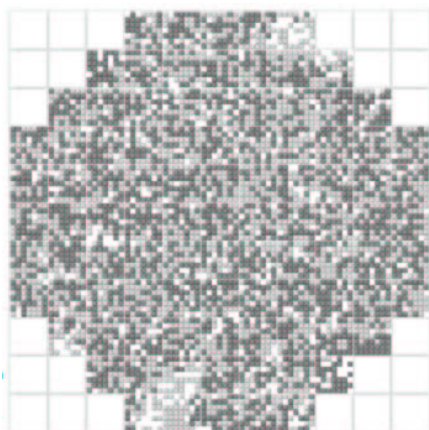
$P = 50$ ; Vision = 1;  $D = 0.26$



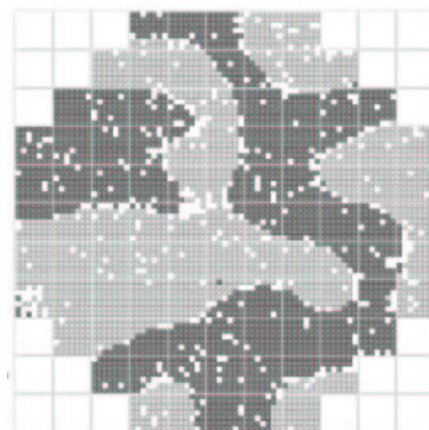
$P = 30$ ; Vision = 3;  $D = 0.17$



$P = 50$ ; Vision = 3;  $D = 0.67$



$P = 30$ ; Vision = 5;  $D = 0.03$



$P = 50$ ; Vision = 5;  $D = 0.79$

**FIGURE 2** Final (right) landscapes from simulations replicating the Laurie-Jaggi analyses investigating the interaction of preferences for co-ethnic contact and vision

school districts, and other large-scale bounded areas; also, there is no basis for assuming otherwise. Regarding the second policy recommendation, we show that Laurie and Jaggi seriously underestimate the segregation-promoting potential of preferences and thus the magnitude of the social change needed to eliminate the impact of preferences for co-ethnic contact on segregation. We establish these and other points by exploring variations of the Laurie-Jaggi model. We conclude that Laurie and Jaggi's central findings and the interpretations they assign to them must be qualified in two important respects. First, when specifications of vision and search move away from certain stylized forms used in the literature on agent-based modeling and toward forms consonant with substantive theory and research on residential segregation, the impact of preferences on segregation becomes stronger and more robust; interactions involving vision take on much less importance. Second, when ethnic demography is varied to include values typical in real cities, it produces higher levels of segregation than Laurie and Jaggi predict because they overlook the fact that ethnic demography conditions the impact of preferences on segregation and causes the 50/50 ethnic mix they use in their simulations to yield the most *optimistic* results possible for integration.

### Commentary and Critique on the Laurie-Jaggi Model Specifications

Researchers drawing on simulation methods must make many choices. One option is to strive for realism to enhance the ability to draw implications for empirical systems. Laurie and Jaggi conform closely to an alternative strategy of making small changes to a simple but well understood model. They are clear about why they do so; it ensures that their model is similar to those used in previous studies in the literature on agent-based simulations. The benefit of this approach is that it makes clear what effects are produced by manipulating vision. In this regard, Laurie and Jaggi's choices are reasonable and their conclusions about the consequences of varying vision are sound *in the context of the specific models they investigate*. However, Laurie and Jaggi do not limit their discussion of the consequences of varying vision to the context of the stylized models found in the literature on agent-based simulations. *They explicitly suggest that their results have broader relevance for understanding residential segregation in real urban systems*. When they do so, it leaves them open to criticism regarding whether their model specification choices are suitable for investigating residential segregation dynamics.

Laurie and Jaggi, like most researchers using agent-based models to explore segregation, are not specialists in segregation. Their study is anchored not in substantive theory and research on residential segregation but rather in previous research using agent-based models.<sup>11</sup> Accordingly, they focus more on how their model compares with previous agent-based models and less on issues concerning the relevance their model may have for residential segregation. Consider, for example, their rationale for implementing the city landscape as a "torus." They defend this choice by stating that their goal is to understand the consequences of varying vision while "minimizing computational artifacts" (2003, p. 2692). But their choice of the torus makes sense only if computational artifacts are identified in terms of departures from previous developments of agent-based models, not in terms of maximization of model relevance for residential segregation. If size and edge effects are important for segregation outcomes, adopting the torus landscape clearly *reduces* the relevance of the model for segregation in real cities, which of course have edges and vary in size.

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<sup>11</sup> See Charles (2003) for a recent review of the literature on residential segregation.

We do not find any evidence that this particular choice is crucial to the relationships that interest us. Our point about the general orientation of their study stands, however, because we can offer similar comments regarding their choices to implement a 50/50 ethnic mix; definitions of neighborhood that are very small in scale and do not consider bounded areas; and a search process where households can occupy the same housing unit forever, in some cases without ever moving on the basis of search. These choices are not strongly grounded in the broader literature on residential segregation but instead follow practices in the literature on agent-based models.

We do not necessarily object to Laurie and Jaggi's model specification choices *as long as they place their model-generated results in proper perspective*. Thus, we do not criticize their findings regarding the complex interaction of vision  $R$  and preferences for co-ethnic contact  $P$ . We can replicate these findings, and we believe they may be relevant to understanding segregation dynamics in certain situations, specifically, situations that are short in duration and involve *only* small spatial scales. We grow concerned, however, when Laurie and Jaggi offer their analyses as a basis for understanding patterns of *residential* segregation. In our view, *their model limits their ability to speak to this subject*. Indeed, their choices regarding model specification obscure some of the Schelling model's most important implications for *residential* segregation. For example, real-world cities have imbalanced ethnic mixes; population turnover is continuous; and nonminimal neighborhoods are relevant to location decisions. We show that model specifications crafted to reflect these patterns generate results that either diminish the relevance of Laurie and Jaggi's central findings or contradict them altogether by providing strong support for the view that moderate preferences for co-ethnic contact can produce high levels of segregation under a wide range of substantively plausible conditions.

### **Observations on the Laurie-Jaggi Search and Movement Process**

The search and movement process in the Laurie-Jaggi model drives the city landscape to a static equilibrium where all household movement has ceased. The residential distribution freezes for eternity for two reasons: (1) households move *only* when they can improve their satisfaction, and (2) households are immortal and, if satisfied, can occupy the same residence *forever*. This observation differs significantly from real residential systems that have continuous residential movement resulting from demographic processes of migration and household life-cycle dynamics. The absence of these basic population dynamics attenuates the creation of *random* vacancies in the Laurie-Jaggi model and suppresses movement. Consequently, their search process can generate equilibrium residential patterns that are idiosyncratic and misleading with regard to segregation dynamics.

For example, consider what happens when the Laurie-Jaggi model is run for a city with a 50/50 ethnic mix, vision set to  $R = 7$ , and preferences for co-ethnic contact set to 0 ( $P = 0$ ). Because households move only to improve their satisfaction and all are satisfied at initialization, no residential movement occurs. The initial and final city landscapes are identical because the city is in static equilibrium at initialization. Superficially, the result is consistent with Laurie and Jaggi's conclusion that weak preferences for co-ethnic contact are compatible with integration. However, *their model also implies that weak preferences are compatible with complete segregation*. To see this conclusion, we make one change to the above simulation: we initialize the city landscape to be *segregated* rather than integrated by packing all households from one

group into a single, circular ghetto at the center of the landscape.<sup>12</sup> Under the Laurie-Jaggi search process, no residential movement occurs. No household can improve its satisfaction by moving, and the city remains unchanged and perfectly segregated! Thus, preferences that obviously would permit complete integration to emerge under regular population movement are not registered by the Laurie-Jaggi model.

This illustration shows that Laurie and Jaggi's basis for optimism about the possibilities for integration under regimes of modest preferences for co-ethnic contact is crucially tied to the initial conditions of their model. Under their specification of residential search and movement, integration thrives under modest preferences for co-ethnic contact *only if the city is initially integrated*. Their model does not provide a basis for optimism about the possibilities for *reducing* segregation in real cities. On the contrary, a literal interpretation of the implications of the Laurie-Jaggi model suggests that *pre-existing* segregation would not decline even if preferences for co-ethnic contact were eliminated entirely. We do not take this implication of their model as a meaningful basis for understanding segregation in real cities. We note it only to show that the Laurie-Jaggi search process is not a good choice for exploring important aspects of segregation dynamics. We conclude that a model that implies that segregation is an equilibrium state when all households are indifferent to neighborhood ethnic mix is unsatisfactory. Segregation in this situation is inherently unstable and gives way to integration if any demographic process is operating to produce household movement. Thus, a simulation model of segregation dynamics should be capable of revealing this fact.

The SimSeg model meets this requirement because it can implement alternative search processes that better simulate the continuous household movement seen in real cities. Our preferred approach is to specify that a random fraction of households, say 1 of 20, is required to move when households engage in search. This approach simulates basic demographic dynamics of migration and household dissolution and formation as follows. The randomly selected household "exits" the population, creating a vacancy at a random location. A new household then enters the population, taking the place of the one that exited. It engages in search and chooses a residential location from among available residential opportunities. Exits represent instances of out-migration or the dissolution of a household; entries represent instances of in-migration or the formation of new households.<sup>13</sup>

While we prefer this approach, it is a significant departure from the Laurie-Jaggi model because it produces a dynamic rather than a static equilibrium.<sup>14</sup> For this paper, we implement a much slighter modification of their search and movement process: we require only that households move the first time they are selected for search. After their initial move, the households are guided by the original logic of the Laurie-Jaggi process and move again only when it increases their satisfaction. Under this process, the city landscape moves toward a static equilibrium in which movement ceases. The process is still highly stylized and follows practices

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<sup>12</sup> To the extent possible, fill out a circle in the middle of the landscape with the households from one group and surround it by vacancies. Simulations following this approach are reported in Appendix A, Figure A.3.

<sup>13</sup> Since entries match exits, the process produces a net migration rate of 0 and/or a rate of "natural increase" for households of 0.

<sup>14</sup> Real cities are in dynamic equilibrium; urban ecological theories of natural and social areas stress that these neighborhoods maintain their social character even as households move into and out of the neighborhood on an ongoing basis.

used in agent-based modeling rather than in representations of substantively important residential dynamics. Even so, using this alternative process has important implications for segregation patterns in many situations. Consider, for instance, the situation introduced above where households are indifferent to neighborhood ethnic mix ( $P = 0$ ) and the city is initialized as perfectly segregated. Under the original Laurie-Jaggi process, the city is in static equilibrium at initialization and no households move. Under our process, every household moves once, and the city undergoes a rapid transition from segregated to integrated.<sup>15</sup> Under our search process, a household searching for the first time randomly surveys available vacancies and takes the first one it finds because all ethnic mixtures will be satisfying. Since moves are random with respect to ethnic mix, the process strongly promotes integration. Movement ceases when all households have been selected for search at least once. The final city landscape is integrated and, in contrast to the Laurie-Jaggi model, the distribution of households is determined by preference-guided search, not random assignment by an outside entity.

Our search procedure yields a substantively sensible outcome in this situation, and, as already shown, our model replicates Laurie and Jaggi's central findings.<sup>16</sup> Thus, we conclude that it is a superior alternative for investigating the impact of preferences on residential segregation. This point takes on greater significance later in this paper when we perform simulations where city ethnic mix varies from the Laurie-Jaggi 50/50 specification. We show that the Laurie-Jaggi search process can produce pathological results in these situations, while our process produces substantively sensible results.

### Implications of the Relevance of Nonminimal Neighborhoods

Laurie and Jaggi's findings about nonsimple segregation behavior deriving from the interaction of vision and ethnic preferences apply only in the restricted parameter space where agents consider ethnic mix in small-scale, immediate neighborhoods. A fundamental condition must be met for this model parameterization to have practical relevance for *residential* segregation: it must be plausible to assume that households consider ethnic mix *only* in relation to minimal, immediate neighborhoods ( $R \leq 2$ ).<sup>17</sup> Laurie and Jaggi do not note this point, nor do they provide any basis for assuming that households restrict their vision to minimal, immediate neighborhoods when taking account of ethnic concerns in residential decisions. In our view, this possibility is utterly implausible. Both casual and systematic observation suggest that households are sensitive to the ethnic mix of nonminimal neighborhoods, including small-scale, immediate neighborhoods considered by Laurie and Jaggi, to a variety of medium- to large-scale "bounded areas," such as city blocks, apartment complexes, subdivisions, school districts, and suburbs.<sup>18</sup>

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<sup>15</sup> This result is documented in simulation results presented in Appendix A, Figure A.3.

<sup>16</sup> We document this finding in Appendix A, Figures A.1 and A.2 and Table A.1.

<sup>17</sup> Laurie and Jaggi describe vision as "myopic" when  $R \leq 2$  and moderate when  $R = 3-5$ .

<sup>18</sup> One line of research on residential segregation has considered the question of whether residential segregation may reflect inadequate information about housing options (Charles, 2000; 2001; Farley et al., 2000); a question closely related to some of Laurie and Jaggi's policy recommendations. Significantly, the research focuses on knowledge of the social characteristics of *nonminimal* neighborhoods, signaling that segregation specialists view them as highly salient in residential decision making and reporting that respondents are generally knowledgeable.

We know of no accepted statement setting forth the position that nonminimal neighborhoods are irrelevant for residential location decisions. This view cannot be traced to Schelling (1971), as he gives bounded neighborhoods extended treatment.<sup>19</sup> Thus, we conclude that the interaction between vision and preferences documented in the Laurie-Jaggi study has little relevance for *residential* segregation.

Note that this conclusion stands even if the ethnic mix of minimal, immediate neighborhoods *is* salient in residential decisions. Residential decisions may involve considerations of ethnic mix in both small- *and* large-scale neighborhoods; there is no need to portray the issue as involving an “either-or” choice. But the segregation behavior documented by Laurie and Jaggi under conditions of minimal vision is manifest *only* when nonminimal neighborhoods are strictly irrelevant.<sup>20</sup>

We do not mean to suggest that Laurie and Jaggi’s careful analysis of how segregation behavior varies when vision is restricted to small-scale, immediate neighborhoods is without value. Indeed, we believe their work is relevant for understanding segregation in small-scale, short-duration situations, such as seating patterns in auditoriums and school lunchrooms and conversation groups at social gatherings. At the same time, however, we accept the conventional view that vision, as it pertains to residential decisions, involves consideration of nonminimal spatial domains. We conclude, therefore, that *for residential segregation*, the most important interaction in the Laurie-Jaggi model is *not* the interaction of vision and preferences. *The most important interaction in their model is one that they do not consider at all: it is the interaction between ethnic demography and preferences.*

## THE INTERACTION OF PREFERENCES AND ETHNIC DEMOGRAPHY

The impact of preferences on segregation is profoundly conditioned by ethnic demography, but Laurie and Jaggi hold ethnic demography constant in their simulations. They characterize the 50/50 mix used in their simulations as a worst-case scenario for achieving integration.<sup>21</sup> In fact, this ethnic mix is *optimal*. To see this, assume that perfect integration is achieved by strategically arranging households to ensure that ethnic mix is uniform throughout the city landscape.<sup>22</sup> In this situation, all households experience the same ethnic mix. Since all households hold the same preference for co-ethnic contact, they will be universally satisfied when this preference is compatible with the ethnic mix of the city. Specifically, universal

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<sup>19</sup> Schelling’s discussion of segregation dynamics for bounded neighborhoods draws on analytic models that he does not explicitly tie to his discussion of agent-based models. Our agent-based model incorporates bounded neighborhoods as well as immediate neighborhoods.

<sup>20</sup> In analyses not reported in this paper, we implement model parameterizations where households consider ethnic mix in both minimal, immediate neighborhoods and larger-scale bounded areas. The segregation behavior seen in these simulations follows that of nonminimal neighborhoods even when households assign greater “weight” to the conditions in the minimal neighborhood. These results indicate that the segregation behavior Laurie and Jaggi document for minimal neighborhood specifications is not robust.

<sup>21</sup> Laurie and Jaggi offer no rationale for this characterization, and we are unaware of any supporting theory.

<sup>22</sup> For this discussion, we set aside the technical problem of achieving a particular demographic mix from an integer count of households. It is a separate issue from the one we are emphasizing.

satisfaction occurs when  $P \leq \min[C, (100 - C)]$ .<sup>23</sup> The highest level of  $P$  that is compatible with universal satisfaction under integration is determined by the value of  $\min[C, (100 - C)]$ . This, of course, reaches its maximum value of 50 when the ethnic mix is 50/50.

On the basis of this observation, the 50/50 city is hardly a worst-case scenario; it can sustain universal satisfaction with integration at higher levels of  $P$  than any other ethnic mix, a fact Schelling noted (1971, pp. 148, 179). Consider the 90/10 ethnic mix, which is not uncommon in real cities. Integration in a city with this ethnic mix can be universally satisfying only when preferences for co-ethnic contact are within the range of 0 – 10%. If desired co-ethnic contact rises above 10%, all households in the smaller group will be dissatisfied under integration. For example, if  $P$  is set at 50 in this city, there would be considerable *latent* potential for segregation to emerge since all members of the smaller group would be 40 points shy of their preferred level of co-ethnic contact.

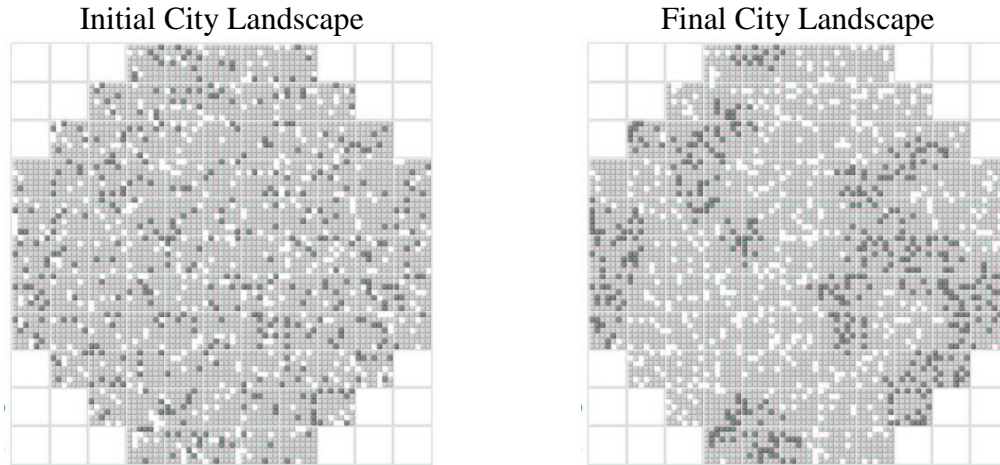
In the Laurie-Jaggi model, dissatisfaction occurs when co-ethnic representation falls short of preferred co-ethnic presence; it increases monotonically as the discrepancy increases. Consequently, integration produces dissatisfaction for all members of a group when the group's population percentage falls below its desired level of co-ethnic contact; the level of the dissatisfaction varies directly with the magnitude of the discrepancy. Guided by the assumption that integration is less stable when it produces higher levels of dissatisfaction, we advance two hypotheses regarding segregation behavior in agent-based models where groups hold symmetric, homogeneous preferences, as they do in the Laurie-Jaggi study, and where households consider ethnic mix in nonminimal neighborhoods.

- **Hypothesis 1:** Segregation should be expected when the relative size of any group falls below the prevailing preference for co-ethnic contact.
- **Hypothesis 2:** The level of segregation should vary directly with the size of the discrepancy between the “demand” for co-ethnic contact and the demographic “supply” of co-ethnic neighbors under conditions of integration.

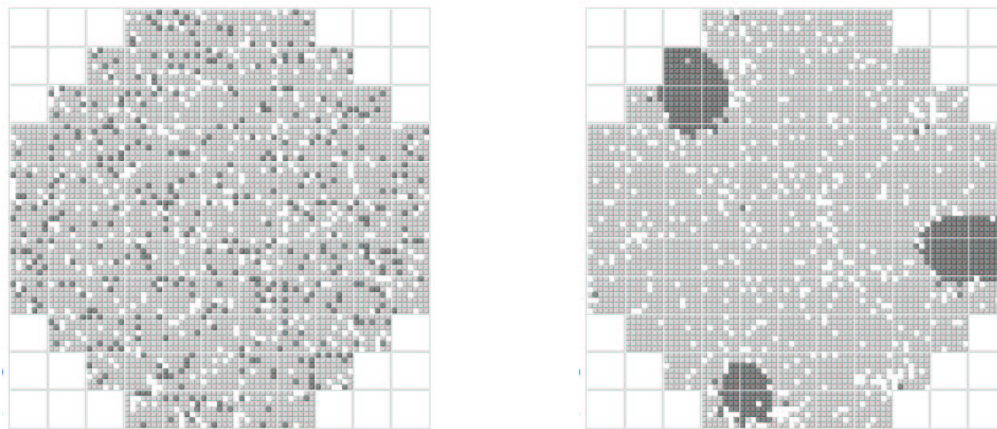
We present evidence supporting these hypotheses below. Before introducing these results, however, we first demonstrate that our hypotheses cannot be adequately tested by using the Laurie-Jaggi model because their search process can produce pathological results in simulations where city ethnic mix departs from 50/50. This fact is documented in the two panels of Figure 3, which present initial and final city landscapes from two simulation experiments. Both experiments share several things in common. In each one, vision is based on site-centered areas with  $R = 5$ , preferences for co-ethnic contact are 50%, and ethnic mix is 90/10. The first two settings were used in simulations reported earlier in this paper. The setting for ethnic mix is a departure from the 50/50 ethnic mix used in earlier simulations. The two experiments differ as follows. Panel 1 presents an experiment using the Laurie-Jaggi search process. Panel 2 presents an experiment using our alternative search process where households must move on first search.

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<sup>23</sup> The expression  $\min[C, (100 - C)]$  represents the minimum value of percent White and percent Black.



Panel 1: Original Laurie and Jaggi Search Process;  $D = 38$ ;  $BP * B = 21$



Panel 2: Modified Search Process;  $D = 85$ ;  $BP * B = 72$

**FIGURE 3** Results for experiments where vision  $R = 5$ , preference for co-ethnic contact  $P = 50\%$ , and city ethnic mix is 90/10 or 10/90

The final city landscape under the original Laurie-Jaggi search process has a relatively low level of segregation ( $D = 38$ ). This value is much *lower* than the high level of segregation ( $D = 79$ ) obtained earlier when the same settings were used for  $R$  and  $P$  but city ethnic mix was set at 50/50.<sup>24</sup> The low segregation for the experiment in Panel 1 might be seen as support for Laurie and Jaggi’s characterization of the 50/50 mix as the worst-case scenario for integration. That assessment is flawed, however, because the integrated residential pattern seen here is an artifact of their idiosyncratic search process.

Laurie and Jaggi interpret integrated city landscapes generated by their model as reflecting possibilities for achieving integration that is “stable for arbitrarily long times” (literally *forever*, since no household will move once equilibrium is reached). However, careful

<sup>24</sup> The relevant comparison experiment is reported in the lower right cell of Figure 2 and in Appendix A, Figure A.1b.



examination of the equilibrium residential pattern of low segregation seen in the final city landscape in Panel 1 shows that this interpretation is unacceptable. The integration seen in this static city landscape is inherently unstable and could not persist over time in the real world.

The reason for this conclusion is that every Black household in the city is dissatisfied. All Black households live in neighborhoods that are approximately 20% Black.<sup>25</sup> Since all households seek 50% co-ethnic contact, *every* Black household is about 30 points shy of their preferred neighborhood ethnic mix. The resulting dissatisfaction creates considerable *latent* potential for segregation. All Black households would move to areas with greater Black representation *if they could move*. But, under the Laurie-Jaggi search process, the opportunity to move never arises. There are two reasons why this is so and both are artifactual in nature:

- No White households ever move in this simulation.
- An artificial shortage of vacancies prevents most Black households from acting on their preferences to move to neighborhoods with higher levels of Black representation.

The two reasons are not unrelated. The random assignment of households and vacancies in the city landscape at initialization creates neighborhoods that reflect the city's demography. With vision at 5, immediate neighborhoods contain 60 housing units and thus will, on average, contain 6 vacancies, 5.4 Black households, and 48.6 White households.<sup>26</sup> The ethnic mix in the average neighborhood is 90% White, so all Whites are satisfied with the ethnic mix of the area. Under the Laurie-Jaggi model, these households will never move unless the neighborhood ethnic mix changes sufficiently to make them dissatisfied. *But this can never happen because the average neighborhood has only 6 vacancies*. If Black households fill all of them, the ethnic mix in the neighborhood increases to approximately 20% Black.<sup>27</sup> Thus, all Whites remain satisfied by an average margin of 30 points and none ever moves.

At initialization, all Blacks are dissatisfied; on average, they are 40 points shy of the co-ethnic contact they seek. All are highly motivated to move. When presented with the opportunity to do so, Black households in areas of lower Black representation move to areas with higher Black representation. This is the only movement that occurs in the simulation. However, since areas have limited vacancies, Black representation in areas of Black in-migration quickly "tops out" at around 20% as vacancies are filled. As the simulation progresses, two kinds of neighborhoods emerge — all-White areas with a 20% vacancy rate and areas that are 20% Black and have no vacancies. Movement ceases and the city landscape freezes in an equilibrium residential pattern with relatively low segregation. It is obvious, however, that the residential pattern is inherently unstable. Latent potential for segregation to emerge exists because *all Blacks are dissatisfied and are motivated to move*.

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<sup>25</sup> This is reflected in the value of the exposure index measuring the average Black household's residential contact with Blacks (i.e.,  $B P^* B$ ) reported in the figure.

<sup>26</sup> These values are mathematical expectations with the citywide vacancy rate set at 10. Of course, in individual neighborhoods, the counts will be integers.

<sup>27</sup> When integer counts are used, the typical neighborhood would have no vacancies and either 12 Black and 48 White households, or 11 Black and 49 White households. In these cases, the percentages of Blacks would be 20.0 and 18.3, respectively.

The simulation produces an equilibrium with stable integration under the rules of the Laurie-Jaggi model. But it would be fundamentally misleading to interpret this result as relevant for segregation in residential systems. The only reason extensive segregation fails to emerge in the simulation is that opportunities for Black households to pursue their residential preferences are artificially restricted by the immobility of White households and the severely truncated availability of vacancies in areas with greater Black representation.

Restrictions of this sort are not found in real residential systems. On the contrary, households are not eternally immobile; basic demographic processes, such as migration and household life-cycle dynamics, generate steady population “turnover” wherein some households exit the population and are replaced by new households. These demographic processes produce regular vacancies in *all* areas of the city. The occurrence of such vacancies is all that is needed to unleash the latent potential for segregation in the result shown in Figure 3, Panel 1; vacancies create opportunities for Black households to move to areas of greater Black representation. The Laurie-Jaggi model does not include a mechanism for household turnover and consequently restrains residential movement in a way that artificially short-circuits Schelling-like segregation dynamics.

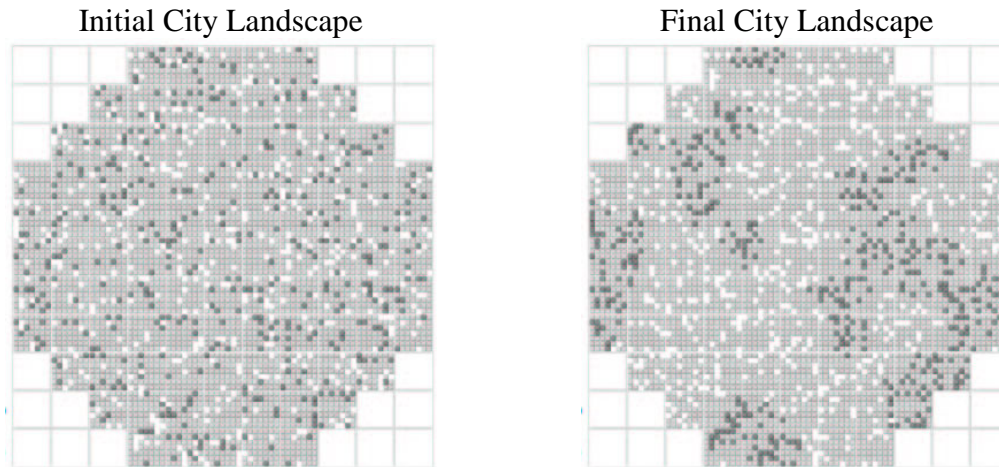
The simulation presented in Panel 2 demonstrates this point. The simulation is identical to the one just reviewed with one important exception: it implements a search process in which all households are required to move on their first search. This step stops short of generating the kind of ongoing residential turnover seen in real residential systems. Still, it lifts the artificial “cap” on vacancies sufficiently to unleash the segregation potential of the preference/ethnic mix combination. Initially, White households move randomly, taking the first housing unit they survey; all neighborhoods are about 90% White; thus, White households are satisfied with any available housing unit they encounter. The random movement of Whites does not directly promote segregation; however, it has important consequences for segregation. It creates vacancies in all areas of the city, and these vacancies permit Black households to act on their preferences to seek higher Black representation. As a result, neighborhoods where Blacks are congregating increase from 20% to 50% Black and beyond. At this point, White households in these areas become dissatisfied and begin moving to primarily White areas. As shown in Panel 2, the dynamic is powerful and generates intense segregation.

The simulation highlights the inadequacies of the Laurie-Jaggi search specification. Their model produces results that suggest that equilibrium segregation outcomes in this situation are *lower* than in their baseline simulations where the ethnic mix is set at 50/50. Our modified model suggests that it is *at least as high or higher and is certainly not lower*.

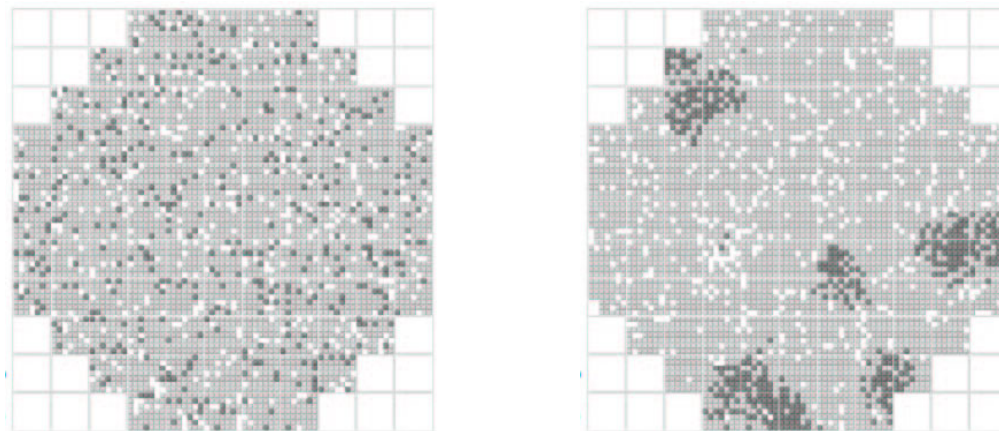
Figure 4 shows that the impact of modifying the search process to generate a greater volume of random vacancies has equally important consequences when the simulations are repeated by using a lower setting for the preference for co-ethnic contact. In these simulations, the preference for co-ethnic contact is reduced from 50% to 30%. Laurie and Jaggi reported that stable integration emerges under these preferences when the ethnic mix is 50/50.<sup>28</sup> What happens when the ethnic mix is set at 90/10? The results in Panel 1 in Figure 4 show that the Laurie-Jaggi model produces a relatively low level of segregation ( $D = 0.38$ ). This result is very similar to that shown in Figure 3 when the preference for co-ethnic contact was higher. In fact, the two simulations are close to identical.

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<sup>28</sup> We replicated this finding by using both their original search process and our modified search process.



Panel 1: Original Laurie and Jaggi Search Process;  $D = 0.38$ ;  $BP * B = 21$



Panel 2: Modified Search Process;  $D = 0.74$ ;  $BP * B = 45$

**FIGURE 4** Ending landscapes from analyses where vision  $R = 5$ , preference for co-ethnic contact  $P = 30\%$ , and ethnic mix is 10/90 or 90/10

This is not a mistake. The two experiments use the same “random seed” and thus have the same initial city landscape. As before, all White households are satisfied with the neighborhoods in which they live. In fact, their average satisfaction “cushion” has increased from 40 to 60 points. Accordingly, none ever moves. As before, all Black households are dissatisfied; all households seek areas that are 30% Black but initially reside in areas that are 10% Black. Their average margin of dissatisfaction has declined from 40 to 20 points, but none is satisfied. Accordingly, the same Black households who had the opportunity to move to areas of higher Black representation in the first simulation make identical moves in this simulation. As before, movement ceases when vacancies fill up in areas with greater Black representation; these areas quickly “top out” at about 20% Black, which is 10 points below the level needed to satisfy Black’s preferences for co-ethnic contact.

The results in Panel 2 in Figure 4 show that the modified search process produces a dramatically different outcome. Black households in this simulation are not artificially “blocked”

from moving toward areas of higher Black representation because satisfied and immortal White households never move, effectively preventing the percentage of White from ever falling far below 80% in any area. Instead, the simulation of elementary demographic events creates random vacancies in these areas, and these give Black households opportunities to satisfy their preferences for 30% co-ethnic contact. Searching Black households that encounter these opportunities move to areas of higher Black representation and become more satisfied. Black households that are left behind in neighborhoods with declining Black representation become even more dissatisfied. Initially integrated neighborhoods bifurcate into two types — predominantly White and predominantly Black. The dynamic produces a high level of segregation in the resulting equilibrium city landscape. Interestingly, the level of segregation is only slightly lower than that seen in Panel 2 in Figure 3. This result is consistent with the Schelling position that high levels of segregation can emerge even when no household is seeking the kind of ethnically homogeneous areas found in a highly segregated city.

The results in Panel 2 in both Figures 3 and 4 support our hypothesis that segregation is higher when demographic supply under integration cannot satisfy preferences for co-ethnic contact. These simulations implement a search process that generates sufficient opportunities (i.e., random vacancies) for households to satisfy their preferences for co-ethnic contact. Under this specification, segregation is higher under the 90/10 ethnic mix than it is under the 50/50 ethnic mix. This fact is not the case in Panel 1 in Figures 3 and 4, where the original Laurie-Jaggi search algorithm is used. The reason is that the movement of Black households toward areas of higher Black representation is artificially short-circuited before any areas can reach even 30% Black.

The unusual nature of the Laurie-Jaggi search process has powerful consequences for segregation outcomes. The results above show that it can lead their model to produce “equilibrium” residential patterns with low levels of segregation when, in fact, there is tremendous *latent* potential for higher levels of segregation to emerge. In our view, their search process is inadequate for investigating the dynamics of residential segregation. It assumes away basic demographic events that are (1) ubiquitous in real cities and (2) demonstrated here to play an important role in segregation dynamics. Households move for a host of reasons unrelated to ethnic concerns; thus, all neighborhoods experience regular, ongoing population turnover. Research on ethnic succession establishes that this plays a crucial role in neighborhood ethnic transitions; neighborhoods undergo succession in large part because they lose their ability to fill regularly occurring vacancies with new entrants who reproduce the social characteristics of the households who are exiting. The Laurie-Jaggi model ignores this dynamic entirely. In their model, vacancies may *never* be produced, much less be produced on a regular basis in all neighborhoods.

Before proceeding to the next section, we note that, while the Laurie-Jaggi search process is inadequate for modeling segregation dynamics in *residential* systems, it might be appropriate for modeling segregation in other situations. For example, seating patterns in a high school cafeteria or a basketball gymnasium are not necessarily subject to the regular creation of vacancies. As seats begin to fill up, agents settle into vacancies that offer satisfying ethnic mixes among immediate neighbors. They may also have opportunities to move if they become dissatisfied with the ethnic mix of their neighbors. However, the seating arrangement will eventually freeze into a stable equilibrium that will not be perturbed until the lunch hour or basketball game is over. Thus, it is possible that the segregation outcomes we view as implausible for residential systems may be sensible in this alternative social context.

Here, as before, our criticisms of the Laurie-Jaggi findings center on their suggestion that their model yields important insights about *residential* segregation in real cities. Our view is that their model results are narrowly correct but have limited relevance for residential segregation.

## ANALYSIS

We now turn to a more systematic investigation of segregation outcomes under varying conditions of ethnic demography and specifications of vision. Figures 5–9 present results from five sets of simulation experiments; they lend strong support to our hypotheses. Preferences for co-ethnic contact are fixed at 30% in all five sets of experiments, but the ethnic mix of the city is varied across the five sets. The set of experiments depicted in Figure 5 uses a 90/10 ethnic mix. In each successive figure, the ethnic mix is moved toward balance. The progression is 75/25 in Figure 6, 70/30 in Figure 7, 65/35 in Figure 8, and 50/50 in Figure 9. As before, group labels are arbitrary in these models. Consequently, the effects of imbalanced ethnic mix are symmetric, and the results for the 90/10 ethnic mix, for example, would be the same as those observed for a 10/90 ethnic mix.<sup>29</sup> Accordingly, we do not present results for ratios less than 50/50.

For each ethnic mix, we report experiments based on four different implementations of vision. The simulations in the upper panels of each figure implement the Laurie-Jaggi notion of vision based on cardinal moves with  $R = 1$  and 5. The simulations in the lower panels of each figure implement vision based on bounded areas. The search process in all of the simulations is our modified version of the Laurie-Jaggi algorithm.

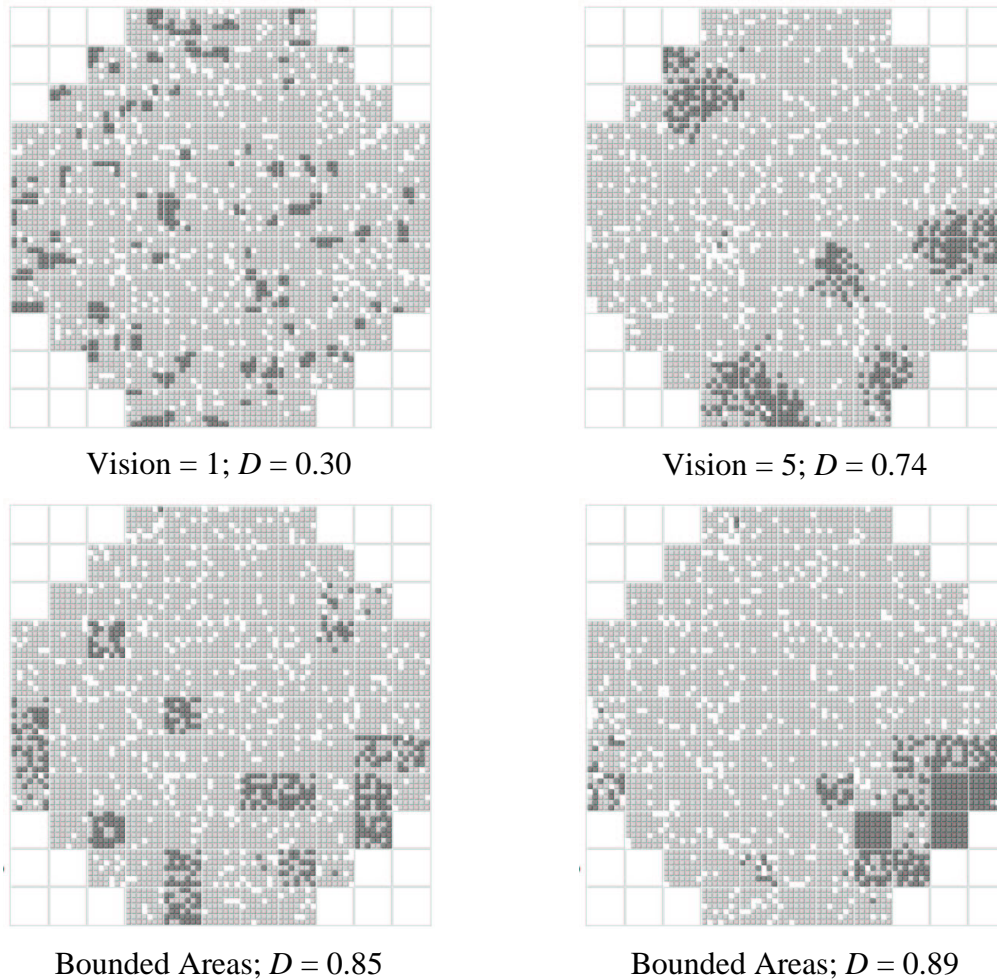
We begin by considering the results obtained when vision is specified in terms of site-centered, immediate neighborhoods, that is,  $R = 5$ . Experiments based on this specification are presented in the upper right quadrants of each of the five figures. The pattern is straightforward; the level of segregation is a monotonic function of the discrepancy between ethnic demography and preferences. Thus, the highest level of segregation is seen when the ethnic mix is 90/10 ( $D = 0.74$ ), and segregation declines steadily as the ethnic mix moves closer to 50/50. This pattern is exactly as predicted by our hypothesis.

The same pattern is seen in the outcomes shown in the lower left quadrants of Figures 5–9. In these experiments, segregation scores are highest under the 90/10 ethnic mix, and they decline as the ethnic mix moves toward 50/50. These experiments implement a variant of vision where households evaluate housing choices not on the basis of ethnic mix for site-centered, immediate neighborhoods but on the basis of ethnic mix *within* bounded areas. We view this implementation of vision as interesting for substantive reasons reviewed earlier and note that Schelling explicitly recognized the relevance of bounded areas in his writings on segregation dynamics.

One impact of implementing vision in this way is that ethnic settlement patterns tend to follow the borders of bounded areas, and thus area-to-area transitions in ethnic mix are sometimes abrupt. This pattern is not uncommon in real cities where ethnic mix sometimes changes abruptly with subdivision or school district boundaries. Significantly, the findings for segregation obtained by using this implementation of vision correspond closely with those

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<sup>29</sup> This symmetry hinges crucially on the fact that both groups hold identical preference for co-ethnic contact.

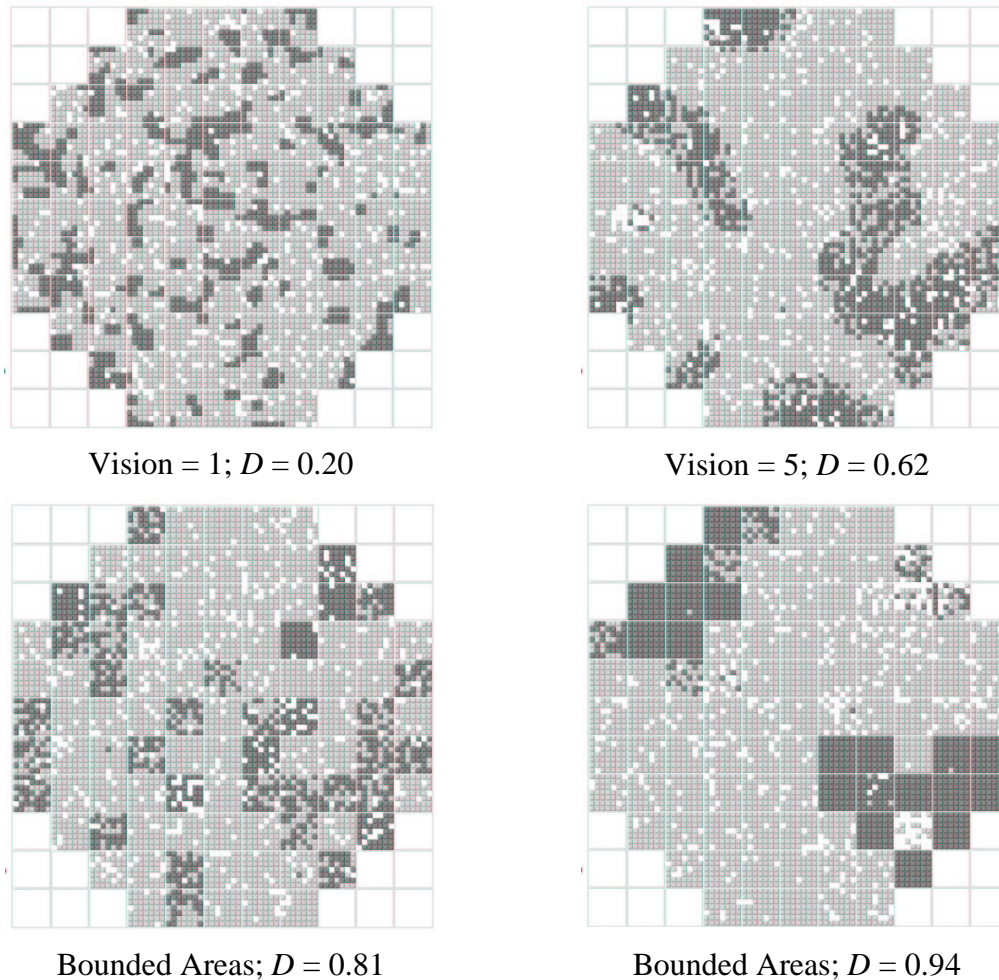


**FIGURE 5** Ending landscapes from analyses where vision  $R$  is varied, preference for co-ethnic contact  $P = 30\%$ , and ethnic mix is 90/10 or 10/90

obtained by using the Laurie-Jaggi implementation of vision (with  $R = 5$ ). Values of  $D$  are slightly higher when the bounded area implementation of vision is used but only because we calculate  $D$  from these same fixed areas. The central pattern is the same: segregation levels decline steadily as city ethnic mix declines from 90/10 to 50/50.

The results for the experiments shown in the lower-right quadrants in Figures 5–9 also manifest the same pattern. They are based on an additional variation in the implementation of vision, where households evaluate housing choices on the basis of both the ethnic composition of bounded areas and the ethnic composition of the *adjacent* bounded areas.<sup>30</sup> This implementation of vision produces the highest levels of segregation seen in these figures. It also produces strong patterns of clustering not unlike those seen in many cities.

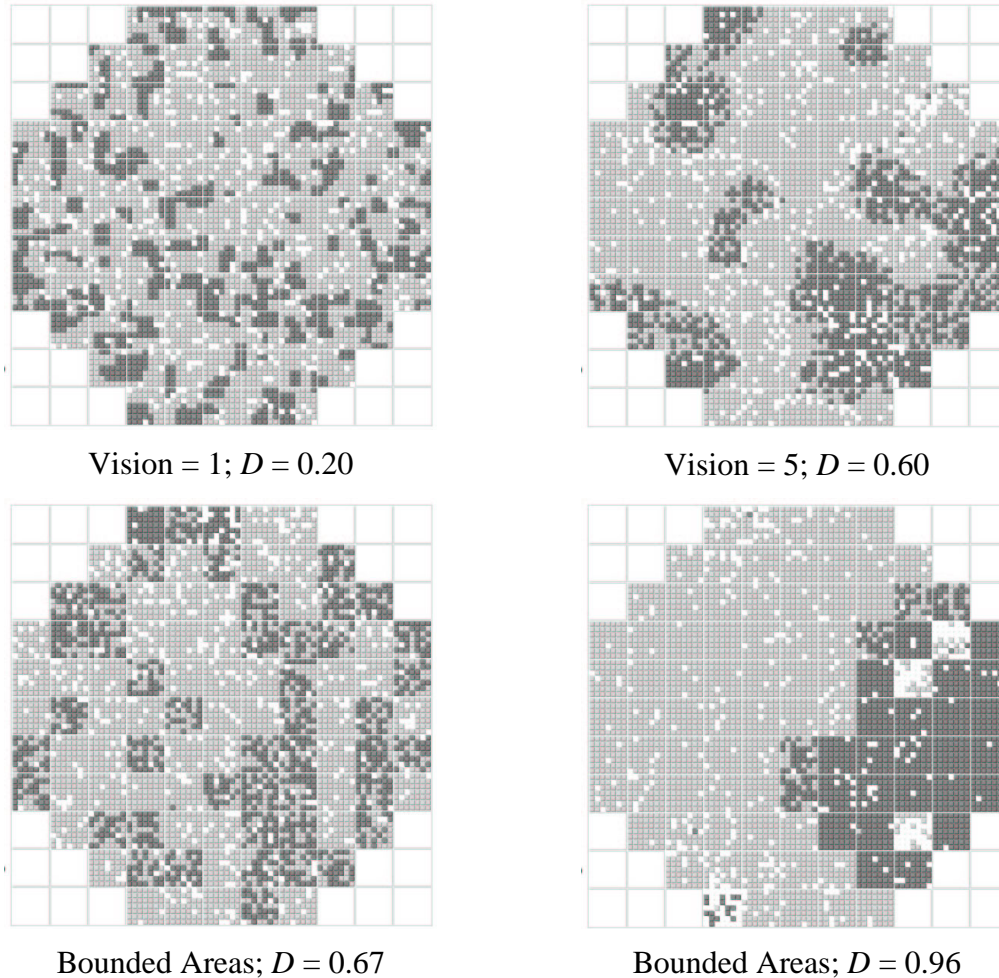
<sup>30</sup> It is similar to using a “Moore” neighborhood of bounded areas where satisfaction with ethnic mix in the bounded area is given priority. Specifically, satisfaction with the ethnic mix of the aggregated population in adjacent bounded areas counts as half of the satisfaction with the ethnic mix in the bounded area.



**FIGURE 6** Ending landscapes from analyses where vision  $R$  is varied, preference for co-ethnic contact  $P = 30\%$ , and ethnic mix is 75/25 or 25/75

The comparison of results using these three specifications of vision is interesting. In one important respect, they all generate the same finding; namely, when vision involves moderate to large spatial domains, segregation takes on high values when demand for co-ethnic contact exceeds the demographic supply. In other respects, segregation patterns vary across these three specifications of vision. Vision implemented as site-centered, immediate neighborhoods with a moderate  $R$  setting of 5 produces slightly lower levels of segregation but clear patterns of clustering.<sup>31</sup> Vision implemented in terms of both bounded areas and adjacent bounded areas produces a similar pattern, with even higher levels of segregation and more pronounced patterns

<sup>31</sup> Laurie and Jaggi refer to larger clusters as “ghettos” (2003, p. 2695). We use the term *cluster* to tie the pattern to established measurement theory for segregation, which identifies clustering as a “dimension” of segregation (Massey and Denton, 1988).



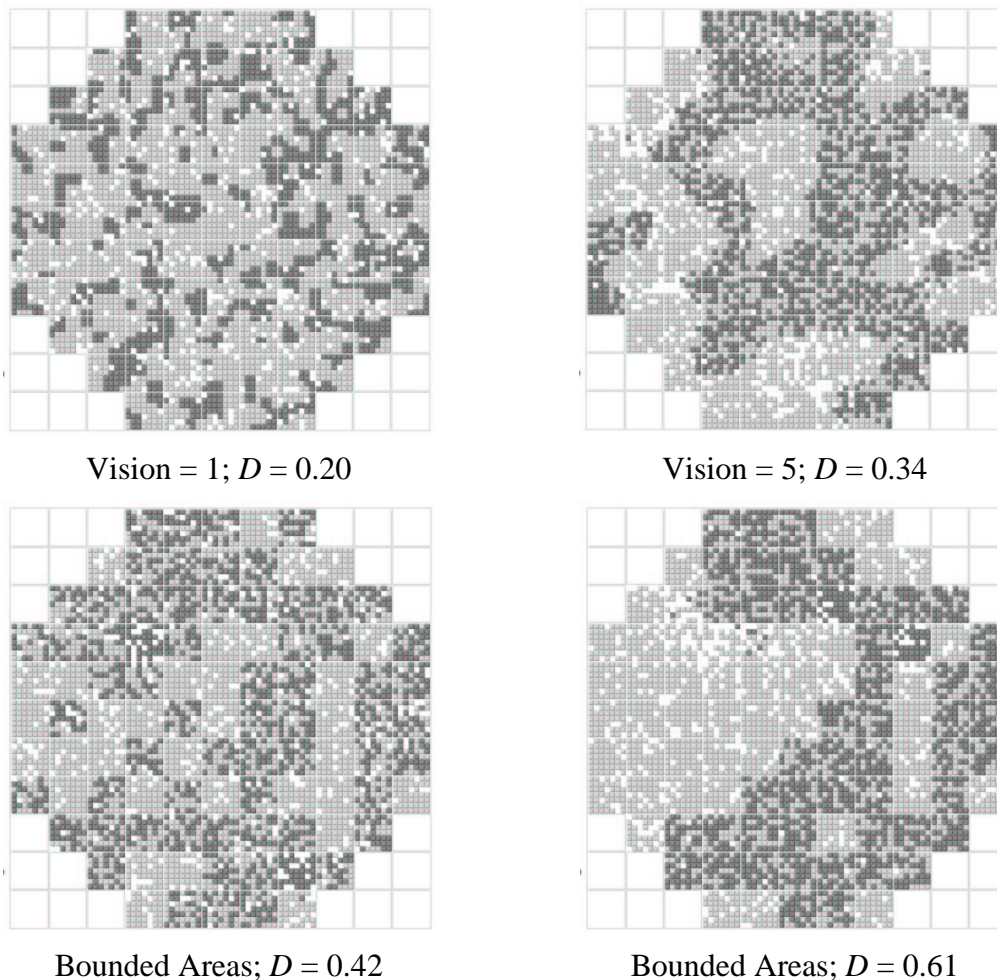
**FIGURE 7** Ending landscapes from analyses where vision  $R$  is varied, preferences for co-ethnic contact  $P = 30\%$ , and ethnic mix is 70/30 or 30/70

of clustering. Vision implemented in terms of single bounded areas produces intermediate levels of segregation but less clustering and more “checkerboarding.”<sup>32</sup>

The variations across these three specifications suggest that at least two dimensions of vision affect segregation patterns: scale and bounding. “Scale” is indexed by the number of housing units in the spatial domain used in evaluating ethnic mix. It appears to have a clear effect on the dimension of segregation known as uneven distribution. Specifically, once scale climbs above very small values, measures of uneven distribution, such as the index of dissimilarity, increase with scale, all else being equal.

<sup>32</sup> Checkerboarding refers to the pattern in which the adjacency of bounded areas with a homogeneous ethnic mix is no more common than would be expected by chance.



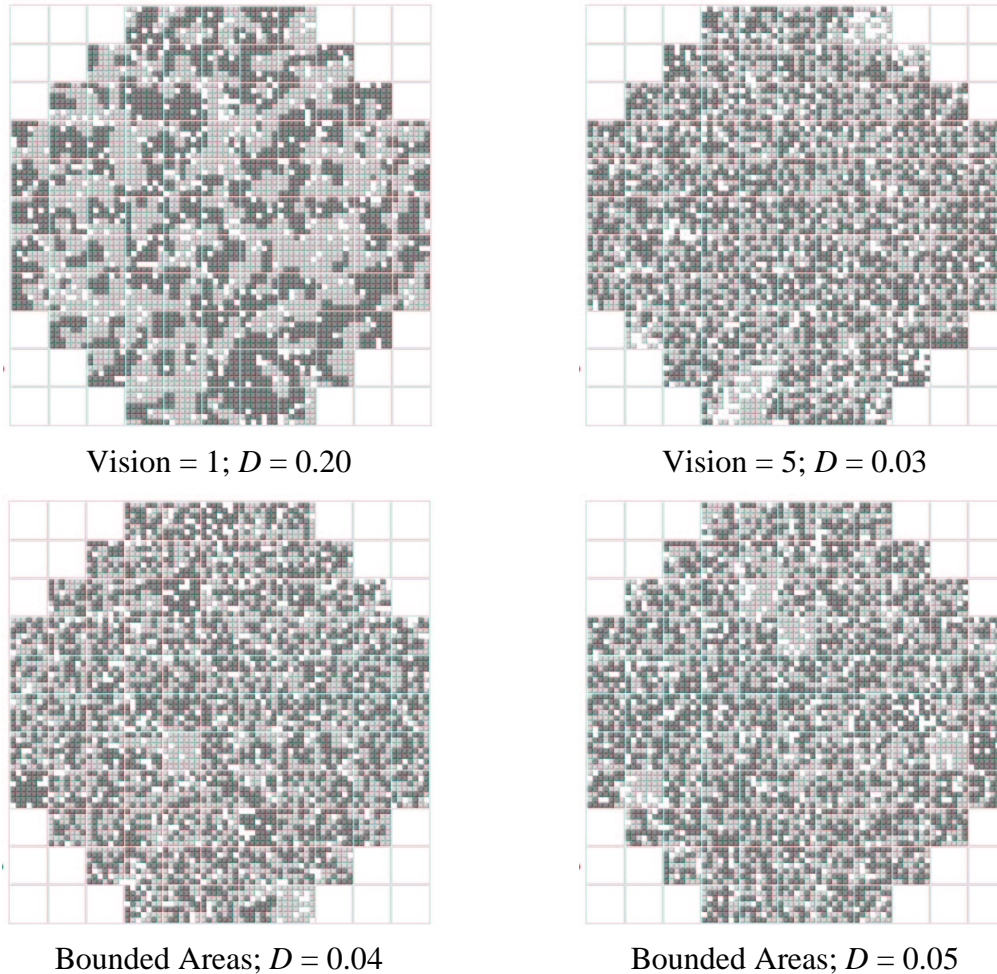


**FIGURE 8** Ending landscapes from analyses where vision  $R$  is varied, preference for co-ethnic contact  $P = 30\%$ , and ethnic mix is 65/35 or 35/65

“Bounding” refers to whether vision is confined to a fixed region or is site-centered. This aspect of vision has implications for the dimension of segregation known as clustering. Strict bounding (the limitation of vision to single bounded areas) produces checkerboarding, a pattern where the ethnic mix in adjacent bounded areas is uncorrelated. Implementing vision based on site-centered areas with  $R = 5$  produces clear visual evidence of clustering. Implementing vision based on a single bounded area produces clear visual evidence of checkerboarding. Implementing vision based on the hybrid combination of the bounded area *and* its adjacent bounded areas also produces clustering. The principle appears to be that clustering emerges when vision is site-centered in some respect.<sup>33</sup>

In our simulations, uneven distribution and clustering are most pronounced when vision is based on bounded areas and adjacent bounded areas, but this result is primarily a scale effect

<sup>33</sup> The implementation of vision based on adjacent bounded areas is a type of site-centered spatial domain.



**FIGURE 9** Ending landscapes from analyses where vision  $R$  is varied, preference for co-ethnic contact  $P = 30\%$ , and ethnic mix is 50/50

of vision, not of using bounded areas. The ring of adjacent bounded areas can include up to 392 housing units; thus, examining ethnic mix in adjacent areas increases the scale of vision by a considerable degree, even after allowing for the fact that more weight is given to the ethnic mix in the immediate bounded area. In simulations not reported here, we found that equally high levels of uneven distribution and clustering were produced when vision was implemented by using large  $R$ , immediate neighborhoods of the type used by Laurie and Jaggi. For example, when  $R = 10$  rather than 5, the scale of the immediate neighborhood increases from 60 to 204 housing units and produces higher levels of both uneven distribution and clustering.<sup>34</sup>

The results shown in the upper left quadrants of Figures 5–9 are based on analyses where vision is implemented as the minimal, four-unit, von Neumann neighborhood ( $R = 1$ ). They document a pattern that runs counter to the results obtained by using the three previous specifications for vision. Vision specified in this way does not support our hypotheses. As the

<sup>34</sup> It also significantly increases the computational burden, and this fact may help to account for why most agent-based models consider low settings for  $R$ .

figures show, segregation changes little as city ethnic mix moves from 90/10 to 50/50, and thus, ethnic demography does not condition the impact of preferences on segregation.

The vision implemented in these simulations is the minimum that can be specified and should be seen as a special case.<sup>35</sup> As Laurie and Jaggi note, this setting for vision tends to produce small-domain segregation that forms a dendritic pattern with “snaking” ribbons of ethnic homogeneity running randomly through the bounded areas of the SimSeg city landscape. This “small-domain” segregation tends not to register at high levels when segregation is measured by computing the index of dissimilarity from data for bounded areas. The ribbons of darkly shaded households for the smaller group tend to increase in length, width, and overall “coverage” as ethnic mix moves from 90/10 to 50/50.

This is an unsurprising function of the changing demography of the city, but it warrants mention because it accounts for the fact that the segregation scores are slightly higher when the ethnic mix is 90/10 compared to other ethnic mixes. In the 90/10 case, the availability of households from the smaller group is low, and the “ribbons” that arise are spread farther apart in space and, because of the less extensive coverage, are less likely to join into long sections over the course of the simulation experiment. Because their average length is shorter, they are less likely to cross area boundaries, and  $D$  computed for fixed neighborhoods is slightly higher.

Table 1 summarizes the dissimilarity scores for the experiments just reviewed. It also includes dissimilarity scores for several additional experiment sets we prepared to cover all ethnic mix combinations on five-point intervals from 95/5 to 50/50. These data further support our hypotheses. When vision involves nonminimal spatial domains, ethnic demography conditions the impact of preferences on segregation such that high levels of segregation emerge when preferences for co-ethnic contact equal or exceed the smaller group’s percentage in the population and the level of segregation increases with the magnitude of the discrepancy. Significantly, this pattern is seen whether vision is implemented by using either site-centered areas (as in the Laurie-Jaggi study) or the variations involving bounded areas.

Table 1 also documents an interaction between ethnic demography and segregation when vision is implemented as the minimal, small  $R$  formulation ( $R = 1$ ). We do not view this as support for our hypotheses, however; as suggested previously, we believe it should be seen as an artifact of the fact that, when segregation is computed from fixed area data, small-scale segregation patterns tend to register better when ethnic mix is low.

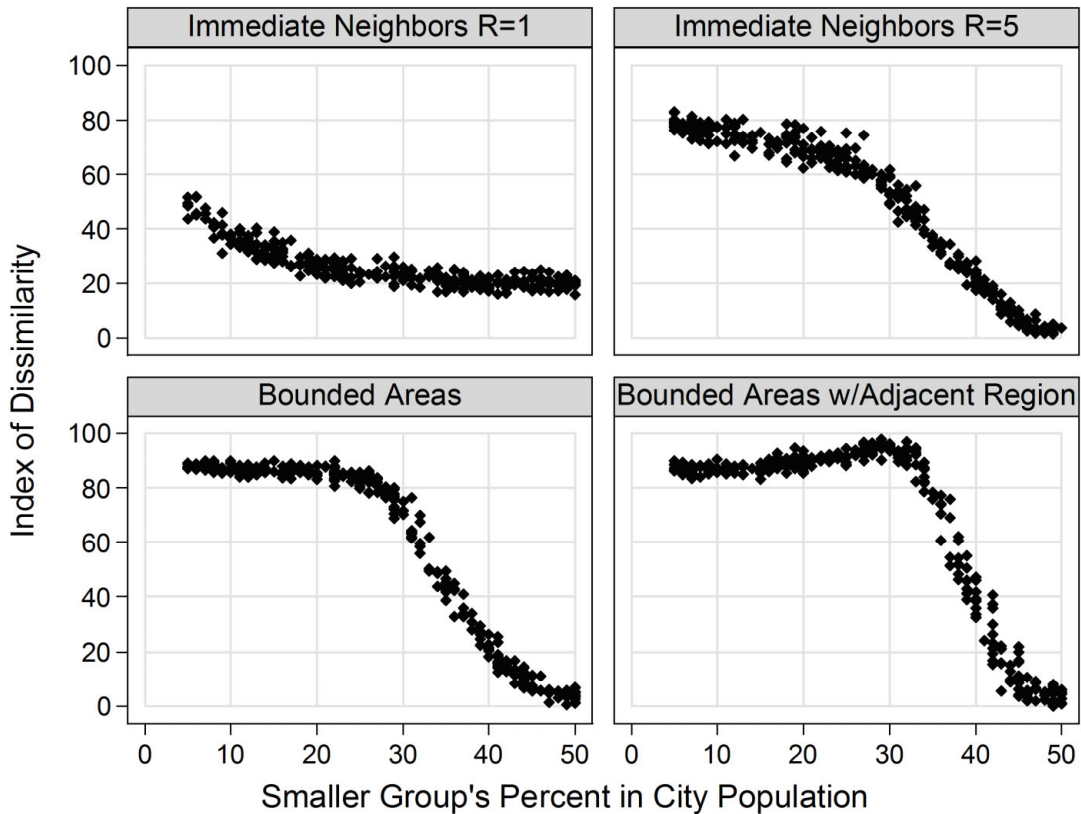
The patterns seen in Table 1 are documented more systematically in Figure 10. This figure plots the index of dissimilarity from the final city landscapes of 1,200 separate simulation experiments by the smaller group’s percentage representation in the city population. Each graph in the figure depicts the results from 300 experiments conducted by implementing the four versions of vision used in the experiments reported in Figures 5–9 and in Table 1. In each of these simulations, the preference for co-ethnic contact is set at 30%, and the size of the smaller group in the population is randomly varied from 5 to 50. The three graphs for nonminimal vision show that the impact of preferences for co-ethnic contact for segregation are strongly conditioned by ethnic demography and in a manner consistent with our hypotheses. Segregation is low when ethnic preferences can be “easily” satisfied under integration. But when demand for

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<sup>35</sup> At least, it is the minimum, nonzero vision that can be specified when vision is uniform in all directions.

**TABLE 1** Scores for the index of dissimilarity for the simulations shown in Figures 5–9 plus scores for additional experiments

Ethnic Demography Mix	Moderate to Large Domain Vision			
	Site-centered Vision, $R = 1$	Site-centered Vision, $R = 5$	Bounded Area	Bounded Area + Adjacent Region
95/5	0.43	0.79	0.86	0.88
90/10 (Figure 5)	0.30	0.74	0.85	0.89
85/15	0.22	0.73	0.82	0.86
80/20	0.24	0.68	0.84	0.87
75/25 (Figure 6)	0.20	0.62	0.81	0.94
70/30 (Figure 7)	0.20	0.60	0.67	0.96
65/35 (Figure 8)	0.20	0.34	0.42	0.61
60/40	0.21	0.22	0.14	0.35
55/45	0.19	0.09	0.07	0.08
50/50 (Figure 9)	0.20	0.03	0.04	0.05



**FIGURE 10** Index of dissimilarity by the smaller group's percentage representation in the city population under four implementations of vision with preferences for co-ethnic contact at 30%

co-ethnic contact exceeds supply under integration, segregation emerges and moves to high levels as the discrepancy increases.

Two interesting patterns are evident in Figure 10. One is that once demand for co-ethnic contact approaches and exceeds supply, segregation climbs to high levels. The transition is less abrupt than a “step” function, but the effect involves a region of rapid increase leading into a “plateau” where segregation is at consistent high levels. Another pattern is that segregation begins to elevate well *before* demand exceeds supply. Thus, as documented in Table 1 as well as in Figure 10, a high level of segregation is generated under the 65/35 ethnic mix, even though the percentage representation of the smaller group is a full five points above the relatively low preference for 30% co-ethnic contact.

Fossett and Waren (2004) provide insight into this result. They report that segregation outcomes in agent-based models are consistently higher than outcomes that can be achieved under planning and strategic placement. Under strategic placement, the 65/35 ethnic mix could easily sustain stable integration where all households are satisfied. However, in our simulations, the initial household placements are random, and many households are unsatisfied and move to achieve the co-ethnic contact they desire. Their moves are uncoordinated, not strategic. Stable integration is logically possible, but the moves of individual households produce steady “drift” toward ethnically polarized neighborhoods and stable segregation.

Fossett (2003, 2004) has termed the powerful interaction of preferences and ethnic demography documented in Table 1 and Figure 10 the “paradox of weak minority preferences.” The essence of the paradox is that relatively weak preferences for co-ethnic contact can produce high levels of segregation when population groups are small. Of course, the broader principle involved is not paradoxical. If demand for co-ethnic contact cannot be met under integration, goal-directed moves by individual households will create a drift toward segregation that is self-reinforcing and unlikely to be reversed. When the preferences for co-ethnic contact are very high, this fact is not surprising. But, it is not widely appreciated that the effect can be strong when relatively weak preferences combine with unbalanced ethnic ratios. Since such demographic conditions are typical, not rare, the paradox takes on particular substantive significance.

### **Contrary Results under Minimal Vision Specifications**

The paradox is not evident in the results for experiments conducted by using minimal vision. Laurie and Jaggi reported that segregation behavior under minimal vision follows unexpected and often curious patterns. Our results support that finding. As noted earlier, we differ from Laurie and Jaggi on the question that these results hold much relevance for understanding *residential* segregation. We are guided by theory and research on residential segregation and know of no influential perspective in that literature to support the view that vision should be restricted to the minimal case.

Laurie and Jaggi are guided by theory and research on agent-based modeling where segregation behavior under minimal vision receives greater attention. Following model specifications of vision from this literature is relevant when von Neumann and Moore neighborhoods are reasonable analogs to interaction patterns in the real world. Thus, for example, minimal vision models are relevant for segregation in voluntary seating patterns in

classrooms, lunchrooms, lecture halls, movie theatres, and assembly halls. Segregation patterns in these contexts are substantively meaningful and deserve attention. But we believe caution should be exercised before concluding that macro-spatial patterns of residential segregation in cities are generated by the same dynamics as segregation in micro-spatial settings. Research on segregation in minimal vision contexts should be pursued. Until a clear substantive basis for doing so is provided, however, it should not be taken as instructive for understanding residential segregation patterns.

### Varying Preferences for Co-ethnic Contact across Groups

The results to this point are consistent with a simple principle: segregation outcomes under voluntary choice by individual households are determined not by the absolute magnitude of the preference for co-ethnic contact but by the discrepancy between the preferences individuals hold and the demographic supply that can satisfy these preferences under conditions of integration (i.e., even distribution). We explored this hypothesis in greater depth by performing several thousand experiments in which we set the SimSeg model to implement vision based on site-centered areas defined by  $R = 5$  and using our specification for search. For these experiments, we sampled the parameter space for the model as follows. We randomly varied Whites' preferences for co-ethnic contact from 0 to 90; we randomly varied Blacks' preferences for co-ethnic contact from 0 to 90; we randomly varied  $R$  from 1 to 7; and we randomly varied city ethnic mix from 95/5 to 5/95.

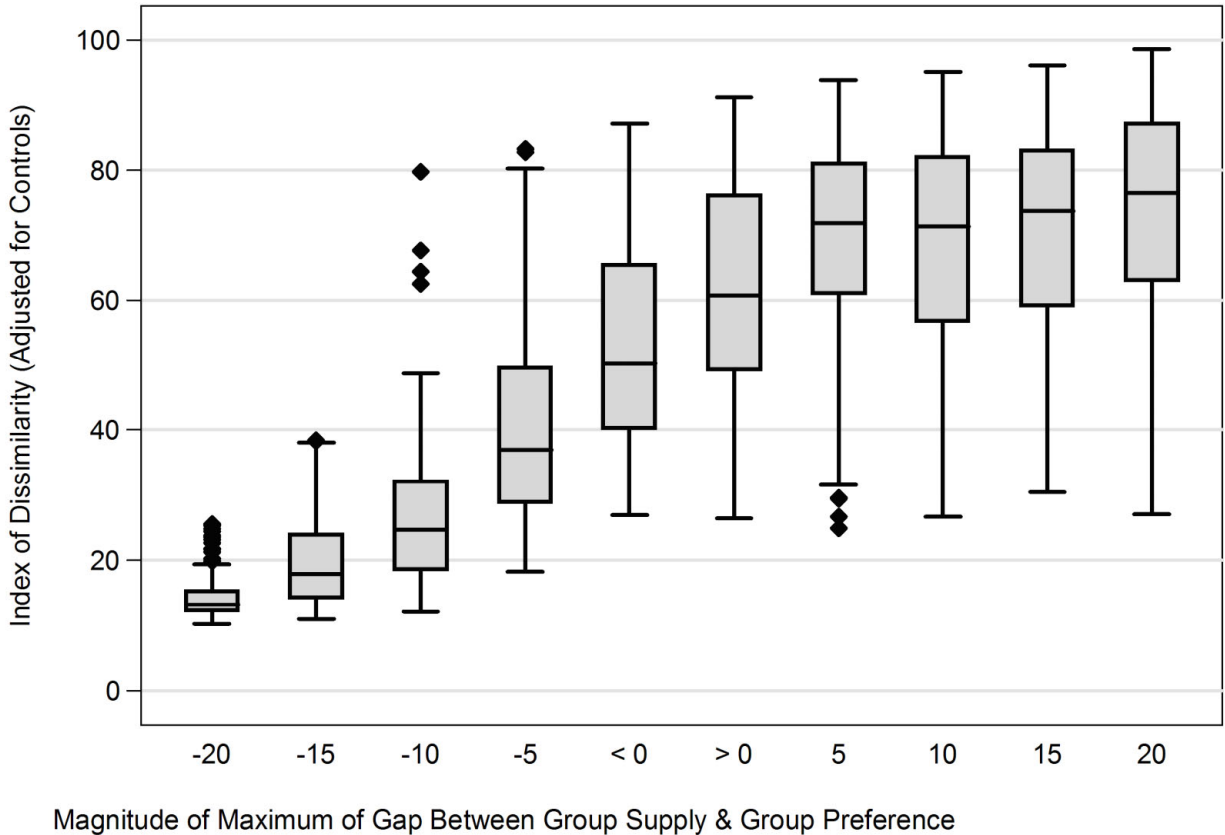
For each simulation experiment, we computed the maximum discrepancy between an ethnic group's supply and its percentage in the population. We then categorized this variable into five-unit intervals and plotted the distribution of scores on the index of dissimilarity as shown in Figure 11.<sup>36</sup> The results provide strong support for our hypothesis. The level of segregation is always high when the co-ethnic preferences of at least one group equal or exceed the supply available in integrated neighborhoods. As seen in Figure 10, the level of segregation is distinctly elevated when the balance between supply and demand is merely "tight." For example, when the surplus of supply is under five points, the median value of the index of dissimilarity is about 50. Perfect integration is clearly feasible under planning and strategic placement, but it does not emerge under the uncoordinated location decisions of individual households despite the fact that the city landscape is initially integrated. It is not until supply exceeds demand by a full 10 points that segregation levels fall to those that would be expected under random assignment!

Two outcomes in the parameter space for the model merit comment. One is that simulations with low levels of preference for co-ethnic contact for both groups produced high levels of segregation in cities with imbalanced ethnic mixes.<sup>37</sup> This outcome strongly supports the Schelling notion that high levels of segregation can emerge when location decisions are not

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<sup>36</sup> The plotted values are residuals from an analysis of variance that controls for categories of vision (1–7) and the continuous covariate for percent Black.

<sup>37</sup> This echoes the results presented in Table 1 and Figure 10.



**FIGURE 11** Distribution of index of dissimilarity by the magnitude of the maximum difference between group supply and group demand for co-ethnic contact

specifically motivated by the desire to live in ethnically homogeneous areas.<sup>38</sup> The other is that simulations where *one* group with strong preference for co-ethnic contact held sometimes produced low levels of segregation in cities with imbalanced ethnic mixes. This result occurred when the group holding the strong preference for co-ethnic contact was a demographic majority *and* the other group had a low preference for co-ethnic contact. For example, segregation will be low in cities with an 80/20 ethnic mix, if the larger group's preference for co-ethnic contact does not exceed 70% *and* the smaller group's preference for co-ethnic contact does not exceed 10%. The key factor that permits stable integration in this situation is that both groups' preferences can easily be met under conditions of even distribution. This factor further supports Schelling's basic insight that the implications of preferences for segregation are complex and cannot be deduced on the basis of knowledge of preferences alone.

<sup>38</sup> In the interest of space, we do not systematically explore the effects of vision and percent Black. The strongest effects in the analysis are those presented. As noted earlier, the level of segregation is low when vision is at its logical minimum ( $R = 1$ ), but segregation increases dramatically as vision moves past 2. All effects considered are statistically significant at 0.001 or better. The adjusted  $R$ -square for the analysis of variance is approximately 0.84.

## POSITIVE PREFERENCES FOR DIVERSITY: A POTENTIAL BASIS FOR OPTIMISM

Laurie and Jaggi characterized their study as providing a basis for “optimism” regarding ethnic segregation. They interpreted their results as suggesting that policies aimed at expanding vision and promoting moderate preferences for co-ethnic contact could lower segregation. Our results suggest that their optimism must be tempered. Laurie and Jaggi stated that preferences need not be “unrealistic” or “Gandhian” to achieve integration. But they did not take account of the interaction of preferences and ethnic demography and based their conclusions on results obtained by using an ethnic mix that was optimal for producing integration. Our results show that, even with expanded vision, moderate and weak preferences for co-ethnic contact can produce high levels of segregation under the ethnic demographic conditions typical in most cities.

This finding is important and sobering. Realistic reductions in preferences for co-ethnic contact may not necessarily be enough to drive existing segregation down and promote stable integration. But we do not believe that this finding implies that ethnic segregation is inevitable. Rather, we suggest that additional directions in policy options concerning preferences need to be considered. One new direction that deserves attention is the potential role that positive preferences for ethnic diversity (or aversion to extreme ethnic homogeneity) may play in reducing ethnic segregation. Laurie and Jaggi follow the literature on agent-based modeling and focus exclusively on preferences for co-ethnic contact. But research on residential preferences indicates that people may simultaneously hold both positive preference for co-ethnic contact *and* preferences for contact with other groups.

For ethnic minority groups, this may reflect the mixture of desires to maintain connection with the ethnic community while assimilating with the broader society, including greater contact with ethnic majority groups. The preference to seek significant levels of out-group contact may reflect instrumental motives for assimilation, such as gaining access to the residential amenities available only in majority ethnic areas. Alternatively, it may reflect a willingness to relinquish ethnic bonds and seek full incorporation into primary social relationships with the majority group, including friendship and kin networks. Or it may reflect some combination of these and other motives. For ethnic majority groups, desires for out-group contact may reflect a willingness to at least partially embrace the diversity of ethnic culture in modern societies and especially urban areas and a desire to avoid living an “insulated” life in “bland,” overwhelmingly homogeneous residential areas.

What role might such preferences play in segregation? We use the SimSeg model to implement simulation scenarios relevant to this question. First, we elaborate ethnic preferences to allow for positive preferences for both co-ethnic and out-group contact. These must be constrained to be logically compatible, but otherwise, they can be implemented in a straightforward way. For example, we modified the experiment set presented in Figure 7 as follows. We maintained ethnic demography at 70/30 and preference for co-ethnic contact at 30%, but we added a preference for out-group contact at 30%. Under this scenario, all households would be completely satisfied with neighborhoods that ranged between 30% and 70% Black, and all households would be dissatisfied in some degree with neighborhoods that were less than 30% or more than 70% Black. We implemented the diversity preference in a relatively conservative way. We calculated satisfaction scores on out-group contact in the same way as satisfaction scores on co-ethnic contact, but we assigned them only *half* the weight given



to the satisfaction scores for co-ethnic contact. This scenario corresponds to a situation where households sincerely have the goal of seeking diversity but assign it less importance than the goal of seeking co-ethnic contact.

We also performed a set of experiments that used a variation in preferences that was even more conservative. Specifically, we departed from the Laurie-Jaggi practice of maintaining symmetric preferences for both groups and assigned stronger preferences for co-ethnic contact to the demographic majority group (Whites). We set the preference for co-ethnic contact for Whites at 50% while keeping the similar preference for Blacks at 30% and maintaining the preference for out-group contact at 30% for both groups. Thus, Whites are not satisfied if they are a demographic minority but also wish to live in ethnically diverse areas.

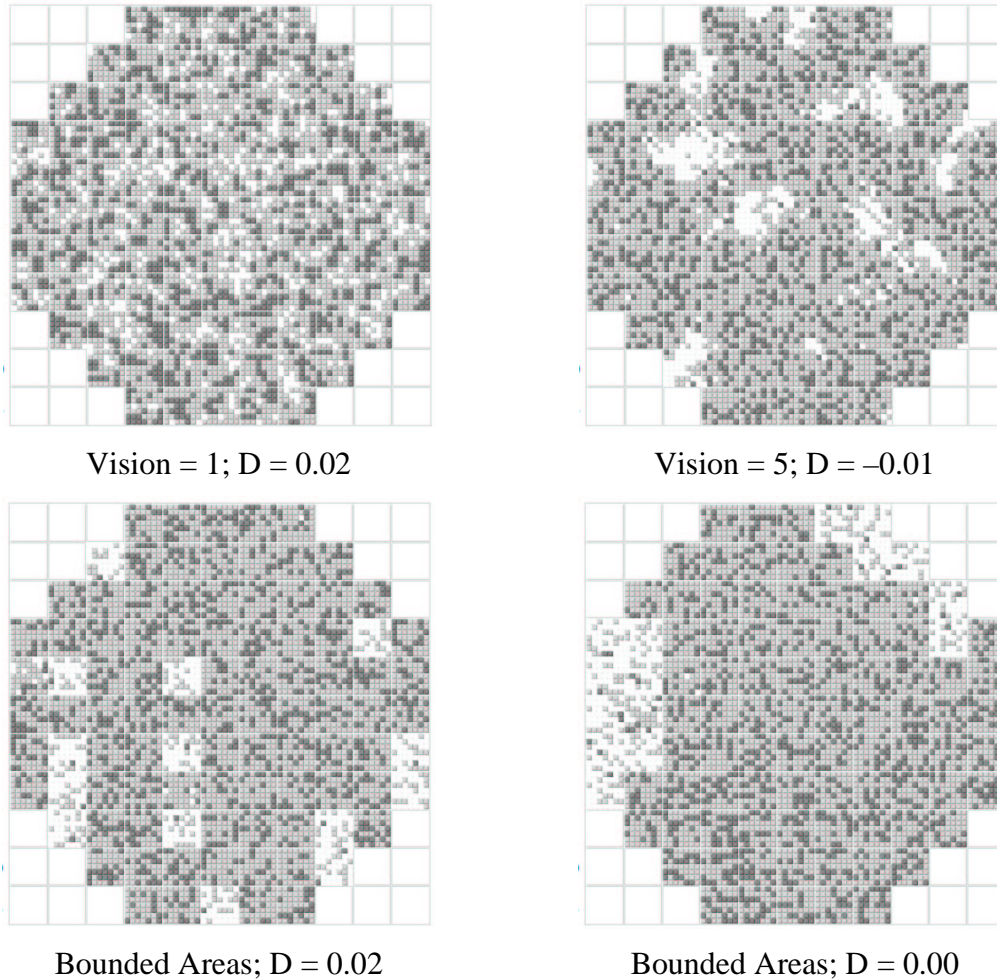
Figures 12 and 13 show the results for these experiments. They suggest that positive preferences for ethnic diversity have the potential for dampening the segregation-promoting consequences of preferences for co-ethnic contact established in previous sections of this paper. Across the board in both figures, segregation is at very low levels. The comparison with the results presented in Figure 7 are compelling. In Figure 7, segregation was high in all three scenarios with nonminimal vision. These high levels of segregation are eliminated by introducing positive preferences for diversity. This finding, as so many others, is anticipated by Schelling (1971, pp. 165–166).

In our view, this finding provides a realistic basis for optimism regarding the possibilities for ethnic integration under unconstrained choice dynamics. The results are encouraging because preferences for out-group contact are assigned only half the weight of preferences for co-ethnic contact. Future research should direct attention to the question of how diversity preferences may reduce segregation. However, the exploratory results here should be kept in perspective because the simulations implement conditions that are favorable to integration in two important respects:

- Neither group's preference for co-ethnic contact exceeds its representation in the population. This factor makes it possible for White and Black households to meet their preferences for co-ethnic contact and diversity by residing in areas that mirror the city's 70/30 ethnic mix. Obviously, this would not be possible in a city with a 90/10 ethnic mix. Future research should investigate that situation to assess the limits of the diversity preference effect seen in Figures 12 and 13.
- Preferences that depart substantially from those documented in surveys have been implemented. Surveys suggest that most White households prefer at least 80% co-ethnic contact. Relatively little evidence suggests that the average White household specifically seeks diversity and assigns this goal a high priority.<sup>39</sup> The more common "optimistic" interpretation is that Whites "tolerate" diversity, and their level of "tolerance" has increased appreciably

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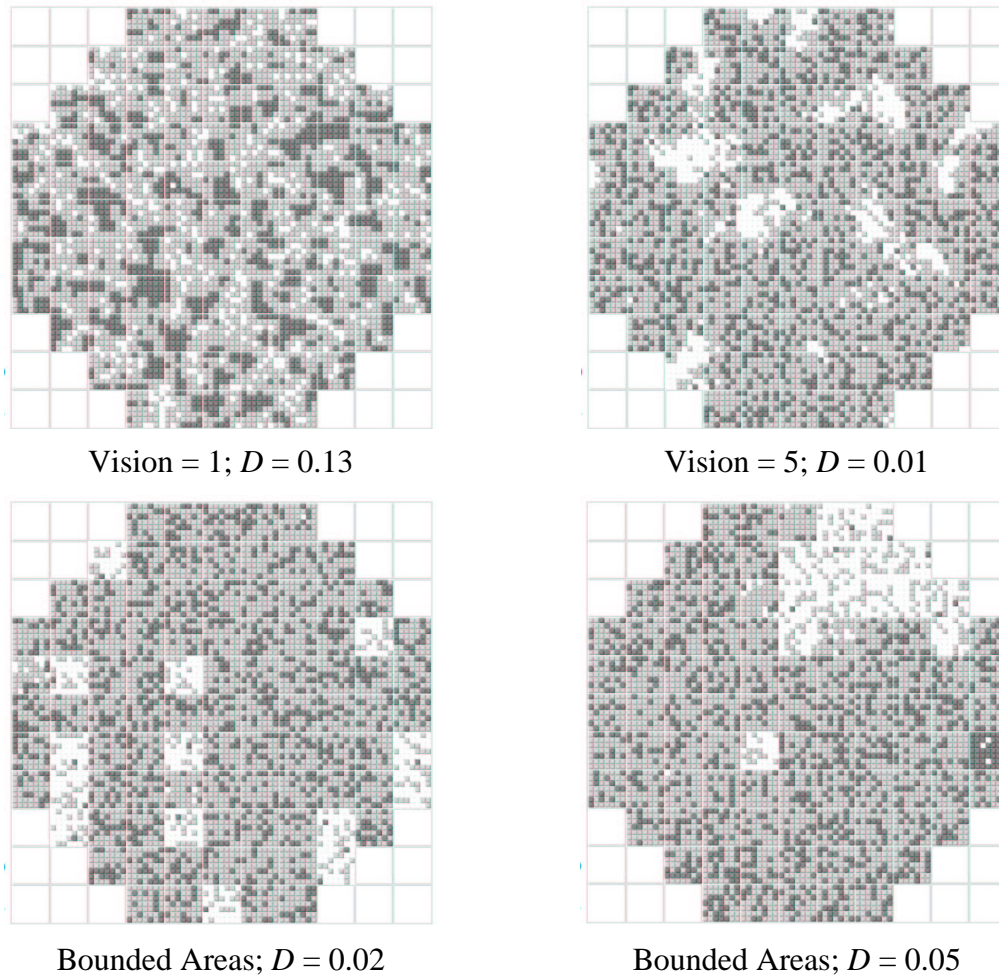
<sup>39</sup> Our analysis of data on residential preferences taken from the Houston Area Surveys (Klineberg, 2003) provides some evidence that Whites in Houston, Texas, display a discernible preference for ethnic diversity. White respondents in this survey indicate they are more willing to move into neighborhoods that are 10% to 20% non-White than neighborhoods that are all White. At present, this is an isolated empirical result, but it merits closer examination.



**FIGURE 12** Ending landscapes from analyses where vision  $R$  is varied, preference for co-ethnic contact  $P = 30\%$ , preference for out-group contact is  $30\%$ , and ethnic mix is  $70/30$

over the past four decades. Our earlier results suggested, however, that mere tolerance is not likely to be a powerful mechanism for *promoting* integration. That is, tolerance of out-group contact is *permissive* of greater integration, *but it does not specifically generate movement toward integration*. The models explored here show that, when preferences for co-ethnic contact exceed demographic supply under integration, neighborhoods drift steadily toward ethnic polarization via irreversible neighborhood “tipping” dynamics of the type considered by Schelling. The results presented in Table 1 and Figure 10 show that mere tolerance of diversity does not serve as a “brake” on this dynamic.

We stress that we are couching our assessment of the relative inconsequence of tolerance of diversity in the context of models that assess only the *direct* effects of preferences. In a broader view, the permissive role of tolerance may be more important. Residential choices are



**FIGURE 13** Ending landscapes from analyses where vision  $R$  is varied, preference for co-ethnic contact  $P = 50\%$  for Whites and  $30\%$  for Blacks, preference for out-group contact is  $30\%$ , and ethnic mix is  $70/30$

driven by non-ethnic residential goals, such as seeking better municipal services, higher-quality housing, and closer proximity to employment — all influential factors in residential decisions. Tolerance of ethnic diversity allows households pursuing non-ethnic goals to consider a wider range of neighborhood ethnic mixes. Thus, while tolerance of diversity may not directly counter the segregation-promoting effects of preferences for co-ethnic contact, it may still facilitate integration indirectly by allowing non-ethnic dynamics to undermine the “drift” toward segregation seen in “pure” preference effect models.

Our analyses indicate that those who wish to *promote* integration via preference-related interventions should give attention not only to reducing desires for co-ethnic contact but also to educational efforts that would foster a meaningful desire for ethnic diversity. With respect to majority group preferences, this goal may be “within reach” in cities with imbalanced ethnic mixtures such as the  $90/10$  and  $75/25$  scenarios used in the experiments presented in Figures 5 and 6. Cities with ethnic mixtures along these lines are not uncommon. Surveys suggest most Whites will tolerate neighborhoods with  $90/10$  to  $75/25$  ethnic mixes. If Whites actively *sought*

such neighborhoods, it could help to promote large reductions in segregation. Considering the significant changes in attitudes in the past four decades, it is not altogether unrealistic to imagine such changes are possible.

This scenario is more complicated, however, because surveys suggest that typical Black households have preferences for at least 50% co-ethnic contact. These preferences are not compatible with stable integration in cities with 90/10 or 75/25 ethnic mixes due to the paradox of weak minority preferences. Blacks' preferences for co-ethnic contact are markedly *lower* than those held by Whites', but they are not integration-promoting relative to ethnic demographics found in most metropolitan areas. On a more encouraging note, survey evidence suggests that Blacks, more than Whites, often hold positive preferences for nontrivial diversity. The paradox of weak minority preferences suggests that demographic minority groups may bear a disproportionate "burden" in achieving integration. In most American metropolitan areas, integration requires Whites to embrace only moderate levels of out-group contact while still maintaining high levels of co-ethnic contact. In contrast, minority groups often must seek very high levels of out-group contact and accept low levels of co-ethnic contact, a point noted by Schelling (1971, p. 179). For minorities, spatial assimilation implies the potential demise of geographically based minority ethnic communities in urban areas. These issues are likely to be important and complex and thus deserve attention in future research.

## **SUMMARY AND DISCUSSION**

The primary purpose of this paper has been to investigate the implications of a theoretical model of ethnic preference effects on segregation. As in the Laurie-Jaggi study, the crucial variables in the model are ethnic demography, ethnic preferences, and vision. Laurie and Jaggi stressed the interaction of vision and preferences. We conclude that this interaction may be relevant to understanding segregation in small-scale, short-duration settings such as lunchroom and auditorium seating. However, we do not see it as important to understanding residential segregation because larger-scale spatial domains are salient in residential choices in metropolitan areas, and basic demographic processes generate random vacancies that unleash the full segregation-promoting potential of preferences.

We direct attention toward the interaction of ethnic preferences and ethnic demography. This interaction is powerful and, in our view, has clear relevance for understanding residential segregation in metropolitan areas. Because Laurie and Jaggi did not recognize this interaction, their study adopted a setting for ethnic demography that was optimal for achieving integration. We believe this helps to account for their premature willingness to question the Schelling model of segregation and offer conclusions about ethnic preferences and integration that were more optimistic than those advanced by previous researchers. We provide a more nuanced assessment of the implications of ethnic preferences under ethnic mixtures common in American metropolitan areas. Our analyses lead us to be more cautious about the possibilities for integration under unconstrained ethnic preferences. We find support for the hypothesis that preferences are segregation-promoting when demand for co-ethnic contact cannot be satisfied by demographic supply under integration. On the basis of this finding, we have a more sober view of the changes that may be needed to dramatically reduce segregation, given prevailing preferences for co-ethnic contact and the ethnic demographics of most metropolitan areas.

We end on a more optimistic note by pointing to the role that positive preferences for diversity could play in reducing segregation. We distinguish “diversity preferences” from the more passive “tolerance” of diversity. Tolerance of diversity is not inconsequential and may play an important “permissive” role in situations where factors other than ethnic considerations may promote residential integration. But in models that highlight the segregation- and integration-promoting effects of preferences, positive preferences for diversity appear to directly retard the segregation-promoting effects of preferences for co-ethnic contact to a much greater degree than mere tolerance of diversity.

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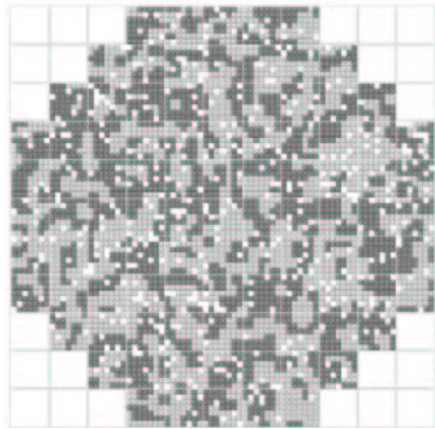
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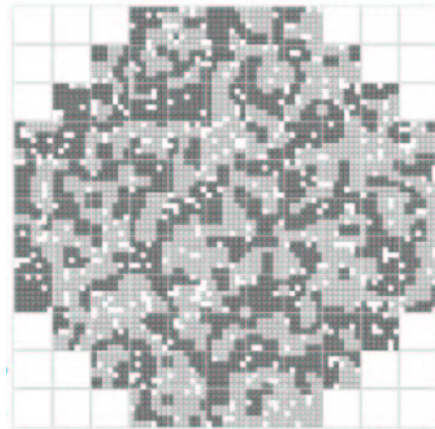
**APPENDIX A**



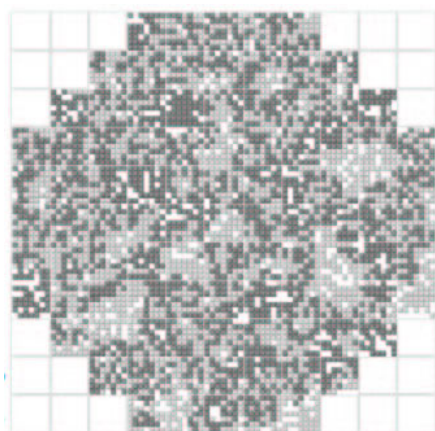




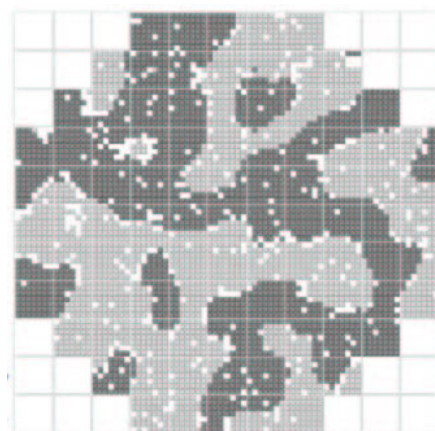
$P = 0.30$ ; Vision = 1;  $D = 0.17$



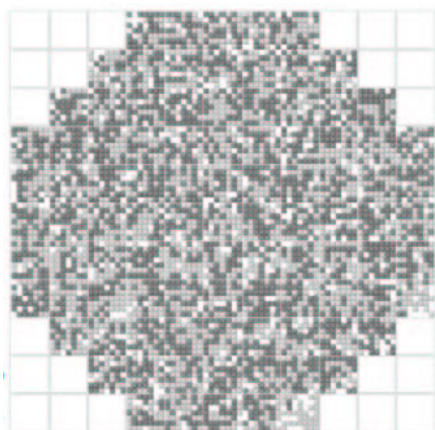
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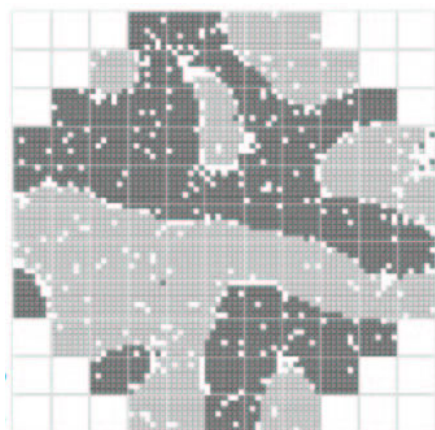
$P = 0.30$ ; Vision = 3;  $D = 0.14$



$P = 0.50$ ; Vision = 3;  $D = 0.63$

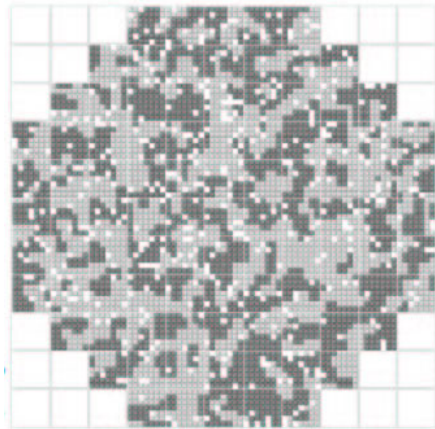


$P = 0.30$ ; Vision = 5;  $D = 0.03$

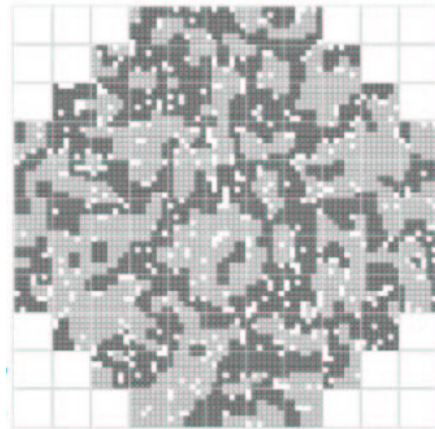


$P = 0.50$ ; Vision = 5;  $D = 0.78$

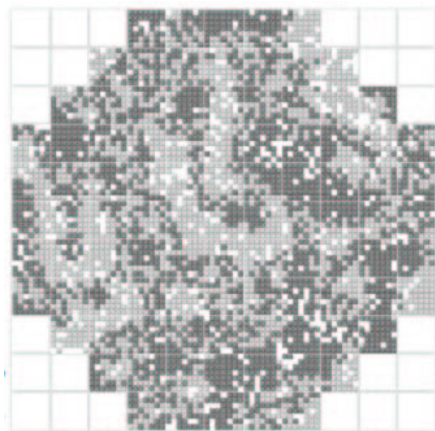
**FIGURE A.1a** Ending landscapes from replications of Laurie and Jaggi's analyses investigating the interaction of preferences for co-ethnic contact  $P$  and vision  $R$  when ethnic mix is 50/50 using the original Laurie-Jaggi search algorithm where satisfied households need never move



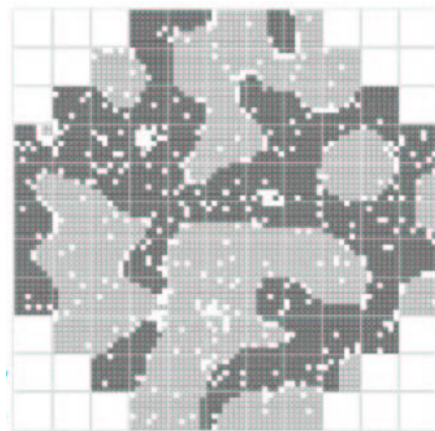
$P = 0.30$ ; Vision = 1;  $D = 0.20$



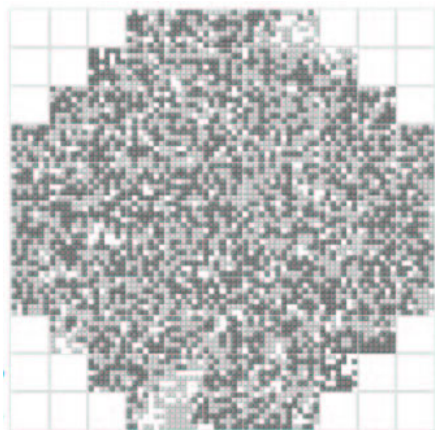
$P = 0.50$ ; Vision = 1;  $D = 0.26$



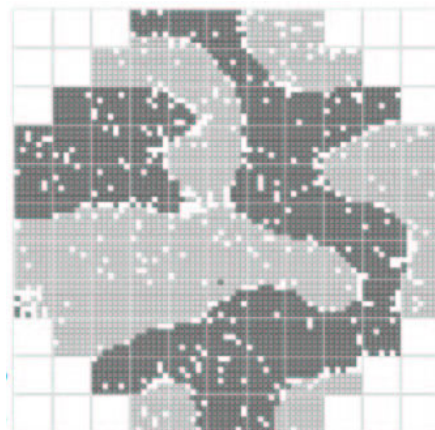
$P = 0.30$ ; Vision = 3;  $D = 0.25$



$P = 0.50$ ; Vision = 3;  $D = 0.67$



$P = 0.30$ ; Vision = 5;  $D = 0.03$

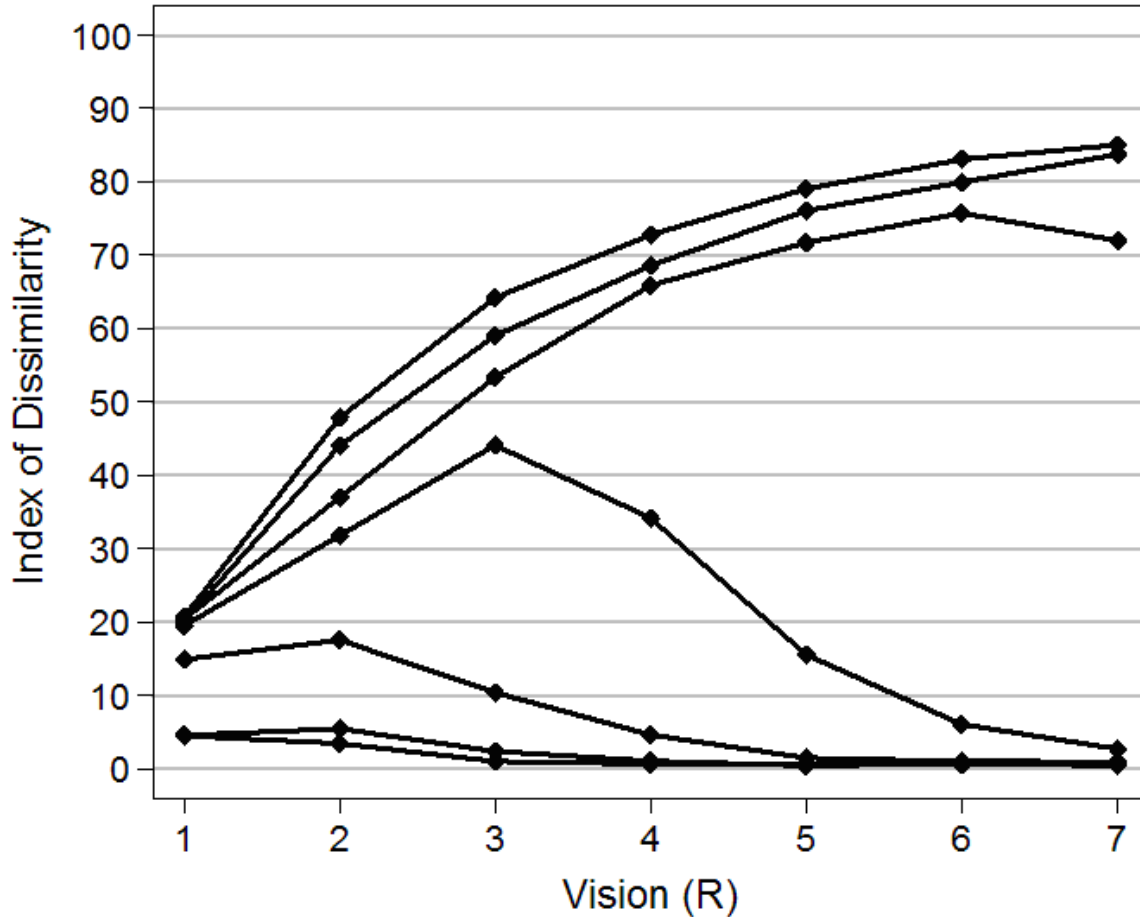


$P = 0.50$ ; Vision = 5;  $D = 0.79$

**FIGURE A.1b** Ending landscapes from replications of Laurie and Jaggi's analyses investigating the interaction of preferences for co-ethnic contact  $P$  and vision  $R$  when ethnic mix is 50/50 using the modified search process where households are required to move on first search

**TABLE A.1** Means for the index of dissimilarity for final landscapes by vision  $R$  and preference for co-ethnic contact  $P$  for repeated simulation experiments where ethnic mix is 50/50

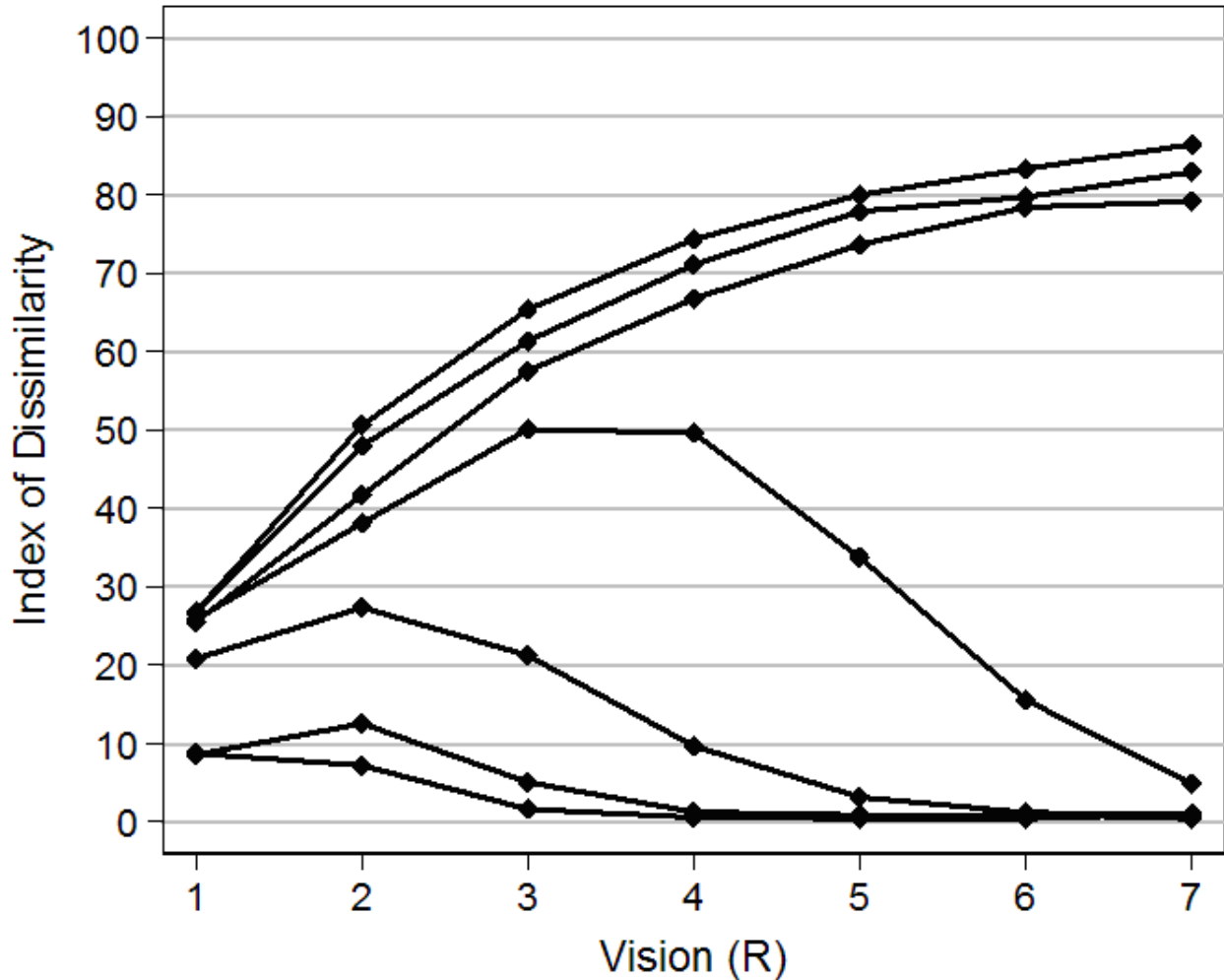
$P$	Vision, $R$						
	1	2	3	4	5	6	7
<b>Panel 1: Search Process Specifies Satisfied Households Need Never Move</b>							
20	4.5	3.5	1.1	0.6	0.7	0.6	0.5
25	4.6	5.5	2.4	1.1	0.5	0.7	0.6
30	14.9	17.6	10.4	4.7	1.5	1.0	1.0
35	19.6	31.8	44.1	34.2	15.6	6.1	2.7
40	20.4	37.0	53.3	65.9	71.7	75.8	72.0
45	20.1	44.1	59.0	68.6	76.1	79.9	83.8
50	20.8	47.9	64.2	72.8	79.1	83.1	85.0
<b>Panel 2: Search Process Specifies Households Must Move on First Search</b>							
20	8.8	7.3	1.7	0.6	0.5	0.5	1.1
25	8.6	12.6	5.1	1.3	0.9	1.0	0.5
30	20.8	27.4	21.3	9.7	3.2	1.2	0.9
35	25.9	38.1	50.1	49.6	33.8	15.6	4.9
40	25.6	41.8	57.5	66.8	73.6	78.4	79.1
45	26.8	48.0	61.3	71.1	77.9	79.8	82.9
50	26.8	50.6	65.4	74.3	80.0	83.3	86.4



**FIGURE A.2a** Index of dissimilarity for final landscape by vision  $R$  and preference for co-ethnic contact  $P$  for repeated simulations where ethnic mix is 50/50 and search algorithm specifies satisfied households need never move

*Note:* Figure A.2a replicates results presented in Figures 5 and 7 of Laurie and Jaggi (2003). The plotted lines are in descending order of the preference for co-ethnic contact. Thus, the top line is for  $P = 50$ , the next highest line is for  $P = 45$ , and so on. The data plotted in this figure are provided in Table A.1.

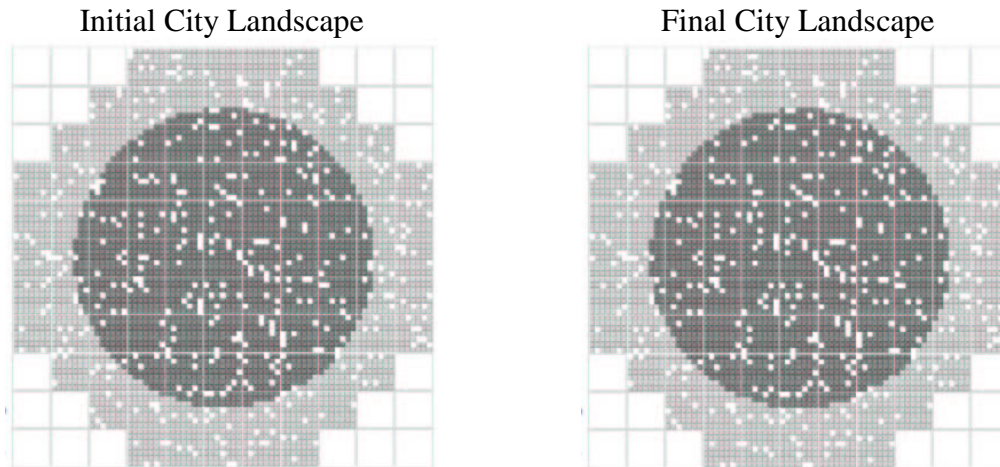
*Commentary:* Figure A.2a documents that when  $P \geq 40$  (top three lines), segregation is high at high levels of vision. However, when  $P \leq 30$  (bottom four lines), segregation is low at high levels of vision.



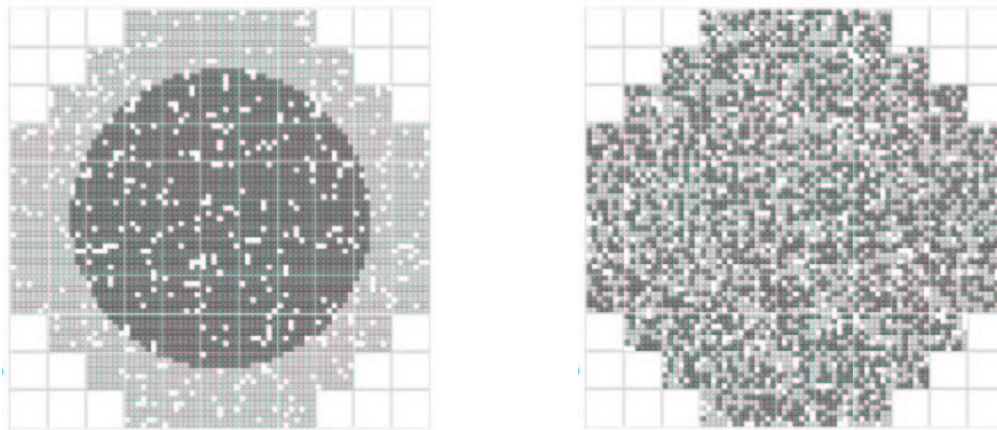
**FIGURE A.2b** Index of dissimilarity for final landscape by vision  $R$  and preference for co-ethnic contact  $P$  for repeated simulations where ethnic mix is 50/50 and search algorithm specifies households must move on first search

*Note:* Figure A.2b replicates results presented in Figures 5 and 7 of Laurie and Jaggi (2003) and Figure A.2b of this paper, but using the modified search algorithm where households are required to move on first search. The plotted lines are in descending order of the preference for co-ethnic contact. Thus, the top line is for  $P = 50$ , the next highest line is for  $P = 45$ , and so on. The data plotted in this figure are provided in Table A.1.

*Commentary:* Figure A.2b documents that when  $P \geq 40$  (top three lines), segregation is high at high levels of vision. However, when  $P \leq 30$  (bottom four lines), segregation is low at high levels of vision.



Panel 1: Laurie and Jaggi Search Process Where Satisfied Households Need Never Move



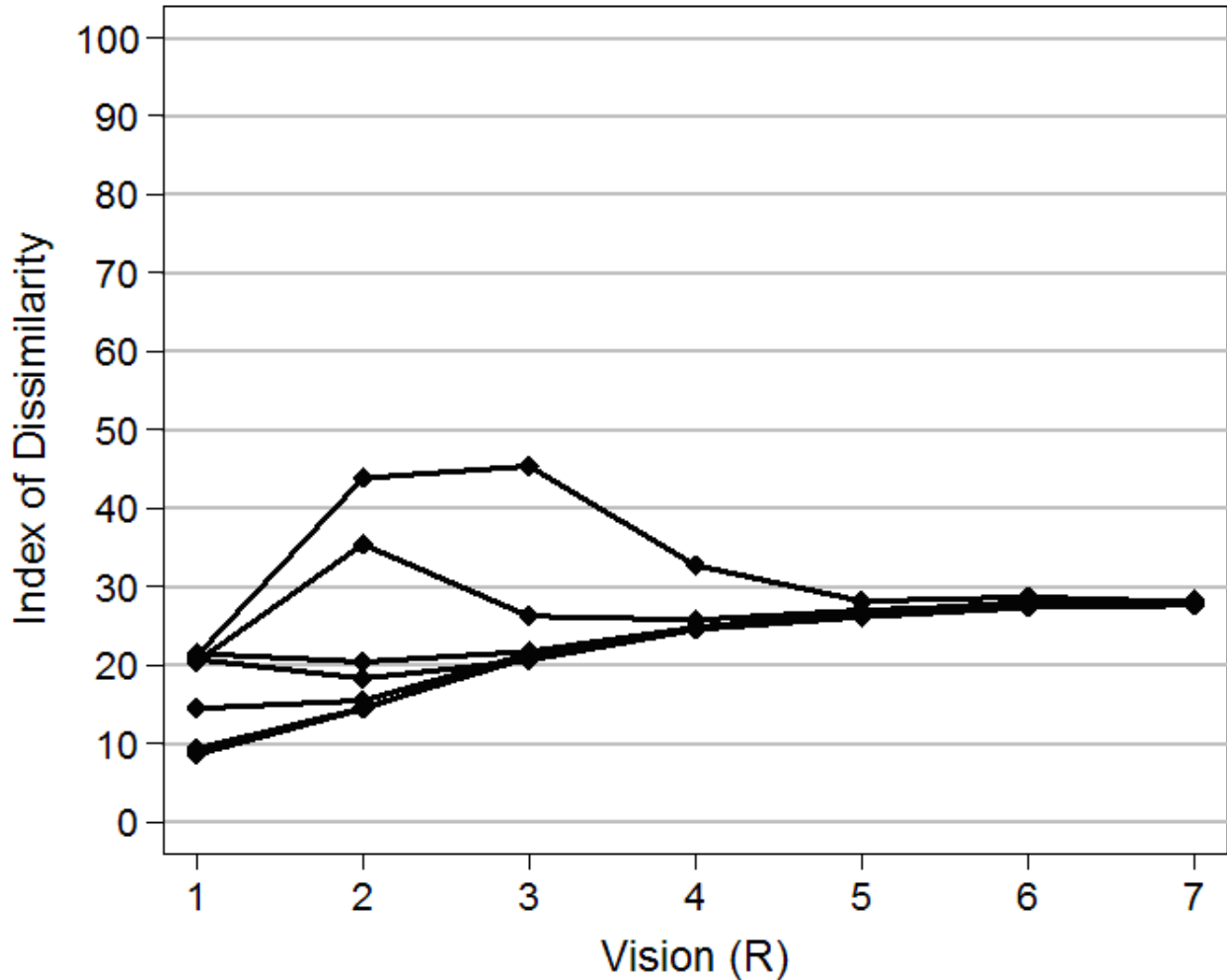
Panel 2: Modified Search Process Requiring Households to Move on First Search

**FIGURE A.3** Beginning and ending landscapes from simulations where ethnic mix is 50/50, preference for co-ethnic contact  $P$  is 0%, and vision  $R = 5$  by using the original Laurie-Jaggi search process and a modified search process

*Commentary:* The results in Figure A.3, Panel 1, show that the Laurie-Jaggi search process does not reveal the potential for preferences to permit integration. In fact, no movement occurs because households cannot improve satisfaction by moving. The results in Panel 2 show that the modified search process produces integration because final residential outcomes in Panel 2 are produced by preference-guided search, whereas final residential outcomes in Panel 1 are produced by initial assignment, not search.

**TABLE A.2** Means for the index of dissimilarity for final landscapes by vision  $R$  and preference for co-ethnic contact  $P$  for repeated simulations where ethnic mix is 80/20

$P$	Vision, $R$						
	1	2	3	4	5	6	7
<b>Panel 1: Search Process Specifies Satisfied Households Need Never Move</b>							
20	9.4	14.6	21.0	24.5	26.1	27.4	28.3
25	8.6	14.5	21.4	24.6	26.8	28.1	27.9
30	14.5	15.5	21.4	24.8	26.7	27.7	27.7
35	20.8	18.3	20.6	24.5	27.0	27.5	27.6
40	21.5	20.4	21.7	24.8	26.9	27.9	27.9
45	20.4	35.4	26.3	25.8	27.0	27.8	27.8
50	21.2	43.8	45.4	32.7	28.2	28.7	28.0
<b>Panel 2: Search Process Specifies Households Must Move on First Search</b>							
20	13.43	25.43	35.53	40.82	44.65	47.26	49.84
25	13.51	32.08	45.42	53.69	58.11	61.78	64.32
30	25.02	41.80	54.49	63.14	68.99	72.26	75.02
35	31.94	47.78	60.90	71.57	76.47	78.96	80.92
40	31.94	49.90	63.91	73.25	79.67	83.02	84.04
45	31.11	55.48	67.96	76.45	81.86	84.76	86.08
50	32.24	56.51	71.48	78.80	83.65	85.68	88.33

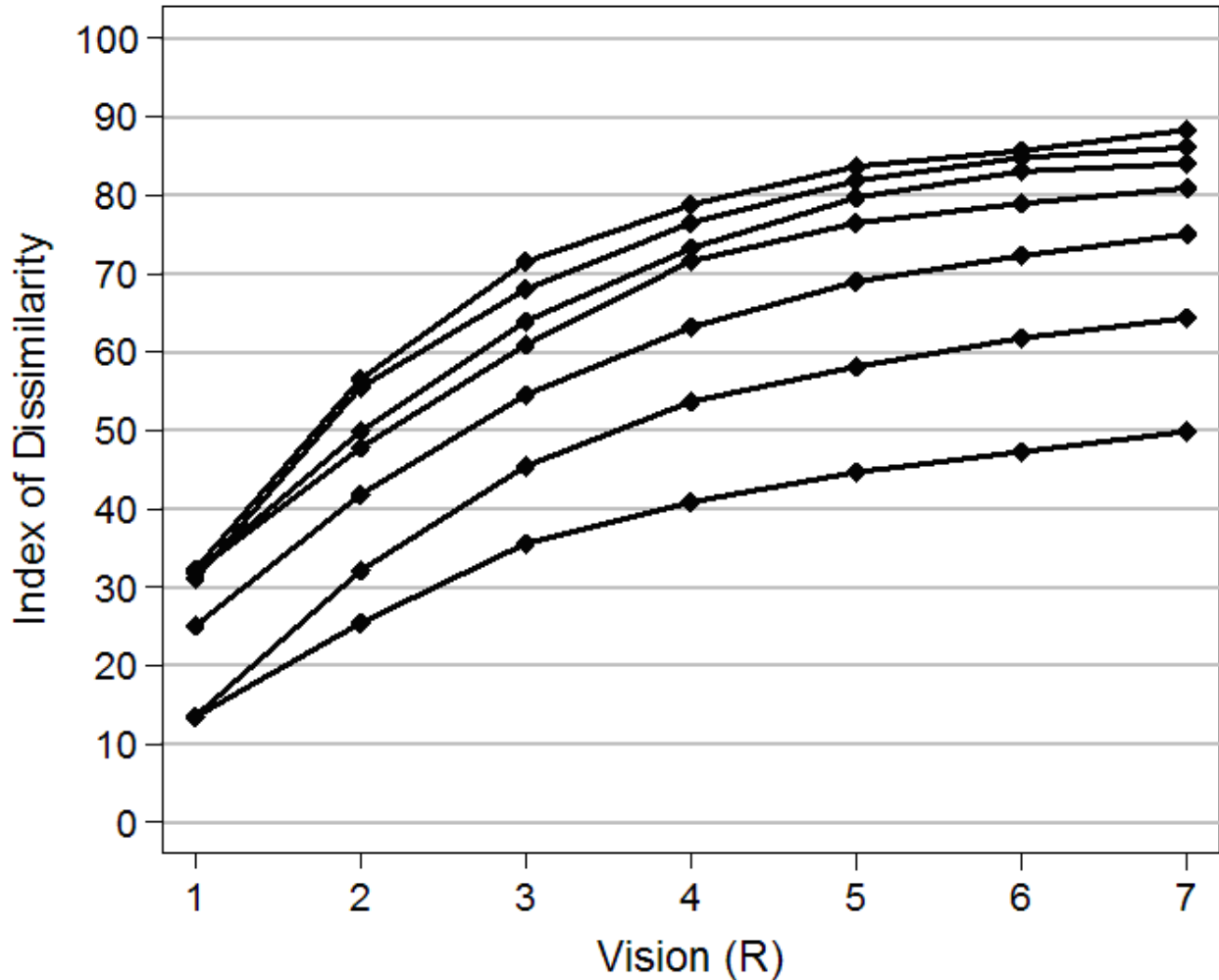


**FIGURE A.4a** Means for the index of dissimilarity for final landscapes by vision  $R$  and preference for co-ethnic contact  $P$  for simulations where ethnic mix is 80/20 and search algorithm specifies satisfied households need never move

*Note:* The plotted lines in Figure A.4a are in descending order of the preference for co-ethnic contact. Thus, the top line is for  $P = 50$ , the next highest line is for  $P = 45$ , and so on. The data plotted in this figure are provided in Table A.2.

*Commentary:* When compared with Figure A.2a, this figure documents that the Laurie-Jaggi search process produces low segregation at high levels of vision under all settings for co-ethnic contact considered in Table A.2 (i.e.,  $P = 20$ – $50$ ). This illustrates how the Laurie-Jaggi search process fails to permit the full expression of latent potential for high levels of segregation under high levels of vision. “Stable integration” results not because households are satisfied with integrated neighborhoods, but because movement promoting segregation ceases when vacancies in areas receiving Black in-migrants “fill up.” The resulting city has two kinds of neighborhoods: all-White neighborhoods with a 20% vacancy rate and 80/20 neighborhoods with no vacancies.





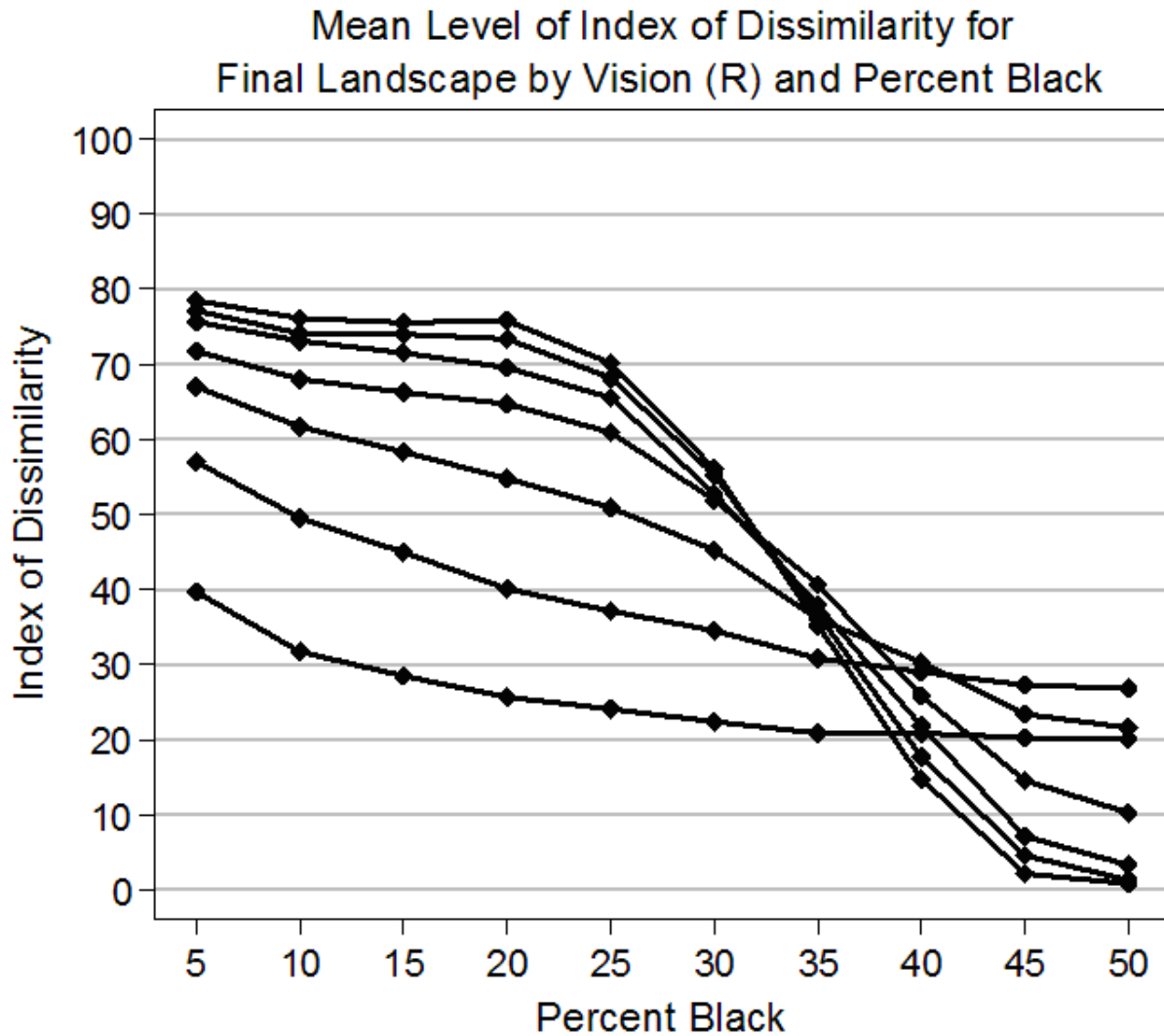
**FIGURE A.4b** Means for the index of dissimilarity for final landscapes by vision  $R$  and preferences for co-ethnic contact  $P$  for repeated simulations where percent Black is 20% and search algorithm specifies households must move on first search

*Note:* The plotted lines in Figure A.4b are in descending order of the preference for co-ethnic contact. Thus, the top line is for  $P = 50$ , the next highest line is for  $P = 45$ , and so on. The data plotted in this figure are provided in Table A.2.

*Commentary:* When compared with Figure A.4a, this figure documents that our modification of the Laurie-Jaggi search process “unleashes” the latent potential for segregation in simulations where demand for co-ethnic contact equals or exceeds its supply under integration (i.e., when  $P \geq C$ ). Segregation is much higher in these simulations because our search process creates random vacancies that permit households to act on their segregation-promoting preferences. Under this search process, segregation increases with vision and is higher when the discrepancy between demand for co-ethnic contact and its supply under integration is greatest.

**TABLE A.3** Means for the index of dissimilarity for final landscapes by vision  $R$  and percent Black  $C$  for repeated experiments where preference for co-ethnic contact  $P$  is 30% and search algorithm specifies households must move on first search

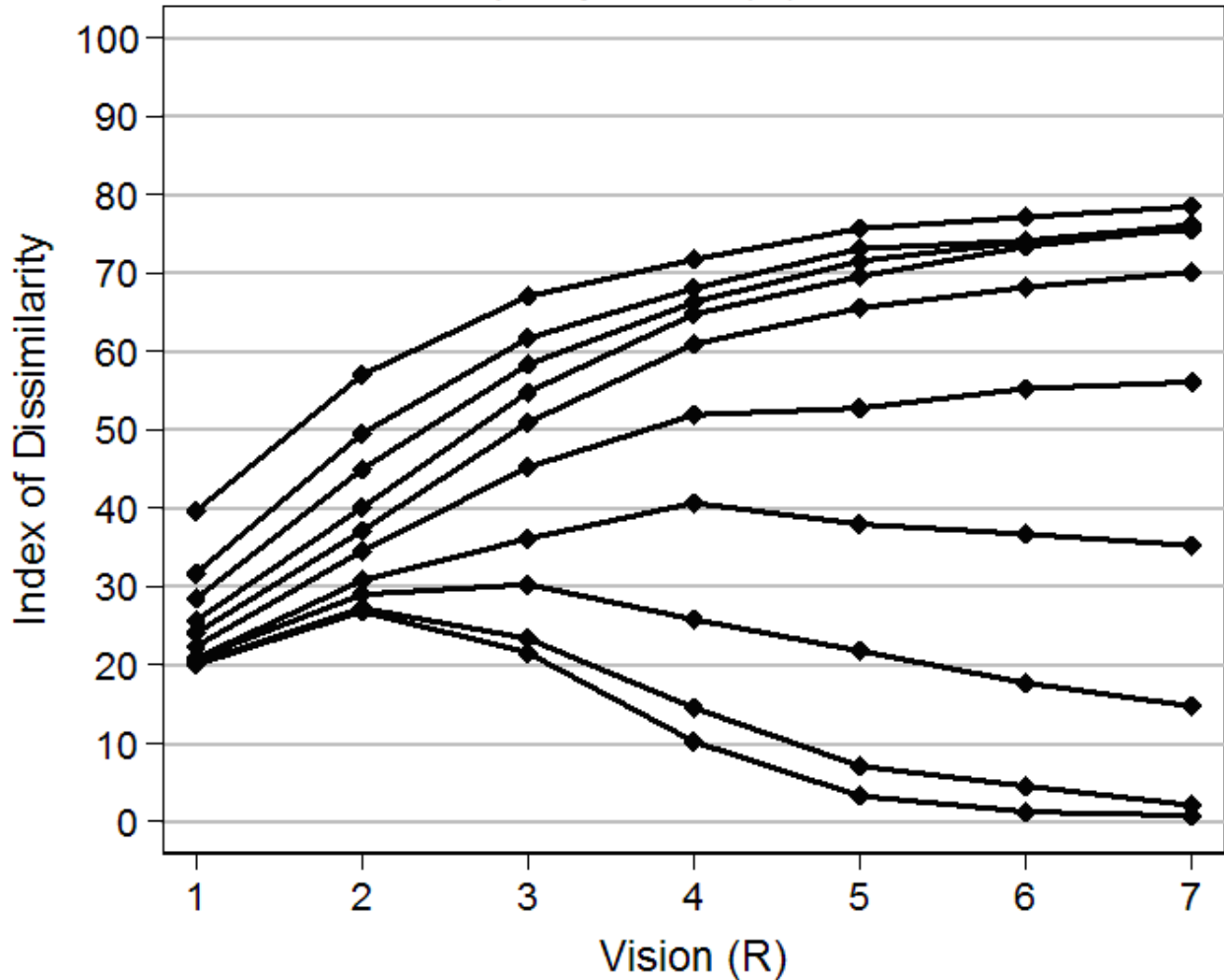
Percent Black, $C$	Vision, $R$						
	1	2	3	4	5	6	7
5	39.7	57.0	67.0	71.7	75.6	77.2	78.5
10	31.7	49.5	61.6	68.0	73.1	74.1	76.2
15	28.5	45.0	58.3	66.3	71.5	74.0	75.6
20	25.7	40.1	54.8	64.8	69.6	73.4	75.8
25	24.1	37.1	50.9	60.9	65.5	68.2	70.1
30	22.4	34.5	45.3	51.9	52.8	55.2	56.1
35	20.8	30.8	36.1	40.7	38.0	36.7	35.3
40	20.9	29.0	30.3	25.9	21.8	17.7	14.8
45	20.3	27.3	23.4	14.5	7.1	4.6	2.1
50	20.1	26.8	21.6	10.2	3.3	1.3	0.8



**FIGURE A.5** Means for the index of dissimilarity  $D$  for final landscapes by percent Black in the city  $C$  and vision  $R$  for repeated experiments where preference for co-ethnic contact  $P$  is 30% and search algorithm specifies households must move on first search

*Note:* At the furthest point on the left on the X axis (percent Black = 5), the plotted lines are in descending order of vision; that is, the top line is for  $R = 7$ , the next highest line is for  $R = 6$ , and so on. The data plotted in this figure are provided in Table A.3.

*Commentary:* Figure A.5 shows that segregation outcomes are strongly conditioned by ethnic mix when vision involves nonminimal spatial domains (e.g., when  $R \geq 3$ ). The interaction grows stronger at higher levels of vision.



**FIGURE A.6** Means for the index of dissimilarity  $D$  for final landscapes by vision  $R$  and percent Black in the city  $C$  for repeated simulations where preference for co-ethnic contact  $P$  is 30% and search algorithm specifies households are required to move on first search

*Note:* At the furthest point on the left on the X axis (vision is  $R = 1$ ), the plotted lines are in ascending order of percent Black; that is, the top line is for percent Black = 5, the next highest line is for percent Black = 10, and so on. The data plotted in this figure are provided in Table A.3.

*Commentary:* Figure A.6 shows that city ethnic mix conditions segregation outcomes under all settings of vision. The pattern is complex. When ethnic mix is balanced, as in the Laurie-Jaggi study (e.g., the lowest line corresponding to percent Black = 50), segregation is lower overall and is generally lower at high levels of vision. When ethnic mix is imbalanced (e.g., the top line for percent Black = 5), segregation is higher overall and increases monotonically as vision increases.

## TECHNOLOGY TRAJECTORIES — MODELING THE EFFECTS OF SOCIAL AND TECHNICAL DIVERSITY ON TECHNOLOGICAL DEVELOPMENT

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### ABSTRACT

What are the general dynamics of technological development within diverse social and technical environments? This paper describes an agent-based model designed to investigate this question. Simulation results are also discussed. The model consists of a heterogeneous population of innovators with different sets of values and social types (e.g., mimics, rebels, balancers, and dominators). All have access to several technical paradigms that offer different capabilities. Over time, innovators improve the performance of products within these paradigms, as a function of their inherent values and relationships with other innovators. Preliminary results provide insight into the influence of social identity, network density, paradigm structure, and other factors on the shape and content of technological development.

**Keywords:** Social agents, technological development, agent-based modeling

### INTRODUCTION

Modern technologies are developed in a complex environment. Diverse social agents, such as individuals, organizations, and states, pursue various technical alternatives for numerous interdependent reasons. Although social and technical context are key determinants of innovative activity, the interactions between technological development and even simple rules of social and political behavior are poorly understood. Nevertheless, these interactive dynamics influence the direction and rate of technological change. As such, they are consequential for a wide variety of issues, ranging from economic growth to national security.

This paper discusses how agent-based modeling and simulation (ABMS) can be used to investigate how a range of social relationships, coupled with different measures of value and multiple technical options, affect the trajectory of technological development. First, I highlight some of the problems presented by technological development in a heterogeneous environment. Then I describe the model (named TecTrajec) and discuss how my treatment of technological development relates to the literature on technology and other ABMS approaches. Next, I present preliminary simulation results. I conclude by addressing some of the implications of these early findings, as well as avenues for further investigation.

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## THE PROBLEM

The complexities of technological development are a major barrier to successful theorizing. The innovative process is characterized by a high degree of contingency and uncertainty, but there are also hints of underlying regularities. This juxtaposition of patterns and particulars is most apparent in systems where innovation is influenced by a heterogeneous population of individuals, organizations, and states, which all have different values, relationships, and capabilities. The analytical problems are only compounded by the diversity of technical substitutes, complements, and novelties that are available and often pursued in series or parallel. In light of these realities, many theories of technological development are too simplistic to account for the variety of outcomes observed or are so caught up in the details of a particular historical case that their general applicability is suspect.

Understanding the effects of social and technical diversity is difficult but important. Critical outcomes — from the success or failure of commercial ventures, to national security and economic competitiveness — all hinge on the interactions between these interdependent and overlapping factors. Moreover, analytical progress is possible through ABMS techniques, which provide leverage over what might otherwise be intractable problems.<sup>1</sup> Although a general theory of technological development is far beyond the scope of this paper, the model and simulations I discuss offer some insight into the systemic dynamics of social selection, as manifest in the direction and rate of technological change.

## STRUCTURE OF THE TecTRAJEC MODEL

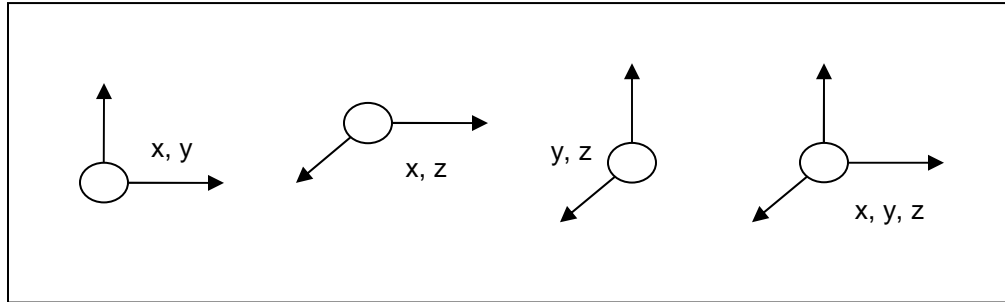
There are many ways to model a phenomenon as complex as technological development, and while the model presented here is useful, it is neither definitive nor all-inclusive. TecTrajec is built with Java and Repast, and it consists of a population of agents that interact within a social and technical environment. It also includes several graphical interfaces, so that various aspects of the simulation's behavior can be easily visualized.

The agents in the TecTrajec model are *innovators*. They represent the individuals, firms, governments, and other organizations that develop new technologies. The identity of each innovator is defined by two inherent characteristics — its values and social type. It also possesses one or more technological artifacts, which it improves as a function of these inherent characteristics and its relationships with other agents.

An innovator's values determine which aspects of technological performance it is predisposed to appreciate. Since individuals, organizations, and states all pursue multiple ends, innovators are modeled as having multidimensional value systems in order to accommodate a variety of interests. Because real-world actors also share some ends, the innovators in TecTrajec have value sets that overlap with others in the population. As do all of the concepts addressed in this model, these values are treated abstractly, so they simply consist of a short set of characters that form the compass rose of an innovator's interests (see Figure 1).

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<sup>1</sup> If satisfactory representations of the relevant actors and factors can be defined, then their interactions can be played out in a dynamic, multi-agent system. As long as the computer code is clear and accessible, then the rules governing simulation behavior are transparent, which permits critical assessments of the underlying theory and implementation. Finally, the histories of the artificial systems generated through ABMS can be repeatedly re-run and modified, permitting both quantitative and qualitative analysis.



**FIGURE 1** Innovator value types (All are present and randomly distributed among the social types in the population [except in simulations with only the X,Y paradigm, where just the x,y value set is used].)

The innovator's social type is the collection of rules that govern how it will interact with others it encounters over the course of the simulation. One can imagine a virtually endless list of possible decision rules or strategies. Here, seven intuitively appealing ideal types provide a plausible spectrum of social behavior (see Table 1).

Innovators are situated in a technical and social environment. The social environment is defined by the number of innovators, the values and social types present in the population, and the density of contact between the agents (i.e., their social overlap). The *density of the social network* between innovators can range from a maximum, where every agent is linked to every other agent (i.e., an interactive “soup”), to a minimum where each is locked into an isolated dyad.

The technical environment consists of one or more *paradigms*,<sup>2</sup> within which innovators develop particular *artifacts* (or products). These paradigms are abstract representations of real-world domains like biotechnology or information technology. The artifacts symbolize specific instances of these technologies, like a particular drug or software application. Because some paradigms are broadly applicable and offer a wider array of capabilities than others, TecTrajec includes two-dimensional (2D) and three-dimensional (3D) design spaces. Just as different innovators have overlapping sets of values, different technical paradigms are modeled as overlapping along common dimensions of performance. Thus, the technical environment is characterized by the number of paradigms present, their dimensionality, and the extent to which they overlap along common performance dimensions.

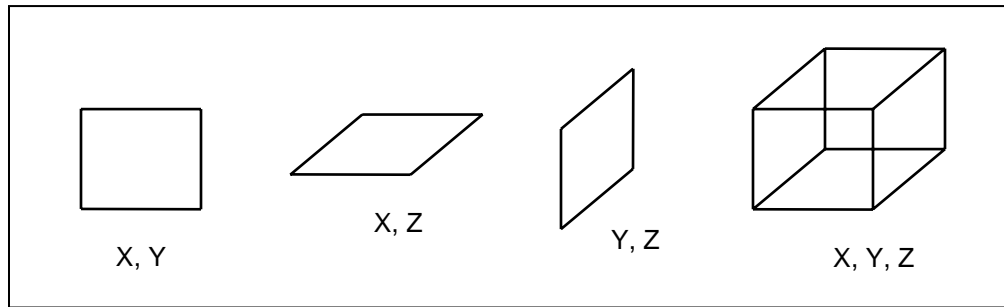
A paradigm defines and constrains the multidimensional design space within which the artifacts it contains can develop (see Figure 2). Since artifacts provide a particular combination of capabilities, they are visualized as points within this space, and the orthogonal axes of the paradigms serve as abstract scales along which the performance of different artifacts can be

<sup>2</sup> What I refer to as a “paradigm” is synonymous to a regime, design space, and several other terms used in the technology literature. Although I use the paradigm's axes to define abstract performance scales for comparing the artifacts, *it does not matter if the constraints imposed by the paradigms are thought of as being cognitive, material, social, or economic*. The word “paradigm” is used here to be consistent with the terminology associated with technological trajectories as described by Dosi (1982), not to indicate any particular stance on the origin or constitution of the constraints they impose.

**TABLE 1** Social types and decision rules (All investments are made in the innovator's own artifacts, with one unit of investment providing one unit of performance improvement.)

Social Type	Stimulus	Response
<i>Random</i>	No social stimuli	<ol style="list-style-type: none"> <li>1) Select a paradigm at random.</li> <li>2) Randomly pick a performance dimension valued by self in this paradigm and invest in it.</li> </ol>
<i>Mimic</i>	Partner's last action	<ol style="list-style-type: none"> <li>1) Select the same paradigm that the partner last invested in.</li> <li>2) If the performance dimension that the partner last invested in is valued by self, invest in it too. Otherwise, randomly pick a valued dimension in this paradigm and invest in it.</li> </ol>
<i>Rebel</i>	Partner's last action	<ol style="list-style-type: none"> <li>1) Note the paradigm that the partner last invested in, and if possible, randomly pick any other paradigm.</li> <li>2) Note the performance dimension that the partner last invested in, and randomly invest in any other dimension valued by self.</li> </ol>
<i>Balance</i>	Partner's capabilities	<ol style="list-style-type: none"> <li>1) Select the paradigm where partner's cumulative capability is greatest.</li> <li>2) Pick the dimension <i>where the partner is strongest</i>. If valued by self, invest in it. Otherwise, randomly pick a dimension in this paradigm valued by self and invest in it.</li> </ol>
<i>Dominate</i>	Partner's capabilities	<ol style="list-style-type: none"> <li>1) Select the paradigm where partner's cumulative capability is smallest.</li> <li>2) Pick the dimension <i>where the partner is weakest</i>. If valued by self, invest in it. Otherwise, randomly pick a dimension in this paradigm valued by self and invest in it.</li> </ol>
<i>Comparative balance</i>	Partner's capabilities, relative to one's own	<ol style="list-style-type: none"> <li>1) Compare partner's cumulative capability in each paradigm to one's own. Pick the paradigm where partner's relative lead is greatest.</li> <li>2) Select the dimension <i>where the partner is strongest relative to one's own performance</i>. If valued by self, invest in it. Otherwise, pick their next strongest dimension to invest in.</li> </ol>
<i>Comparative dominate</i>	Partner's capabilities, relative to one's own	<ol style="list-style-type: none"> <li>1) Compare partner's cumulative capability in each paradigm to one's own. Pick the paradigm where partner's relative lead is smallest.</li> <li>2) Select the dimension <i>where the partner is weakest relative to one's own performance</i>. If valued by self, invest in it. Otherwise, pick the next weakest dimension to invest in.</li> </ol>





**FIGURE 2** Paradigm options in TecTrajec (Single-paradigm simulations include either the X,Y or X,Y,Z paradigm. Multi-paradigm simulations include up to three 2D paradigms and one 3D paradigm.)

compared (e.g., speed in miles per hour or memory in megabytes). Improvements are made through innovation. Over time, a technological trajectory emerges as a line connecting the points of past performance as these products are improved over the generations.

The dynamics of the simulation are as follows. All innovators begin with one artifact in each of the available paradigms (since they all offer performance along at least one dimension that every innovator is predisposed to value). During every time step or “tick,” each innovator randomly establishes a relationship with another innovator in its social network. After noting its partner’s past decisions or technological capabilities, each improves the performance of one of its own artifacts, based on its social type and values (see Table 1).<sup>3</sup> At the next time step, these relationships dissolve and the sequence begins again.

Agent behavior is governed by both inherent and relational considerations. Innovators’ inherent value sets determine which performance dimensions they are predisposed to appreciate, but they rely on their relationships to identify the artifact and capability they will improve at any given time. Although related, an innovator’s value set is not the same as the performance dimensions provided by the paradigms (when labeled with the same letters, they can be thought of as being parallel but not equal).<sup>4</sup> Combinations of intrinsic values and social context provide the frames of reference necessary to give the paradigms’ performance measures meaning and to make innovation an intentional and socially motivated activity.

## LITERATURE ON TECHNOLOGICAL DEVELOPMENT

TecTrajec incorporates several aspects of technology that are frequently discussed in the innovation literature but rarely simulated together. The model relies on the concepts of paradigms and trajectories, following the analogies drawn by Giovanni Dosi between

<sup>3</sup> Here the details of the innovative process are simplified, and the complexities of converting innovative intent into an actual product are not addressed (except in simulations involving uncertainty).

<sup>4</sup> The origin of the performance space is fixed, providing a constant point of reference for visualizing outcomes. Although the orientation remains constant, the origin of each innovator’s value compass can be thought of as changing at every tick, as a function of its social type and technical stock relative to that of its partner.

**TABLE 2** The independent and dependent variables studied through TecTrajec (See the preliminary simulation results for descriptions of the uncertainty conditions and measures of the dependent variable.)

Independent Variable(s): Social and Technical Diversity	Dependent Variable(s): Technology Trajectories
Innovator identities: <ul style="list-style-type: none"> <li>• Social type (see Table 1)</li> <li>• Values (see Figure 1)</li> </ul>	Direction and rate of technological development (qualitative assessment)
Population size (2 → 240+)	Rate of unique artifact creation
Network density or social overlap (min, max)	Rate of divergence (from the trajectory of a hypothetical nonsocial innovator)
Number of technological paradigms (1 → 4)	
Paradigm dimensionality (2D or 3D, see Figure 2): number and dimensionality determine the extent of technological overlap	
Uncertainty: <ul style="list-style-type: none"> <li>• Innovative realism (on, off)</li> <li>• Random initial artifact (on, off)</li> </ul>	

technological development and Thomas Kuhn’s influential theory of scientific revolutions (Dosi, 1982; Kuhn, 1962).<sup>5</sup> The recognition of multidimensional paradigms within which artifacts are represented as points is common in the literature, although rarely abstracted away from real-world product characteristics as done here.<sup>6</sup> Technological overlap rests at the core of many theories, including work on the innovator’s dilemma (Christensen, 1997), technological succession (Windrum, 2003), and other models addressing substitution, but it is often implied rather than treated explicitly. Finally, social framing and the heterogeneous agents involved in innovation are discussed at length by constructivists and others but have not found their way into many simulation studies of technology.<sup>7</sup>

All of these varied concepts are pulled together in this model, but several important aspects of technological development are left out — most notably, the sort of selective environment necessary for evolution. In TecTrajec, innovators choose to improve artifacts in some ways as opposed to others, but every choice is preserved in the analysis of the resulting trajectories. Moreover, the social type and value content of the innovator population is constant throughout any given simulation. As such, TecTrajec is a complex “reactive” system rather than

<sup>5</sup> TecTrajec simulates dynamics within overlapping paradigms. For an example of a simulation approach to competition between paradigms, see Wittenberg and Sterman (1999).

<sup>6</sup> Inherent to the multi-dimensional nature of the paradigms in TecTrajec is the notion of orthogonal or qualitatively different technological characteristics, a point often emphasized by evolutionary economists. See Saviotti (2003).

<sup>7</sup> For example, see the “social shaping of technology” literature (Sorensen and Williams, 2002).

a true complex adaptive system, since the agents respond to their environment through preset rules that do not evolve.

I do not include a selective environment in my basic model for the sake of simplicity and generality.<sup>8</sup> Addressing selection requires building in additional assumptions about technological fitness, which is a complex and contentious issue, particularly in nonmarket contexts (Nelson and Winter, 1977). “Fitness is a relative phenomenon that depends not only on the characteristics offered by a set of rival technologies but also the evaluation of norms and selections made by a series of political, economic, and other agents” (Windrum, 2003). TecTrajec abstracts away from the specific details of any particular selective environment, in an attempt to investigate the effects of social and technical diversity on sequential decisions made without (or prior to) external selective pressure. The cost of this approach is that the model cannot directly address those aspects of technology that are grounded in evolutionary selection and adaptation, like learning.<sup>9</sup> The benefit is a clear and general analytical platform that provides important insight and can be extended to incorporate these additional factors.

## PRELIMINARY SIMULATION RESULTS

Although TecTrajec is a relatively simple model, it has numerous variables and degrees of freedom, generating a large parameter space that is yet to be fully explored. Nonetheless, I have sampled some of this space by perturbing the settings and rules, in order to check the internal validity of the code and root out any behavior resulting from programming mistakes.<sup>10</sup> Output generated by the asocial random type was used to confirm that the model conformed to analytically anticipated results and as a baseline for judging experiments involving social types.<sup>11</sup> While more testing is always desirable, it appears that the version of the model used to produce the results reported here is sound, and any persistent biases are negligible.<sup>12</sup>

In addition to the prerequisite testing, I ran several experiments on how social and technical diversity affects technological trajectories. Some aspects of the simulated behavior were retrospectively obvious, even though they were not initially expected. Other outcomes were more surprising. In short, social type and social density significantly affect systemic dynamics. In a fully connected soup, innovators with the same social type share similar sets of trajectories that often differ from those of other types. When they are only minimally connected, this difference is no longer true, and all the artifacts collapse into a few common trajectories. Larger populations influence some outcomes but not others. Technical overlap and paradigm

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<sup>8</sup> On the advantages of following the “KISS” principle in ABMS design, see Axelrod (1997).

<sup>9</sup> Diffusion may fall into this category of dynamics as well.

<sup>10</sup> On the importance of internal validity and perturbation as a method for finding idiosyncratic code, see Axelrod (1997) and Axtell (2000).

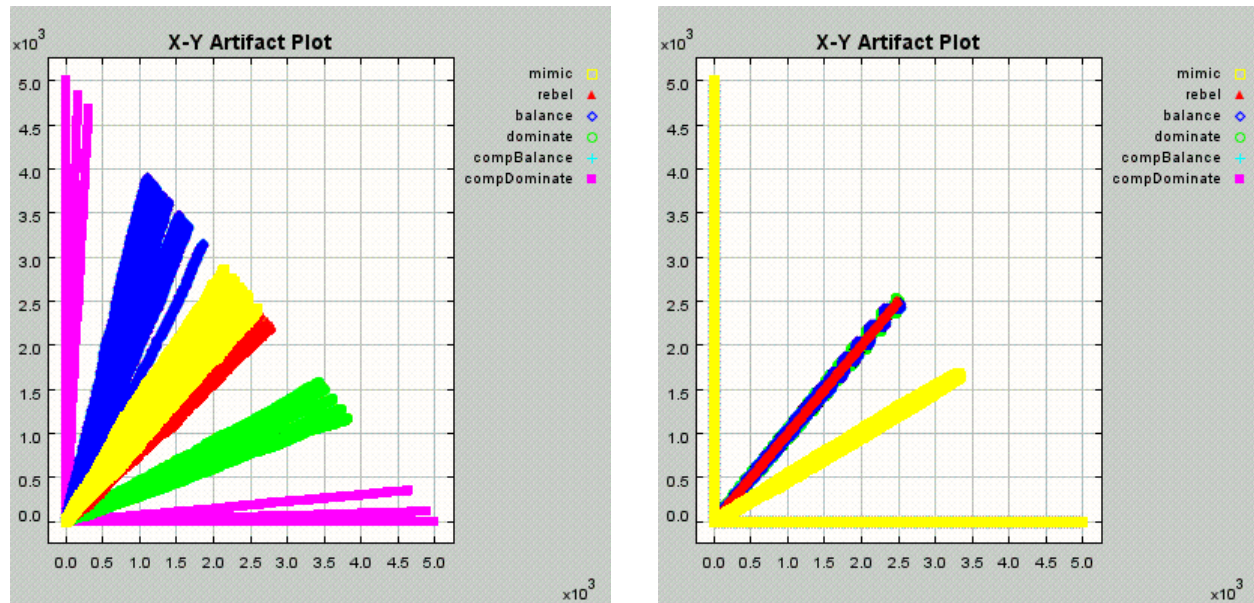
<sup>11</sup> In the simple case where one 2D paradigm (X,Y) is available and only random-type innovators with x,y values are present, the model’s behavior should mirror that of a fair coin toss, with outcomes approximating the Bernoulli distribution. The mean artifact coordinates and variance appear to do so. Averaging across 80 runs of 10,000 ticks, the rate of divergence (or the slope of the residual) of such simulations from the analytically expected value is small and close to zero (i.e., 0.0045). In contrast, the comparable rates of divergence for all experiments involving mixed social types are orders of magnitude larger.

<sup>12</sup> The source code for TecTrajec is available upon request. Please contact flsmith@uchicago.edu.

dimensionality affect behavior, but not necessarily as one might expect. The same can be said about the outcomes observed when elements of uncertainty are introduced into the simulation. The direction of some of these trends corresponds to changes in the behavior of the random baseline, however, indicating that further testing and mathematical analysis of the system are necessary.

When the density of the social network between innovators is at a maximum, the artifacts improved by the different social types coalesce into distinct sets of trajectories (Figure 3). These trajectories tend to fall into one of several patterns that reoccur under a variety of settings. What I call “diagonal fingers” are common (especially for the mimic, balancing, and comparative balancing types), where artifacts reflect equal tradeoffs between the performance dimensions offered by the paradigm, just like the random-type baseline. “L-shaped” trajectories emerge when innovators consistently improve one dimension or another but not combinations thereof. (Usually, comparative dominators follow this pattern of specialization; as a result, they push out the edges of the technological frontier faster than other types in mixed runs). “Fan-shaped” trajectories that uniformly explore the whole space are also seen under some conditions, as are “spirals,” where the trajectories of two social types (often balancers and dominators) twist around each other.

Two quantitative measures were used to compare the behavior of the model under different settings. The first gauged the rate at which artifacts with new combinations of capabilities were generated within each paradigm. Since an innovator can only improve one artifact at a time, the improvements it makes in its technological stock may replicate capabilities already provided by another innovator’s artifact. Hence, not every improved artifact is unique, and the rate that new artifacts are developed is a good proxy for how much of the design space provided by the paradigm is being explored. The second quantitative measurement was the rate



**FIGURE 3** TecTrajec artifact trajectories in a single 2D paradigm (For the simulation on the left, social density was at a maximum; on the right, it was at a minimum. All social types except random are present [These simulations contained 60 innovators run for 5,000 ticks].)

at which the capabilities of the artifacts developed by each social type diverged from the expected value for a hypothetical nonsocial innovator (i.e., the rate of change of the residual).<sup>13</sup>

Preliminary findings on the rate of unique artifact creation are summarized in Figures 4 and 5.<sup>14</sup> Because of the limited number of simulation runs conducted, the results should be considered statistically suggestive rather than statistically significant (especially given the stochastic aspects of this model).<sup>15</sup> Nonetheless, it appears that the rate of creation of unique artifacts increases with the number of innovators and when a paradigm with higher dimensionality is present, but the rate decreases with an increased number of overlapping paradigms.

The random-type baseline also follows these trends, however, indicating that some of this behavior may be explained by a mathematical account of these outcomes.<sup>16</sup> Nonetheless, there are significant and persistent differences between the high rate of unique artifact creation in maximally dense networks versus the low rate in minimal networks, for which the random baseline provides no explanation. Furthermore, in both the 2D and 3D + 2D paradigm cases, the results for the minimum density simulations do not neatly follow the baseline trend (although more testing is required to verify the extent and direction of any differences).

The data for the rate of divergence from the expected value of a hypothetical trajectory provide a different perspective on simulation behavior. The rate of change of the residual is sensitive to the social types present but seemingly not affected by the number of innovators in the simulation. All social types diverge from the expected value faster than the random baseline, and in virtually every case, divergence is greatest when social density is at a minimum. (Greater divergence under minimum density does not refute the conclusion that minimally dense systems create fewer unique artifacts. Given the collapse into a few common trajectories, less new space is explored, but more innovators are caught up in trajectories that diverge from the hypothetical diagonal finger.) Higher dimensionality appears to increase the rate of divergence in all cases, but the effect of additional paradigms on this measure is complicated, may differ for different social types, and requires further analysis.

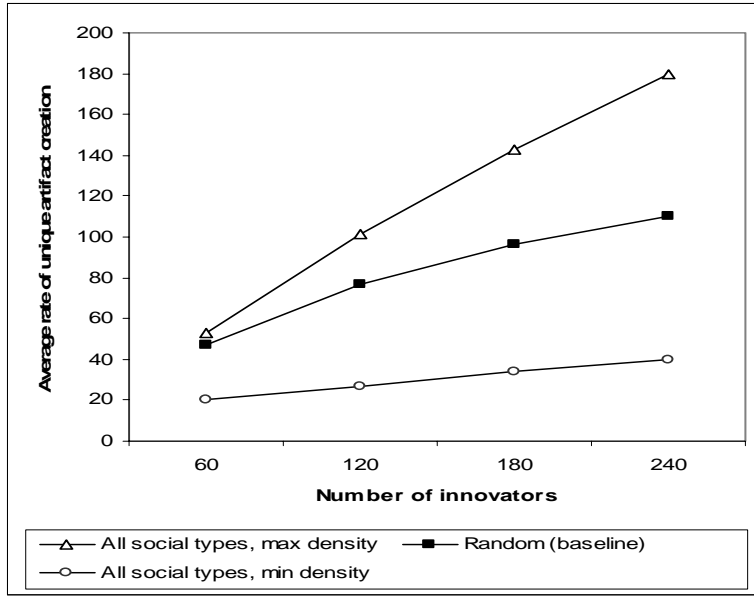
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<sup>13</sup> The trajectory used to calculate the expected values was that of a single imaginary random-like innovator with an all-inclusive value set, which pursued an equal tradeoff between performance dimensions (or a straight “diagonal finger”) at a constant rate within each paradigm present in the simulation.

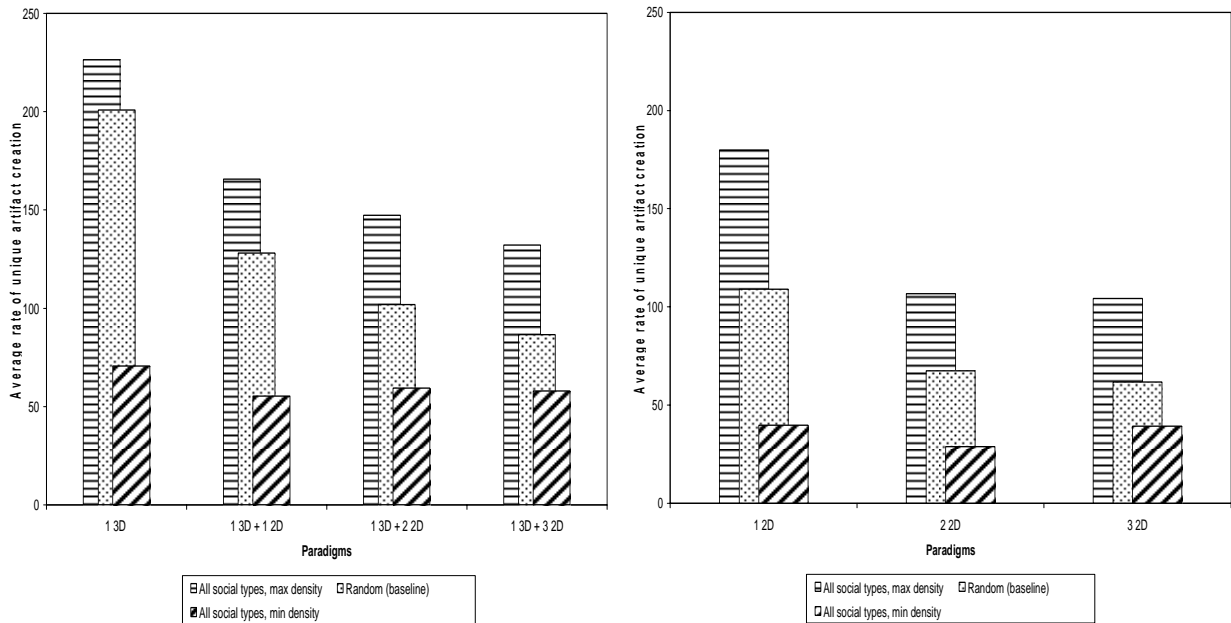
<sup>14</sup> For simulation runs up to 10,000 time steps, both the rate of unique artifact creation and the rate of divergence appear to be roughly linear (indicating that some of the dynamics discussed here are insensitive to time).

<sup>15</sup> Every data point reported here represents an average across at least 10 runs with different random seed numbers. (In some cases, the data for the random baseline represent 2× and 3× as many runs.)

<sup>16</sup> I suspect the decrease in unique artifact creation with increasing numbers of overlapping paradigms is due to a buildup of artifacts along the axes in each paradigm. *When multiple paradigms are available, innovators of all types choose which paradigm to invest in prior to any consideration of how many of their values it might serve* (given their multidimensional value sets, it will serve at least one, but often it is only one). Therefore paradigms that only offer the innovator valued performance along a single dimension are frequently selected, resulting in a buildup of artifacts in trajectories that run along the paradigm axes and explore little new space (e.g., “L-shaped”). This could explain both the random-type trend and limited effect of paradigm population on unique artifact creation in minimally dense simulations (where most artifacts already fall into a limited number of common trajectories).



**FIGURE 4** Total unique artifact creation per tick versus population size (Data are from simulations with one 2D paradigm run for 10,000 ticks. “All social types” includes every type of innovator except for random.)



**FIGURE 5** Total unique artifact creation per tick versus the number (and dimensionality) of paradigms present (Data are from simulations with 240 innovators, run for 10,000 ticks.)

Brief studies were also conducted on the effects of two additional parameters: “innovative realism” and “random initial artifact.” As the name implies, innovative realism seeks to achieve a greater resemblance of the innovative process by introducing elements of uncertainty. Here the returns gained by each innovator’s attempted improvements randomly vary over the course of the simulation, and all innovators experience serendipity, whereby they sometimes realize improvements in performance dimensions or artifacts other than those intended. Similarly, the random initial artifact setting scatters the capabilities of the products that each innovator begins the simulation with, so all the innovators do not start from the origin of the paradigm’s performance space.

When both innovative realism and random initial artifact are in effect, the rates of unique artifact creation and divergence for the random type are greater than in simulations where this uncertainty and variability are not present. When all social types are run together, however, unique artifact creation in maximally dense simulations remains above the baseline but decreases relative to the rates observed for runs without uncertainty. In minimally dense networks, new artifact creation is substantially greater than it is in networks without uncertainty, surpassing the random baseline and approaching the rates observed with maximum density. The rates of divergence in minimally dense runs with uncertainty are lower for all social types but remain well above the random-type baseline, whereas the changes in divergence for maximally dense simulations are mixed.

## **IMPLICATIONS AND CONCLUSION**

More experiments are needed to determine the full extent and significance of these preliminary results. Nonetheless, a few lessons can be drawn from the output generated by TecTrajec so far. Persistent differences between the behavior of social innovators and the asocial random type support the claim that social identity is consequential. The same is true for the social environment, since the density of the interaction topology has substantial effects on systemic outcomes. Within sufficiently dense networks, heterogeneous populations generate a variety of trajectories not observed in homogeneous or sparsely connected environments. More unique artifacts are created in technological paradigms that provide more performance dimensions (i.e., the 3D versus 2D cases), but this may not be true when higher dimensionality is achieved by overlapping distinct paradigms. These results must be regarded with caution, however, and there may be mathematical explanations for some of this behavior.

TecTrajec is a developmental rather than evolutionary model because it does not incorporate selection through fitness. Nevertheless, it draws attention to factors that should be addressed in simulations that impose stronger selective pressures. In particular, the structure of social networks between innovators warrants attention when accounting for the supply of technological alternatives.<sup>17</sup> Similarly, theories based on the assumption of a homogeneous innovative community may be of limited utility when applied to populations that are heterogeneous and interconnected. For example, the trajectories and relationships between artifacts created in a world consisting entirely of balancers are different from those that emerge when both balancers and dominators are present. This has implications for theories of arms races between states (some of which assume homogeneous social types), as well as for technological outcomes where government, industry, and academia are involved. While uncertainty has

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<sup>17</sup> For an example of a simulation study addressing this point, see Gilbert et al. (2001).

profound effects and deserves further investigation, its influence does not necessarily negate these conclusions.

The structure of the technical environment is also important. A tentative implication of the results reported here is that the real-world convergence or overlap of biological, information, material, and nanoscale technologies (Anton et al., 2001) may actually reduce the diversity of products that might otherwise be developed.<sup>18</sup> The trajectories that emerge within broad or multidimensional paradigms also differ from those in paradigms providing limited performance sets. This may restrict the applicability of comparisons made between the nuclear revolution, for example, and what we might expect for more general paradigms like biotechnology.

The TecTrajec model can be extended to explore these and other implications. Graphics for visualizing developments in 3D space would facilitate further observation. Deriving additional analytical solutions for the behavior of the random-type baseline and incorporating dimensions beyond the  $x,y,z$  set used here could shed more light on the influence of the technological environment. Finally, adding population flow (whereby paradigms and innovators are born and die over the course of the simulation) may offer insight into technological development in nonvirgin environments and provide the foundation for evolutionary dynamics. To whatever extent these additions support, refute, or expand upon the results generated so far, this model has already proved useful for exploring systemic dynamics of technological development.

## ACKNOWLEDGMENTS

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<sup>18</sup> This hypothesis is difficult to test empirically, but still interesting.



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## EMERGENCE, ENTITIES, ENTROPY, AND BINDING FORCES

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### ABSTRACT

The concept of emergence is defined in terms of entities. An entity is an aggregation that has properties that do not apply to its components and whose definition depends on the forces that bind the aggregation together. Four primary categories of entities are identified. Mass-based and attractor-based entities arise naturally and require no energy to persist. Designed entities are typically human-designed artifacts. Process/structure entities are typically social or biological systems that require the continual consumption of energy to perpetuate themselves. In all cases, entities expel entropy into their environment. Two other categories of entities, temporal and symbolic, are explored in less detail. Entities exist as a result of the binding forces that hold them together. The binding forces for mass- and attractor-based entities are fundamental forces and operate, in some sense, for free: emergence is built into nature. The binding forces for designed and structure/process entities require the application of energy and give rise to entities that have come to be known as being *far from equilibrium*. Entities are built on a substrate consisting of component entities and the forces to which those component entities are subject. This parallels the notion of levels of abstraction in computer science. The approach to emergence in this paper relates to the more traditional notions of nominal, weak, and strong emergence. We suggest a relationship between weak emergence and recursive enumerability. We discuss relationships between emergence and scientific reductionism and downward causation.

**Keywords:** Emergence, entities, entropy, binding forces, persistence, self-perpetuation

### INTRODUCTION

*Emergence* is a central, although loosely defined, concept within the field of complex systems. In a recent paper, Bedau (2002) defined what he called *weak emergence* as a proposed explication for the informal notion of emergence. For Bedau, a phenomenon is weakly emergent if it arises in the course of a simulation (or in reality) but cannot be anticipated in advance.<sup>1</sup> Bedau's primary example is the glider in the Game of Life (Gardner, 1970, 1971). Weak emergence is discussed in more detail in the Background section.

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<sup>1</sup> One often hears that a property is not emergent unless one is surprised by its appearance. This is a naïve form of what is called *epistemological emergence* (see O'Connor, 2003). But whether the observer is surprised is not relevant to much other than his or her psychological state or intellectual powers. The surprise of an observer has nothing to do with a property or whether something displays that property. Bedau's *weak emergence* does not depend on such a surprise factor. It requires only that the amount of (computational) work needed to show that a phenomenon will emerge is at least as great as the amount of work needed to run a system and see the phenomenon emerge.

This paper explores a characterization of emergence from a different perspective. We identify emergence (in at least some of its forms) with entities. In many, if not most, cases, *emergence* refers to the emergence of something (e.g., an entity such as a glider). But entities are troubling to science. Weinberg, perhaps the ultimate reductionist, puts it this way (Weinberg, 1995):

[T]he reductionist view emphasizes that the weather behaves the way it does because of the general principles of aerodynamics, radiation flow, and so on (as well as historical accidents like the size and orbit of the earth), but in order to predict the weather tomorrow *it may be more useful to think* [emphasis added] about cold fronts and thunderstorms. Reductionism may or may not be a good guide for a program of weather forecasting, but it provides the necessary insight that *there are not autonomous laws of weather that are logically independent of the principles of physics*. [emphasis added] Whether or not it helps the meteorologist to keep it in mind, cold fronts are the way they are because of the properties of air and water vapor and so on which in turn are the way they are because of the principles of chemistry and physics. *We don't know the final laws of nature, but we know that they are not expressed in terms of cold fronts or thunderstorms* [emphasis added].

In their hearts, most scientists probably believe that there is something both right and wrong about this perspective. I doubt that anyone believes there are laws of nature that magically spring into being whenever we find it convenient to speak in terms of higher-level entities such as cold fronts. Emergence of this sort is what Bedau calls *strong emergence* (see the Background section). Yet concepts such as cold fronts and thunderstorms are so useful that simply to dismiss them as arbitrary though practical constructs seems wrong, too. One way to frame this tension is as a question about the ontological status of entities such as cold fronts and thunderstorms. Do they really exist, or are they just conceptual or useful conveniences? In this paper, we propose a perspective in which higher-level entities really do exist, and we provide a physical rationale for this perspective.

We also classify entities. Two are of the most interest:

1. *Mass-based entities*, for which one can describe both a physical mechanism for their existence as entities and a metric for the degree to which they qualify as entities, and
2. *Structural/process entities* (the kind that tend to be most interesting), which include biological and social entities.

In both cases (and perhaps the most fundamental point), the mechanisms that lead to the formation and persistence of these entities expel entropy from the entity. In the first case, the mechanisms that expel entropy run, in some sense, for free, illustrating that *emergence is a fundamental feature of nature*. In the second case, the mechanisms that expel entropy require the importation of energy, resulting in entities that are now famously called *far from equilibrium*. Entities in both of these classes are self-perpetuating. Although they are not eternal, they are supported by forces that tend to keep them in existence as entities.

## BACKGROUND

Emergence is typically considered a relationship between macro and micro phenomena — one in which a macro phenomenon in some sense *emerges* from underlying micro phenomena. Bedau defines three increasingly restrictive categories of emergent properties, as follows:

- *Nominal emergence* is characterized by macro-level properties that do not apply at the micro level but that can be reduced to them. Bedau's example here is a circle, which he says consists of a collection of points, each of which individually has no shape. So being a circle is a property of the whole but not its parts. But, he continues, if you know that all the points in a collection of points are equidistant from a given point, then you can derive the fact that the collection is a circle.

Perhaps a more complex example (but not Bedau's) is that of a (macro-level) house that has the property of having some number of bedrooms. The predicate "number-of-bedrooms" does not apply to the (micro-level) components of a house — such as paint, lumber, sinks, nails, roofing, and drywall. But with enough definitional work, perhaps number-of-bedrooms could be defined in terms of these components. This is emergence as little (if anything) more than entailment. See the discussion of the designed entity (the house) and symbolic entity (the circle) in the Categories of Entities section.

- *Weak emergence* is characterized by macro-level properties that could not be predicted from the micro level except by simulation. Bedau uses gliders in the Game of Life as his prototypical example.

All weakly emergent properties are nominally emergent (i.e., they are defined ultimately in terms of lower-level phenomena, but they are derived in so complex a way that the work required to derive them is at least as complex as the work required to allow them to emerge).

Although we do not have time to explore this issue here, Bedau's weak emergence is in some sense equivalent (although Bedau does not make this claim) to recursive enumerability (i.e., a property that must be computed to be observed). In particular, since one can simulate a Turing machine in the Game of Life, it can be proved that certain properties of the Game of Life, such as whether the number of live cells is bounded or whether certain patterns will appear, are recursively enumerable but not recursive depending on the starting state of the board.

- *Strong emergence* is characterized by macro-level properties that cannot be explained by any combination of explanations from the micro level. It is unlikely that there are any such properties (strong emergence is inconsistent with any modern scientific conception of the universe) but if there were, consciousness would be a current candidate. If it were to exist, strong emergence (e.g., laws of weather that are logically independent of the principles of physics) would be emergence that, by definition, is magical,

spooky, and mysterious. From here on, we ignore the possibility of strong emergence.

## DEFINING ENTITIES

When speaking of phenomena or properties that are meaningful at a macro level, one is inevitably forced to speak of entities that either participate in those phenomena or that have those properties. In this paper, we approach the issue of macro vs. micro as one of macro entities vs. their micro components. Our task is to distinguish between (a) macro entities that are composed of micro entity components and (b) simple aggregations of micro entities that do not deserve to be considered (macro) entities.

We say here that a property of an aggregation is *emergent* if its definition depends on the means (i.e., the mechanisms, design, structures, forces, or constraints), if any, that bind the aggregation's components together. Thus, if a property of an aggregation depends solely on the components of the aggregation, that property is not emergent. To be emergent, the property must also depend on whatever (if anything) binds the aggregation together. If there are no such binding forces, the aggregation cannot, by definition, have emergent properties.

Here are two examples of aggregate properties that are and are not emergent:

- The mass of a bag of marbles is not emergent because mass does not depend on the fact that the marbles are in the bag. (As we will see later, a bag of marbles is what we will call a designed entity.)
- The miles-per-gallon rating of an automobile is emergent. The property of miles-per-gallon does not mean anything with respect to the components of an automobile simply as a collection of parts. It has meaning only with respect to the components when bound together as an automobile. (An automobile is also a designed entity.)

This definition of emergence is consistent with Bedau's notion of nominal emergence — which includes weak emergence. The distinction we are making is that a property is emergent when its nominal derivation depends not only on the component elements but also on how those component elements are bound together.

This seems quite straightforward and reasonable, almost obvious. But the focus on how elements are bound together has profound implications. In particular, any property that does not apply directly to fundamental particles is emergent because any such property necessarily depends on how the elements to which it does apply are constructed. This definition of emergence thereby alerts us to pay special attention to the means that bind aggregations together. It is the binding mechanisms that lead to emergence. Given this definition of emergent properties, we can define an entity simply as follows:

*An aggregation is an entity if it has one or more emergent properties.*

Thus, an automobile is an entity because it has the emergent property of miles-per-gallon.

## CATEGORIES OF ENTITIES

It is useful to group entities into categories. Table 1 summarizes our categorization. Mass-based and attractor-based entities are at equilibrium and require no additional energy to persist. Process/structure entities and designed entities are not at equilibrium. Mass-based and process/structure entities are intrinsically bound, being held together by forces internal to themselves. Attractor-based and design entities are extrinsically bound, being held together by forces external to themselves.

### Mass-based Entities

A mass-based entity has a mass that is less than the mass of its components. The clearest example is an atomic nucleus. The mass of any atomic nucleus that has more than one nucleon is always strictly less than the sum of the masses of the protons and neutrons that compose it when considered in isolation. As illustrated in Figure 1, a helium nucleus (an alpha particle) has a mass of 4.00153 u, whereas its components, when considered separately, have a total mass of 4.03188 u.

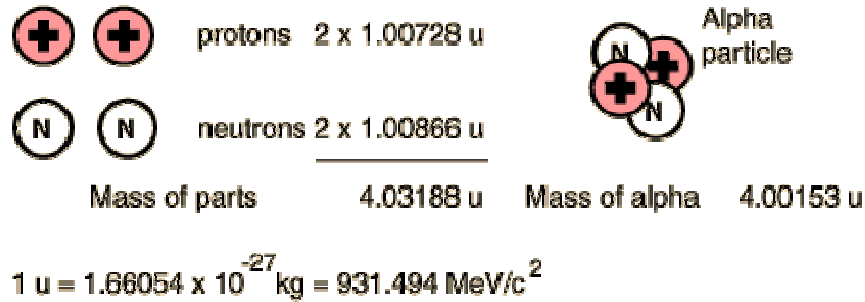
This mass differential exists because less binding energy is needed to hold an alpha particle together than is needed in total to hold the quarks in the four nucleons together when they are independent of each other. It is that difference that yields the release of energy in a nuclear reaction, either fission or fusion. Similar effects occur with other primitive forces:

- Atoms are less massive than their components (nuclei and electrons) considered separately.
- Molecules are less massive than the atoms of which they are composed.
- Gravitational systems (such as the solar system or a galaxy) are less massive than the components of which they are composed.

Although the preceding statements may sound strange, they are trivially true. Since energy is required to break these entities into their components, and since (at least some of) the energy that is applied when doing so is retained by the components after the breakup, according to the equivalence of mass and energy and the conservation of mass/energy, the total mass of the components after the breakup must be equal to the mass of the original entity prior to the

**TABLE 1** Categories of entities

Does category require energy to be sustained?	Intrinsically Bound Entities	Extrinsically Bound Entities
No. At equilibrium.	Mass-based (e.g., atomic nucleus)	Attractor-based (e.g., lake)
Yes. Far from equilibrium.	Process/structure (e.g., living cell, nation-state)	Designed (e.g., automobile, woven cloth)



**FIGURE 1** Mass of a helium nucleus (Source: Georgia State University, 2004)

breakup plus the retained applied energy. So the sum of the masses of the components must exceed the mass of the original entity. Thus, even a handful of wet sand has less mass than the sum of the masses of the sand and the water used to wet it.

This perspective even yields an entity metric. One can define the degree to which a physical aggregation is an entity as the amount of energy required to separate it into its components. “Entityness,” at least for physical objects, thus becomes a property with a naively intuitive measure — not a Boolean property.

## A Programming Metaphor

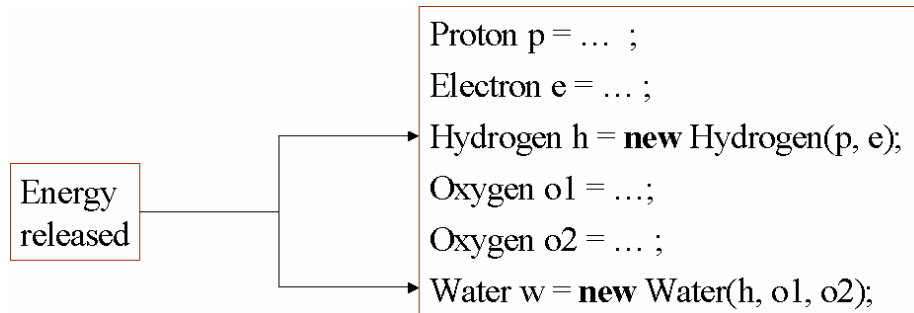
As a computer scientist (not a physicist, mathematician, engineer, social scientist, or philosopher), I find it convenient to think in terms that can be expressed in programming language constructs. Consider the object-oriented pseudo-program in Figure 2: The two lines in which energy is released are the lines in which new objects (entities) are created. Another way of putting this is that object constructors (entity constructors or what might be called *emergence operators*) are built into the universe. They have the property that they release energy when invoked. In other words, in some sense, they run for free.

## Entropy

The Second Law of Thermodynamics tells us that nothing really runs for free. So what happens to entropy when an entity is created? Constructors of mass-based entities have the property that they expel entropy from the newly created entity into the environment. The entropy of a mass-based entity is strictly lower than the entropy of the entity’s components when not bound together as an entity. Whatever binds the components together limits the states they may assume and hence lowers the overall entropy. But since entropy cannot decrease overall, the entropy of the new entity’s environment must increase.

The significance of this phenomenon is that entity-forming forces have the effect of aggregating component entities into new larger entities while expelling entropy from the resulting entity into the environment. That this occurs universally and at the most fundamental





**FIGURE 2** Program for building a water molecule

levels of physics seems to me to be quite significant. Without becoming too mystical about it, this illustrates that emergence (i.e., the emergence of entities) is a fundamental feature of the way the universe works.

### Attractor-based Entities

An attractor-based entity is an entity that exists by virtue of the structure of its environment. For example, a lake exists as water that collects in a basin of attraction. It is not the water that defines the lake, it is the attractor, which is part of the environment, that defines it. Attractor-based entities are similar to mass-based entities, except that the entity (the lake) is separate from the forces that define it. The stuff collected in a basin of attraction has emergent properties (e.g., the volume of a lake), but the basin itself also has emergent properties (e.g., its capacity). Energy is required to separate the components from the entity (i.e., to remove components from the basin).

In this case and the previous case, the entropy flow is the same: from the entity to the environment. Of particular interest is that in both cases, no energy is required for the persistence or perpetuation of entities in these classes. Mass-based and attractor-based entities are formed and persist on the basis of primitive forces.

### Designed Entities

Designed entities are a structured collection of components that exhibit properties that the components would not exhibit either individually or collectively if they were not arranged according to that structure. Typical examples, which are almost always human-manufactured, range from cloth, clothing, furniture, and mechanical, electrical, and electronic appliances to computers and entities that include embedded computers, such as automobiles, houses, satellites, and semiconductor chip fabrication facilities. The structures of these entities, if not maintained, typically deteriorate over time — especially through use.

One of my favorite examples of entities in this category is woven cloth, which consists of thread arranged according to a weave pattern. Being essentially a two-dimensional object, cloth has a property (area) that its components (threads, which are essentially one-dimensional objects) do not. Cloth comes into being when a weave structure is (externally) imposed on a collection of

thread components. Unlike mass-based entities, cloth has no intrinsic processes to bind itself together. Nor is cloth bound together by a simple attractor, although perhaps one could argue that it is bound together by the many little attractors that create friction. Although cloth is stable if untouched, it may wear, fray, and unravel with use. It requires mending (the application of additional external energy to rebuild and repair its structure) to maintain its structure. Like virtually all manufactured objects, cloth has a lower entropy than the unstructured threads of which it is composed. But the process of making cloth is a result of the application of energy; it does not arise spontaneously as a result of fundamental physical forces.

At the other extreme of sophistication from cloth is a notion that most computer scientists are familiar with: *level of abstraction*. This is the conceptual framework defined by a programming language or computer application program. A level of abstraction is a designed entity or, more frequently, a collection of designed entities along with a collection of operations that may be applied to them. The binding forces that are used to combine lower-level elements into a new level of abstraction are the operations that exist at the substrate level. An executing computer program is the design that combines these lower-level entities into higher-level entities.

In computer science, one typically ignores the need to import energy: the binding forces operate as if they are free once the computer is powered on. When executing a program, a computer reduces the entropy within the computer and expels entropy into the environment as heat.

## Process/Structure Entities

Process/structure entities are characterized by the fact that they have an abstract structure that is maintained by one or more internal processes. The internal processes use energy supplied externally, and they operate only as long as such energy resources are available. Most (perhaps all) biological and social entities are process/structure entities, although not all process/structure entities are biological or social. (See the fire, hurricane, and tornado examples below.) The abstract structure that organizes a process/structure entity persists even as the physical material of which the entity is composed cycles through it. Process/structure entities are distinguished by the fact that they tend to be self-perpetuating.

As an example, consider a corporation, which is defined (in this case formally, although a formal definition is not a requirement for process/structure entities) by a combination of state law, its articles of incorporation, and its by-laws. The people and property that occupy any particular role in the corporation at any specific time may come and go. It is the formal structure and processes defined by the corporation's charter that persist. (The fact that most articles of incorporation and by-laws provide a mechanism for their own modification does not change the fact that, at any time, it is the structure and processes defined by that charter and those by-laws that characterize the corporation.)

Most social and biological process/structure organizations are not built in so formal a manner. Yet they are similar in that they generally have a structure that persists even as the physical material of which these entities are composed comes and goes. It is the job of a process/structure entity's internal processes to use the continually recycled physical materials to

maintain the entity's abstract structure. Consider, for example, how the physical substance of any biological entity is constantly being renewed.

A process/structure entity's ongoing internal binding processes are the means that keep it bound together as an entity. These binding processes are analogous to the ongoing processes (the exchange of virtual particles) that bind mass-based entities together. The forces that bind a process/structure entity together are typically quite complex and not as simple as those that bind mass-based and attractor-based entities together.

Process/structure entities require a source of energy to power their binding processes and hence to hold themselves together. This contrasts with mass-based and attractor-based entities, whose binding processes run for free. This need for energy is similar to the need that designed entities have for external energy (in the form of maintenance) to hold themselves together. The difference is that designed entities need energy to allow an external agent to repair their externally imposed structures. Process entities need energy to run the internal processes that bind them together. Since they tend to persist if that energy is available (old age is a separate issue) but also depend on the continual consumption of energy to hold themselves together, process/structure entities are what has come to be known as *far-from-equilibrium systems*. These entities are thus self-perpetuating. They are built in such a way that if the environment within which they exist remains relatively stable and if the energy they require to power their internal processes is available, they perpetuate themselves.

The framework within which a process/structure entity's binding processes operate defines the entity's *infrastructure*. The prototypical example is the circulatory system of a biological entity. Like mass-based and attractor-based entities, process/structure entities expel entropy. They differ from mass-based and attractor-based entities in that they import energy to do it. Here we briefly consider three examples of process/structure entities: hurricanes, fires, and a nation-state.

### *Hurricanes and Fires*

Two nonbiological and nonsocial examples of process/structure entity are hurricanes and fires (or flames). Both extract energy from the environment, which they use to perpetuate themselves and to maintain their internal structures.

A hurricane feeds off the pressure and temperature differential between the warm ocean and dense lower atmosphere and the cooler and less dense upper atmosphere. Here is a description of hurricane formation from the National Center for Atmospheric Research (2004):

One ingredient [in hurricane formation] is a low pressure area which forms over a large area of warm water. The air being drawn into the central low pressure is curved due to the Coriolis Effect. Surface friction also causes the wind around the low to spiral toward the center. This gives the hurricane a circular rotation. The incoming air must go somewhere so it rises. This rising air, which is saturated with water, cools and condenses to form clouds. The latent heat given off when the water condenses causes the upper air to warm and increase in pressure. This high pressure area is the reason why weather is nice in the eye of a

hurricane. This is the start of a feedback mechanism which continues to intensify the hurricane as long as there is warm water from which to draw energy.

Figure 3 illustrates the structure of a hurricane in cross section.

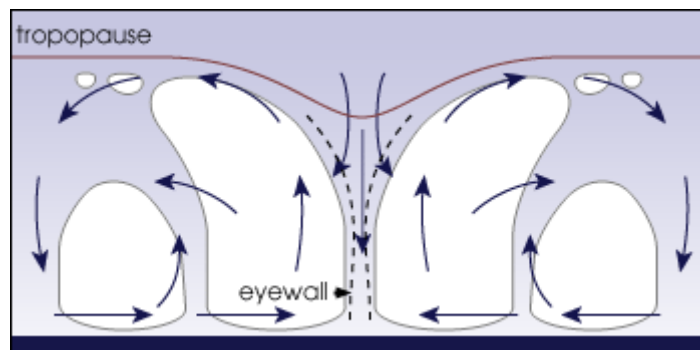
Similar (but not identical — typically there is no central downdraft) mechanisms produce tornados, flames, and fire storms. In all cases, energy is necessary to heat the inward flowing air to perpetuate the cycle. A hurricane, or so-called *warm-core* storm, is unusual (as Figure 3 shows) in that the core consists of *downward*-flowing air and the heating takes place in the upper atmosphere as a result of condensation of moisture from the rising moist ocean air. The condensation occurs at the top of a ring around the eye, called the eye wall. This heating causes both increased pressure within the eye and decreased pressure at the top of the eye wall, drawing up more moist air.

What is common to hurricanes, tornados, flames, and fire storms is the operation of a heat engine (i.e., the performance of work, typically the movement of some physical material, through the application of heat energy). A hurricane is unusual in that the heat is generated as a result of condensation in the upper atmosphere, which effectively pumps additional moist air upward into the condensation area.

Hurricanes depend on moist and relatively warm surface air for their self-perpetuation. The environmental energy sources upon which hurricanes depend are (a) the energy that transfers moisture from the ocean to the surface air before it is pumped upward and (b) the continual cooling or dispersal of heat in the upper atmosphere so that the heat generated by condensation does not overly warm the condensation area. With these environmental conditions in effect, hurricanes can perpetuate themselves indefinitely.

The infrastructure of a hurricane consists of the pathways along which air is transported. If these (especially the upflow of moist air) were blocked, a hurricane's internal process/structure would deteriorate, and the hurricane would die.

A hurricane's primary binding force is the physical forces that cause gases to move from high-pressure areas to low-pressure areas (i.e., along the hurricane's infrastructure pathways). The binding forces are (necessarily) inherent to the medium (the atmosphere) of which the



**FIGURE 3** Cross-sectional diagram of a hurricane  
(Source: NASA, 2004)

hurricane is composed. If gases were not subject to pressure differential forces, there would be no hurricane. But because gases are subject to those forces, hurricane structures, once in place, can perpetuate themselves. Other binding forces are those that generate heat as a result of condensation and those that allow air to absorb moisture.

Similar analyses can be done for tornados and, perhaps more interestingly, for fires. A fire's primary binding processes are its convection currents and infrared radiation, both of which carry heat throughout the area that defines the fire. The convection flows and the radiation vectors also define the fire's (changing) infrastructure. A fire can persist only as long as such an infrastructure can be built and as long as there is enough fuel to maintain that infrastructure.

### *Nation-State*

A nation-state has properties (e.g., capital city, laws, currency, foreign policy) that do not apply to its components; thus, it is an entity. A nation-state has a process infrastructure that provides the means by which it operates as a state and an economy. These include the traditional political and economic infrastructure elements, as follows:

- Political infrastructure: Elective, legislative, judicial, regulatory, police processes, etc.
- Economic infrastructure: Transportation and communication systems (processes), etc.

The multiple ongoing internal processes that define these infrastructures are what bind the nation-state together and allow it to function as a discernable entity. It is the nation-state's structure and infrastructure that persist over time rather than the elements that play particular roles within the structure.

- No one individual fills a political role indefinitely. (Even kings die, yet kingdoms persist.) It is the political (infra)structure that remains stable, although it may evolve.
- No one truck, road, or airport defines a transportation system, for example. It is the economic (infra)structure that remains stable, although it, too, may evolve.

The authors of the U.S. Constitution recognized and affirmed the importance of infrastructure as binding processes by writing a postal system into the Constitution.

Like a hurricane that develops by using the atmosphere as a substrate, a nation-state (and any social organization) is built by using people as the substrate. Consequently, the binding forces that hold a nation-state together must be operations that people can perform and forces that act on people. The attendees at this conference know far more about this than I. So I will do little more than offer a basic list of capabilities and forces that apply to people.

The capabilities are whatever it is that people are able to do. The analogy to a hurricane is that air is capable of both absorbing and releasing moisture. At their most general scope, the

capabilities of people include physical self-propulsion, the ability to understand and use language, the ability to follow instructions, the ability to perform physical acts in the world (e.g., aiming and shooting a gun or digging a ditch), and the ability to manipulate symbols (e.g., voting).

Besides having these capabilities, people are malleable in that they are capable of learning new knowledge, skills, values, and even emotional responses. An extremely important (if seemingly magical) capability — and one upon which a modern market economy (as well as our scientific research infrastructure) relies — is the ability of people to develop new ideas and perspectives. All of these capabilities are available for use in developing a social system.

Besides these capabilities, it is important to catalog the forces that act on people. These include emotional forces (e.g., interpersonal love, tribal loyalty, patriotism, fear, anger, and compassion, which tend to impel people to take actions), physical forces (e.g., being detained, restrained, or killed by force), intrinsic forces (e.g., the need for food, sex, community; the impulse for self-preservation; creativity; taking initiative; ethical behavior), and whatever else is inherent in the nature of human beings.

This is certainly a broad and superficial list, which should be elaborated upon much more carefully. But whatever the list eventually evolves into, it is these forces and capabilities upon which a nation-state must be built.

### *We Can Create New Process/Structure Entities*

One nice feature of entity formation is that we can imagine and create new ones. Clearly, any designed object is a human-created entity. So are many of the social systems we have created. Perhaps more interestingly, we are also capable of creating the means for creating new entities. Most of the infrastructures of modern nation-states provide a basis for the creation of new entities. The internet is the latest example of such a generic infrastructure around which new entities can grow.

### **Other Categories of Entities**

Besides the categories of entities sketched above, there are a number of other categories of entities that do not fit the preceding paradigm. It is not yet clear how to describe the binding forces for the following classes of entities.

#### *Temporal Entities*

Temporal (performances) entities exist in time. They carry and apply energy. Examples include a performance of a musical note/chord/melody, a performance of an algorithm (or a play), or virtually any performance. All of these entities exhibit emergence in that they have properties that do not apply to their components. A chord, for example, may be dissonant — a property that does not apply to individual notes. A performance of an algorithm (or a play) may achieve a computational (or an emotional) result that differs from the results achieved by the performance of their individual components.

Performance entities are different from the descriptions of how they are produced. The performance of a note is not the specification of the note. It is the actual production of the sound. The same goes for the performance of an algorithm or a play. See the next section on Symbolic Entities for a brief discussion of algorithm specifications as entities.

Two other examples of temporal entities that I do not understand (and that may be related) are a ripple on the surface of a liquid (or more generally, a wave carried by a medium) and the domino effect (e.g., dominos fall in sequence, as one topples the next).

It seems to matter that temporal entities are applied to other entities (i.e., they do not stand alone).

### *Symbolic Entities*

Symbolic entities require interpretation. Examples include a pair of socks,<sup>2</sup> a sentence, the set of prime numbers, the constitution of a government, the specification of an algorithm, and Bedau's circle. All these entities exhibit emergence in that they have properties that their components do not have.

An algorithm (specification) may be proved to compute a result that the individual steps do not compute individually. An algorithm depends on the control structures that bind its components together. Thus, the control structures define an organization for an algorithm, but they exert no control over the components other than during its execution. The control structures of an algorithm are not binding forces in the sense used earlier. They do not compel components to stay together.

A sentence has a meaning that depends crucially on its syntax, which binds its components together. The situation is similar to that of an algorithm. But syntax has an effect only in the mind of the interpreter. It is not, in itself, a physically binding force.

Bedau's circle is bound together by its definition (i.e., a set of points equidistant from a distinguished point). Again, the binding structures exist, but they have no force on their own. The definition must be interpreted by an interpreting agent.

In all cases, an interpreter is required for a symbolic entity. Without something to interpret the syntax or other binding connectives of a symbolic entity, it would not exist as an entity.

## **DOWNWARD CAUSATION**

We agree with Weinberg that strict downward causation (macro to micro) is as unlikely as strong emergence. We do not expect new forces to appear magically at a macro level and then have an effect at the micro level. However, downward causation is virtually essential from a practical perspective.

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<sup>2</sup> An individual sock is a designed entity. It is the pair that is a symbolic entity, with the individual socks as components.

Consider the trajectory of a proton in a molecule in one of the blood cells flowing through the body of a passenger on an airplane. That trajectory depends on the passenger's mechanical and physiological structure and activities. It also depends on the trajectory of the airplane in which the passenger is riding. That trajectory, in turn, depends on the weather the plane encounters during the trip. It also depends on the rotation of the earth, the earth's revolution around the sun, the solar system's revolution around the galaxy, etc. This is a more elaborate form of the example given originally in Sperry (1969): the trajectory of an atom in the rim of a wheel rolling downhill.

Perhaps more interesting, the plane's trajectory also depends on decisions made by the pilot and various flight controllers. These depend, in part, on regulations adopted and distributed (on paper or electronically) by the Federal Aviation Administration (FAA), a governmental entity. The passenger's decision about which flight to book depends on the schedule and rates set by the various airlines, which depends on decisions made by analysts and executives of the airline companies. These scheduling decisions also depend, in part, on regulations promulgated by the FAA, etc.

It would be impossible to compute any of these effects without taking into consideration the entities involved as entities. It would be completely hopeless to attempt to describe all that in a purely bottom-up manner, in terms of the laws of fundamental particle physics.

## **SUMMARY AND CONCLUSIONS: BINDING FORCES DRIVE EMERGENCE**

A property of an aggregate is emergent if it depends on whether and how the aggregate is bound together. Entities are aggregates that have emergent properties. Mass-based entities occur naturally and "for free" in that their construction releases energy. The universe is set up to produce entities and thus to exhibit emergence. Process/structure entities, although also naturally occurring, are not free and exist far from equilibrium. Their persistence and self-perpetuation require the continual consumption of energy. We as human beings are capable of imagining and creating both new designed entities and new process/structure entities that have properties we want. We are also capable of creating new infrastructures that often provide a basis for the development of new entities — whose emergent properties sometimes surprise us.

## **ACKNOWLEDGMENT**

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**DISCUSSION:****STRUCTURE AND EMERGENCE****(Friday, October 8, 2004, 1:30 to 3:30 p.m.)**

Chair: *M. Dawson, Harvard University*  
 Discussant: *D. Lee, The University of Chicago*

**Toward a Gendered-based Agent Model**

**Michael Dawson:** This session is on “Structure and Emergence.” Our first speaker is Luis Antunes of the University of Lisbon. The title of his presentation is “Toward a Gender-based Agent Model.”

**Luis Antunes:** Thank you. My name is Luis Antunes. I am from Lisbon, Portugal. This is a joint work with Rosa Del Gaudio (University of Lisbon) and Rosaria Conte (Italian National Research Council). Basically, we are just starting this project, so I’m going to present our ideas and some of our preliminary results. I tried to design my presentation to last less than 30 minutes, so we can allow time for lots of discussion, which I think would be very useful.

I’ll start by explaining the context of our research, presenting some agent models and some preliminary experimental results, then giving a short conclusion and some prospects.

Basically, my background is in artificial intelligence, and I studied some problems related to utility in decision problems. I introduced a choice framework that tried to overcome some of the problems with traditional utility in neoclassical economy, and I tried to use social simulation to test some of the issues. This idea about gender studies just comes as an application setting we are using to produce an evaluation system and reinforce these arrows backward to test this decision model and also to try to obtain insight into some problems related to social simulation, some methodological problems I’ve been addressing.

[Presentation]

**Unidentified Speaker:** What is the meaning of traditional and nontraditional child caretakers in the context of this research?

**Antunes:** Traditional means that the women take care of the kids. So in traditional populations, the contribution of women is just one-quarter of the total, and in the nontraditional their contribution is 40%. When we have mixed populations, it depends on whether the environment is competitive or noncompetitive. If it is competitive, the nontraditional and the utilitarians end up with zero total members. And if the environment is noncompetitive, they (nontraditional and utilitarians) can survive. Both populations are minorities, but they can survive.

[Presentation Continues]

**Dawson:** Thank you very much. We’ll now take questions while the next speaker gets prepared. We’ll start the discussion with Doowan Lee, who is the discussant for this session.

**Doowan Lee:** I am Doowan Lee from The University of Chicago. I really enjoyed the second set of experiments in your paper because you have different types of agents and you let the different types of agents compete with one another. Then you have some population dynamics. I think the second part is really interesting.

My fundamental question deals with the division between sex and gender. When you talk about biosocial theory, I think you're talking about biology and sociology. I think sex can be very biological, but gender can be socialized, or at least it can be adaptive. But my fundamental question is, then, about the fact that gender identity is kind of hard-wired in your model. It is really difficult to see whether the results are coming from that hard-wired gender identity or some kind of dynamic aspect of the model. So the question is, is it going to change the basic findings of your model quite a bit once you allow the gender identity to be endogenously generated, as opposed to exogenously given?

**Antunes:** I don't think — well, except for particular cases — one can choose to change his gender, even if it is socially constructed. So I don't see it as a problem. I think the problem is mainly a decision problem. Sex is determined at birth, and when you look at gender as a set of constraints or norms or role you define, even though it is socially imposed on you, you cannot change it.

Some decisional aspects can change because of the societal dynamics, but for that we need more a complex mechanism, such as the ones that come from education. For example, 30 years ago, it would have been stranger than it is today for a man to do certain jobs or for a man to help out in the house. But as we speak, we are looking at a society — for instance, in Portugal — where women are a major force in the labor world. Inevitably, that will probably change the way that we look at gender as a role. But the mechanisms for that change are very complex because it depends on children not being educated by their mother or their grandmother, but by some institution like school, and increasing the role of fathers in their education. That is the type of mechanism I would like to include, but it is very complex and those things change very, very slowly. Of course I would like to study those factors, and one of the advantages of simulation is that you can speed up the process and look at what happens. Surely, it is important, but right now our model is far too simplistic to consider that.

**Craig Stephan:** Craig Stephan, Ford Motor Company. You showed that in the competitive environment, traditionalists did better than both utilitarians and nontraditionalists. Could you describe the utilitarians in greater detail? I would have thought that under those circumstances they would simply become traditionalists because that seems to be the best way of surviving.

**Antunes:** No, because some stochastic things are going on. They don't have the power to become traditionalists. The utilitarians are somewhere in between both extreme cases. They can go for one place or the other. They are always in the middle and therefore cannot reach the full traditional behavior. Again, one thing I would like to change is to have more fluidity, more flexibility in the way that people choose.

**Robert Reynolds:** Bob Reynolds, Wayne State University and University of Michigan Museum of Anthropology. One of the things I was wondering about is that in traditional agricultural societies and hunter-gatherer societies, men, for example, will focus on hunting, but women will collect wild plants — herbs and medicinal plants — and also deal with food

preparation and those sorts of things. In some studies I'm aware of, it turns out that often in a group, a male skilled in hunting will be mated with a woman who is skilled in plant collection, etc. In other words, there are skill levels involved with individuals, not just speed, and the skill levels actually play a role in the mating activity. You might think about adding skills in here within each group; I think that would be an interesting thing to study.

**Antunes:** That is a very good idea, thanks.

**William Lawless:** I am Bill Lawless, and I have a brief question: What about technology, such as the pill, which changes the dynamics? Have you considered that?

**Antunes:** No, not yet. Another good suggestion.

**Michael Macy:** I am Michael Macy from Cornell. It's an interesting model, but I have a question regarding what specifically you are using the computation to find out. It seems that, from what I understand from the presentation, the nontraditional strategy is not in equilibrium. That is to say, if you have a population of nontraditionalists, anyone who switches to a traditionalist will gain a higher payoff in both the competitive and the noncompetitive worlds. That should be rather straightforward from the assumptions of the model. So if you know that nontraditionalists are not in equilibrium and you know that traditionalists are in equilibrium, what is the computation showing us?

**Antunes:** I'm not very interested in the new equilibrium. I'm more interested in observing individual trajectories, for instance, of a different agent inserted into a set of homogeneous agents or to set up a group of interacting agents and try to use another strategy just for one agent and see it propagate.

In fact, you've spotted the weakest point of this model: that it can be solved. Everything is obvious here. But, as I said, this is preliminary work, and perhaps we kept it too simple. The idea is to set up the grounds to push forward.

**Unidentified Speaker:** One feature that might be interesting to add would be to consider choices that are asymmetric — where men can have more than one woman.

**Antunes:** Half of the students wouldn't allow that. I should really ask about religion because that is not allowed in some religions or sociocultural groups. I would like to consider several religions. I talked with Rosa about that, and she is just now starting that research. That is one thing I would find very interesting. For instance, consider a Muslim who has several women, so they form a stronger family. We would see if it is more effective in this environment than in a traditional couple family.

Another thing I would like to consider — and I have also talked with Rosa about this and it probably will be done — is to have two different choices for the reproductive activities, two completely different sets of measures set up for the reproductive activity and for the mating activity, so you can choose to work with someone that's very effective and cooperates well with you. However, when you are going to choose your mate, you use different criteria, as we do in real life. For example, we choose a lovely girl or something, but we don't choose to work with a lovely girl if it's not efficient. Try to put together two strategies and see what happens. So there's lots of ground to explore, yes.

## Overlooked Implications of Ethnic Preferences for Residential Segregation in Agent-based Models

**Michael Dawson:** Our next speaker is Mark Fossett, who's going to talk about "Overlooked Implications of Ethnic Preferences in Residential Segregation."

**Mark Fossett:** I want to thank the organizers for including us in the program. We're having a great time and appreciate being here. We'll try to come back.

Our paper focuses on a well-known topic in agent-based modeling: the effect of preferences on residential segregation in the modeling framework. We are looking at a recent paper that claims to contradict Schelling's major insights, which I don't need to review in detail here. We find that although the claims of the authors are strong and published in a very prominent place that reaches a lot of sociologists, the claims are overdrawn. We build off that to elaborate on some insights about Schelling's findings that we think are useful to discuss.

One of the implications that comes from this is that the connection between the work undertaken by agent-based modelers and researchers and the work done by those involved in the broader tradition of research on residential segregation is not well connected. Most groups probably need to learn from each other a little bit more. That learning will be discussed in a couple of places in this presentation.

[Presentation]

**Doowan Lee:** I really enjoyed your paper. I think it has very powerful implications for three reasons. First, the model is designed to answer a clearly defined, concrete question. In that sense, it's really easy to follow where you're going. Second, it sets up a benchmark (namely, Laurie and Jackie) to which you compare your own results. That is really nice to follow as well. More important, you actually follow a very wide space of permutations in the sense that your findings are very universal and thus yield very strong positive implications. At the same time, your positive implication is that the minority group will have to bear the burden of having to love diversity for a highly segregated society to overcome that kind of structure.

It's nice that you have found that kind of search space within Schelling's paradigm. But the question is, well, you are a really small minority, and it's very, very difficult to accept the burden of having to have diversity purposes. The question is probably a little beyond the scope of the paper, but I'd really appreciate if you could speculate on this question: How can minority groups actually achieve those diversity preferences, especially when the distribution of ethnic groups is highly skewed?

**Fossett:** I have a couple of thoughts. One is that there's a very strong bias in the broad body of literature that segregation is a bad thing. It's implicit in most of the work. Sometimes it's not explicit, and maybe it should be. If someone feels that way, it ought to be more explicit. But it does have very powerful implications for minority populations that should be reconsidered a bit. It implies that community-building among minority populations is a negative thing, and in this multicultural world, I think people should gravitate to that policy position slowly, and it should not be presumed. Ethnic enclaves may be meaningful to people, providing warm, fuzzy experiences for life and family that people want to seek out, not just as a refuge from discrimination and ill treatment but as a positive thing in itself. So that's one thing.

The other thing (where most of my attention has been focused) is in pointing out the role of minority preferences, because both groups' preferences matter, and minority group preferences have been ignored... The presumption in the broader literature — not necessarily the agent-based literature — has been that the preferences of Whites dictate the residential system. They certainly have in the past. In recent decades, that may be changing. If it is changing, we need to consider more fully what everybody's preferences mean and how they interact.

Some researchers have accused the measurement strategies in this area of being implicitly racist by setting zero — the score of integration in the integration measures — as something that can only be achieved when minority populations essentially dissolve and integrate fully in all neighborhoods. They're saying, "Why would everybody want to have that goal?" I haven't pursued that myself, but some people have.

**Michael Macy:** Michael Macy from Cornell. This is a wonderful paper — a beautifully crafted study. I enjoyed it very much. I want to thank you for presenting it and look forward to reading the full paper.

Now for the bad news. Elizabeth Brook and Rob Mayer at UCLA have developed a really devastating critique of Schelling. What they show is that Schelling uses a deterministic threshold function, in which one is indifferent to any change in the ethnic composition both below and above the trigger point. More plausibly, as the composition changes, people have a monotonic change in their probability of moving. So they replaced the strict deterministic function, which you can think of as a Z shape, with a sigmoid; they just smoothed it out. And the sigmoid has a slope that is pretty close to a cumulative normal distribution. They played around with a number of different slope parameters for the sigmoid.

They found that you don't get segregation; you get stable integration over the usual parameters. Do you have any thoughts about how the Schelling model might be tweaked again so that it can be robust, even under the assumption of a stochastic threshold function as opposed to a deterministic one?

**Fossett:** Yes, it's a bit frustrating. I've heard about this paper, but I haven't seen it. Lincoln Quillian [Associate Professor of Sociology, University of Wisconsin] has told me a little bit about it. It's hard for me to comment on something I haven't seen.

The SIMSEG development, the prototype for the SIMSEG program we're distributing here, has such a function. It does not have a step function for evaluating satisfaction. It has a graduated function, so if you're a little bit close, that's better. You know, it's not all or nothing. In my own explorations using a wide variety of satisfaction functions, I find the Schelling effects to be extremely robust.

In fact, here is a little personal history. I came to this modeling because I wanted to discredit Schelling. I was irritated with some of the conclusions. I thought they were too simple. I thought that when you introduced some complexities, you would find that in real urban systems, they would go away. I've given up trying to make them go away. So I'm looking forward to seeing this paper. I know Mayer. I don't know Brook. Mayer's book is first-rate, so I'm nervous. But I'll wait until I see the model. It will be interesting.

**William Bulleit:** Bill Bulleit, Michigan Tech. On your second-to-last slide, the one with diversity preferences in it, what caused the dead zones?

**Fossett:** That was reported in Schelling's 1971 paper. Those dead zones emerged because they are neighborhoods. If you move into them, you'll be in a homogeneous neighborhood. You'll be surrounded either by many White households or by many Black households. So if he's surrounded by Black households, a Black who moves in will be in a homogeneous neighborhood, which he wants to avoid. So the vacancies separate integrated neighborhoods. A very interesting pattern emerges. Maybe there are some implications that might be drawn from that. But Schelling first noted it. It's not an artifact. It's been seen before, so it appears to be a regular property of that type of preference structure.

**Seth Tisue:** Seth Tisue, Northwestern University. You studied the effect of actual preference for diversity. In ethnically imbalanced situations, like 70/30 or 90/10, did it matter more? Did diversity preference matter more if you found it in the minority group or in the majority group, or was it the same?

**Fossett:** The effects are often complicated, so understand this is a very great oversimplification. The in-group preference effects — in fact, all of the preference effects — are stronger for minorities. The reason is because it's easier for their preferences to be out of synch with demography. In Minneapolis, Minnesota, if Whites want to live in a 95%-White neighborhood, segregation is not needed for that to happen. It's a very White city. Their preferences are inconsequential for segregation. But if minorities in Minneapolis want 30% in-group contact, it can't be achieved under integration in the standard sense of proportional representation. They have to gravitate toward an enclave. So their diversity preferences to counter that dynamic must be very high. That's stating the extreme case. Minneapolis is kind of 'out there' with regard to the distribution of city ethnic mixtures.

Many more cities, like Los Angeles and Houston, are more diverse, and Whites are only about 50% of the population, depending on how that group is defined. But in those cities where you have multiple pan-ethnic groups — Asians, Latinos, African-Americans — Whites are 50%, but the individual minority groups are only 10% to 15%. So the diversity preferences become important. That's what the mathematics would say. If you look at the implications of preferences through this lens, that's what it would say.

## **Technology Trajectories — Modeling the Effects of Social and Technical Diversity on Technological Development**

**Michael Dawson:** Our next speaker is Frank Smith from The University of Chicago, and he's going to talk about "Technology Trajectories."

**Frank Smith:** I am a Ph.D. student in political science at The University of Chicago, primarily studying international relations and national security concerns. What I'm going to talk about today is an agent-based model that I have built using Java and Repast to explore some of the dynamics of technological development. I also will discuss my preliminary results. This is definitely a work in progress. Please, as I go along, don't hesitate to interrupt if you have questions or if I'm unclear on something.



## [Presentation]

**Doowan Lee:** First, I want to congratulate you on this paper. I have to confess that I actually spent an entire summer with Frank [Smith] at ANL [Argonne National Laboratory], and I know his work like the back of my hand, so it's really difficult to find some criticism of this paper, but I'll do my best.

First of all, I think this model is really elegant in its design. It's very simple, yet it captures some of the most important things in international relations, that is, heterogeneous social types. I think that is the real strength of the paper. So in that sense I also think this paper is theoretically very original. Those are the real strengths of the paper: simplicity and theoretical originality.

At the same time, one thing I'd like to push you a little bit about is real-world analogies. I think you presented a few in the beginning, but I think, for example, one of your examples is that when you have high connectivity you will have more diversity in the artifacts. I think it would be very interesting to see some real innovators in the world, or some kind of technological paradigms out there where they show a high degree of natural connectivity and then the whole ecological distribution of the outcomes is sort of diverse. I think this kind of real-world example perhaps will harness the nature of this model. That is one direction I'd really like to push you more.

At the same time, I think in your paper you talk about paradigms and fitness. You talk about ecological or population dynamics and selective pressure. And I think you defend your position in two ways. On one hand, you really want to see how networks and social types affect technological development over time. I think that that's a legitimate justification. But on the other hand, you also make this methodological justification that ... pressure might complicate the overall dynamics of your model.

I'm not so sure about that because you do mention Winter and Nelson, and from their perspective, the whole distribution of technological innovation hinges upon individual fitness functions. Then that actually drives the whole paradigm, so to speak. I think even programming-wise, it would not be that difficult to include selective pressure. On the domain-specific issues, I'm totally aboard. However, on the methodism side, I'd like to know more about why you decided to drop selective pressure from your model because you do have performance in your model. For me, it is not very easy to think about performance without some kind of selective pressure. If you look at innovators or tech companies, there's a very high rate of death, and it is selective pressure that drives the death rate. Without that I think it's really difficult to say how diversity in artifacts or performance will be properly captured in your model. I'll end my comments here, but I really want to push you on selective pressure and real-world analogies.

**Smith:** I'll take the real-world analogies point as just something to consider. As for the selective environment and/or fitness, that will be the next step extension of my model. The reason why I didn't include it at the initial stage was that fitness is a semi-contentious issue, and I didn't want a global fitness function driving the outcomes of my model. In some senses, I wanted to see in situations prior to environmental selection based on energy access or whatever, what sort of outcomes arise, if you need to care about networks in those situations prior to selective pressure. But that is unequivocally the next step. One of the ironies is that I draw heavily on ... evolutionary and economist literature, and yet I don't have the evolutionary

dynamics in my model. It is a reactive model, as opposed to a truly adaptive model with populations and rules changing. That would be a point for an extension, but deliberately bracketed for this version just to see what sort of dynamics emerge ... to external selective pressure.

**Spiro Maroulis:** Spiro Maroulis from Northwestern University. I want to ask you a question about the network density piece. I'm assuming that in that initial dense network there was already a lot of nonredundant information, in that all the social types were represented. And when you look at real social networks that are dense, they tend to already be homogeneous, and you have to import ideas through brokers or through some other method. So I guess that it struck me as a little counterintuitive to say that the maximum density was what resulted in more innovation, when really it was the heterogeneity that was able to be passed around in a dense network that created that, right? If they were already homogeneous to begin with, then you would have had redundant ideas.

**Smith:** Even when you have a homogeneous (I didn't present this) population of social types, only balancers or only dominators, network density still has an effect. So network density is not new to network analysis. That was the simplest measure, the simplest network, variable. Other things I'd like to test are things like centrality. But even when you have homogeneous social types, the density affects general systemic outcome.

**Maroulis:** In the same direction? More innovation? And if so, did that vary by what type of social ...

**Smith:** It varies by social type. I don't have on the tip of my tongue whether dominators were more or less, but it continued to have an effect though, even in situations where you had homogeneous populations.

**Luis Antunes:** I'm Luis Antunes, from the University of Lisbon. I quite liked your presentation. In fact, I already took some of your ideas for my own Ph.D. project some years ago and like the idea of considering values and utilities and multiple values. I also experimented with some of the types of characters you have, and I even tried to use some kind of nontransitivity function for choice, which led to very interesting results.

One thing I like to see is that you took things further and more systematically than I did, but I found it funny that you found the same problem that I did — the lack of fitness and a lack of purpose of the entire system. And throughout this day we have been listening to people like Michael Macy urging us not to look for realism, and we've been listening to people urging us not to strive for predictions. It's very important, I think, that you should keep not looking for some kind of perfection in your system or even in your agents, because we ourselves are not perfect. And I think in our choices we are adaptive, but not really going toward something, because I don't think there's anything to find. That's the methodological problem I mentioned in my talk: the lack of evaluation or the problem about evaluation in simulations is exactly the one you found. And I would like to know your ideas about this.

**Smith:** I am a little unclear about the specific question. In terms of the realism versus abstraction, not necessarily predicting or exactly mapping real-world dynamics, my personal bias is toward simple models, not trying to model reality, but seeing what a few critical variables, a few critical simple rules, can get and how far that can get you before you start to add complexity.

In fairness, though, to the critics on this point in the sense of adding a fitness function, I am not thinking in terms of adding a single fitness function, but perhaps of adding a mixture of fitness functions as my solution to not wanting one global function. Because evolution is so potentially important in my particular substantive domain (technological development), however, it is a serious criticism. It puts serious bounds on how far I can run with my results until I more fully account for it. So I think that there are good reasons to not incorporate it in the base model. I also think that there are good reasons as I move forward for adding another dimension of complexity to seriously look at those sorts of dynamics.

**Unidentified Speaker:** I am Bill Ellis. I think your paper was provocative. I've come to different conclusions, and I just want to pose them. Maybe you can give a brief comment.

I think the idea that maximum density leads to more innovation might be true within Kuhnian and normal science, where the innovation is incremental, but certainly it is not true for revolutionary science, such as a patent clerk coming up with a theory of relativity. If it were true, in the U.N. Human Development Report (2002) about the great density in Muslim countries and extraordinarily low innovation, they would have found just the opposite. I also think that overlap is actually quite important because of the stimulative effects, the transference effects, and the diffusion effects, and that is why we have such things as universities like Stanford or MIT that are great, not only as diffusers of knowledge and innovation, but also as creators.

**Smith:** In terms of incremental versus revolutionary change, because I'm looking at intraparadigm dynamics, I can't really speak to the failing of one paradigm and the rise of another. If I incorporated an 'evolutionary population flow' dynamic, one thing I would want to look at is the flow in and out of these paradigm constraints. But as my model stands now, as you point out, my density calculations or conclusions can't speak to incremental versus revolutionary change.

As for overlap, I agree, and one of the reasons why I wanted to look at it is because I believe it is important. It was just a counterintuitive, potentially counterintuitive, outcome in that it reduced the diversity that overlapped and caused a 'clustering' of artifacts along the axes as opposed to exploring the middle space. And so that is a hypothesis that now, as I go back to real-world cases that interest me, I'm taking into consideration as opposed to taking *de facto* that technological overlap will lead to greater diversity. This has forced me to look at the question, Does it? And if it does, what are the mechanisms and how do those mechanisms differ from things that are potentially represented in my work?

## **Emergence, Entities, Entropy, and Binding Forces**

**Michael Dawson:** Our next speaker is Russ Abbott, from California State, who is going to talk about "Emergence, Entities, Entropy, and Binding Forces."

**Russ Abbott:** Thank you. First, I have to say that I'm nervous in doing this talk because it is not similar to the other talks in the session; in fact, it is probably not similar to most of the talks in this conference. One reason this talk makes me particularly nervous is because of its title. You can see all these big words: emergence, entity, entropy, and I'm actually claiming to say something interesting about this. I hope you find it useful.

My field is not social science. I'm a computer scientist from Cal State, Los Angeles, and the Aerospace Corporation. You probably have not heard of the Aerospace Corporation. It is in the same category as Miter and Rand and JPL [Jet Propulsion Laboratory], but it has a much more limited focus. What it does is help the Air Force put satellites up.

As a computer scientist, I think of computer science as something like applied philosophy. I think of a computer as a reification machine, if you think of reification as meaning "to make the abstract concrete." If you can think of something, and you can write a program to do it, that makes it real. It takes an idea and makes reality of it because the computer is real. And this is my view of the universe.

[Presentation]

**Doowan Lee:** As a modest practitioner of agent-based modeling I have always had this computer science envy, so if you think you are nervous, you can't imagine how nervous I am to comment on your paper. You are a computer scientist, and [this is] agent-based modeling, so I think you should feel fairly comfortable here.

When I was reading your paper, it reminded me of *Hidden Order* by John Holland because he says that there are so many different definitions when it comes to complex data systems. We really need to have some kind of typology or some principles by which we can evaluate different types of modeling or different types of systems. So from that perspective, I do think you provide a very useful typology of entities in this paper. Also, I like that you provide some pseudocode, some programming principles for each type of entity. I see some utility — in fact a lot of utility — in the typology you provide in this paper.

At the same time, I would like to make one request and pose two questions. The request is that you provide some more programming principles for each of the four entities that you expound in this paper. I think you do that only for one type of entity. If you expand that pseudocode practice for the rest of the entities, I think it would help us quite a bit in following the typology and trying to understand how this typology of entities might affect our actual programming practices.

As I said, I also have two questions. When it comes to mass-oriented entities, it sounds to me very much like simple aggregation. To go back to John Holland, he has four properties and three mechanisms for general complex data systems. Those properties are aggregation, nonlinearity, flows, and diversity. And the three mechanisms are pegs, identification mechanisms, internal models, and building blocks.

Your first noted category, mass-based entity, sounds very much like aggregation as defined by John Holland. So my first question from that comparison is that when you have those four distinct entities, are they continuous hierarchies or are they just nondescript? If we want to have a complex entity, do we have to include the first three and then we ... [inaudible] ... entities? So that's the first question: How would you elaborate the fourth category of entities, especially compared to John Holland's typology of complex entity systems?

The second question deals with what you describe as binding forces. That sounds very much like flows [as defined] by John Holland. When you have ecological systems, they are very unstable, but once you have some flux of food chain or some kind of prey/predator relations, you

can actually sustain the system. Then it is the flux that should drive the interaction of heterogeneous agents in a system. It seems like what you described as binding forces are quite equivalent to what John Holland defines as flows. Could you elaborate on the differences? I think you would help us relate your work to John Holland's typology much better.

**Abbott:** First, it has been a while since I read Holland's stuff because it's fairly old now, about five years ago. Let me say that I find it difficult to distinguish between saying something that's rather trivial and saying something that's significant. I almost titled this talk, "Walking the Line between the Trivial and the Significant." When you read a lot of the things that people write, often it sounds like lots of words. You try to put your hands on it and say, "Well, what's really there?" My hope, my goal, is to try to make some of these concepts more concrete. So when I talk about mass-based entities, I claim that there's a reality to mass-based entities, and it's not just an aggregation. I distinguish aggregation from mass-based entities in terms of mass-based entities having less mass than the components separately. So I try to make a distinction there.

Regarding the notion of entities that hold themselves together with a flux, I don't have much more to say about it other than it does seem to me, as Holland said, that internal processes that hold the entities together are really important. That is an important category to think about, independently from everything else. It's not like they're built upon mass-based entities, but that's an independent category, and it's a worthwhile category to think about. What is also important about them is that they require energy from the outside. They consume energy, and there is some sort of internal structure that you as social scientists know a whole lot more about than I do, and I would like to see you elaborate. What is that internal structure? What is necessary to keep organizations, or states, or social systems together? I don't have much more to say about that in detail.

**Unidentified Speaker:** Well, maybe I'll jump in here for a second. If we are going to acknowledge John Holland, I would like to also acknowledge Ilya Prigogine, who has given us the concept of ... [inaudible] ... far from equilibrium process entities. That is indeed a very powerful concept and one that's worth some reflection. So I appreciate your articulating it and putting it into context.

Now, I don't think I'm held too responsible for soccer moms because the thrust of what I was saying had to do with fragmentary, fluid, and attributed entities. Calling our assumption of discreteness about entities into effect, I would point out that soccer moms are raised precisely because coherent behavior is attributed to them. I don't know if that makes them an entity or not, just probably one of my subentity categories, and I don't even know if it's true or not that they exhibit coherent entity in an electoral sense. But I do have a great deal of confidence that they exhibit coherent behavior after school on weeknights and that may give them a certain element of "entityness."

Finally, I want to say that your presentation allows me to take heart because I came to the conclusion that a model of meaning-oriented agents gives us perhaps the best gross model of its movement that we have available right now.

**Luis Antunes:** Luis Antunes from the University of Lisbon. I have a problem with the difference between an aggregation and an entity. It strikes me that an aggregation is an entity because its aggregatedness is emergent. So where does that leave us?

**Abbott:** When you say its aggregatedness is emergent, I'm not quite sure what you're saying.

**Antunes:** The fact that it is an aggregation. It is in your eyes, not in the aggregation itself, so it's emergent.

**Abbott:** Well, a pair of socks is a good example, I think. A pair of socks is a pair of socks because we call it a pair of socks. So a pair of socks is two socks that were aggregated together. It's a designed entity because we impose that design on it. But there's nothing about two socks, even if they match, sitting around that holds them together independently of us looking at them so.

**Antunes:** I'm arguing that two of them were made equal to constitute a pair of socks. So they're both, in your eyes and in the eyes of the manufacturer, in everyone's eyes, an entity.

**Abbott:** Well, again, it requires someone's eyes to make it an entity.

**Antunes:** Well, what doesn't? Can you give me an example of an aggregation that doesn't require anyone's eyes?

**Abbott:** An atomic nucleus. That is my example of an aggregation that doesn't require anyone's eyes to be an entity.

**Antunes:** I'm not so sure. I think it's an abstraction also, built by men to talk about the world.

**Abbott:** Well, to the extent that anything we say is an abstraction we construct to talk about the world. I mean, this is the sort of realism — science is realism — that what we talk about really exists. If it doesn't, where are we?

**Dawson:** I'd like to thank everyone for their comments. Our time is up. Let's take a short break.

# **Social Networks and Agent Cognition**







## SOCIAL NETWORKS AND SIMULATIONS

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### ABSTRACT

In standard introductions to agent-based modeling, agents have attributes, use decision rules, and occupy a space. Although the interactions between agents drive the model, the actual pattern of local interactions (random, grid, or torus based or in a circle) are often an afterthought. Recent work on the small-world effect in interaction networks (Watts and Strogatz, 1998; Watts, 1999) led to the introduction of new agent network topologies: typically circles with a few long-distance ties. Do these modifications accurately capture the properties of the social networks of interest?

It may not be immediately apparent that the shape and form of agent interactions could substantially affect simulation results. However, Gould (1993) showed that behaviors spread very differently through different types of networks. Gould found that the structures of the interactions between individuals shape the spread of cooperation, even when initial individual attributes and decisions are the same. Similarly, Macy and Skvoretz (1998) found that a neighborhood's size and interaction frequencies affect outcomes and successful strategies in prisoner's dilemmas.

This paper extends this line of research by looking systematically at the effects of network structure on a very simple threshold model of contagion. It begins by reviewing what is known about the composition of social networks, noting structural differences between different kinds of social networks. It then compares five techniques for constructing agent interaction patterns. First, agents may look at global, not local, information. When agents look at local information, they can model local networks in four basic ways. Three are standard: random graphs (Rapoport, 1979), two-dimensional lattices, and small-world one-dimensional lattices (Watts and Strogatz, 1998). A fourth rarely used technique generates biased random graphs (Jin et al., 2001). The paper looks at how well these techniques reflect social networks and at whether simulation results vary depending on the network construction technique. It finds that biased random graphs (Rapoport, 1979; Skvoretz, 1985, 1990) are unique in allowing the researcher to manipulate both the average size and average density of local agent networks, and that the average density of local agent networks has a substantial independent impact on simulation results. Biased network construction represents a promising technique for researchers interested in studying social phenomena through simulations, although more work in this area is necessary.

**Keywords:** Social networks, small worlds

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## SOCIAL NETWORK PROPERTIES

The driving force behind agent-based simulations is local interactions among agents who use decision rules. Together, these multiple local interactions form a network. The agents form the nodes or vertices of the network, and the interactions between them form the links or edges. While it is possible to talk about contagion or the spread of innovations in a relatively small class of well-defined networks (Rapoport, 1979), in the complex social networks found in everyday life, it is clear that simulation is the best way to look at the spread of innovations.

The properties of the various social networks in which real people participate on a daily basis can be observed. Moreover, these everyday social networks are likely to form the reference group used by most people when they are making the sorts of decisions that are of great interest to social scientists (e.g., who to vote for, whether to invest or consume, which policies to support, or where to send a child to school). Before assessing which network construction methods are the most suitable to use for the decision to be modeled, one must know something about who is likely to affect that decision.

In social network research, two different types of networks may be of interest. The personal or ego-centered network is used most often. This type of network can be represented as a list of all of the different people, or alters, with whom the individual, or ego, has relations, as well as of the interrelationships among the members of the ego's personal network (Wasserman and Faust, 1994). Since there are a variety of types of relationships (kin, neighbor, co-worker, political discussion partner, church member), a full representation of an ego-centered network will capture both the numbers and types of ties between the ego and all of the other alters in his or her network.

Networks in which all the members of a well-defined group are enumerated, sometimes termed whole or sociocentric networks (McCarty and Bernard, 2003; Wasserman and Faust, 1994), are more comprehensive, so data collection is more difficult. In order to represent interesting sociometric properties, such as centrality, cliques, and structural equivalence (Wasserman and Faust, 1994), it is necessary to have information on social ties from a complete and bounded population. A researcher with the inclination can construct very successful and highly descriptive stories of social action from such data (Galaskiewicz, 1976; Krackhardt and Porter, 1985; Krackhardt, 1990; Padgett and Ansell, 1993). In these stories, it is the structure of the network that is as important, if not more important, than the individual-level ties; the influence of a person depends on his or her structural location and the structural properties of the network.

The problem for agent-based modelers is that although a simulation model maps the sociocentric network of agent populations, estimates of sociocentric social networks are not commonly available. Creative examples of sociocentric networks on which data have been collected include marriage and business relationships between medieval Italian families (Padgett and Ansell, 1993), coauthorship or citation networks (Newman et al., 2001), actors in the same movie (Amaral et al., 2000), and cosponsors of legislation in the U.S. Congress (Skvoretz, 2002, citing Burkett, 1997). The major drawback to these data sets is that they typically do not reflect the structure of intimate interpersonal relationships but instead reflect the verifiable transactions within a bounded population. With the exception of the work by Padgett and Ansell (1993), these data do not represent the structure of the fundamental relationships likely to affect much of everyday human behavior.

Therefore, although there are valid concerns about the reliability of network data collected directly from respondents (Bernard et al., 1979; Newman et al., 2001; Butts, 2003), there is too much information in egocentric network surveys to overlook this rich source of data on the structure of network interactions. The following section quickly reviews the methods used to obtain information on egocentric methods. It then summarizes available estimates of two key properties of personal networks — average size and density — in each of three “types” of commonly described social networks.

## Surveys of Personal Networks

Collecting information about ego-centered networks is similar to collecting information about other individual attributes. A set of individuals can be surveyed and asked about relations, and from the responses, estimates can be made about the shapes and compositions of the personal networks in some larger group. A handful of collection methods are commonly used; most often, they are survey questions involving name generators, such as these: With whom do you discuss important matters? To whom do you turn for help? With whom do you socialize? With whom do you discuss politics? (See Fischer, 1982; Burt, 1984; and Huckfeldt, 2000.) Other methods include small-world and reverse-small-world (reverse-S-W) experiments used to elicit the composition of larger functional personal networks and phone book and first-name list methods used to generate weak-tie or acquaintance networks (Milgram, 1967; Travers and Milgram, 1969; Killworth and Bernard, 1978; Pool and Kochen, 1978; Bernard et al., 1990; Killworth et al., 1990; McCarty et al., 1997).

This literature produces rough but remarkably consistent estimates of the average degree (number of friends of actor  $i = k_i$ ) and density (percent of friends who know each other) in three distinct types of networks. (McCarty et al., 1997, has a good review and introduction.) The three types of networks can be roughly described as acquaintance networks (past and current), regular contact networks (past and current), and core personal networks.<sup>1</sup> These networks are characterized by differences in average degree, density, and method of collection.

Acquaintance networks are very large (500–20,000 people) and include people who the respondent would recognize and call by first name. Typical methods of eliciting acquaintance networks include phone book methods (Pool and Kochen, 1978; Freeman and Thompson, 1989; Bernard et al., 1990) and subpopulation estimates (Killworth et al., 1984). Past acquaintance networks (i.e., “Name people you have ever known”) are much larger than current acquaintance or “weak tie” networks (Granovetter, 1973), which can be collected through use of a contact diary (Pool and Kochen, 1978, reporting Gurevich, 1961). Acquaintance networks are very similar to scale-free networks (Newman et al., 2001) in that the distribution of degree is very skewed to the right-hand side (a few people have very many contacts) (Pool and Kochen, 1978; Freeman and Thompson, 1989), and they are probably well-represented by the small-world

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<sup>1</sup> This is, of course, a vast oversimplification, which is rightly the subject of debate among network analysts. However, this simple schema still captures important differences in the types of interactions likely to be simulated.

**TABLE 1** Estimates of personal network size and density

Study	Method	Degree	Density
Gurevich (1961)	Contact log	500–200	–
Pool and Kochen (1978)	Phone book	3–4,000	–
Killworth and Bernard (1978)	Reverse-S-W	35–210	–
Hammer (1980)	Observation	39	–
Wellman (1979)	“Feel closest”	4.7	0.33 (non-kin)
Fischer (1982)	11 support items	18.5	0.44
Killworth et al. (1984)	Reverse-S-W	134 (65)	
Marsden (1987)	GSS impt. matters	3.0	0.40
Willmott and Young (1967)	Non-kin support	12	0.34
Campbell and Barrett (1991)	Neighbors	14.7	0.52
McCarty (2002)	Free list	60.0	0.27
McCarty et al. (1997)	First names	14/432	0.36
Freeman and Thompson (1989)	Phone book	3–5,000	–
Killworth et al. (1990)	Subpopulations	5,000	–
Bernard et al. (1990)	GSS impt. matters	6.88 (4.89)	–
–	Fischer 11	21.8 (16.7)	–
–	Reverse-S-W	128.6 (67.6)	–
–	Phone book	–	–

network topology. There are no good estimates of the density of acquaintance networks, although any estimate is likely to be small.<sup>2</sup>

Regular contact or support networks are much smaller (10–60 people on average) and include neighbors, coworkers, and family members with whom the respondent has regular social contact and from whom the respondent receives help and support. Examples of questions, or name generators, used to elicit regular contact networks include these: Who are neighbors you’ve talked to? With whom would you spend Saturday night? From whom would you borrow a cup of sugar? Whom would you ask to watch your house while you’re gone? (See Fischer, 1982; McCarty et al., 1997.) Included also would be an invitation to list friends freely (McCarty, 2002). A larger network of up to 300 current and past friendships is often elicited by use of the small-world and reverse-S-W methods (Killworth and Bernard, 1978; Bernard et al., 1987; Bernard et al., 1990). The distribution of degree in regular contact networks is still somewhat skewed, but much less so than it is in acquaintance networks.

<sup>2</sup> Imagine an individual with acquaintances in many spheres: high-school friends, parents’ friends, family members from two to four extended families, current coworkers, coworkers from a previous job, friends from church or another organization, etc. Although density within the spheres will be high, few ties will exist across the spheres, resulting in a low percentage of possible ties being present; therefore, the network will not be very dense (McCarty, 2002).

Core personal networks are very small egocentric networks (0–10 people) and include people with whom the respondent discusses “important matters” (Wellman, 1979; Fischer, 1982; Marsden, 1987). The variation in average degree in these networks is quite small, and clustering varies with the size of the network and respondent attributes. In general, if the costs associated with maintaining ties are low, then degree distributions are often exponential; otherwise, they tend to return to slightly right-skewed but with relatively normal distributions (Newman et al., 2001).

In some cases, a respondent is asked if his or her friends know one another, producing an estimate of the density of his or her personal networks. These density estimates typically range from about 0.25 to 0.45 in both core and regular contact networks. However, attempts to validate the existence of close ties among the friends of a respondent through use of a snowball sample have found that respondents may overestimate the existence of ties among friends (Fischer and Shavit, 1995). Also, the use of different questions to measure tie existence between alters (i.e., Do ‘j’ and ‘k’ know each other? or Do they know each other well?) complicates comparisons across studies. Including household members in density estimates also greatly changes them. Campbell and Barrett (1991) found that an average personal network density of more than 50% drops to about 33% after household members are excluded. A variety of considerations suggest that the median (not mean) density in personal networks may be around 15% to 35%.

The survey work on personal networks has two major implications for agent-based modelers. First, the network type chosen (acquaintance, support, or core) and the subsequent distribution of network degree and density chosen reflect a substantive question about who is likely to influence an agent’s decision. Acquaintances are probably not particularly likely to influence important decisions (such as who to vote for or where to send a child to school), but they may influence tastes in clothing or food (although there is little evidence that addresses this concern). An important question for a simulation researcher to ask, therefore, is this: What are the properties of the interaction networks being modeled?

Second, the network construction technique chosen should ideally reflect a sample of the likely patterns of interactions between agents. The following section takes a closer look at five different interaction patterns that could be used by agent-based modelers. Two questions are asked: How well do the techniques capture the network degree and density reported in egocentric surveys? Do the differences in network structure that were induced by the selected technique result in substantive differences in simulation results?

## **NETWORK CONSTRUCTION TECHNIQUES**

Once a decision has been made about the type of interaction to study and the likely structure of that interaction, it is necessary to implement this theoretical construct through the choice of a network construction technique. Modelers typically can choose from one of a few network construction techniques: global information about other agents, random graphs, two-dimensional lattices or grids, and one-dimensional lattices or circles. Another alternative, rarely used, is biased random net construction.

## Global Reference or Full Information Networks

In a global reference network, agents have information on, can respond to, and are affected by the actions of all other agents in a population. Global reference networks may be chosen to represent the influence of mass media or the behavior of crowds (Granovetter, 1978). Global reference groups vary only in the size of the population  $n$  being modeled.

## Random Graph Local Networks

Another approach is to create a population of  $n$  agents in which the links between agents are generated randomly, called a random graph in network terminology (Rapoport, 1979). In the simplest form, the projected degree  $\hat{k}_i$  is assigned uniformly across agents ( $\hat{k}_i = \bar{k}, \forall i$ ). Thus, the probability that a link exists between any two agents (represented as  $i \leftrightarrow j$ ) is simply the density of the sociocentric network:<sup>3</sup>

$$P(i \leftrightarrow j) = \frac{\bar{k}_i}{n-1} = \frac{\bar{k}}{n-1} .$$

This method produces a network in which the degree across agents follows the binomial distribution, approaching the Poisson distribution as network size increases (Newman et al., 2001). Because the nodal degree of many networks follows a skewed distribution (as opposed to a Poisson distribution), Newman et al. (2001) considered an interesting extension of this random model, in which they allowed the nodal degree to vary across agents and generated random networks by using a predetermined degree distribution.

The primary drawback to random graph methods is that they create networks in which any two agents who are friends are not likely to know each other's friends. In other words, random graphs create personal networks that have a very low density relative to surveyed egocentric networks. Random network construction methods create little, if any, overlap between friendships. The probability of having an overlapping friendship is independently determined and thus simply the square of the density of the network, or

$$\left( \frac{\bar{k}}{n-1} \right)^2 .$$

This is a very small probability compared to the clustering percentages found in the survey literature on personal networks, and this increase in indirect contacts increases the effective size of personal networks for spreading behaviors relative to the size of networks constructed by using different methods.

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<sup>3</sup> This notation assumes symmetric friendships, a necessary assumption for comparison to lattice-based networks. However, one benefit of the random and biased random methods is that this assumption can be relaxed, thereby allowing networks to further reflect observations of real social networks.

## Two-dimensional Lattice- or Grid-based Networks

Two-dimensional lattices or grids are the most commonly used method for creating networks in ABM simulations. While this is a simple method and may be preferred for spatially constrained networks, it is inconsistent with the data gathered on actual social networks in three important ways. One problem is that the agents are spread too far apart from one another in networks that consist of more than 100 people or so. This violates the “six degrees of separation” rule (i.e., “Kevin Bacon” rule) that a short chain of intermediaries separate any two people, even in the larger American or global world (Pool and Kochen, 1978; Watts and Strogatz, 1998).

The second problem with the grid method is that friends are shared perhaps too closely. The social network of an agent’s friends (or ego network) has a density of more than 40%. The 8-person local network of *A* is illustrated in Figure 1(a), and the overlap between the friends of *A* and those of *A*’s friend *B* is shown in Figure 1(b). By looking at each of *A*’s friends, one can see that a total of 24 friendships out of 56 potential ones exist, for a personal network density of 0.43.<sup>4</sup> In 4-person neighborhoods, however, the personal network density is 0; no overlapping ties are present. The available data indicate that the clustering percentage in 8-person networks is almost too high, and the percentage in 4-person networks is too low.

The final issue is that degree in a grid network does not vary across agents. All agents have exactly the same number of friends.<sup>5</sup> This is not a property of core networks in the real world (Marsden, 1987). Moreover, grid-based networks make it difficult to study the effects of centrality or network variation on the basis of personal attributes. (Lustick and Miodownik, 2004, has an innovative exception.)

## One-dimensional Lattice or Small-world Method

The inaccurate representation of the small-world character of social networks mentioned above has drawn attention from researchers (Watts and Strogatz, 1998). The small-world or

	<i>a</i>	<i>a</i>	<i>a</i>	
	<i>a</i>	<i>A</i>	<i>a</i>	
	<i>a</i>	<i>a</i>	<i>a</i>	

(a) Friendships of Person *A*

	<i>a</i>	<i>a,b</i>	<i>a,b</i>	<i>b</i>
	<i>a</i>	<i>A</i>	<i>B</i>	<i>b</i>
	<i>a</i>	<i>a,b</i>	<i>a,b</i>	<i>b</i>

(b) Overlapping Friendships of *A* and *B*

**FIGURE 1** Two-dimensional lattices or grids

<sup>4</sup> The personal network density of *A* is calculated as follows: *A* has four friends who are middle agents, like *B*, who know four out of the other seven friends of *A*, and *A* has four friends in the corner who have 2/7 possible ties present, so the sum across all eight friends is  $4 \times 4 + 4 \times 2 = 24/56$ .

<sup>5</sup> At least if a torus is used. Otherwise, agents at the edge of the graph do not have as many friends as do the other agents in the center of the graph.

Watts-Strogatz method represents one possible solution. It makes an important modification to the simple grid method in order to create networks that are likely to have the *six degrees of separation* property (Watts and Strogatz, 1998; Newman, 2000). A small number of existing one-dimensional lattice links are broken and then reattached to a randomly selected agent from the population. The result is a network of agents who have friends primarily drawn from proximate agents, with a small number of links that span geographic areas to create shorter paths to agents in different areas. While this method successfully addresses the problem of widely separated agents, it does not address the problem of an excess of overlapping friendships or uniformity of degree distribution. It also lacks the ability to associate personal characteristics with network characteristics to any great extent.

The density of Watts-Strogatz circles varies in relation to the size of the network and the number of long-distance ties. With no long-distance ties, 4-person neighborhoods (two steps) have a density of about 0.5. In 8-person neighborhoods (four steps), the density increases to almost 0.64 (36/56). Long-distance links decrease the average density. Larger personal networks constructed by using the Watts-Strogatz method are much denser than actual social networks, whereas density decreases as the network size increases in most social networks (Fischer, 1982; McCarty, 2002). As a result, Watts-Strogatz networks are effectively smaller than surveyed personal networks.

### Biased or Structured Random Networks

Another approach is to create networks that accurately reflect actual social networks through the use of known network biases. The construction of biased random networks achieves this goal by re-creating the process of actual friendship formation and the biases that typically affect the process (Rapoport, 1979; Skvoretz, 1985, 1990; Skvoretz et al., 2004). There are two sources of bias to consider in the creation of a network (Skvoretz, 1990): structural bias and node or compositional bias. Structural bias is inherent in the structure of the network itself. It includes processes such as reciprocity, or the trend toward mutual friendships, and triad closure, or the trend toward mutual friends of person  $i$  to become friends as well (Skvoretz, 1985, 1990). Node bias is the bias in the network created by differences in agents and their attributes. Sources of node bias include agents who choose more friends than others or who have a tendency to choose friends with similar attributes (homophily) (Fararo, 1981; Fararo and Skvoretz, 1984).

Despite the potential importance of node or compositional biases, particularly homophily, in affecting interactions in the real world, this paper looks at a biased net technique, which works primarily through a triad closure bias to increase the density of personal networks above the density typically found in random graphs.<sup>6</sup> The method described by Jin et al. (2001) is used for this work, although approaches that focus on a more comprehensive account of network structure directly may be more accurate and/or flexible (Skvoretz, 1990; Snijders, 2002).

The basic logic of the Jin et al. (2001) method is that it proceeds in steps. During each step, a few pairs of actors are first selected to be friends, and the appropriate ties are added to the

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<sup>6</sup> A variation in personal network degree could easily be incorporated, and this paper has done so by specifying the proposed distribution of  $k$  from which  $\hat{k}_i$  will be drawn (Newman, 2000). The incorporation of both node and structural biases in the same framework is difficult and left for future work.



network. Then, mutual friends of these actors are selected to also be friends. This process is repeated until all actors have the maximum number of friends, although a third step could be added in which ties would be removed, and thus the network would always be gradually changing itself. In the Jin et al. model, the average density of personal networks can be changed by changing the relative proportion of selections made in the first (random) and second (mutual friends) substeps of network creation.

Biased network construction is unique in that it allows researchers to build networks with user-designated properties of interest. These properties can be based on existing empirical evidence about the properties of the networks that the user is trying to simulate. A table gives parameter values to use with the Jin et al. (2001) method in Repast (Collier, 2002) to create networks of approximately the desired average degree and density (contact the author to find out parameters used). While the Jin et al. method does seem to replicate variation in personal network density, results suggest that there is still “additional social structure in the network that is not captured by the graph” (Jin et al., 2001, p. 1).

## COMPARISON OF RESULTS

To assess whether the network construction method affects simulation results, a very simple threshold decision model (Granovetter, 1978) was replicated. The choice of a simple model with derivable asymptotic properties and intuitive sample properties allowed for a relatively independent consideration of network construction techniques. This paper first describes the model and then presents the simulation results.

In a threshold model, a community of  $n$  agents ( $i \in [1, 2, 3 \dots n]$ ) is created. Agents are assigned  $k_i$  friends, with a friendship from  $i$  to  $j$  denoted  $i \leftrightarrow j$ . The agents can take one of two actions: participate ( $d_i = 1$ ) or not participate ( $d_i = 0$ ). They decide to participate only when a threshold ( $t_i$ ) percentage of other actors also participates:

$$(t_i \leq \frac{d_j}{k_i}, \forall i \leftrightarrow j).$$

Agent thresholds  $t_i$  are randomly assigned and are drawn from the uniform (0, 1) distribution. A first-mover percentage is also chosen (e.g., 1% of all agents), and all agents whose thresholds fall below that percentage are willing to move in the first round (time = 0).<sup>7</sup> The simulation continues with additional agents joining in at each time step if their thresholds were met in the previous round. The simulation stops when no agents are willing to participate, either because full participation has been reached or because no agents have sufficiently low thresholds. Some threshold models have a tendency to snowball and add many participants under some conditions, while others induce little or no participation (Granovetter, 1978). Therefore, this paper looks at both Granovetter’s original model, with 1% acting as first movers, and a second threshold model, with 10% acting as first movers, to see if network construction has a different effect depending on expectations of what the model results will be. On the basis of Granovetter’s results, one would expect to see much higher participation in the populations with 10% of the agents acting

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<sup>7</sup> Technically, it is necessary to lower all thresholds by the first-mover percentage,  $f \in [0, 1]$ , to  $t'_i = t_i - f$ . Then all agents whose thresholds fall at or below 0 move in the first round.

as first movers. These two threshold models were run by using five different reference group construction techniques (i.e., methods of assigning  $i \rightarrow j$ ): global, random, grid, Watts-Strogatz, and biased random (Jin et al., 2001). Median participation levels in the final round appear in Table 2. Row entries are for the average personal network size (4, 8, 12, 16, or 20 people in the local networks) and either 100 or 1,000 in the global reference networks.

Simulations with 1% first movers confirm Granovetter's original conclusion that in 100-person groups with global information, participation rarely snowballs. The median turnout in these groups is 1% of the population, or 1 person. More surprising is the result found for 1,000-person global reference groups: more than 20% of the population participates. This finding points to the potential impact on simulation results that could result from how interactions are modeled, even when agents have no local networks.<sup>8</sup>

Completely random networks provide a large indirect source of information to agents and also produce substantial participation rates, in a range of 15% to 22% of the population, on average. These networks clearly produce more turnout than the other local network interaction patterns, and they appear to be close to, or even more effective than, global reference groups in encouraging the spread of innovations. One interesting point is that there is not a uniform size effect at work in this 1% first-mover uniform threshold model. The small increase in median turnout between the 1,000-person global reference populations and those where agents refer to randomly constructed local networks is the result of an interaction between two emergent properties of contagion models: the ability of smaller groups to incubate the nascent participation when it is less likely to spread easily, and the ability of larger and less dense personal networks to remove barriers to the spread of participation when it is likely to spread (Rolfe, 2004).

The differences between grid, Watts-Strogatz, and biased random networks are largely minimal, as shown in Table 2. Participation in all of these agent populations is higher than in a

**TABLE 2** Final-round participation by 1% first movers

No. in Network	Type of Network				
	Global	Random	Grid	Watts-Strogatz Circle	Biased
4	–	111	42	40	38
8	–	220	61	54	50
12	–	200	71	61	71
16	–	241	–	75	87
20	–	150	–	62	87
100	1	–	–	–	–
1,000	218	–	–	–	–

<sup>8</sup> In a paper in progress, I discuss the theoretical implications of this finding. The tendency for riot behavior to spread more easily in large crowds than in small ones may reflect the statistical anomalies of sampling and sample size, and reflect nothing unique about the physiological or psychic reactions of humans to crowds (LeBon, 1995).

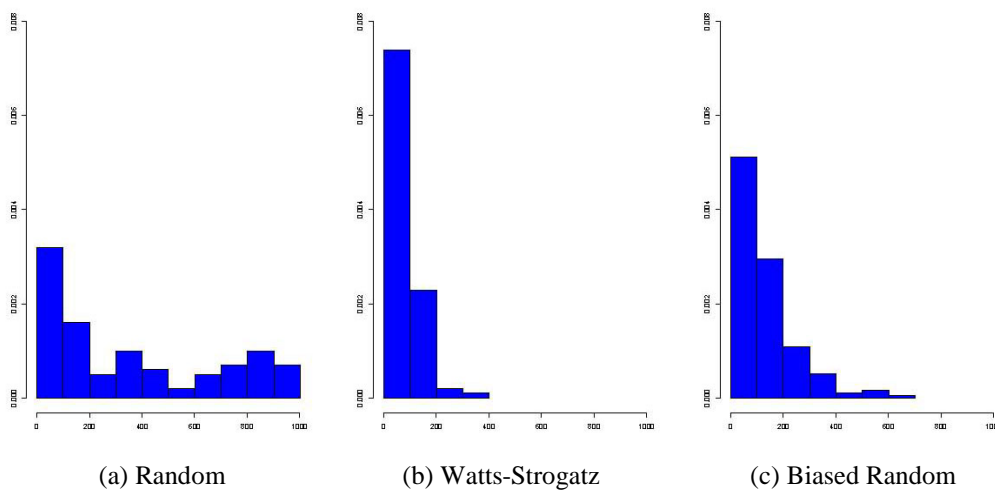
100-person global reference population (4%–9% versus 1%), an outcome traceable to the ability of small groups to incubate cooperation (Rolfe, 2004). None of the network construction methods produce consistently high or low median levels of participation. However, the differences between Watts-Strogatz networks and biased networks are somewhat more pronounced as average network size increases. This is because the extremely high density of the Watts-Strogatz networks decreases the ease with which innovations can spread through the population. This point is reinforced by a breakdown of simulation results in the biased network populations by average personal network density, as shown in Table 3.

**TABLE 3** Final-round participation by 10% first movers in biased networks, by density

Density	No. in Network				
	4	8	12	16	20
0.15–0.25	46	49	83	93	89
0.25–0.35	37	65	86	91	80
0.35–0.45	38	53	61	56	89
0.45–0.55	29	42	55	–	–

Table 3 shows relatively systematic changes in median participation relative to network size. In general, increases in density correspond to decreases in median participation. This finding is not surprising, given that network size increases participation in the 1% first-mover uniform threshold model. Since increases in network density split the population into tightly knit clumps, network density serves as a barrier to the spread of cooperation. Small deviations from the pattern in Table 3 appear to stem from the difficulty of creating networks directly comparable in terms of size and density and not from any discontinuities in the relationships among size, density, and participation.

The median level of participation, while a useful statistic, actually understates the difference in simulation results that these network construction methods produce. In many of these simulated populations, the range of participation is more diverse than indicated by the median. For a point of comparison, a histogram of participation among agents placed in 16-person networks constructed by using random, Watts-Strogatz, and biased networks of appropriate density (0.15–0.25) appears in Figure 2.



**FIGURE 2** Final-round participation by 1% first movers in 16-person local networks

A comparison of Figure 2(b) and 2(c) reveals a clear difference in the distribution of simulation results from using the Watts-Strogatz and biased random methods. While the Watts-Strogatz method produces participation rates that go above 15% of the population only 1 time out of 10, the agents in populations using the biased random method reach participation rates of 15% of the population more than twice as often, or in about 25% of simulated populations. This is a substantial difference in simulation results.

Agent participation in simulations of the uniform threshold model with 1% first movers clearly varies in relation to the patterns of interactions in which the agents are engaged. In addition to striking differences between global and random methods and the other three local methods, there were smaller but still noteworthy differences between the Watts-Strogatz method and biased random method. However, a second model was run to confirm the differences noted between the network construction methods.

The second model run was again a uniform threshold model, with the sole exception being that this time, 10% instead of only 1% of the population was willing to participate during the first round. This model should produce very high participation in large populations and provide a similar but distinct test of the differences that interaction structure may induce in simulation results. Table 4 summarizes median final-round participation by reference group type.

Results for the global reference groups indicate that, as expected, these simulated populations regularly achieve nearly universal turnout. As noted earlier, the 1,000-person groups have higher median participation (96%) than the 100-person groups (75%), which confirms the need to consider not only agent interaction patterns but also agent population size when designing simulations. The random networks also encourage the nearly universal spread of participation, with the spike at 16-person networks noted and accounted for. All four local methods exhibit the expected relationship between size of personal networks and participation rates in easily contagious models (Rolfe, 2004).

The differences in participation rates induced by local network patterns are even more obvious in the 10% first-mover model than in the 1% first-mover model. Around 100 more people in 1,000-person populations are willing to participate if they are embedded in biased

**TABLE 4** Final-round participation by 10% first movers

No. in Network	Type of Network				
	Global	Random	Grid	Watts-Strogatz Circle	Biased
4	–	843	369	351	336
8	–	974	463	426	435
12	–	980	525	476	530
16	–	984	–	531	606
20	–	970	–	569	662
100	75	–	–	–	–
1,000	963	–	–	–	–

random networks instead of Watts-Strogatz networks. The difference in the two methods is again largely due to the difference in personal network density. As a comparison with Table 5 shows, participation is very similar in the high-density biased networks and the Watts-Strogatz networks in all networks except the very small personal ones ( $\bar{k} = 44$ ).

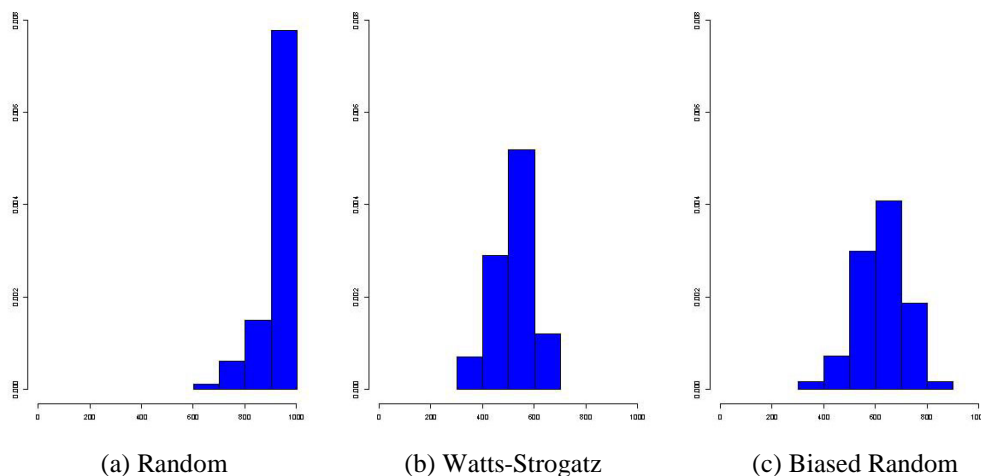
Figure 3 offers a final look at the histograms of participation in simulated populations where agents referred to 16 friends when making decisions. Here again, the differences among the three network construction methods are highlighted. Random networks encourage very high levels of participation, and Watts-Strogatz networks encourage participation in a very small range, while some of the biased random populations come close to nearly universal participation.

**TABLE 5** Final-round participation in biased networks, by density

Density	No. in Network				
	4	8	12	16	20
0.15–0.25	373	487	595	618	689
0.25–0.35	362	460	552	576	613
0.35–0.45	325	441	523	583	605
0.45–0.55	284	357	460	–	–

## DISCUSSION

This paper systematically compares five methods for creating reference groups for agents in simulations. The goal of this exercise was to determine whether the choice of reference group construction affected simulation results, when the choice of the model to be simulated was held constant. Two variations of a simple threshold model were used. The social network construction method was found to have a substantial, significant impact on simulation results. Much of the difference between the two methods that attempt to more accurately replicate observed social networks — biased random networks and the Watts-Strogatz circles — was traceable to the overestimation of personal network density by the Watts-Strogatz method in intermediate-size networks of 8 to 20 people.



**FIGURE 3** Final-round participation by 10% first movers in 16-person local networks

While the theoretical implications of the relationship between reference group size and density is reported elsewhere (Rolfe, 2004, 2005), this relationship also has clear, practical significance for researchers who model human decision-making and social phenomena. This paper suggests that model results could be misleading if proper attention is not paid to the creation of agent relationships. Ideally, authors should give a full account of the effects of agent interaction patterns on model results. At a minimum, authors would be well-served if they looked at empirical evidence to constrain their choices of both the network construction method and the projected size and density of the network. For those who wish to experiment with the method used in this paper, please consult the author.

Finally, this paper suggests that more work is needed before the same sorts of network patterns observed in the real world of intimate personal connections can be simulated. One modification that could easily be implemented in the Jin et al. (2001) method would be to allow variation in the projected degree across agents. Preliminary results suggest that this approach produces a more natural-looking distribution of personal network degree. However, further modifications would undoubtedly produce more useful and realistic biased network methods that would also allow the researcher to associate personal characteristics or network position with behaviors, attitudes, or influence.

Rolfe (2005) shows that the known relationship between demographic variables and network structure may account for much of the relationship between turnout and education. However, a full test of this and similar hypotheses would require a biased network technique that would incorporate compositional biases, such as homophily, and would also perhaps address the structural biases in network creation more rigorously. The ability to actually model the process of network creation would allow researchers to create populations of agents who not only created their own networks but also made decisions about other behaviors either sequentially or simultaneously — a prospect that would open up doors in pragmatic and theoretical simulation research.

## ACKNOWLEDGMENTS

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## GLOBAL COORDINATION IN MODULAR NETWORKS

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### ABSTRACT

We investigate how the efficiency of a system performing a density classification task is affected by a modular structure of the network, that is, a structure where the units can be divided into communities. We find that noise plays a fundamental role in allowing the system to reach global consensus. We also observe that to reach consensus the system needs at least a minimum fraction of the connections to be established outside the communities and that this fraction depends mainly on two factors: the number of connections per unit and the intensity of noise.

**Keywords:** Modular networks, self-organizing systems, density classification

### INTRODUCTION

Many systems in nature organize themselves into collectives without the need for centralized controls. Well-known examples in biology include flocks of birds, schools of fish, and swarms of insects. In social settings, examples include conventions and norms (Young, 1996; Boyd and Richerson, 1995), social learning in animals and humans (Boyd and Richerson, 1995; Heyes and Selten, 1996), as well as fads, rumors, and revolts (Bikhchandani et al. 1998). Such emergent goal-oriented behavior results often from simple local individual behavior rules, where the system is capable of adapting to new environments. Moreover, such behavior is robust; it does not rely on a fixed leader and does not easily get derailed in the face of disturbances.

Insights from self-organizing natural systems can also be fruitfully used in the design of man-made systems. Possible applications include the design of communication networks and protocols in social organizations, computational devices, and even “man-made swarms,” for example, in military applications. Such systems would have to satisfy various performance requirements, such as:

- *Accuracy.* Agents need to coordinate on the desired collective behavior.
- *Speed.* The desired behavior needs to be reached in a realistic time.
- *Error tolerance.* Removal of agents or mistakes in processing information should only lead to a moderate decrease in system performance

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- *Scalability.* The resources (e.g., time) to perform the collective task should increase at a slow rate as the number of agents (and the system capabilities) grows more rapidly.

Given a desired emergent behavior, we then need to know (1) what capabilities are needed of the individual agents to accomplish such design requirements, and (2) how to design the interaction rules to achieve the desired behavior.

## MODEL

We model systemwide coordination as a computational task. Specifically, we use density classification as a measure of coordination and global information processing (Crutchfield and Mitchell, 1995). For a system comprised of units whose state is a binary variable, the density classification task is completed successfully if *all* units converge to the same state *and* the coordinated state is identical to the *majority state* of the initial configuration.

Density classification is a trivial task for systems with centralized control; one span of the system immediately yields the correct result. In contrast, a decentralized system performing density classification has to overcome two challenges: (1) information aggregation — the ability to extract global information from local interactions, since each unit accesses only a small fraction of the units in the system — and (2) system coordination — all units have to converge to the same state. Moreover, noise is an unavoidable component of real-world systems. The noise acting on a system may originate from external factors, such as fluctuations in the environmental conditions, as well as from intrinsic properties of the units comprising the system or the way in which they communicate. Naively, one might surmise that the presence of noise must increase the difficulty in completing the classification task.

We generalize a standard cellular automata dynamics in order to incorporate noisy communication among units. To update its state, each unit takes into consideration the states of its neighbors. We consider the case where the presence of noise may corrupt the information obtained from the neighbors. Formally,

$$\tilde{\sigma}_j^i = \begin{cases} \sigma_j & \text{with probability } 1 - \eta/2 \\ -\sigma_j & \text{with probability } \eta/2 \end{cases}, \quad (1)$$

where  $\tilde{\sigma}_j^i$  is the value unit  $i$  reads for the state of unit  $j$ ;  $\sigma_j$  is the true state of  $j$ ; and  $\eta$ , which parametrizes the intensity of the noise, ranges from  $\eta = 0$  (noiseless dynamics) to  $\eta = 1$  (random dynamics). Note that the noise *is not* the probability that a unit chooses a state in disagreement with the majority of its neighbors, but the probability that a unit receives a false input from a particular neighbor.

In addition, for practical applications the time to reach the correct classification should scale, at most, linearly with the number of units in the system. For example, for a system comprising 99 units, initially in a configuration where 50 units are in state “1” and 49 are in state “−1,” the density classification task is successfully completed if all units converge to state “1” within  $2 \times 99 = 198$  time steps. To estimate the efficiency of the system, we perform 1,000 evolutions, changing the initial condition and network pattern for each evolution, and measure the fraction of times in which the correct classification is reached.

In a recent paper (Moreira et al., 2004) we have shown that, under the general conditions of noisy environments and complex topologies, a strategy as simple as the majority rule — where a unit changes its state to agree with the majority of its neighbors — can successfully reach consensus and perform the classification task with high efficiency. Surprisingly, the presence of noise plays a fundamental role in allowing the system to achieve consensus. Here, we investigate how the efficiency of a system performing a density classification task is affected by a modular structure of the network, that is, a structure where the units can be divided into communities.

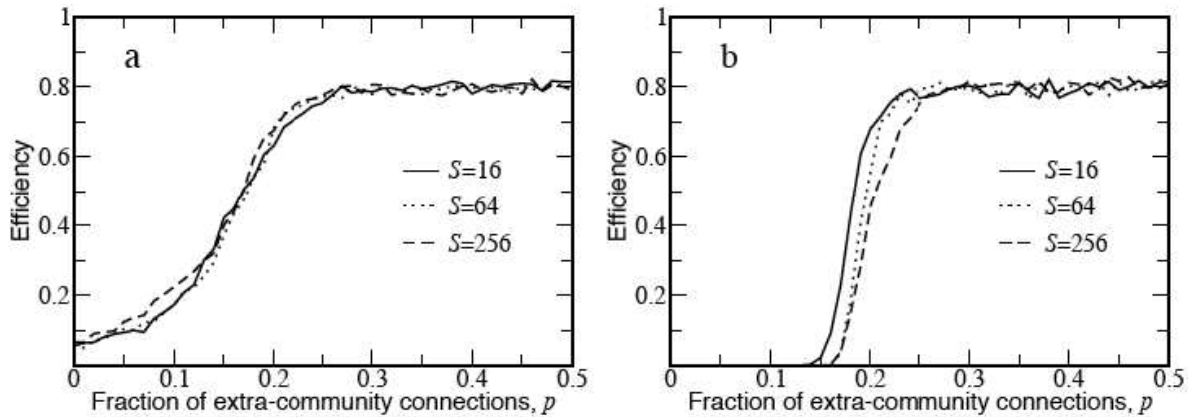
To build a modular network, we start with  $N$  individual units divided into communities of equal size  $S$ . Then, each unit establishes  $k$  connections; with probability  $p$ , the connection is directed to a random unit in the network and with probability  $(1 - p)$ , the connection has to be established within the unit community. The fraction of extra-community connections  $p$  controls the network topology: for  $p = 0$ , one has completely disconnected communities, while for  $p = 1$  one has a random graph.

## RESULTS

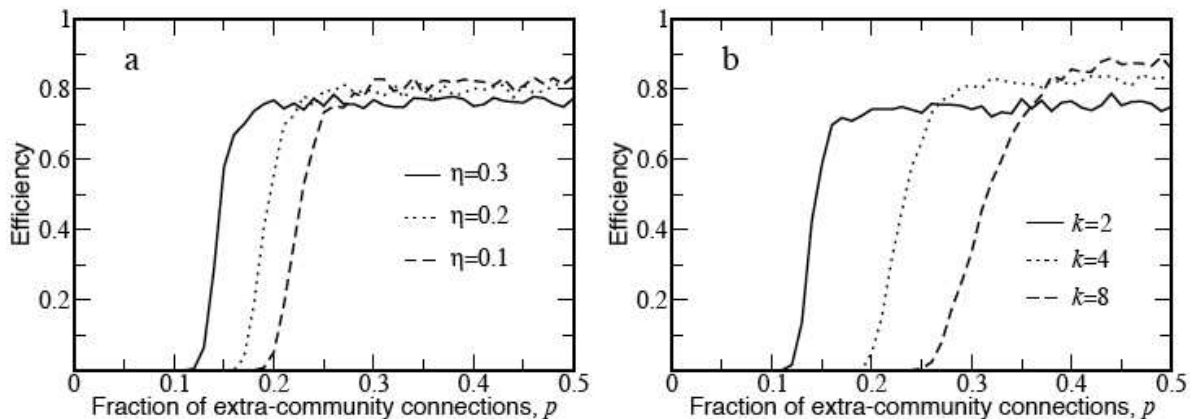
In the density-classification problem, each unit has to evolve toward the final state with only local information about the current configuration of the whole system. A modular structure of the network may result in a configuration where consensus is reached only within each community but not in the system as a whole. If the fraction of extra-community connections *and* the noise intensity are low, this configuration will be stable and global consensus may never be reached. In Figure 1, we show the system efficiency versus fraction of extra-community connections  $p$  for systems with noise intensity  $\eta = 0.2$ . When the number of communities is large, there is a minimum fraction of extra-community connections  $p_c$  below which the system never reaches consensus. Note that when the majority of inputs come from within a unit's community, the units will tend to agree only within their communities and the global consensus may never be reached. Yet, with as much as 3/4 of the connections solely among units of the same community, the system is still able to achieve global consensus.

To understand why the system converges to consensus even with a low fraction of connections outside the communities, we study the effect of the noise intensity  $\eta$  in the efficiency of the system. In Figure 2a, we show that the critical threshold  $p_c$  decreases as the noise intensity  $\eta$  increases. These results suggest that noise and intergroup connections work as substitutes. Noise can drive the system to a global consensus even in cases where most of the connections are inside the respective communities. In Figure 2b, we show the efficiency curves for different values of the number of connections  $k$  and noise intensity  $\eta = 0.2$ . With a larger number of connections, the onset of the transition for fixed noise shifts to larger values of  $p$ .

We can now understand how the noise enables the system to reach consensus. Suppose that the system evolves toward an intermediary configuration, in which the larger part of the system converges to the correct state, but a few communities reach local consensus on the opposite state. If the noise acts on some of the connections inside these communities with positive probability, a fraction of the units in the communities will switch their states. These units then act as seeds, promoting other units inside the community to switch their state.



**FIGURE 1** The minimum fraction of connections outside the communities to reach consensus (We show the efficiency of the system as a function of the fraction of  $p$ . These results are for networks with  $k = 6$  and noise intensity  $\eta = 0.2$ . We study networks comprising [1a] 5 communities and [1b] 100 communities, for different community sizes  $S$ . System classification efficiency does not show a strong dependence on the size of the communities. As expected, the efficiency grows with  $p$ , starting from a value close to zero in  $p = 0$  and saturating in a value above 0.8. Interestingly, as we increase the number of communities, the curves go from a smooth to a sharp transition. This means that large systems will have a minimal value of  $p$  below which a global consensus is never reached.)



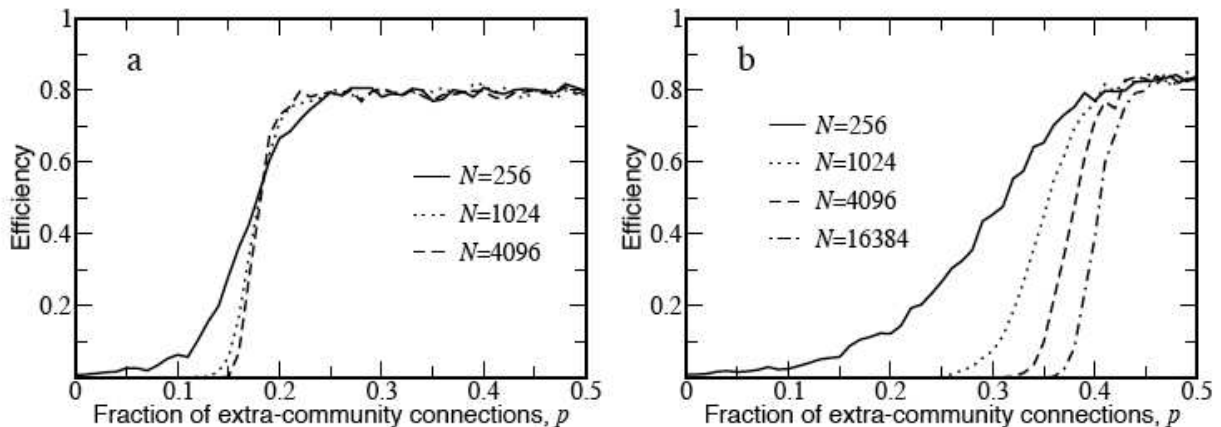
**FIGURE 2** The roles of noise and the number of connections (These results were obtained for networks comprising 100 communities of size  $S = 64$ . In 2a, we show the efficiency curves for networks with  $k = 6$  and noise intensity  $\eta = 0.1, 0.2,$  and  $0.3$ . Increasing the noise causes the onset of the transition to shift toward smaller values of  $p$ . This shows that noise plays a fundamental role in allowing the system to reach consensus. In 2b, we show the efficiency of systems with  $\eta = 0.2$  and different values of the number of connections  $k$ . As we increase  $k$ , the onset of the transition shifts to larger values of  $p$ . This happens because with more connections the units are more robust to the effect of noise.)

Eventually, most units in the respective communities will switch to the correct state until the system reaches consensus. The number of inputs that the seed units need to disregard to switch their states is proportional to  $k(1 - 2p)$ . This explains why  $p_c$  increases with  $k$ . On the other hand, more densely connected networks are also more robust to noise. This suggests that there is an optimal noise intensity that depends on  $k$  in which the system is most efficient.

The effect of noise on the efficiency of the system is stressed by the results present in Figure 3. In Figure 3a, we show the efficiency curves for networks for noise  $\eta = 0.2$  and different sizes  $N$ . As  $N$  increases, the transition becomes sharper, but the onset of the transition remains approximately the same. In contrast, when  $\eta = 0$  the onset of the transition moves toward larger values of  $p$ . In a system of infinite size one may expect a noise-free system to reach consensus only when the majority of the connections are outside the communities, that is,  $p > 0.5$ .

## DISCUSSION

Simple heuristics, such as the majority rule investigated here, are efficient in achieving global coordination and information aggregation in interaction systems characterized by complex topologies and noisy information transmission.



**FIGURE 3** The transition to the efficient regime (These results were obtained for networks with  $k = 6$ , comprising communities of size  $S = 64$ , and with different system sizes  $N$ . As we increase  $N$  while keeping  $S$  constant, we also increase the number of communities in the system. In 3a, we show the efficiency curves for a noise intensity  $\eta = 0.2$ . As  $N$  grows, the curves become more steep, but there is no shift in the onset of the transition. In contrast, in 3b in a noiseless system,  $\eta = 0$ ; as we increase the system size the onset of the transition moves toward larger values of  $p$ . One may expect that in the limit  $N \rightarrow \infty$ , there will be no efficient regime unless  $p > 0.5$ , that is, the number of connections outside the communities surpasses the number of connections inside the communities.)

Many complex networks exhibit a modular structure, that is, they are comprised of smaller communities that may interact only in a limited fashion. Our results demonstrate (1) that a modest level of intergroup connections can lead to systemwide coordination and (2) that the presence of noise can overcome insufficient cross-community interaction, ensuring efficient global coordination on the correct state.

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## MNEMONIC STRUCTURE AND SOCIALITY: A COMPUTATIONAL AGENT-BASED SIMULATION MODEL

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### ABSTRACT

How does group memory affect sociality? Most computational multi-agent social simulation models are designed with agents that lack an explicit internal information-processing structure in terms of basic cognitive elements. In particular, memory is usually not explicitly modeled. We present initial results from a new prototype called “Wetlands,” which is designed to investigate the effect of group memory characteristics and interaction situations on emergent patterns of sociality, or collective intentionality. Specifically, we report on initial computational experiments conducted on culturally differentiated agents endowed with finite and degradable memory that simulate bounded mnemonic function and forgetfulness. Our principal initial findings are that memory capacity and engram retention both promote sociality among groups, probably as nonlinear (inverse) functions. Wetlands 1.1 is implemented in the new MASON 6 (Multi-Agent Simulator of Networks and Neighborhoods) computational environment developed at George Mason University.

**Keywords:** Memory, collective intentionality, MASON, wetlands, agent-based modeling, computational social science

### INTRODUCTION

Mnemonic storage capacity is fundamental for computational human and social dynamics, because every real-world agent, whether individual or group, necessarily relies on memory — and other internal cognitive structures (such as learning) — to estimate its own state, compute a plan, and produce behavioral acts based on experience.<sup>1</sup> Accordingly, systems of short- and long-term memory are essential (functionally and logically) for retaining and accessing information concerning external situational environments and internal states. Without memory capacity, an agent cannot function, making memory a cross-cultural universal for both individuals and cultures. Memory thus links micro- and macro-scales in human and social dynamics.

Interestingly, memory is not uniform across agents, whether individuals or aggregates (groups, societies, or nations), because different agents have different mnemonic structures.

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<sup>1</sup> This ontology is based on a view of agents as consisting of knowledge, goals, and behavior/acts. Throughout this paper, an “agent” may refer to an individual, such as a single person, or an aggregate of individuals, such as a group, society, nation, or system thereof. However, as explained later in this paper, the agents in our computational model (Wetlands 1.1) consist of groups, not individuals.

Exactly how does memory affect “sociality”<sup>2</sup> or collective intentionality? Is memory significant or secondary for collective action? How do different mnemonic structures — diverse memory attributes such as capacity and retention — affect collective social behavior? How do societies interact when agents have heterogeneous cultural identities? How do mnemonic transformations affect human and social dynamics?

Most computational multi-agent-based social simulation (MABSS) models are designed with agents often capable of generating collective intentionality, in a generative sense (Epstein, 2004), but computational social agents commonly lack an explicit internal information-processing architecture in terms of basic cognitive structures. Cognitive structures include memory, learning, affect, and other common human cognitive properties. As a result, the “internal environment” (Simon, 1999) of agents often remains a black box.

We present preliminary results from a prototype model designed to investigate the effect of mnemonic function on emergent patterns of sociality or collective intentionality. We have intentionally kept our model simple in order to easily identify experimental results caused by manipulations of mnemonic structure. Specifically, we present a series of computational experiments derived from an initial model (Wetlands 1.1) populated by group-level agents endowed with memory and bounded rationality. We explore the effects of variations of memory capacity and retention on sociality or collective action. Our principal findings seem to suggest that both memory capacity and engram retention promote or facilitate the emergence of collective behavior.

## METHOD

We are interested in collective intentionality and cognitive processes such as memory and learning. Among the senior authors, we combine expertise in computational social science (Cioffi), computer science and artificial intelligence (AI) (Luke), and computational neuroscience (Olds). Our investigative procedure involved two stages. First we constructed an experimental model — the first of several — to generate a minimal, but nonetheless interesting, artificial society of agents endowed with mnemonic structure and communication, in a simple multi-agent social simulation model called “Wetlands” (as described below). We then conducted two initial experiments in Wetlands 1.1 to examine the effects of memory capacity, retention, and simple communication on emergent behavior.

### Wetlands Model

Wetlands 1.1 is based on Paus’ earlier “Floodland” model (Paus, 2003) and uses the MASON 6 multi-agent simulation framework for complex adaptive systems.<sup>3</sup> The architecture, dynamics, initial social calibration, and other aspects of Wetlands are described below.

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<sup>2</sup> “Sociality” means the essence of — what fundamentally constitutes — social phenomena, similar to physicality, chemistry, religiosity, or musicality in their respective domains.

<sup>3</sup> MASON [Multi-Agent Simulator of Networks and Neighborhoods (Luke et al., 2003)] is an open source simulation code written in Java, available at <http://cs.gmu.edu/~eclab/projects/mason/>. MASON is a collaborative project of the Evolutionary Computation Laboratory and the Center for Social Complexity of George Mason University.

## Architecture

Wetlands 1.1 consists of a class of situated, autonomous, adaptive, bounded-rational (in the sense of Simon, 1999), group-level *agents* interacting at two levels: (1) among themselves and (2) with an environment composed of physical *landscape*, simple *weather* (moisture from rain), sites with *food*, and sites with *shelter*. The Wetlands 1.1 landscape is composed of hexagons to avoid the limited orthogonal interaction opportunities of a von Neumann neighborhood, or the arbitrary corner effects of a Moore neighborhood (Gilbert and Troitzsch, 1999; Cioffi-Revilla, 2002). Wetlands' hexagons may be thought of as elementary Thiessen polygons, commonly used for modeling neighboring social interactions among sites or interaction nodes on a regional scale. Socially, each agent in the Wetlands model corresponds to a small *group* of kin-related individuals in a real (“target”) world, on the scale of a family or extended family (approximately 2 to 20 individuals).<sup>4</sup>

Wetlands 1.1 is inhabited by two types of groups (societies), called Atis and Etis, on the basis of the culture attribute defined on the group class. Ati and Eti groups are shown in black and red (or black and gray), respectively, in Figures 1a and 1e. In addition to having cultural identity, agents also have memory, such that each group-agent can “remember” at most some  $N$  stored engrams, which degrade over time. Thus the memory has both a capacity and a retention quality.<sup>5</sup> In addition, each society — Ati and Eti cultures — will have its own memory in future versions of Wetland.

Moisture, food, and shelter are randomly distributed over the Wetlands landscape, as shown in Figures 1b–d. Food grows where the landscape has sufficient moisture.

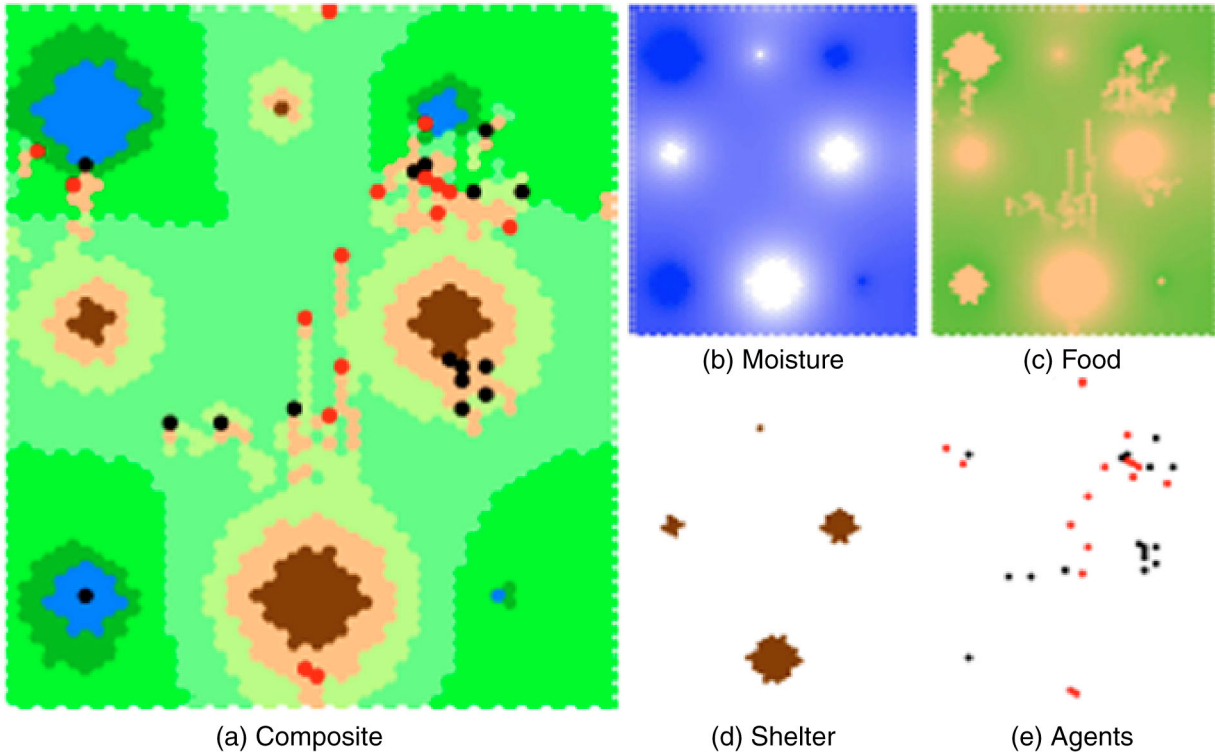
## Dynamics

Each agent-group goes about searching for food, avoiding rain, and seeking shelter to stay dry. The main simulation loop may be described as follows. Each time-step begins with agents located at various sites in the landscape with a given memory state containing an engram (record) of food and shelter locations stored in memory as an n-tuple. Each agent looks around its neighborhood to acquire additional information on food quality and locations nearby. In addition to discovery, information on food and shelter is also acquired through exchange during an encounter (within radius 2) between culturally similar groups (e.g., Ati-Ati or Eti-Eti). Information is not exchanged during encounters between dissimilar groups (Ati-Eti or Eti-Ati), to model the idea of lack of trust between “foreigners” (Polk, 1997). We expect to make further use of this in-group (“we”) vs. out-group (“they”) feature in subsequent work; here we use it only for expressing simple communication between similar groups.

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<sup>4</sup> We identify the scale of each computational *agent* in Wetlands as a kin-based *group*, rather than an *individual person*, because all agents exhibit formally homogeneous dynamics in searching for food, shelter, and avoiding rain. Such behaviors are anthropologically (ethologically) consistent with kin-level societal aggregation, not with strictly individual behaviors.

<sup>5</sup> An *engram*, in the sense of Lashley (1929), is a physical (in our case computational) memory trace that records information. Sociologically, an engram can be the computational representation of an *infor*, in the sense of Devlin (1991).



**FIGURE 1** Wetlands initial visualization and layers (Composite visualization [a] consisting of moisture layer [b], food sites layer [c], shelter sites layer [d], and agents layer [e]. Agents are mobile, but all environmental components are fixed in Wetlands 1.1 [although environmental components may change in value]).

Fresh information is entered into the agent's memory. If memory is full, then new information will dislodge prior information that is inferior, *even if (by Simon's Satisficing Principle) the new information is only locally (not necessarily globally) superior*. Once memory is updated, the agent moves one step toward its preferred food (or shelter — depending on whether or not it is raining). The agent moves toward the “best” food or shelter it remembers by using a weighting scheme that considers both the believed distance from the food/shelter (closer is better) and the “quality” of the food/shelter (higher-quality shelter is surrounded by other shelter; high-quality food is based on the moisture content). In a future version of the model, agents' engrams will be degraded through the addition of random noise and other loss processes.

### Interactions

The two main agent-based interactions in Wetlands are (1) between agents and their environment (food, moisture, shelter), and (2) among groups of similar or different culture (homogenous or heterogeneous interactions).<sup>6</sup> Memory plays an explicit and key role in each

<sup>6</sup> Other object-based interactions not involving agents include those between weather (moisture) and food. In Wetlands 1.1, food grows around moisture concentrations and propagates toward arid areas. Moisture regenerates food after agents consume it as the agents move around the landscape.

form of agent-based interaction. In the environmental context, memory stores qualitative and locational information about food, moisture, and shelter. In the cultural context, memory is updated by — and hence benefits from — homogeneous, or within-culture, contacts. Contact with “foreigners” (dissimilar groups, i.e., Ati-Eti or Eti-Ati) (Polk, 1997) does not produce information exchange.

### *Emergence*

On the basis of these minimal simple attributes and rules, we are able to generate and observe two significant emergent collective patterns in the Wetlands artificial world. The first, and arguably most important, consists of *clustering among groups of Atis and Etis*, as shown in Figure 1a. This basic pattern occurs for both feeding and seeking refuge, thereby lending additional external validity to the model: culturally similar groups ultimately tend to seek food and shelter *collectively* as a community (*qua comunitas*), not autonomously, as they exchange memories of high-quality food and shelter. The model purposively avoids generating any other more complex social patterns in order to provide a simple experimental bench for conducting memory experiments.

The second significant emergent pattern of collective behavior that is observed is diachronic: after the initial burn-in period of a few hundred time-steps, we observe *periodic migrations* between food areas and shelter areas, similar to the daily movement of groups, or the seasonal movement from hunting and gathering regions in the summer to refuge areas in the winter. The food cycle would seem to indicate the former, but in any case the periodic movement of groups is distinct.<sup>7</sup>

### *Calibration*

In relative chronology, the Wetlands target world may be akin to a Holocene environment inhabited by Paleolithic to early Neolithic human groups of hunter-gatherers searching for food to survive and seeking shelter away from rain to protect themselves from the elements. Wetlands 1.1 contains no other phenomenology, making it somewhat comparable to hunter-gatherer models by Reynolds (2002) from a social evolutionary perspective. In addition, Wetlands lacks any explicit technology.

In this study, we used Wetlands as an experimental artifact for conducting memory experiments. In principle, other MABSS models that display comparable sociality (e.g., Schelling’s segregation model, HeatBugs, Sugarscape, and others [Epstein and Axtell, 1996; Gilbert and Troitzsch, 1999, pp. 158–193; Macy and Willer, 2002]) could be adapted for conducting similar memory experiments, but this would require modifying the architecture of agents. We chose to develop Wetlands because it provides an initial model for early social evolution with minimally complex and yet interesting collective intentionality (“sociality”), desirable properties for investigating memory.

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<sup>7</sup> We are developing an appropriate indicator of collective migratory behavior to portray collective “swarming” in terms of a time-series metric  $M(t)$ . We thank G. C. Balan and L. Panait for their assistance in this task.

## Memory Experiments

Agent mnemonic structure and dynamics, or how information is maintained and accessed in the short- and long-term memory of an agent, can be modeled in variety of ways as part of an agent's "inner environment" (Simon, 1999). In this initial study, we conducted two experiments, as described below.

### *Experiment 1: Variation of Memory Size or Capacity*

In the first computational experiment, we conducted a series of variations of the agent's memory size. Specifically, we varied the *memory capacity*,  $C$ , of each agent by using values of 1, 10, and 25 engrams to observe if any effects occurred in the qualitative or quantitative emergence of collective behavior (swarming). Our research hypothesis in this first experiment was that more memory capacity would accelerate the emergence of collective action, because memory capacity can support a larger volume of interagent information exchange. However, the precise form of such covariation — whether linear, nonlinear, concave, convex, polynomial, exponential, or other — seems impossible to derive from first principles. Some form of nonlinearity would seem likely (albeit not certain), given the nonlinear properties of information.

### *Experiment 2: Variation of Engram Duration or Retention*

In the second experiment, we varied *memory retention*,  $R$ , by manipulating the duration of engrams stored in an agent's memory. Our research hypothesis in this experiment was that the longer the time that engrams lasted in an agent's memory, the more efficient the agent's movements — searching for food and finding dry shelter — would be, especially when boosted by information exchange from encountering other culturally similar groups. Operationally, variation in memory retention was implemented by varying the number of time-steps that a given engram would remain stored in memory. In Wetlands 1.1, engram loss was modeled as a simple step function without noise, not as a gradual process (e.g., exponential or logistic memory loss). This process will change in future versions.

### *Other Memory Experiments*

We are continuing other memory experiments with the Wetlands model to test for episodic effects, noise, memory loss and degradation, traumatic stress memory disorders, and other cognitive conditions related to mnemonic structure. Results will be reported in future papers. All simulation runs are being conducted with MASON 6.

## RESULTS

### **Emergent Sociality and Memory Capacity**

Repeated simulation runs showed that the time required for the emergence of sociality (collective behavior)  $T$  decreased with increasing memory capacity  $C$  confirming our first

research hypothesis. Groups take *less* time to display spatially clustered formations (they start “hanging together” more quickly) when their memory capacity is *larger*. Conversely, they take *longer* to gather as a culture when the lower group-level memory is *lower*.

Moreover, our initial results also indicate that the observed negative relationship appears to be both monotonic and nonlinear (concave), with time to emergence  $T$  decreasing in approximately inverse, and marginally decreasing, proportion to memory capacity  $C$ , or

$$T \simeq \frac{a}{C^k}, \quad (1)$$

where  $a$  and  $k$  are scale and shape parameters, respectively, both positive.

### Emergent Sociality and Memory Retention

In terms of our second experiment, repeated simulation runs also showed that the time required for the emergence of collective behavior  $T$  decreased with increasing memory retention  $R$ . This finding confirmed our second research hypothesis. Here again, groups employ *less* time to achieve spatially clustered formations when they are able to retain memory for a *longer* period of time (number of time steps). Conversely, groups take longer to “start hanging around together” when their group memory is brief.

In the second experiment, our results indicated a similar relationship to that found in the first experiment — the observed negative relationship again appears to be both monotonic and nonlinear (concave), with time to emergence  $T$  decreasing in inverse, and marginally decreasing, proportion to memory retention  $R$ , or

$$T \simeq \frac{b}{R^h}, \quad (2)$$

where  $b$  and  $h$  are scale and shape parameters, respectively, both positive.

## DISCUSSION AND FUTURE RESEARCH

Moving from the specific focus of this investigation to broader considerations beyond the experiments reported here, in the following discussion we examine our results in terms of computational findings, broader theoretical implications for sociality and collective intentionality, and future research directions.

### Computational Findings

Results from this study within Wetlands demonstrate that sociality or the social behavior of groups — for example, groups’ propensity to cluster together — is not independent of group-level memory structures and processes. Both memory capacity and engram retention seem to have significant effects on how promptly sociality emerges among groups. Both features also

have qualitatively similar effect in terms of increasing the probability of emergent collective behavior (Equations 1 and 2). This preliminary finding would appear to argue against the idea that more and longer memory in multi-ethnic societies degrades or hampers sociality. Instead, memory capacity and engram retention accelerate the emergence of sociality.

### *Verification*

Our initial Wetlands 1.1 model has undergone extensive verification, so we feel confident about the veracity of the observed experimental effects of memory capacity and retention on the emergence of collective action. We also rule out the possibility that sociality or intracultural aggregation may be caused solely by weather or food patterns. Nonetheless, we continue to examine the simulation runs closely to ensure that sociality remains unaffected by bugs.

### *Robustness*

Repeated simulation runs of both experiments under different stochastic conditions have thus far failed to invalidate our main results. In the future, we can use MASON's intrinsic separation of computation from visualization to execute a large number simulations in a short amount of time to explore the parameter landscape for robustness.

## **Theoretical Implications**

What theoretical inferences from the computational world of Wetlands 1.1 may be warranted in terms of our computational experiments? Our findings suggest a number of plausible theoretical implications extending beyond “the observed facts” (Lave and March, 1993) in terms of broader social science themes, Simon's Conjecture, social scale, and subsequent formal analysis of computational results.

### *A Broader Social Science and A Life Perspective*

Thus far, our research with Wetlands has touched upon half of the six major research themes in Max Steuer's recent assessment of the social sciences, *The Scientific Study of Society* (Steuer, 2003): migration, kin-groups (family), and shelter (housing).<sup>8</sup> While Steuer's survey covers only statistical research on these topics, our computational analysis of the effect of memory on social patterns takes advantage of the unique experimental environment provided by an agent-based model such as Wetlands. Whereas most statistical social science research is based on survey research, even when cross-cultural in scope, computational social science research can contribute new insights through virtual experimentation (Epstein and Axtell, 1996).

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<sup>8</sup> The value of Steuer's survey cannot be overstated, particularly in terms of highlighting the growth of positive knowledge about society. However, the absence of *conflict* as a major research topic across the social sciences — according to Steuer's otherwise excellent survey — is unfortunate, particularly in light of the growing body of knowledge that exists in this area (Conflict Research Consortium, 2004; Diehl, 2004).



In terms of social science and ALife perspectives, our progress with Wetlands so far seems promising, especially in the area of providing cognitive attributes to agents. Experience with Wetlands should also prove helpful as we attempt to generate other emergent patterns of sociality, such as trade or conflict (Min et al., 2003).

### *Simon's Conjecture*

Herbert A. Simon (1916–2001) hypothesized that emergent social complexity — observed patterns of sociality and collective intentionality — is caused primarily by the *adaptive* behavior of bounded-rational agents (individuals or groups) interacting in complex environments, *not* by any internal complexity of the agents themselves (Simon, 1999, pp. 7–8). Social complexity is environmentally induced, not the product of agent complexity (“Simon’s Conjecture”). Holland’s (1995) approach to modeling complex adaptive systems is similar. Simple agent rules can generate complex emergent patterns if the environment or task is sufficiently challenging.<sup>9</sup> Indeed, one could argue that the epistemology of generative or computational social science is fundamentally based on what may be called Simon’s Conjecture: social complexity emerges from the adaptation of simple agents to complex environments, not from inherently complex agents.

In terms of Simon’s Conjecture, our computational findings from the Wetlands experiments — summarized by Equations 1 and 2 — thus far suggest that complex adaptive behavior (such as social aggregation) could indeed result from simple internal mechanisms, and, interestingly and beyond Simon’s Conjecture, simple linear variations in mnemonic structure (namely, capacity  $C$  and retention  $R$ ) cause nonlinear effects on the timing  $T$  of emergent behavioral complexity. This theoretical (“generative”) implication is new, based on computational findings, and does not seem to follow (nor arguably contradicts) Simon’s Conjecture.

### *Memory and Social Scale*

Scale and complexity are long-standing classical puzzles in the physical and biological sciences (Asimov, 1983; Labrador, 2002; Morowitz, 2002). Unfortunately, social scientists pay less attention to issues of scale and complexity, with some notable exceptions (Singer, 1961; Schelling, 1971; Eulau, 1996; Young, 1998).

Memory is essential to understanding different human and social scales, from individual to societal (and perhaps to global). Our findings offer new insights on multiple scales of sociality. For instance, although agents in Wetlands seem to approximate groups, our results may suggest new research hypotheses on the effect of mnemonic structure on individual (micro) or supra-group (macro societal) collective behavior. To wit, are individuals and entire societies (i.e., social entities below and above the group level modeled in Wetlands) affected in the same way by changes in memory characteristics? Would true experiments confirm or refute these results on other scales?

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<sup>9</sup> In computational social science, the view of society as “a complex adaptive system” was formulated shortly after World War II by Karl W. Deutsch (1940–1949, 1951a,b, 1963), under the influence of W. Ross Ashby and Norbert Wiener. Among early pioneering works, see also W. Buckley (1967, 1968).

### *Formal Analysis from Computational Results*

From a more formal perspective, Equations 1 and 2, which for now we view only as approximate computational generalizations, suggest a number of implications. Both functions represent *power laws* in terms of the independent variables  $C$  and  $R$ , so their asymptotic behavior is intrinsically interesting. Estimating the necessary parameters in Equations 1 and 2 is possible by running a very large number of fast simulations, a core task for which MASON is designed (Luke et al., 2003).

In addition to formal inferences that can be derived from Equations 1 and 2, estimating the numerical value of the corresponding exponents,  $k$  and  $h$ , is important because such values have implications for the relative (marginal) effects of memory capacity and retention. For instance, knowing even just the values of these parameters (which is larger?) can shed light on their relative importance to derive “dominance principles” (Cioffi-Revilla, 1998, p. 289). In turn, such theoretical principles can be used to answer questions such as: Is the emergence of sociality (collective behavior) more sensitive to variation in memory capacity or to variation in engram retention? In general, since Equations 1 and 2 are computational laws generated by code (not by nature), can such laws also be derived from classical mathematical (noncomputational) models? If not, then clearly Equations 1 and 2 represent unique contributions by generative computational science.

## **CONCLUSIONS**

This investigation began by asking the question: How does group memory affect sociality? More specifically, we asked, How does memory capacity and the duration of engrams in memory affect the probability of sociality or collective intentionality? Most computational MABSS models are designed with agents that usually — or most typically — lack an explicit internal information-processing structure in terms of basic cognitive elements. In particular, memory is usually not explicitly modeled.

We presented initial results from a new prototype called Wetlands, an MABSS model designed to investigate the effect of group memory structures (such as capacity and retention) and interaction situations on emergent patterns of sociality or collective intentionality. Specifically, we reported on initial computational experiments conducted on culturally differentiated agents endowed with finite and degradable memory that simulate bounded mnemonic function and forgetfulness.

Our main initial findings are that memory capacity and engram retention both promote sociality among groups, probably as nonlinear (inverse) functions. Wetlands 1.1 was implemented in the new MASON 6 computational environment developed at George Mason University as a collaboration between the Evolutionary Computation Laboratory and the Center for Social Complexity.

## ACKNOWLEDGMENTS

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## CONSENSUS VERSUS TRUTH SEEKING: MODELING PERCEPTION VERSUS ACTION

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### ABSTRACT

Game and other rational theories built on “methodological individualism” assume that the value of an organization is constituted by the sum of its members. This means that nothing about an organization is unique. From this perspective, where “social” means a simple aggregation of individuals in a stable and fully accessible reality, a single rational worldview, business model, or government policy makes sense. But game theorists have known for some time that the claims and interpretations of individuals shift during the social interaction; it is no longer a surprise that measuring individuals does not reproduce a group, nor does measuring a group tell us about its members. But this measurement problem from a rational or “methodological individualism” perspective should not exist. As part of our quantum perturbation theory, the measurement problem is fundamental to the difference between the belief convergence common to rational cooperation processes under consensus-seeking rules (CR) and the truth-seeking common to competitive processes under majority rules (MR) found in democracy and science. In a recent field test, we had found that CR groups focus more on values and MR groups more on instrumental action. We are making plans to simulate group decision making with a quantum-based, multi-agent approach, designed using Wagner’s Agent-Object Relationship Modeling Language. This formalism will allow identification of agent states and the process of shifting states.

**Keywords:** Consensus-seeking rules, quantum-based social modeling, organizational uncertainty gap theory, multi-agent perturbation model, bistable models

### INTRODUCTION

A wide-ranging scientific approach is needed to understand the various dimensions of the micro-macro link in social and cognitive sciences. According to this general idea, the goal of our research is to propose a multi-paradigm approach to the study of relationships between individual and social cognition. More specifically, we propose the adoption of *multi-agent quantum-based modeling of social relationships* to the current context of decision making in organizations, extending this model to organizational structure in the future. This approach allows representation of micro and macro interaction effects simultaneously, permitting a broader perspective of complex phenomena in social science.

Considering recent propositions adopting quantum principles to explain agency in society, application of the quantum model to social representations illustrates cognition not as a

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collection of stable cognitive structures, but as composed of stable and transient parts. The quantum model is not constructed by simply relating whatever quantum theory says about the atomic world as a metaphor to whatever social and cognitive scientists say about individuals in society. Instead, the quantum method is applied directly to the elements of observation and action in the interaction as Bohr (1955) and Heisenberg (1958) intended. Such analytical models have specific domains of application, like the explanation of consciousness phenomena (Wendt, 2003), describing the quantum principles of the particles comprising the brain, or the Quantum Perturbation Model (Lawless and Grayson, 2004), formalizing uncertainty in the interactions between agents or organizations in a multi-agent system of bistable agent states. The paradigm shift permitted by the quantum approach for the first time allows representing with mathematics or agents the duality between interdependent, conjugate, or bistable states of observation and action; membership in an in-group or out-group; or membership in organization 1 or organization 2 or culture 1 or culture 2.

At its simplest, bistability occurs when an agent exists in one of two tightly coupled or interdependent states, as when an agent observes another in an attempt to model its behavior, or an agent in action may be performing a target behavior for the benefit of an observing agent; (e.g., teacher and student, actor and audience member, basketball player and fan). A different but related example is when agents are members of different political parties, religions, or organizations, each group competing for the goal of gaining the energy  $E$  to survive and control its environment (Eldridge, 2004).

Another example is to be in the same organization but at different states, as a job tutor to another agent, as two sequential members of a production line, or with one as a member of a planning section for strategy and another in an operational section to execute strategy. All organizations are organized to exploit bistable states (e.g., military counterintelligence attempts to increase the uncertainty between friendly and enemy troops or the self-serving behavior of competing attorneys in a courtroom, considered the best path to justice [Freer and Perdue, 1996]). The key point from Bohr and Heisenberg, who were the first to apply their uncertainty principle directly to a model of social systems, is that not only does uncertainty exist in these interdependent states, but it is mathematically linked so that as uncertainty decreases in one state, interdependently, uncertainty in the other state increases (Lawless and Grayson, 2004). Beyond the simple model of bistability illustrated here, from computational quantum theory (Rieffel and Polak, 2000), our model poses that neutral or undecided agents can be in two incommensurable states simultaneously.

## **JUSTIFICATION FOR BISTABLE SOCIAL MODELS**

Our quantum model, as at the atomic level, is not meant to represent or copy social reality or phenomena. Instead, just as at the atomic level, our quantum model serves to organize theory, mathematical structure, and human experience. Axtell (2002), however, has questioned the application of the quantum model to the social interaction. But from our perspective, there is ample evidence to justify its consideration. It is well established that the measurement of social, psychological, and organizational phenomena changes the properties of what is measured (Lipshitz, 1997; Carley, 2003). Humans focus on only one interdependent aspect of an object at a time (Cacippo et al., 1996), such as either the meaning of a painting or its construction (Gibson, 1986), and cognitive convergence processes within a group or organization increase out-group uncertainty (Tajfel, 1970), generating what Schama (1995) labeled as “social memory” to



describe the series of competing history beliefs that spontaneously arise between all groups, like in the courtroom, different scientific schools of thought, or merger opponents.

These findings make no sense from a stable and individual rational perspective, nor does deception, denial, or corruption. However, if human interactions are bistable, measurement collapses interaction information  $I$  into classical  $I$ , the convergence processes within the brain or an organization or culture reducing in-group uncertainty, consequently precluding the reconstruction of the original bistable state. Further, in his review of receiver operating characteristics curves versus the discrete  $E$  levels of the quantum model proposed by Békésy in the 1930s and Stevens in the 1940s, Luce (1997) concluded that the quantum model remained a satisfactory alternative. The eye is a quantum  $I$  processor (French and Taylor, 1979), and Bekenstein (2003) has proposed that reality from the mind's eye is a quantum illusion. Penrose has suggested that, if the uncertainties of  $E$  and time  $t$ , given as  $\Delta E$  and  $\Delta t$ , are interdependently related by  $\Delta E \Delta t \geq c$ , with  $c$  assumed to be Planck's constant  $h$ , with  $E = h\omega$  from quantum mechanics, it becomes  $\Delta (h\omega) \Delta t \geq h$  or  $\Delta \omega \Delta t \geq 1$ . This suggestion has been confirmed with data averaged over 30 subjects in a study by Hagoort et al. (2004, Figure 2, p. 440), who reported that object acquisition in the brain with 40-Hz gamma waves should occur in no less than 25 ms, while working memory tasks with theta waves at 5 Hz should take no less than 200 ms, illustrating  $E \cdot t$  interdependence in the brain.<sup>1</sup> While this basic physics is important, it is the collapse into individual histories that cannot be recombined to recreate the interaction that makes the measurement problem at the organizational level analogous to the atomic level (Zeilinger, 1999), alone justifying the quantum model for competing social organizations.

## THEORY AND A QUASI-FIELD EXPERIMENT

Game theory and other rational theories built on “methodological individualism” (Nowak and Sigmund, 2004) assume that the value of a group or organization is constituted by the sum of the value of the individuals in the group. This rationale means that nothing about the group or organization is unique. From this perspective, a single rational worldview, business model, or government policy makes sense, such as the anti-free market merger policy of France to protect its national security, industry, and jobs. France employed this policy recently when it coerced Aventis, a French-German company, to merge with a hostile bidder Sanofi, a French company. (French officials threatened Novartis, an open contender for Aventis, against its friendly merger attempt.) In this view, the “social” is a simple aggregation of individuals, and reality is stable, is fully accessible, and can be apprehended by elites or scientists to produce a single best interpretation or representation. However, Luce and Raiffa (1967) raised theoretical questions about these assumptions, and from a practical perspective, government intervention in the European Union has motivated the more competitive pharmaceutical companies to relocate to the United States.

Game theorists have known for some time that the claims and interpretations made by individuals shift during the social interaction (Kelley, 1992), leaving it as the major unsolved problem in social psychology (Allport, 1962); a related unsolved problem is why individual humans have a poor grasp of how their behavior and self-identity relate (Baumeister, 1995). It is

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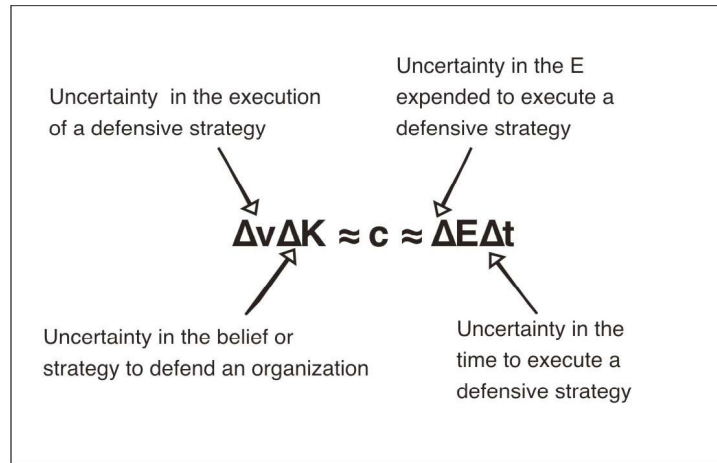
<sup>1</sup> That is, with gamma waves at 40 Hz,  $\Delta \omega \Delta t \geq 1$  leads to  $\Delta t \geq 0.025$  s, and with theta waves of 5 Hz,  $\Delta \omega \Delta t \geq 1$  leads to  $\Delta t \geq 0.2$  s. Similarly, shortening by one-half the time of a digital voice track doubles its energy (i.e.,  $\Delta \omega \geq 1/\Delta t = 1/(1/2) = 2$  Hz [Kang and Fransen, 1994]).

no longer a surprise that measuring individuals does not reproduce the group, nor does measuring the group tell us about the individuals who comprise it (Levine and Moreland, 1998), what has been termed the measurement problem (Lawless et al., 2005). This measurement problem means that the collected histories of individuals who form a group cannot be summed to recreate the group (Schama, 1995). It explains the common occurrence of multiple interpretations for every context, which, from a “methodological individualism” perspective, should not exist. The measurement problem is fundamental to the difference between the belief convergence of consensus-seeking common for command decision makers (dictatorships) and the self-organizing cycles of belief challenges, information processing, and action feedback loops common to democracy and science.

### **PERTURBATION MODEL: THE MEASUREMENT PROBLEM**

In our perturbation model (Lawless and Grayson, 2004), instead of disturbances that must be avoided or resolved from the traditional perspective, the perturbation of an organization generates feedback that becomes the primary source of  $I$  for the attacker and attacked as well as for observers of the conflict, the latter being the all-important but often overlooked social dimension. In our model, there is no need to determine the value of cooperation or competition. Instead, observers neutral to an attack contribute to the solution of an ill-defined problem reflected in the attack by choosing or selecting a winner (as in the courtroom), by buying a car from a dealer, or by watching or listening to a media channel. Winners gain power by securing sources of  $E$  or its distribution (Eldridge, 2004). Thus, we avoid the unsolvable problem of determining preferences or normative values in “methodological individualism” by measuring the result of a perturbation. For example, the outcome of Southwest Airline’s low-fare maneuver in 2004 against US Airways in Philadelphia was predatory, but beneficial to consumers; the inability of AT&T Wireless to enact phone number portability made it prey for a merger; and in the 2003 Iraq War, the plan for multiple attacks to get “inside of the enemy’s decision cycle” (Franks and McConnell, 2004, p. 466) executed by the coalition forces caused the Iraqi troops to panic and its military organizations to break apart (Keegan, 2004).

We replace the unsolvable “normative” problem of values with a difficult but solvable one — the measurement problem. Measuring an interdependent or bistable phenomenon, such as a human organization, produces classical  $I$  that cannot recreate the original phenomenon. In the bistable model, uncertainties between acting and observing are interdependent, as they are between individuals and organizations, and between two organizations contemplating a merger. Thus, mathematically and phenomenologically, reducing uncertainty in the observable of interest increases the uncertainty in its conjugate factor. That is, the more that is known about, say a plan to merge, the less that can be known simultaneously about its execution, or the more known about the costs to merge, the less that can be known simultaneously about the time involved in completing the merger. These uncertainties are illustrated in Figure 1, with  $K =$  knowledge,  $\Delta K = I$ , and  $v = \Delta K/\Delta t$ , and given the inertial effects of reactance  $j$ ,  $\Delta v\Delta K = \Delta (\Delta K/\Delta t) \Delta t/\Delta t \Delta K = j\Delta (\Delta K/\Delta t)^2 \Delta t$ , giving  $\Delta v\Delta K = \Delta t\Delta E \geq c$  (Lawless and Grayson, 2004).



**FIGURE 1** Measurement problem from the perspective of a merger target (parallel uncertainty relations exist for the acquiring organization)<sup>2</sup>

In sum, if “methodological individualism” is all about accessible  $I$ , the mathematical physics of organizational behavior is all about information that is mostly inaccessible to an organization and its outsiders. To uncover this hidden  $I$  about an organization requires that it be disturbed, an idea traceable to Lewin (1951). But if social reality is bistable (interdependent), measurement produces classical information that cannot recover the character of the organization, the essence of the measurement problem. A common perturbation in economics is a price war between competing organizations; for our field study below, a familiar perturbation on the Citizen Advisory Boards (herein called “Boards”) providing cleanup advice to the Department of Energy (DOE) is the conflict caused by incommensurable views, interpretations, or beliefs. While “cooperation” rules attempt to dampen conflict, “competition” rules harness it by driving random searches among multiple sources of information for the idea that withstands

<sup>2</sup> For example,

- *Strategy*: After AT&T Wireless put itself on the auction block in early 2004 and Cingular made the first offer, AT&T Wireless did not know whether bids would be received from other players, such as Vodafone, or how much more would be offered.
- *Execution*: Cingular expected that AT&T Wireless would execute its strategy by choosing the best bid by the deadline it had set, an expectation that turned out to be incorrect.
- *Energy*: AT&T Wireless did not know whether Cingular or Vodafone would increase their bids to an amount it considered sufficient.
- *Time*: While the bidders believed incorrectly that the deadline was firmly established, AT&T Wireless was uncertain of the time when the bids would be offered.

Finally, although power goes to the winner, it was not easy to determine who won and who lost in this auction. AT&T Wireless was unable to enact number portability and became the prey, but its CEO exacted a superior premium for his company and stockholders; while the merger on paper made Cingular the number one wireless company in the United States, it may have overpaid for the merger. Also, during the uncertainty of regulatory review (both the length of the regulatory review period and the regulatory decision), AT&T Wireless lost customers as competitors exploited the regulatory uncertainty, so it was unknown how costly the eventual merger would be based on the assets remaining once the merger had been consummated.

all challenges (exemplifying stochastic resonance). From a bistable perspective, the primary difference between the two styles of decision making is that consensus-seeking methodologically converts an organization into accessible individuals, consequently devaluing neutral observers; in contrast, the competition between two or more opponents under majority rule exploits bistability by converting neutral members into judges.

### **CASE STUDY OF A MEASUREMENT PROBLEM: DOE CITIZEN ADVISORY BOARDS**

Recently, we had an unexpected opportunity to test our model in a field test among Citizen Advisory Boards working to help DOE clean up its sites across the United States. (Lawless et al., 2005). Comparison of the two Boards with the largest budgets, of about \$1 billion each, showed that the Hanford Advisory Board (HAB) used consensus-seeking rules (CR) and the Savannah River Site (SRS) Advisory Board (SAB) used majority rule (MR) (see Table 1). In an earlier study, we had found that the HAB with CR relied primarily on promoting its values at Hanford, while the SAB, with its method of MR, focused on the instrumental action of cleaning up SRS (Lawless, 2004).

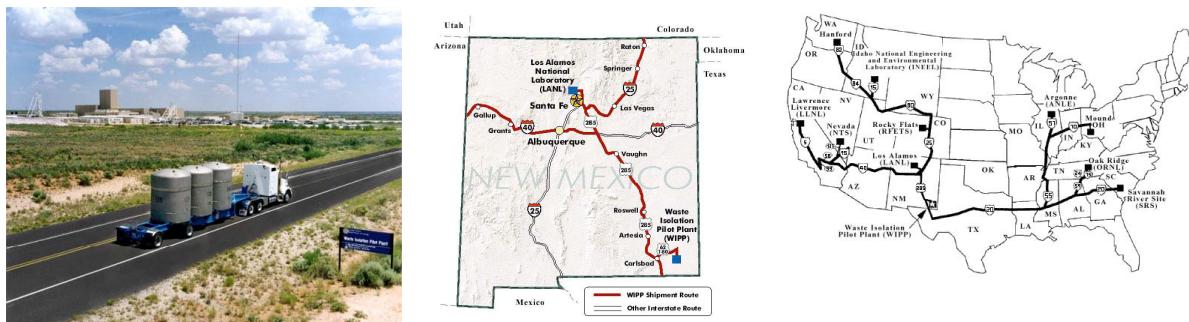
As one example of what we had found, both DOE sites had to consider shipments of transuranic (TRU) wastes<sup>3</sup> to their respective sites for interim storage before eventual transport to the TRU waste repository at the Waste Isolation Pilot Plant (WIPP) in New Mexico (Figure 2). In response, the CR Hanford Board concluded: “The recent shipments of TRU wastes from Battelle Columbus (BCK) and Energy Technology Engineering Center (ETEC) to Hanford

**TABLE 1** Site-specific Citizen Advisory Boards (SSABs) associated with DOE sites

Active SSABs (N = 9)		Inactive SSABs (N = 3)	
Site	Decision Process	Site	Decision Process
Fernald	CR	Pantex	CR
Hanford	CR	Sandia	CR
Idaho (ID)	CR	Monticello	MR
Nevada Test Site	MR		
Northern New Mexico (NNM)	MR		
Oak Ridge (OR)	MR		
Paducah	MR		
Rocky Flats Plant	CR		
Savannah River Site (SRS)	MR		

Source: Lawless et al. (2005).

<sup>3</sup> TRU wastes are contaminated with uranium-233 or elements beyond uranium on the periodic table in concentrations of more than 100 nCi/g. These isotopes have half-lives of more than 20 yr but consist mostly of plutonium-239 with a half-life of about 24,000 yr.



**FIGURE 2** Transuranic (TRU) wastes are being shipped in TRUPACT II containers to the repository in a salt formation at WIPP near Carlsbad, NM ([www.wipp.carlsbad.nm.us](http://www.wipp.carlsbad.nm.us))

caused grave concern to the [Board]” (HAB, 2002). In contrast, the MR SRS Board concluded, “Due to the considerable taxpayer savings, the relatively low risk, and the use of funding external to SRS for the activity, the SRS CAB recommends that DOE-SR accept the [off-site] TRU waste shipments from Mound as long as the following conditions are met: ... DOE receives approval to ship more TRU waste volume from SRS [to WIPP] than received from Mound. The SRS CAB preference is to see at least twice the volume ... ” (SAB, 2000).

Differences in the field as a result of these two decisions were dramatic. Prior to 2003, with the inventory of TRU wastes at Hanford at about twice that of SRS, shipments of TRU waste to the TRU waste repository at WIPP from both sites were about 1% of their respective inventories (see DOE, 2003). However, today, Hanford has made only 2,500 shipments compared to 10,934 shipments by SRS (Lawless et al., 2005). But would this finding for two Boards hold for all Boards?

Assistant Secretary of Energy Roberson called for an acceleration of the cleanup in 2002, including TRU wastes destined for WIPP. In response, DOE scientists developed 13 recommendations to accelerate the disposal of TRU wastes (Table 2). In 2003, these recommendations were submitted to representatives of all of the Boards for their approval.

**TABLE 2** Three of the 13 recommendations by DOE scientists to accelerate TRU waste disposition

- 
- DOE should characterize TRU waste as required to reduce risk and minimize transportation and handling of waste while making the confirmation process cost-effective.
  - **DOE, in consultation with stakeholders and regulators, should reexamine the categorization of TRU waste using a risk-based approach.**
  - DOE should expedite the design, fabrication, and certification of container transport systems (Arrowpak and TRUPACT III) and accelerate the adoption of rail transport as appropriate.
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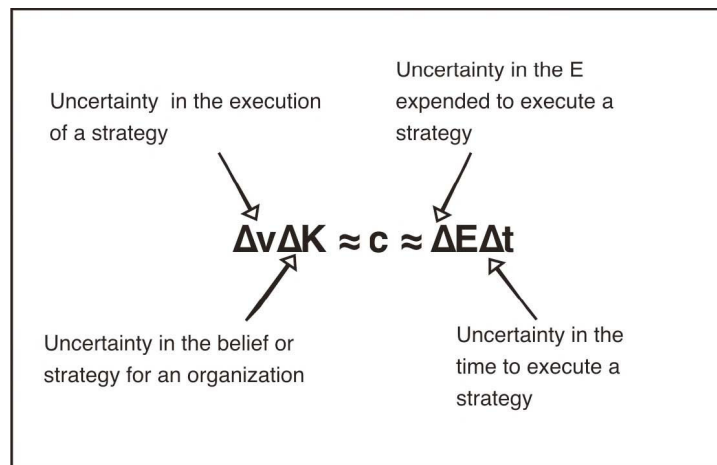
Source: Lawless et al. (2005).

One example of the trade-offs inherent in the recommendations is the middle recommendation (bolded item in Table 2), which indicates that some waste currently classified as TRU waste, requiring it to be packaged and sent to the TRU waste repository at WIPP for its ultimate disposition, might be left at the individual sites if a scientific risk analysis indicated that it could be safely buried *in situ*. If implemented, the decision would save money and time, but it would leave a long-lived waste in near-surface disposal, increasing risk to citizens and the environment.

The measurement problem requires a prediction of how an organization reacts to a perturbation, such as the request by DOE scientists that Boards support their recommendations to accelerate the disposition of TRU wastes. Figure 3 illustrates mathematically the effects of interdependence on uncertainty; that is, as uncertainty in strategy increases (e.g., more emphasis on values), uncertainty in execution decreases, and similarly for  $E$  and  $t$ .

The request by the DOE scientists amounted to a perturbation felt across all of the Boards over four domains. Figure 3 assumes the perspective of DOE:

- *Strategy uncertainty*: Could DOE's sites respond with an aggressive plan to accelerate TRU wastes to WIPP (e.g., SRS planned to dispose of all of its TRU wastes by 2006)?
- *Execution uncertainty*: Could accelerating TRU waste shipments occur when shipments are contingent on new containers for large objects (TRUPACT III) and high-activity TRU (ARROWPAK for plutonium-238 wastes)?
- *Energy uncertainty*: Are sufficient funds available to accelerate the acquisition and licensing of containers to accelerate TRU waste shipments?
- *Time uncertainty*: Could new containers be licensed in a timely fashion?



**FIGURE 3** The measurement problem from the perspective of DOE for its transuranic wastes

Shifting to the perspective of the Boards, the terms in Figure 3 become:

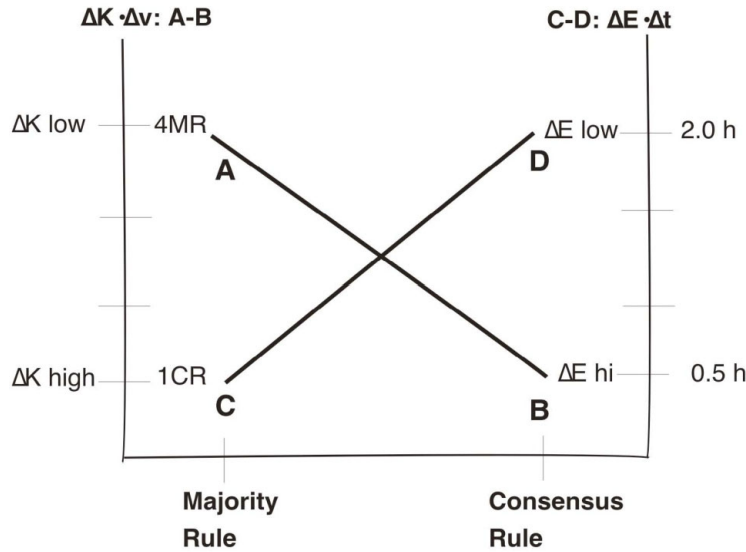
- *Strategy uncertainty*: Would the Boards believe in the plan?
- *Execution uncertainty*: Would the Boards vote for the plan?
- *Energy uncertainty*: Would the Boards expend effort in support?
- *Time uncertainty*: Would support by the Boards be timely?

On the basis of our previous research, we expected that MR Boards would adopt the measures to accelerate TRU waste disposition at their respective sites, that CR Boards would take longer to make this decision, and that ultimately the focus by CR Boards on values would produce less complex decisions than those by MR Boards.

At the SSAB Transuranic Workshop in Carlsbad, NM, in January 2003, representatives (N = 105) from all of the Boards discussed the recommendations by the DOE scientists and reached unanimity. The representatives from each of the Boards were expected to return to their respective sites and present these recommendations to their own Boards for a consensus vote. The result (Figure 4) was as follows: Five of nine Boards approved these TRU waste recommendations (four MR Boards and one CR Board), and four of the nine Boards disapproved (one MR Board and three CR Boards). Figure 4 is interpreted as follows:

- A. MR Boards bring opposing views together to seek the best decision and compromise ( $\Delta K$  low; Lawless and Schwartz, 2002), generating instrumental action ( $\Delta v$  high; shown in Figure 4: 4 MR Boards agreed, *not shown* in Figure 4: 1 MR Board did not).
- B. After expressing multiple reservations ( $\Delta K$  high; Bradbury et al., 2003), CR Boards mostly did not accept the complex request on TRU wastes by the DOE scientists ( $\Delta v \rightarrow 0$ ; shown: 1 CR Board accepts; *not shown*: 3 CR Boards do not).
- C. Conflict on MR Boards is intense ( $\Delta E \rightarrow \infty$ ; e.g., Lawless et al., 2000 Hagoort, 2003) but among few participants and thus short-lived (shown:  $\Delta t = 0.5$  hours).
- D. Instead of instrumental action, CR Boards repeatedly restate values with many speakers over long and uncertain periods of time (shown:  $\Delta t = 2$  hours, suggesting a possible lack of interest in many observers ( $\Delta E \rightarrow$  low; Hagoort et al., 2004).

The interdependence observed in Figure 4 agreed with predictions. The time to complete consensus seeking was much longer than for majority rule (and the energy expended was less). More important, MR Boards mostly adopted the recommendations by DOE scientists, while CR Boards mostly rejected them, possibly reflecting that as participants sought consensus, they became more motivated to reach “understanding,” as claimed in a recent evaluation of these Boards (Bradbury et al., 2003), rather than motivate their respective sites to take instrumental



**FIGURE 4** Mathematical interdependence of uncertainty  
(from Lawless et al., 2005)

action to clean up their sites. Thus, the trade-off observed was that CR Boards were more focused on values, whereas MR Boards were more focused on accelerating cleanup.

From a practical perspective, normative social scientists have long argued that cooperative (consensus) decision making improves social welfare more effectively than the competition used as part of truth-seeking in a democracy. In a recent evaluation of its policy on consensus (Bradbury et al., 2003), the DOE encouraged its SSABs “to work toward consensus” in order to be “fair,” thereby improving American democracy. But no empirical evidence was collected from the field by DOE to validate its policy (Lawless et al., 2005). In contrast, the literature and field data contradicted DOE: consensus-seeking retarded cleanup, the coercion necessary to seek consensus reduced trust, and consensus-seeking favored risk perception rather than scientifically determined risk. As shown by the first application of mathematical physics for heterogeneous competing organizations, we have found that the competition of ideas driven by truth-seeking significantly accelerated DOE’s cleanup and improved trust.

What we have found in this study of organizations is inconclusive because of the incomplete trail of data (Figure 4), but the results fit sufficiently well to provide a well-organized path forward in the laboratory with human subjects and simulations, and in the field for mathematical, theoretical, and applied organizational science.

### **NEW THEORY: ORGANIZATIONAL K GAP THEORY**

Beliefs ( $K$ ) arise and become established or learned as a subset of beliefs within a set of world views of believers, constrained within a range (diameter) of influence (family, school, organization), producing psychological, social, and physical dimensions. Under CR, beliefs are freer to be expressed without constraint (Susskind et al., 1999; Habermas, in Bradbury et al., 2003). However, under MR, beliefs are constrained by the competition of truth-seeking, forming



gaps that take  $E$  to overcome ( $\Delta A$ ). Beliefs are expressed or articulated with waves (brainwaves, vocal waves) but have locality (neurons, individuals, organizations) and thus experience constructive (resonance, reducing  $E$  expenditures) and destructive interference (resistance, increasing  $E$  expenditures) found with agreement or dissonance, respectively. Each belief can be represented uniquely by a wave number, similar beliefs being multiples of the underlying belief; as unique beliefs flow around the circumference of an organization ( $\Delta v$ ), they are restricted to integral numbers, with different beliefs requiring separation, the separation establishing discrete  $E$  values. The smaller the circumferential unit of analysis (brain, group, or organization), the larger the separation required between allowed  $E$  values to moderate dissonance. Thus, a new previously unarticulated belief requires sufficient  $E$  to jump over a “social” barrier ( $\Delta A$ ) into the lowest  $E$  state permissible to be conducted around a group, in turn determining the belief gap and the strength of the group. These belief gaps represent information  $I$ ; the fewer gaps in a group, the more cohesive and ideological the group.

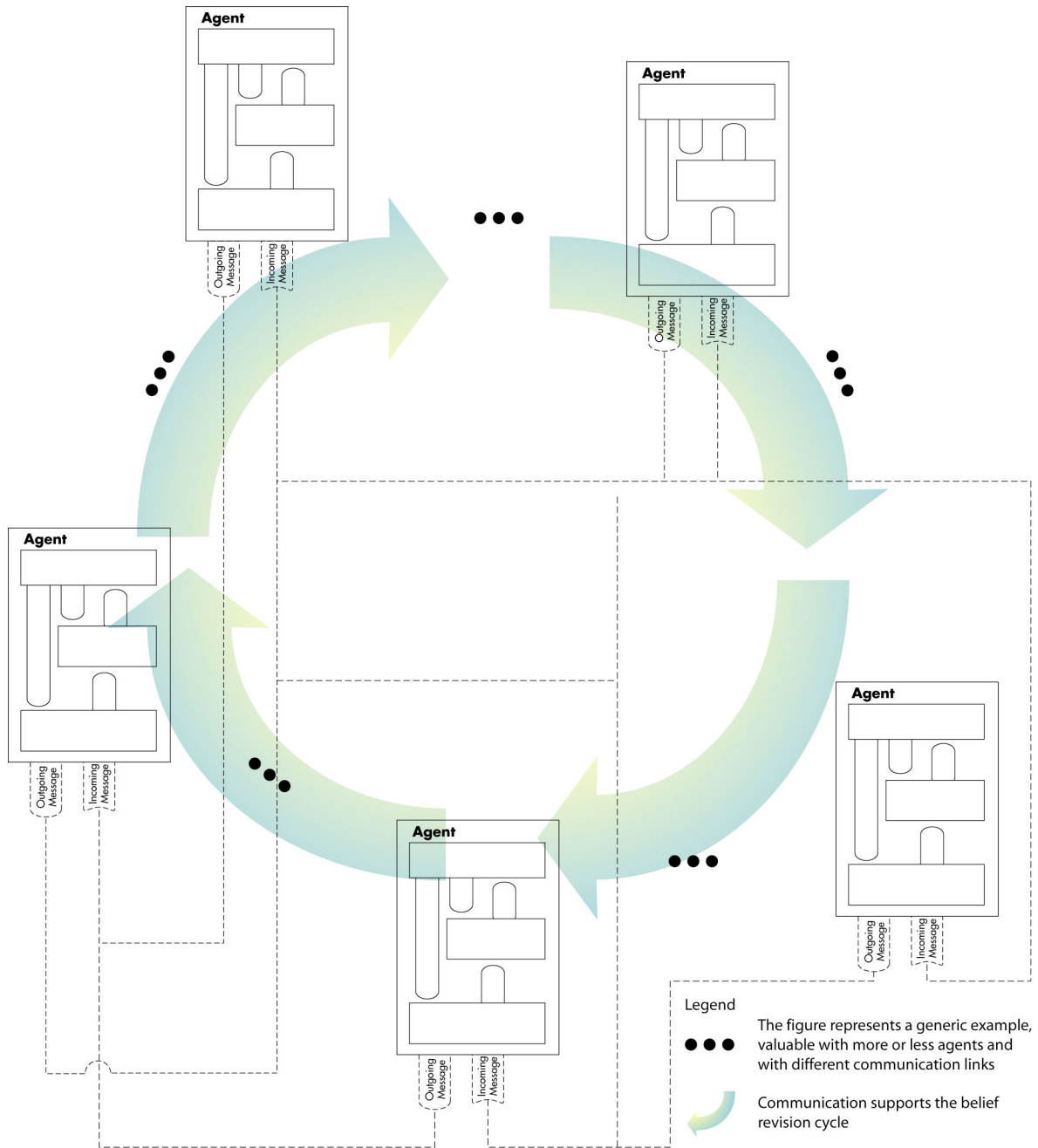
In CR, the widespread freedom to express any belief (increasing  $\Delta K$ ) is associated with a low level of execution by the group (decreasing  $\Delta v$ ), reflecting high inertia. In contrast with MR, the constraints against multiple belief articulations (decreasing  $\Delta K$ ) are associated with a high level of execution (increasing  $\Delta v$ ), reflecting low inertia.

## SIMULATION

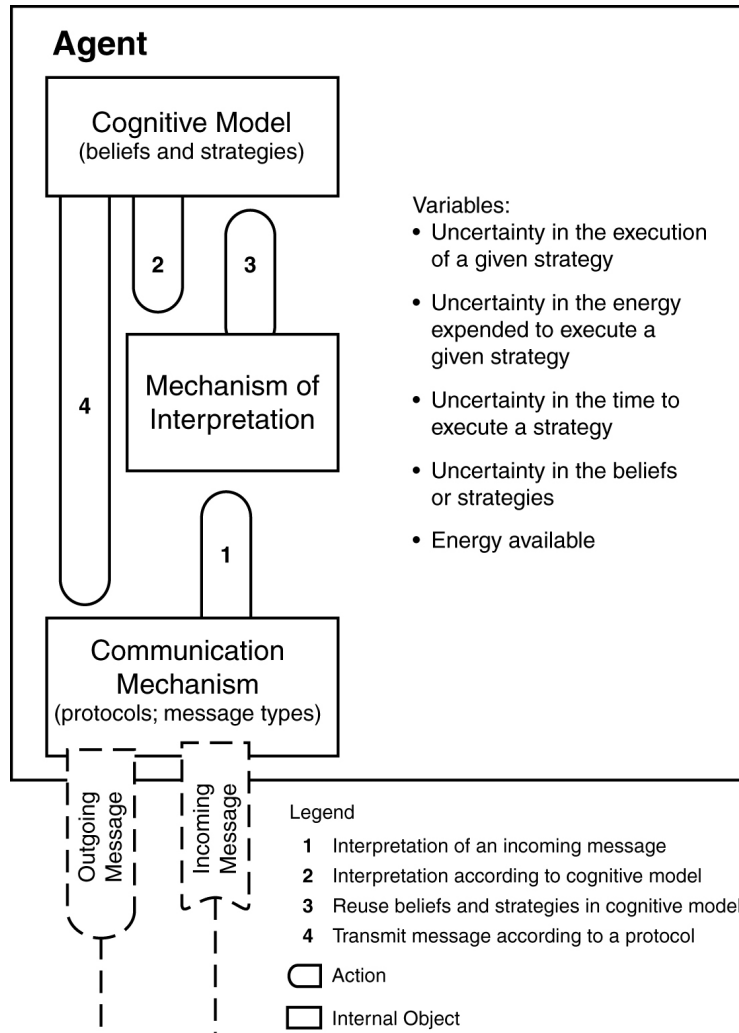
The first task of simulating the model in a computer is the design of the overall system, interaction protocols, and the internal agent architecture. The multi-agent model is illustrated by using AORML — Agent-Object Relationship Modeling Language (Wagner, 2003). The AORML formalism allows the representation of multi-agent systems where several states and behavior models co-exist in one diagram. In addition, the AORML approach distinguishes between *external* and *internal* models, permitting us to take into account the phenomenon of agent *cognitive internalization*. Finally, it uses and visualizes the important concept of *reaction rules* for behavior modeling.

The *external* AOR diagram is depicted in Figure 5, representing a generic situation where agents are individuals participating in an organizational decision-making process. Agents communicate according to a given protocol, allowing the belief revision cycle illustrated in the figure.

On the other hand, an *internal* AOR diagram is used to propose the architecture of a *generic social agent* (Figure 6). An agent consists of three main modules. The *cognitive model* stores decision-making strategies and other nonspecific beliefs. This module also includes reasoning procedures. The *communication mechanism* is responsible for communicating in accordance with some established protocol. Communication protocols concern message types, sequence, and meaning, allowing the implementation of decision-making mechanisms, such as democracy (MR) or consensus. Finally, the *mechanism of interpretation* is in charge of recognizing the meaning of messages received by the agent. Incoming messages, however, are interpreted according to the cognitive model, generating understanding. But incoming messages may also revise beliefs and decision-making strategies that exist in the cognitive model.



**FIGURE 5** Multi-agent modeling — external AOR diagram



**FIGURE 6** Multi-agent modeling — internal AOR diagram

Aiming to implement the idea of linking each aspect of every agent to interdependent uncertainties, the internal state of a social agent is characterized by various variables, representing the availability of  $E$  that an agent can expend; its uncertainty concerning the execution of a given strategy; the energy expended to execute it; and the uncertainty about beliefs, strategies, and the time to execute them. These variables permit us to model agents according to the constraints of the “measurement problem.”

We begin with the traditional assumption that an agent is exclusively in one or another state. As an example with a single agent, if the agent has a well-learned schema of an organization and is performing within that schema, it will be in its lowest energy state. If the agent is criticized while learning its schema, it will be in a higher state. Or, if a well-skilled agent following its schema is reviewing it and notices an error, it shifts from a low to higher energy state. This assumption parallels Hagoort’s data on human cognition and information processing. But in addition, for our simulations, we will apply the more difficult quantum assumption that undecided agents can be in two states simultaneously, with measurement shifting the agent into one state or another, regenerating the measurement problem.

## CONCLUSION

In rational portrayals of social theory, cooperation is assumed to be superior to competition, but this assumption has never been confirmed (Nowak and Sigmund, 2004). This state of affairs permits users of conclusions drawn from these theories by those unfamiliar with its assumptions to make far-reaching claims, such as the one by Dennett (2003) that competition represents a “toxic excess of freedom.” But self-organization is not possible without an excess of freedom. Further, the more rigid the control of a social system (e.g., dictatorship), the greater its instability, requiring the reduction of freedoms, most easily gained by using censorship (May, 2001, p. 5). Contradicting Dennett, by making organizations flatter to permit innovation, competition shifts governance from command decision making to self-organization, one of the key ideas in organizational advertising campaigns and the emerging field of military expeditionary warfare (NEC, 2004).

## ACKNOWLEDGMENTS

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**DISCUSSION:****SOCIAL NETWORKS AND AGENT COGNITION****(Friday, October 8, 2004, 3:45 to 5:45 p.m.)**Chair and Discussant: *M.J. North, Argonne National Laboratory*

**Michael North:** Our next speaker is Meredith Rolfe from The University of Chicago. She will talk about her work on social networks and simulations.

**Social Networks and Simulations**

**Meredith Rolfe:** I was looking at voter turnout. There's a well-known, long-standing empirical correlation between education and voter turnout. People who have higher education in the United States turn out to vote more often than people with lower education. This has typically been attributed to some sort of creation of civic skills or civic concern in the educational system. Each year you sit there, you get a little bit more civic-minded, or something along the lines of you have lower costs of turnout. This, again, is hard to see. My four-year-old is quite good at putting the ballot in the actual voting booth.

[Presentation]

**North:** I'd like to thank Meredith for a very interesting and very concise presentation. That was excellent. First, I was very impressed with the use of sensitivity analysis, testing the assumptions, or at least some of the assumptions, in the model. In this case, one of the critical assumptions that was identified is the structure of the underlying networks, which I thought was a very good thing to do. Also particularly interesting was the use of agent-based modeling as an insight tool to help you understand more about what might be present in the data, and then feeding that back into the data. I thought that was excellent in terms of a use for agent modeling. It was also very good to see that sort of hypothesis-driven research, not only in terms of the overall big question, but also in terms of whether you are seeing the things that the agent model predicts — do you actually see these in the real data — and then going back and finding that in the real data. Even if you didn't find it in the real data, it's a good procedure — a good methodology. Of course, I'm happy to hear that you actually did find the prediction in the data, but even if you didn't, the idea of doing hypothesis-driven research is very interesting.

I have two questions. First, what other important variables do you think are present in this model — other things that should be given sensitivity analysis? Second, does that suggest future research for you?

**Rolfe:** Yes, very much. I think I alluded to that part of the assumptions when I said there could be a relationship between who is more or less likely to be a first mover and what his network position is because right now everyone is equally likely. Another thing is that at this time, an assumption (which is, again, just a basis of computer power) is that I have separated out people with larger and smaller networks into totally different worlds and hopefully (once I get the memory) will actually be able to put them all together.

**North:** That's great. Just as background, we have some big clusters at Argonne, so we can probably help you with that.

**Doowan Lee:** I'm Doowan Lee from The University of Chicago. I have a quick question about your last slide. You said your basic finding was supported by some survey data, etc. Did you actually control for education and everything else, so the only thing that actually affected the turnout rate was social structure?

**Rolfe:** Yes, there was maybe a moderate effect of education at very, very low levels, but I did it through cross tabs — a direct one-on-one comparison. I went back and did some pre-bets, taking care of the fact that people are selecting into the model and everything, and it kept turning up.

**Lee:** Did you try an interaction term between education and social structure?

**Rolfe:** Yes. I tried a few different specifications, and the model I have is actually a dummy variable for social structure. I also have a direct measure; it's the GSS-1985, so it has a direct measure of great size. There are a few different ways I would love to look at. I don't know if anyone here is that interested in the survey part of it, but I've gone about the survey in a bunch of different ways, and it would just keep showing up pretty consistently.

**Daniel Diermeier:** I am Daniel Diermeier from Northwestern. I have a technical question with respect to the threshold models. There is a way to interpret the threshold models with a game theoretic micro-foundation, where you just say people maximizing their utility and then, depending on cost and benefit parameters, there's a likelihood of getting caught that's decreasing and so forth. If you do that, you can show that in the game theoretic analysis, you get multiple equilibria. You get one where everybody participates, and another one where nobody participates. Then you can show if you'd like to write the game as a stochastic process, so you write it down as a Markov chain. You can show there's a limiting distribution and it collapses to a function if you let the noise go to zero. So you identify a unique state, so to speak.

The interesting thing is that this was always independent of the network structure. I'm trying to connect your results with that, and I'm not quite sure how. It seems like a lot is going on if you don't go to the limit, and it would be interesting to look at that. But I'm curious whether that's something that we can connect — those two results at all.

**Rolfe:** I would love to be able to connect them. I think it would be fantastic because I do think there is very much .... I haven't done a lot of work on it because I've been trying to match up what the agents are doing with experimental research on how people play public goods dilemmas. But I would really be interested in matching that back up with a game and limiting distributions. I think the social network part comes in because, in part, it seems like you move away from limiting distributions into limits. The social networks actually place those limits.

**Noshir Contractor:** I'm Noshir Contractor from the University of Illinois in Urbana-Champaign. Actually, you preempted one of the questions that I had by mentioning that your data set was the GSS-85. Was that the one that had the social networks data?

**Rolfe:** That's the only one that is related ...

**Contractor:** So, of course, when you mentioned that, it struck me that in that particular data set, there was the option to guess empirically, without any agent-based modeling, the effects of group structure and education. Did you try that out outside of the agent-based modeling to see if, in fact, based on the empirical data alone, you were able to see any effects of the group structure that overwhelmed or were overwhelmed by education? That's one part. The second part, which is again related, is that you mentioned toward the end of the presentation that social structure made a difference. Could you expand a little more about which particular properties of the social structure made a difference, and talk about in what direction, etc., those differences went?

**Rolfe:** Yes. I guess I should have presented my actual substantive work, not the network work. What I found was that I had the GSS (I mean, everyone's had the GSS for a long time), and I just wasn't thinking about it right. What I found through doing the agent-based modeling was that there was a big difference between the people that had bigger and smaller networks and being in a world where there were, in general, bigger or smaller networks. So I went back, after having been through the modeling, and came up with an indicator (which was already there) for the size of close networks, which, again, I think is probably not the greatest one. It would probably make more sense to think about 8 to 12 people, based on the survey network literature, that are actually doing the influencing — probably a weighted version of those. I then divided up to the stratifying principle, which is segregating people off into worlds.

It turned out that it actually wasn't the individual's education, but it was the education of one's friends that started to have this very "class" connotation. Some people with a high school education had friends (all or a portion of them) that were college educated. The vast majority of the high-school-educated people had no friends with a college education, and they seemed to be living in different worlds. That became the sort of variable that I used to talk about social structure because, again, it was being in a high-network degree, low-density structure that actually made the difference.

**Luis Fernandez:** I'm Luis Fernandez from the University of Michigan and U.S. Environmental Protection Agency. You had an impressive project. I'm looking forward to reading the paper. I have a side comment on the concept of costs related to education level and voter turnout.

I think education levels generally have a pretty strong correlation with household income. Those with lower incomes are much more likely to hold lower-paying jobs that offer less flexibility and less paid time off, so they usually don't have the ability or the time to vote. The question is that given that they're pretty closely correlated, have you taken a look at income, and does it hold when you're trying to control for that?

**Rolfe:** That's a fantastic question. One of the weird things about traditional SES [socio-economic status] that slowly became the civic volunteerism model in survey research was that income really didn't have a huge effect before. This is very counterintuitive in some way. It all seemed to be in education.

One of the nice things that occurred after I put in these controls was that, all of a sudden, income had a really big effect. I'm now exploring that further. I have campaign contributions, and I've got GIF, which I'm getting ready to work with. We're possibly going to get some nice GIF simulations going. I've got political mobilization and candidate locations (where candidates

live). I'm going to start looking at the spatial indirect and direct mobilization idea and also limits. I'll be looking at how much of it is due to direct or indirect contact with the political system and how much is due to the limits that income can place on you. That is actually where I'm going next.

**Michael Macy:** I'm Michael Macy of Cornell University. Meredith, this is fascinating work, and I really enjoyed your paper. My question is (I think it may be similar to the earlier ones) whether these network effects depend decisively on whether there is threshold homophile in the network. If we make the assumption that people are tied to those who have, let's say, identical thresholds, then it's useless because you're preaching to the choir. Also, if their thresholds are random, it doesn't work because you don't have the nice domino arrangement, so the really important thing is to have almost homophile. I'm wondering whether you need to look carefully in the GSS data with regard to whether the homophile of the thresholds violated the assumption of randomness, which I think you have in the model.

**Rolfe:** One of the things that I started off with — and I'm going to address this in a substantive way to give you the best idea that I have — is that this is what I would call the political interest idea (i.e., where people who have similar levels of political interest are grouping together and in some ways reinforcing each other's political interests). So what I did to assume basically the distribution of first movers (who are the most important people with similar interests) was to look at a cross tab along my social worlds idea. I found that the distribution of high, high levels (i.e., first-mover levels) of political interest was the same across the two groups. What varied was the responsiveness of other people to them, so that it was being reinforced in the very high degree/low-density networks, and the political interest wasn't basically spreading.

So, yes, in my models, I assume that across the two types of worlds — those with four to five, six, eight friends versus more friends (lower density) — thresholds are randomly distributed and that people are just grouping up without any responsiveness to that. I was able to check that in the data. I found that the number of first movers (which, according to public goods models experimental work, should be about 10% to 15%) was, in fact, the percentage that was actually in the data. So it's a roundabout way of getting there, but I felt pretty good about it.

## Global Coordination in Modular Networks

**Michael North:** I'd like to introduce Daniel Diermeier, from Northwestern University, who's going to discuss "Efficient System-wide Coordination in Scale-free Networks."

**Daniel Diermeier:** Thank you. It's a pleasure to be here. I've expanded the title a little. I'm going to talk about efficient coordination and information aggregation in complex networks. I'm also going to talk about some related results, but I want to spend one minute on a new initiative at Northwestern called Northwestern Institute on Complex Systems, or NICO (for the Velvet Underground fans). This aim of this university-wide initiative is to bring together in a unit — people from medical school, law school, biology, mathematics, political science, economics, and so forth. We already have a research group of 25 to 30 people. One result of the initiative is a conference with only outside speakers the last weekend in October. If you're interested in attending, particularly if you're local, let me know, and I'll tell you where to register and so forth.

## [Presentation]

**North:** That was a very interesting and thought-provoking paper. I thought it was particularly fascinating about the importance of noise in the system. That also shows up in areas of biological control, where noise is an important factor in keeping the biochemical networks functioning properly. I was interested to hear the correlation between rat nausea and voting. I thought it was interesting. I was also very interested to hear that some of the classic paradoxes or surprises from behavioral economics were actually caused by taking people out of context, essentially, and getting them — really tricking them — into using the wrong rules or using rules inappropriately, rather than actually being strictly wrong or foolish.

I do have a question. You came up with a very provocative conclusion: simple rules in complex environments versus the converse. I was wondering about the generality of the conclusions. Certainly, I believe you in terms of the majority rule in the various networks that you talked about. Have you considered simple rules other than the majority rule in order to draw that conclusion?

**Diermeier:** Yes. So the right question is exactly that: what's so special about the majority rule? Maybe there are others out there. What we are doing now is replicating the Crutchfield approach. We're basically allowing genetic algorithms to run in complex networks, so we ask what type of rules emerge. That's preliminary work; it's not finished yet. But what we see is that the rules that emerge are awfully close to the majority rule. There's an underlying rationale for why these rules would emerge in this context. Of course, the next step you want to think about is whether you can come up with a model where these things co-evolve. That's a much bigger question that we can't conceptualize at this point.

**Unidentified Speaker:** This is very stimulating. The third plane from the bottom is important to keep in mind — the link between social structure and cognitive processes. Without giving anything away, I couldn't agree more. I think the experiment you're about to see in the next presentation is ...

**Diermeier:** That's how we planned the whole conference: one paper is built on the last one.

**Unidentified Speaker:** I noticed that in one of the efficiency graphs — the one on the left — the asymptotic behavior began to level off at about 0.8. I mean, that's three scaled 0.8. You didn't even have a 1.0 there. Why is that? Is that because of the presence of noise? What's causing that?

**Diermeier:** In this particular case, it's like a simulated annealing idea. You let the system run, then you turn off the noise. In this particular case, it would go to 1, but that's not always the case. For large enough " $n$ ", you essentially go to 1 — not really to 1 — the residual noise is driven by the fact that there's underlying noise in the system — persistent noise with respect to the input.

**Robert Reynolds:** I'm Bob Reynolds of Wayne State University and the Museum of Anthropology, University of Michigan. You mentioned the majority rule. In artificial intelligence, majority rule can be viewed as a very simple, basic way of learning and generalizing. Typically when you learn, you learn with positive and negative examples. By

adding noise into your mix, you're providing negative examples. In other words, you can't learn a concept completely unless you have some of each, so by adding in the noise, you are inadvertently or systematically adding in the ability to focus in on and fine-tune your conceptual results.

**Diermeier:** That's a very interesting idea. The way we conceptualized it is that basically, socially, we don't get stuck. I'm not getting in trajectory that kind of self-enforcing in the wrong way. There's enough variation in the system.

**Reynolds:** Basically, what you have is that the majority rule is generalizing, yet the noise is producing the ability to specialize by removing the situation. So specializing and generalizing together provide the flexibility to backtrack, to extend, and then to contract again.

**Diermeier:** That's a very nice connection.

**Kostas Alexandridis:** Kostas Alexandridis from Purdue University. In looking at those dynamics, I couldn't help thinking of the whole mainland/islands dynamics in native population research in ecology. It's very impressive to see the same dynamics in noise. There, the existence of some dynamics — the introduction of in- and out-migration — increases the persistence. The question deals with whether you can think of the noise and its properties. I would agree that it indicates that there is some meaning behind the noise in terms of negative feedback mechanisms that get to the dynamics.

**Diermeier:** I'd love to hear more about that. That's a connection I haven't thought about. How does this connect to those dynamics? That's a very interesting question.

**Scott Christley:** Scott Christley of the University of Notre Dame. I have a somewhat technical question. Do you define the notion of cooperation in the network as a global measure? When you're saying that everything is cooperating, are you saying that all the networks are able to communicate and cooperate? To follow up on that, is a local node able to essentially determine what the result of the local coordination was, without having to resort to global information?

**Diermeier:** Yes. Technically, it's really not cooperation. I think the cooperation metaphor may bring you in the wrong direction because it's more like a classification issue or a coordination problem. Think about the following problems. Do I drive to the left or do I drive to the right? Do I eat with a fork or do I eat with chopsticks? The intuition is that if you go to Thailand, people in Thai restaurants always give you chopsticks. But there, they eat with a fork. So that's something where there's so much social pressure to ask for chopsticks in the United States. You come in and everybody is using chopsticks, so you think that you've got to use chopsticks. So we "miscoordinate" here. If there was enough connection, however, that wouldn't happen. I guess that's the way the model would be structured in this case, so it's not a coordination issue. It's really just about which state am I in, and I determine which state I am in — what I want to do — by looking at other people. That's all.

Now, these types of models can be generalized to do the type of stuff that you're talking about. In this case, though, we're not. It's the simplest possible problem from a coordination point of view. In the structure that we have, you can also interpret it as an information aggregation problem. Because there's information in the system, the majority .... Think about a

jury. Is the person guilty or innocent? Everyone has his own view, but at the end, we all want to agree, and we want to make sure we do the right thing. That's what it is. You get a correct classification, if we all do the same thing, and the state is correct in the sense that it represents the initial majority state.

**William Lawless:** Bill Lawless. I liked your talk and have two quick questions. First, what do you mean by majority rule producing a certain amount of time to reach consensus? Second, what do you mean by linking together majority rule and consensus?

**Diermeier:** Consensus is just another word for what I just said. In this case, consensus means everybody does the same thing, and the state where everybody is ending up is the same state as the majority in the initial state — the more likely state or the more prominent state in the initial distribution, that's what it means.

**Lawless:** I'll show something somewhat similar [in my presentation]. I liked it because most people think majority rule is very "conflictual" and that you don't actually reach consensus and that it leaves people divided. I think that's a good result. The other thing is that you started off showing these networks, but you didn't wind up with those pictures of networks. I wondered if you'd given any thought to using your model to reproduce those networks.

**Diermeier:** This is not a model of how networks form. This is a model of what happens if you live in a network like that. One could think about a model that would do both (that would have a model of how networks form and then how I interact with that), but that's not what this is. It's a dynamic on the network rather than a dynamic off the network.

## **Mnemonic Structure and Sociality: A Computational Agent-based Simulation Model**

**Michael North:** I'd like to introduce Claudio Cioffi-Revilla from George Mason University. He'll be talking about "Group Mnemonic Structure and Sociality: A Computational Agent-based Simulation Model."

**Claudio Cioffi-Revilla:** I want to thank the organizers of this event. I'm particularly fond of this meeting for several reasons. One is that it is medium scale in size. It is larger than a small workshop, but it has more of a workshop flavor than the large national and international meetings, although it has a fair amount of international participation.

This presentation deals with work in progress. We think we have reached a stage where it's "decent enough" to talk about it in public. I'm not going to give the same presentation next year. You will see that there are important aspects of this work that need further analysis and further model building.

I also want to say that this is very much a team effort. The five co-authors of this paper will soon be joined by a sixth member. He's not here because, in the last few weeks, he's been doing a lot of work on features that I will explain in a moment. That would be one of our graduate students. I am a political scientist and a modeler by training. The second author, Sean Paus, is a graduate student in the Computer Science Department and the original designer of the model from which Wetlands came, which is called Floodland. Wetlands evolved from

Floodland. Sean Luke is my Computer Science Department faculty colleague. Last year, he and I brought the first presentation of the MASON [Multi-agent Simulator of Neighborhoods] simulator to this meeting in the workshop session [see page 45 of the Agent 2003 proceedings]. Jim Olds is the director of the Krasnow Institute for Advanced Study. Jim is in this project because he is a neuroscientist. His specialty is the human brain, in particular, the hippocampus and neural processes. You'll see why he is involved with this project. Finally, Jason Thomas is a recent computer science graduate who's a great Java hacker, and he joined the team as well. So you have social science, neuroscience, and computer science in a collaborative team. I think it's fair to say that none of us individually could have pulled this through, and that's the way it's going to continue. One more thing is that this collaboration among the Center for Social Complexity, Evolutionary Computation Lab, and Krasnow Institute is really pretty seamless. We don't have any major institutional obstacles in carrying out this collaboration because the principal people in these groups are all intimately involved with the project. We think that it's a fairly stable collaboration for the foreseeable future, and we're very happy about it.

[Presentation]

**North:** Thank you. I like the simple structure of your model in the sense that it's really clear and expressive. And the overall problem was related to real-world issues, but at the same time was abstract, and yet you can draw some conclusions. I have questions on a couple of levels. First, I'm happy you say "theoretical implications" rather than "conclusions" or something like that because clearly these issues that are being dealt with are huge, and there are many variables that you'd need to investigate in order to list these as conclusions. I'm glad I learned a new word today: sociophile.

The first question basically has to do with intensive versus extensive memory. Another way to think about that has to do with network effects. Clearly, we're talking about a social system, so network effects are a critical thing. What have you done to vary or have network structures — these types of things? My second question has to do with negative experiences, and more generally, the encoding of engrams. You didn't have a chance to talk much about the engram and the details of what the encodings are. I'm particularly interested in whether you dealt with things like negative experiences that people have, rather than just group-forming experiences. Finally, I'm interested to hear more about any variations that were used for the other underlying behaviors because clearly, in this model at least, contact and these types of things are an important part of the memory process. I think that means that the foraging behaviors themselves might be an important thing to explore. Have you had a chance to vary, or will you consider varying, the motion essentially across the surface, which drives at least some of the interactions?

**Cioffi-Revilla:** With regard to your first question about intensive versus extensive memory, I have not given a great deal of thought to that. I'd like to save that question and discuss it. I think that Jim Olds might have some thoughts about it. Do you mean that in the sense of diffused memory in the group?

**North:** Right. I mean memory in the social structure itself versus ...agents for these types of things. Since this is ongoing research, you can't be expected to answer every question. I was just curious.

**Cioffi-Revilla:** I think that all of this memory is probably intensive.



**North:** That's what I had perceived from the paper and your talk. Certainly, I was not criticizing that as being a bad thing, but when we draw conclusions about memory capacity in social systems, we might say that we're dealing with something else.

**Cioffi-Revilla:** That's another level.

**North:** Yes, we're dealing with intensive memory versus extensive, although, again, it's important since you said implications here, that's a great escape.

**Cioffi-Revilla:** I like that idea because, well, there are individuals; those are not expressed here. Then there are groups made up of individuals. That's exactly what is expressed in this model. What you're saying is that groups of the same culture form a community.

**North:** That's right.

**Cioffi-Revilla:** And once they form that community, what happens to that memory? That is not expressed here either, and I think — is that the extensive one?

**North:** That's part of it.

**Cioffi-Revilla:** It's a good point, and we should at least say something about that, even if we don't model it. With regard to the second question on negative experiences, in this model, so far, there are none.

**North:** It's a great world. I'd like to move there.

**Cioffi-Revilla:** It's simple in many ways. All of the information that the groups exchange is perfectly and totally believable. Two ways of exchanging information have been suggested in our group discussions. One is to make the passing of information probabilistic and not deterministic, as it is here. There's another issue, too — that all of these groups are at the same level of credibility. We could do some experiments to see what happens when you identify one or more of the groups as having greater credibility than the others. In fact, some groups are known for being of the same culture but not reliable, so then the question of negative experiences will come up because sometimes we'll be misled to look for food in the wrong place.

Was the third question about how contacts occur and how that may affect the motion of the groups in the landscape?

**North:** Right — or even changing the motion rules.

**Cioffi-Revilla:** It's a very complicated issue, and we're not totally clear on it because the food and moisture gradients induce dynamics on the landscape that are obviously nonlinear throughout that landscape. We've got to be sure that the motion we observe is truly due to real effects of those dynamics, absent any bugs that may exist in the code. We're almost sure, but we still need to do a couple more things to it.

**North:** I like your experimental approach, and the description was quite clear as well.

**Robert Reynolds:** I'm Bob Reynolds of Wayne State University and University of Michigan Museum of Anthropology. I'd like to expand on what Mike was saying. Do you have basic competition and cooperation? You have the ability to do both. By adjusting the variables, you're effectively going to be adding — stressing — one versus the other. It would be interesting to do a sensitivity analysis and see whether these patterns emerge as you emphasize cooperation over competition and vice versa. You can do that, for example, by making the resources scarce. You're going to have more competition; make them less cooperative, etc. It would be interesting to look at your sensitivity analysis in terms of these general issues of competition and cooperation.

**Cioffi-Revilla:** Thanks. That's a good suggestion. As I said, right now they don't have any bad experiences because, for example, they don't lie. Also, if two groups of a different culture come into contact, all that happens is that they don't pass information. They don't attack each other, and there's no conflict.

**Unidentified Speaker:** Are the resources renewable?

**Cioffi-Revilla:** They are. That's why it's raining all the time — that regrows the food. There's not a food problem in this world. The problem is that they need to get away from it. They can't feed all the time because of the health problems involved with getting too wet. But there's no conflict. We want to introduce that in a controlled way, so we have full understanding of its experimental effects.

**Luis Antunes:** I am Luis Antunes from the University of Lisbon. I liked your presentation. Your model seems similar to the one I presented in that there are two groups; there are pressures to compete; there are pressures to cooperate; there's food; and, in a way, there's a Sugarscape model. The thing that worries me about both my work and yours is that there seems to be a lack of content in the dynamics of the decision theoretic problems inside the agents' heads. I mean that at this stage of my work, if I took out sex and put in anything else, I would get the same results. I think it's very important that in the feedback in the adaptation process, you have some kind of content — something that informs us about sex (in my case) and memory (in your case). I think that may be lacking in both of our approaches as they are now.

**Cioffi-Revilla:** It's a good suggestion. I missed your presentation, but it is true. In a certain sense, these two different cultures in the groups are not very consequential, except for the fact that they control the flow of information. Other than that, culture does nothing. But that's done on purpose because we wanted to ensure that it did not also automatically induce, for example, sociality, which it very well could. You could put in an initial rule. By the way, if groups are of the same culture, you try to get close to similar groups as you head for shelter. But that rule is missing; it's not there. Nonetheless, the social — the cultural — aggregation seems to be clustering — to be emerging anyway.

## **Consensus versus Truth Seeking: Modeling Perception versus Action**

**Michael North:** I would like to introduce Bill Lawless who is going to discuss "Consensus versus Truth Seeking: The Quantum Perturbation Model." Bill has provided handouts for the presentation, so I'll distribute those.

**William Lawless:** First, I would like to express my thanks to my co-author, Jorge Louça from Lisbon, who is at ISCTE, a business university, and Margo Bergman, at Penn State. I also want to thank James Ballas, my colleague at the Naval Research Laboratory, for many years of funding.

[Presentation]

**North:** I'd like to thank the speaker and then offer a couple of fast comments. The first is that quantum theory is obviously the best-tested physical theory in human history. As a powerful hammer, though, it's often applied to drive many nails in many places. That's always a concern. I happen to like quantum formalisms, but there's always a question of why quantum theory always comes up here. That's an important question. Let me get to the question in just one second.

Things I like about this are the use of fuzzy or nondiscrete decision making (i.e., decision making on some sort of continuous space rather than discrete space). I also liked the scaling between individual- and group-level decision making. You have a coherent set of rules that do not trivially equate the two, so the individual decision making could behave differently than group decision making, but there's a scaling between those I thought was nice. I would note that any nonlinear voting function does, in fact, have the property of group behavior that's different than individual behavior. In fact, we've seen models today that use nonlinear voting functions. I mention that as background, so there are quite a few computational models and things that, at least in my opinion, have group consensus or group outcomes that are different than individual outcomes.

I think that, in general, however, my simple question is that many fuzzy formalisms, fuzzy logic, nonmonotonic reasoning, and many others allow you to have discrete scaling. Even though the quantum formalism is very powerful, it was obviously developed for a very different area. I wondered first why the quantum formalism is used more generally because it is often applied perhaps outside its normal range of utility. Also, you mentioned a couple of specific Hamiltonians, which are the energy functions for which you solved quantum systems. I'm someone who understood the nuclear stuff. But I'm wondering why you mentioned those specific Hamiltonians beyond just the fact that the shape kind of matches an approach and repulsion. In particular, I've seen this often with quantum theory. We know how to solve a small number of Hamiltonians in some sense, particularly one-dimensional Hamiltonians, and it's interesting that when people first attack a problem with a quantum tool, I almost always see those. I know it's going to be one of five Hamiltonians that I know people can solve. I'm just curious why those showed up.

**Lawless:** What that suggests is an interdependence between the uncertainty in the plan and the uncertainty in the execution.

**North:** Oh, no. For the Hamiltonian you were saying that you chose them.

**Lawless:** Right. Well, I was trying to take them one at a time, and this interdependence is shown in the result. If you drive your uncertainty and if you come up with a very good plan, which, for instance, Jack Welch said you should never do, don't worry about the plan, worry about the execution. There's a trade-off, and that's shown here.

The Hamiltonian is a way to show how much energy is being expended in the interaction. It suggests, for example, that the newer the individual coming into the group is, that individual is first more likely to be put at the bottom because there's less energy expended there for him, and second is the more expensive individual. It's probably someone at the very top, and those at the top have a greater influence from the beginning. So younger people are usually put in at the bottom of the organization, and this Hamiltonian models that very nicely. It's an idea I got from David [Sallach].

**North:** Very good. Thanks. We have time for a few questions.

**Chick Macal:** Chick Macal, from Argonne. I was curious about the Hamiltonian because I wanted to understand what the implications are. My past experience with Hamiltonians has been that they suggest some globally available quantity that is potentially maximizable or minimizable. Is that an implication of a conservative system, perhaps? But yet you're bringing in Lyapanov, suggesting it's a dissipative system.

**Lawless:** Yes.

**Macal:** So could you just briefly discuss that?

**Lawless:** It's not a conservative system, but a nonconservative one. Energy is necessary to come in and keep the organization going. In addition to that, could you just move that aside for a second? The group has a certain expenditure of energy. How does it organize itself? It seems to organize itself to reach an energy minimum, and that's the point.

**Macal:** Exactly. So in terms of modeling social groups or individuals, there is some possibility of not directly summing their individualities into group behavior but yet deriving an equivalent thing — a Hamiltonian, in effect — which is as if that was being maximized or minimized by the groups or individuals. Is that a correct interpretation?

**Lawless:** Right. In addition, though, and what's surprising is that the group is actually going to be at a lower level of energy than if you disaggregated the group. If, for example, you removed from the group all of the employees who work for IBM, they would be at a higher energy level collectively (i.e., aggregatedly, as an aggregation) than they would if you put them back into IBM. And why is that? It's an important question, but it's not one that we've really addressed yet.

**Macal:** Well, is that an implication of some assumption you made and put in the model, by which you may have gotten that result out? Or is that some new aspect that falls out of the model, not necessarily connected with any of the basic assumptions?

**Lawless:** I think that's a wonderful question. One of the difficulties that I have in dealing with it is that it suggests that there's an energy optimum for an organization. I haven't spent a lot of time trying to find what organizations are at an energy optimum because of this confounding element. Most humans, as individuals, are or should be at optimums as well. But the average American is, for example, I think 30% obese, 60% overweight. Well, it's a profound issue when you take that same sort of information into organizations. It seems that if organizations can rapidly zoom past an optimum point, they can start creating a great deal of entropy. You can see this in the decisions that organizations make. For example, Enron was a

world-class organization at the top of the pyramid (number seven, I think). Yet, their management made horrific decisions on the money that was coming in on new investments. It was almost random, which is very surprising. So I don't have an answer for you. I think it's a very good question. I'm very interested in it. I don't know how to attack it because you need some sort of a baseline, and I don't know where that is.

**Macal:** I think it's actually worse than random, based on most of that.

**Lawless:** Yes.

**North:** We have time for one last question.

**Nick Gotts:** Nick Gotts, Macaulay Institute, Scotland. My question is actually on the comment, which goes right on from what Chick Macal was saying. What do you mean by saying that if you disaggregated IBM, the net energy would be higher? What do you mean by energy in that respect? And before you answer that, let me say that this talk was either completely over my head or complete nonsense. I don't know which; I'm not a physicist. But I think if you're going to address an audience that includes nonphysicists, you cannot put that amount in and expect people to follow it. I certainly didn't.

**Lawless:** Well, that's a valid concern. It's one that I think about all the time, but I'm not so much driven by it. This is very complex, and I apologize for that. But I think, as Einstein said, we should always be as simple as possible to explain any phenomena, but no simpler.

**Unidentified Speaker:** Quantum theory is not simple.

**Lawless:** I don't think that I've gotten far enough into this yet to understand just exactly how complex it is. It seems even more difficult for me, since I'm not working for an audience. I appreciate your comment, and maybe I *should* be working for an audience, but I don't have an audience in mind. What I'm trying to do is to better understand two phenomena that I've worked with for a number of years, and that's how the Department of Energy, which is one of the world-class organizations and has some of the top scientists in the world, can make horrendous mistakes. Take, for example, the nuclear waste cleanup in the 1980s, which I did a lot to bring into the public view. I still work with the Department of Energy today, so I wanted to understand how organizations can make these kinds of mistakes. I also wanted to understand how you can reformulate and revise organizations.

**Gotts:** Could you briefly address the specific question I had? What did you mean by saying that if you disaggregated IBM, the sum of the energy of the individuals would be greater?

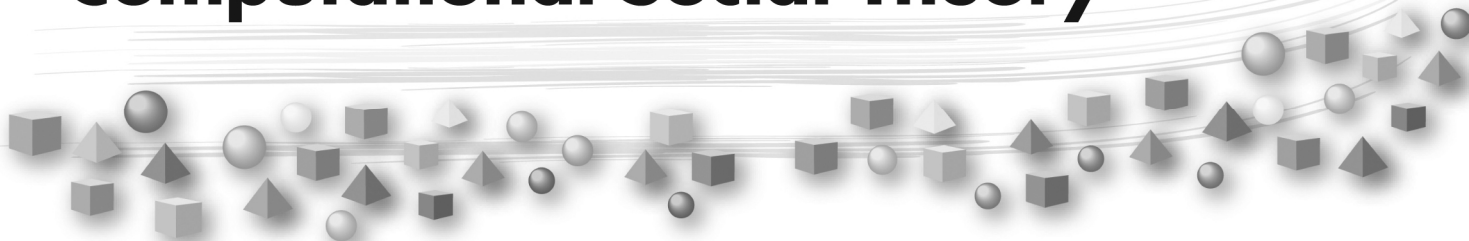
**Lawless:** You had two parts to your question, and I addressed the second part first. I'm sorry. Paul Ehrlich reminds us that one of the driving motivations is not reproduction, but gathering energy. To survive, you need energy, and collectively when we work together, we can expend less energy, I think, in gaining those sources of energy. I think that that's what's happening within an organization. An organization seems to be able to leverage the energy expenditures that individuals make to gain new sources of energy.

**Lawless:** And I also want to say that I think the Department of Energy has done a wonderful job in cleaning up the problems that it created back in the 1980s.



Saturday, October 9, 2004

# Computational Social Theory

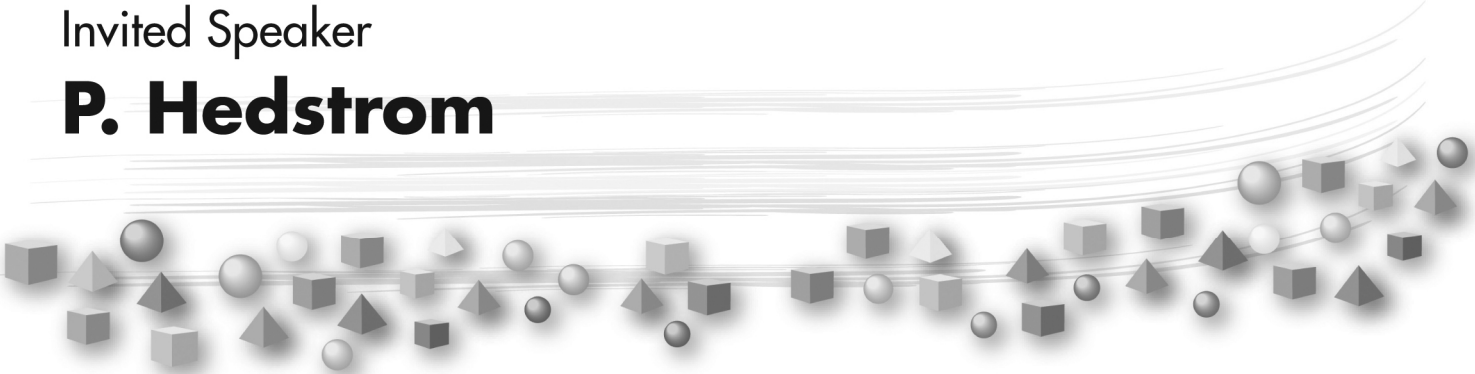






Invited Speaker

**P. Hedstrom**





## SOCIAL MECHANISMS AND SOCIAL DYNAMICS\*

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### ABSTRACT

This paper focuses on how a combination of mechanism-based theories of action and interaction and of agent-based computational models makes it possible to analyze, in a theoretically grounded fashion, how individual desires, beliefs, and actions are the product as well as the producer of large-scale social patterns. In addition to this metatheoretical purpose, some results are presented that emphasize the nonlinearities that characterize many social processes. Small changes in the structure of social interaction are shown to give rise to large-scale change at the social level.

**Keywords:** Mechanisms, agent-based modeling, sociology, intentional explanations, actions, social interactions, DBO theory

### INTRODUCTION

This paper focuses on the relationship between agent-based modeling and the so-called social-mechanisms approach to which I have been a contributor (see, e.g., Hedström and Swedberg, 1998a). The paper is organized into four principal sections:

1. A presentation of the guiding ideas of the mechanisms approach,
2. Discussion of various mechanisms of action and interaction,
3. Discussion of the importance of agent-based modeling for linking individual-level mechanisms to social outcomes, and
4. Concluding remarks.

### GUIDING IDEAS OF THE MECHANISMS APPROACH

One way of characterizing the distinguishing features of the mechanism approach is to compare it with other explanatory approaches (see Table 1). The most important alternatives to the mechanism approach are the so-called covering-law approach of Hempel and other philosophers (Hempel, 1965), and the statistical approach of many quantitatively oriented social scientists (e.g., Lazarsfeld, 1995; King et al., 1994; Salmon, 1971).

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**Table 1** Main types of explanations

Characteristic	Covering-law Explanations	Statistical Explanations	Mechanism Explanations
Explanatory principle	To subsume under a causal law	To identify statistically relevant factors	To specify a social mechanism
Key explanatory factors, entities, and/or activities	No restrictions, except that the factor must exhibit a law-like relation to the event to be explained	No restrictions, except that the factor must be statistically relevant for the event to be explained	Action-relevant entities and activities and the way in which they are linked to one another

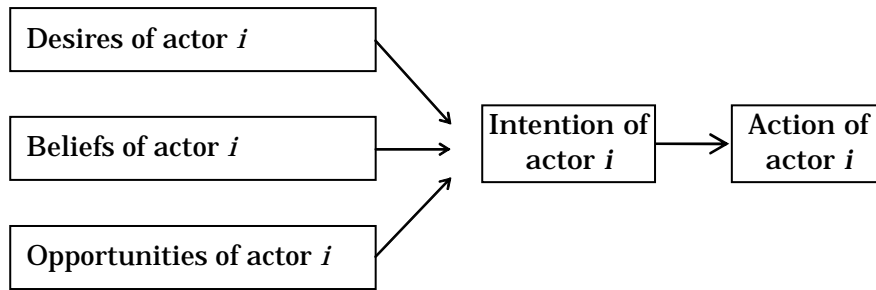
While the covering-law approach takes the position that an acceptable explanation consists of subsuming the event to be explained under a general causal law, the statistical approach, explicitly or implicitly, sets an equal sign between explanation and predictive accuracy. A variable is said to be explanatory if it is statistically relevant for the event to be explained. In contrast to these approaches, the core idea behind the mechanism approach is that we deductively explain a social phenomenon by referring to the social mechanism by which such phenomena are regularly brought about. A mechanism, as here defined, consists of a constellation of *entities* and *activities* that are organized in such a way that they regularly bring about a particular type of phenomena (see Hedström and Swedberg, 1998b; Machamer et al., 2000). We explain an observed phenomenon by referring to the social mechanism by which such phenomena are regularly brought about.

From the viewpoint of the social sciences, Hempel's approach is of limited relevance because, as far as we know, there are no strict Hempelian social laws, and there are good reasons to suspect that such laws do not exist. The statistical approach, as practiced by most quantitative sociologists, is wanting for another reason. As argued by Boudon (1979), Coleman (1986), Goldthorpe (2000), and others, statistical analyses summarize patterns in data, they do not explain them. From the mechanism perspective, correlations and constant conjunctions do not explain but instead are observational phenomena that need to be explained by reference to the mechanisms that brought them into existence.

## MECHANISMS OF ACTION AND INTERACTION

In sociology, the basic *entities* and *activities* of a mechanism always tend to be actors and their actions. Through their actions, actors make society "tick," and without their actions, social processes would come to a halt. Theories of action are therefore of fundamental importance for explanatory sociological theories, but how should we go about conceptualizing action and interaction? In my view, the most attractive alternative is the so-called "DBO" theory. According to this theory, desires (D), beliefs (B), and opportunities (O) are the primary theoretical terms upon which the analysis of action and interaction is based. That is to say, the desires, beliefs, and opportunities of an actor are seen as the proximate causes of the actor's action (see Figure 1).

We can understand why actors do what they do if we perceive of their behavior as being endowed with meaning; that is, that there is an intention explaining why they do what they do



**FIGURE 1** Core components of the DBO theory

(Elster, 1983a; von Wright, 1971). As seen in Figure 1, these intentions, in turn, can be understood in terms of the desires, beliefs, and opportunities of the actor. A *desire* here is defined as a wish or want for something. A *belief* is defined as a proposition about the world held to be true. And *opportunities*, as the term is used here, constitutes the “menu” of action alternatives available to the actor; that is, the actual set of action alternatives that exist independently of the actor’s beliefs about them (for discussions of various aspects of the DBO theory, see Hahn, 1973; Davidson, 1980; Elster, 1989; Lewis, 1994).

Beliefs and desires thus are mental events that can be said to cause an action in the sense of providing reasons for the action. A particular combination of desires and beliefs constitutes a “compelling reason” for performing an action. They have a motivational force that allows us to understand and, in this respect, explain the action (von Wright, 1989).

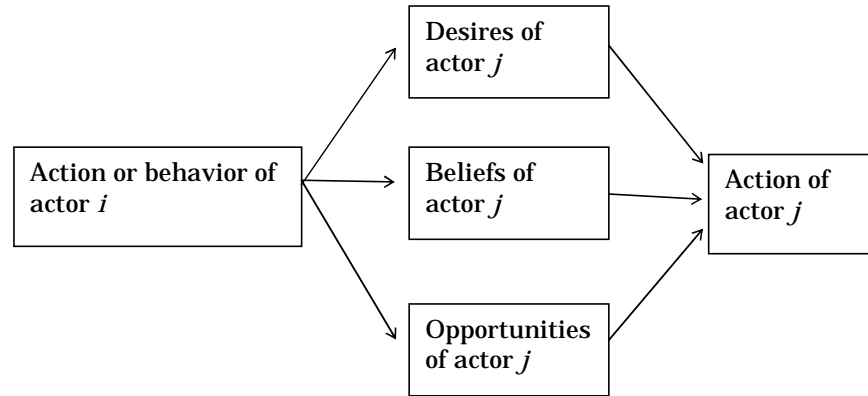
To explain why we observe what we observe, we must seek to understand how beliefs, desires, and opportunities are formed in interactions with others. Simply assuming that beliefs and desires are fixed and unaffected by the actions of others may be plausible in some very specific situations, but it would be an untenable assumption in the general case. Therefore, we must problematize and try to specify the mechanisms through which the actions of some actors may come to influence the beliefs, desires, opportunities, and actions of others.

Social-interaction processes can be conceptualized in numerous ways, but from the perspective of the DBO theory, it appears essential to distinguish between three broad types of social interactions: (1) desire-mediated; (2) belief-mediated; and (3) opportunity-mediated. In the dyadic case, we can describe the interaction between two actors as illustrated in Figure 2.<sup>1</sup>

To the extent that the action of one actor, here referred to as Actor *i*, influences the action of another, Actor *j*, this influence must be mediated via the action opportunities or mental states of Actor *j*. In terms of the DBO theory, the action (or behavior) of Actor *i* can influence the desires, the beliefs, or the opportunities of Actor *j* and thereby the actions of *j*.<sup>2</sup>

<sup>1</sup> To simplify the presentation, I have removed the “intention box” from the figure, but it is still assumed that intentions intervene between desires, beliefs, and opportunities, on the one hand, and actions, on the other.

<sup>2</sup> It is important to note that in many situations, “Actor *i*” may not be a single actor, but rather a small group of actors with whom *j* interacts, or a “generalized other” representing typical actions as perceived by Actor *j*.



**FIGURE 2** Dyadic interaction between Actor *i* and Actor *j* according to the DBO theory

By using the basic concepts of the DBO theory — desires, beliefs, opportunities, actions, and relations — more complex, “molecular” mechanisms can be defined. These molecular mechanisms differ from one another in terms of how these basic entities and activities are linked to one another. Some examples can be seen in Figure 3. The letters D, B, O, and A stand for desires, beliefs, opportunities, and actions, and the letters *i*, *j*, and *k* identify different actors.

The first pattern of entities and activities exemplifies *wishful thinking*. As the term is used here, wishful thinking denotes a causal connection from an actor’s desires to his/her beliefs that makes the actor believe what (s)he desires to be the case (Davidson, 1980). The second type of mechanism, the *sour-grapes* syndrome, exemplifies the opposite causal direction. That is to say, it is a causal connection from an actor’s beliefs to his/her desires, which makes the actor desire only what (s)he believes (s)he can get (Elster, 1983b).

The third type of mechanism, *dissonance-driven desire formation*, is a case where the actions of others lead to a change in the focal actor’s desires and thereby to a change in his/her actions. A classic example is Festinger’s (1957) notion of cognitive dissonance. For example, if I desire *p* but the people I interact with do not, this may cause strong dissonance, particularly if the desire is important to me and I value the relationship with these people. One way to eliminate the dissonance would be to persuade them of the value of *p*. Another, and often easier, way to reduce the dissonance would be to ‘persuade’ oneself that *p* after all was not as desirable as initially thought.

The fourth mechanism, *rational-imitation*, is the case where one actor’s action influences the beliefs and subsequent actions of others. For example, the number of guests at a restaurant is likely to influence other individuals’ choice of restaurant because the number of guests is a signal about the quality of the restaurant likely to influence the beliefs and actions of others (Hedström, 1998).

The fifth mechanism, *vacancy chains*, is a pattern where actions of some create new opportunities and changes in the actions of others. A classic example is White’s (1970) analysis of the vacancy-driven mobility pattern in U.S. clergy. An important feature of job mobility

<i>Entities and Activities</i>	<i>Structural Pattern</i>	<i>Type of Mechanism</i>
Mental states, opportunities, and actions of a single individual		Wishful thinking (see Davidson, 1980)
– " –		Sour-grapes syndrome (see Elster, 1983b)
Mental states, opportunities, and actions of two or more individuals		Dissonance-driven desire formation (see Festinger 1957)
– " –		Rational-imitation (see Hedström, 1998)
– " –		Vacancy chain (see White, 1970)
– " –		Self-fulfilling prophecy (see Merton, 1968)
– " –		The "Old Regime" pattern (see Tocqueville, 1998)

**FIGURE 3** Examples of some action- and interaction-related mechanisms

within organizations, captured in White's analysis, is that individuals' opportunities are constrained by the number of vacant jobs. Vacancies are created either when individuals leave their organizations or when new positions are created. When an individual fills a vacancy, a new vacancy is created in that person's old job, and this represents a mobility opportunity to others. One of these people will get the job, and the vacancy will disappear, but a new vacancy has now been created in this person's old job. Individuals and vacancies thus move in different directions, and the mobility process is governed by these chains of opportunity.

The sixth mechanism, *the self-fulfilling prophecy*, is a sequential concatenation of several rational-imitation mechanisms. Merton (1968) focused on the case in which an initially false belief evokes behavior that eventually makes the false belief come true. The example he used is a run on a bank. Once a rumor of insolvency gets started, some depositors are likely to withdraw their savings, acting on the principle that it is better to be safe than sorry. Their withdrawals strengthen the beliefs of others that the bank is in financial difficulties, partly because the withdrawals may actually hurt the financial standing of the bank, but more importantly because the act of withdrawal in itself signals to others that something might be wrong with the bank. This produces even more withdrawals, which further strengthens the belief, and so on. By this mechanism, even an initially sound bank may go bankrupt if enough depositors withdraw their money in the (initially) false belief that the bank is insolvent.

The seventh and final mechanism in Figure 3, *the "Old Regime" pattern*, is a sequential concatenation of rational-imitation and dissonance-driven desire-formation mechanisms ( $D'i \rightarrow A_i \rightarrow B_j \rightarrow A_j \rightarrow D_i \rightarrow A_i$  where  $D'i \neq D_i$ ). For opportunistic reasons, one actor decides to do something (s)he does not genuinely desire. The action is observed by others, and the rational-imitation mechanism makes them follow suit. Eventually this feeds back on the first actor. The actions of others produce dissonance and a change in the desires of the first actor, which makes him or her genuinely desire what (s)he initially only pretended to desire. A mechanism like this was used by Tocqueville (1998:155) to explain the rapid secularization that took place in France at the end of the eighteenth century:

Those who retained their belief in the doctrines of the Church became afraid of being alone in their allegiance and, dreading isolation more than the stigma of heresy, professed to share the sentiment of the majority. So what was in reality the opinion of only a part (though a large one) of the nation came to be regarded as the will of all and for this reason seemed irresistible even to those who had given it this false appearance.

Why, then, is it so important to specify the mechanisms that are supposed to have generated observed outcomes? From the perspective of sociological theory, one important reason for insisting on a detailed specification of mechanisms is that it tends to produce precise and intelligible explanations without glaring black boxes (Boudon, 1998). Another important reason is that a focus on mechanisms tends to reduce theoretical fragmentation. For example, we may have numerous different theories (of crime, social movements, or whatnot), that are all based on the same set of mechanisms of action and interaction. Focusing on the mechanisms as such avoids unnecessary proliferation of theoretical concepts and may help bring out structural similarities between seemingly disparate processes. Finally, it is the knowledge that the type of outcome we seek to explain regularly is brought about by the entities and activities referred to in the mechanism that gives us reason to believe that there indeed is a genuine causal relationship between a proposed cause and its effect, and not simply a spurious correlation.



## ANALYZING THE LINK BETWEEN THE INDIVIDUAL AND THE SOCIAL

To understand why actors do what they do is not sufficient. We must also address the question of why, acting as they do, they bring about the social outcomes they do. Sociology is not a discipline concerned with explaining the actions of single individuals. The focus on actions is merely an intermediate step in an explanatory strategy that seeks to understand change at a social level.

As the term is used here, “social” refers to collective properties that are not definable for a single member of the collectivity (see Carlsson, 1968). Important examples of such phenomena include:

1. Typical actions, beliefs, desires, etc., among the members of the collectivity;
2. Distributions and aggregate patterns such as spatial distributions and inequalities;
3. Topologies of networks that describe relationships among the members of the collectivity; and
4. Informal rules or social norms that constrain the actions of the members of the collectivity.

Social outcomes like these are *emergent* phenomena, and with emergent phenomena I am not referring to any mystic holistic entities with their own causal powers, but simply to social phenomena or social patterns that are brought about by the actions of interacting individuals. Social outcomes, like other emergent phenomena, are difficult to anticipate because the outcome depends to a high degree on how the individual parts are interrelated (see Holland, 1998). Small and seemingly unimportant changes in the way in which actors are interrelated can have profound consequences for the social outcomes that are likely to emerge. This is because the links between the actors influence the extent to which a belief, desire, or social practice spreads through a population (see Watts and Strogatz, 1998, for some striking examples). For this reason, social outcomes cannot simply be “read off” from the properties of the individuals that generate them. To explain the social phenomena we observe, we need to develop generative models that show how large numbers of actors, in interaction with one another over time, bring about different types of social outcomes.

Because of its flexibility, agent-based modeling is an important tool for analyzing these links between the individual and the social. Unlike traditional mathematical models, agent-based models do not force the analyst to base the analysis on knowingly false assumptions. What, then, would an agent-based model founded on the DBO theory look like? As discussed above, the cause of an action can be seen as a constellation of desires, beliefs, and opportunities in the light of which the action appears reasonable. If we simplify the notion of desires and beliefs in such a way that they can either be said to be or not to be at hand, the possible patterns of desires, beliefs, opportunities, and actions can be described as in Table 2.

**TABLE 2** DBO-patterns and associated courses of action

Pattern	Desire	Belief	Opportunity	Action
(1)	1	1	1	1
(2)	0	1	1	0
(3)	1	0	1	0
(4)	0	0	1	0
(5)	1	1	0	0
(6)	0	1	0	0
(7)	1	0	0	0
(8)	0	0	0	0

An entry of 1 here indicates the presence of the relevant desire, belief, opportunity, or action, and an entry of 0 indicates its absence. The third pattern (3), for instance, represents a situation where an actor desires a certain outcome and has the opportunity to perform the relevant action, but does not believe that the action will bring about the desired outcome, and, therefore, decides not act.

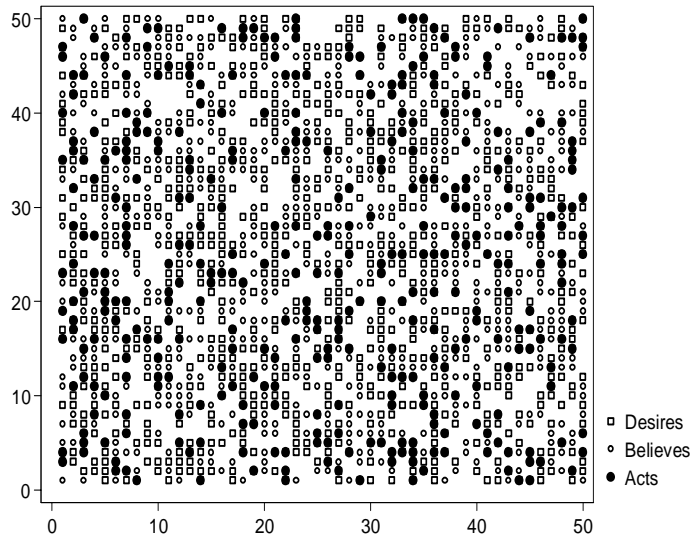
Of the eight possible DBO-patterns shown in Table 2, only the first (1) will bring about an action, because only in this situation does the actor have the opportunity to act in a way that (s)he believes will bring about the desired outcome.

To simplify the presentation, I will focus exclusively on the first four patterns in the table. It is assumed that all actors have the opportunity to act, and the agent-based simulation can be characterized in the following way. It focuses on the desires, beliefs, and actions of 2,500 actors that are situated on a lattice with 50 rows and 50 columns. At each point in time, the relevant properties of an actor can be described in terms of a desire-belief-action triplet,  $\langle D, B, A \rangle$ . If the first entry of the triplet is equal to one, the actor is said to have a “positive” desire, and if the second entry is equal to one the actor is said to have a “positive” belief.<sup>3</sup> If these entries are both equal to one, then the third entry will also become equal to one because actors act when they believe that the action will bring about the desired outcome.<sup>4</sup>

We start from a “state of nature” in which the actors’ beliefs and desires exhibit no social patterning whatsoever — they are entirely random. A typical initial pattern of desires, beliefs, and actions then looks like the one shown in Figure 4.

<sup>3</sup> A positive belief thus means that the actor believes that the action is a good, efficient, and/or appropriate means of attaining the desired result.

<sup>4</sup> As I show elsewhere (Hedström, 2005), this modelling framework also can be used for assessing the social importance of the intra-individual mechanisms discussed above. For example, wishful thinking means that a  $\langle 1, 0, 0 \rangle$  triplet will always be transformed into a  $\langle 1, 1, 0 \rangle$  triplet, and since actors act when they believe that an action will bring about a desired outcome, this pattern will be further transformed into a  $\langle 1, 1, 1 \rangle$  triplet. The sour-grapes syndrome, similarly implies that a  $\langle 1, 0, 0 \rangle$  pattern will always be transformed into a  $\langle 0, 0, 0 \rangle$  pattern.



**FIGURE 4** Initial patterns of beliefs, desires, and actions in a population of 2,500 actors (Each cell describes the current state of an actor's DBA-triplet.)

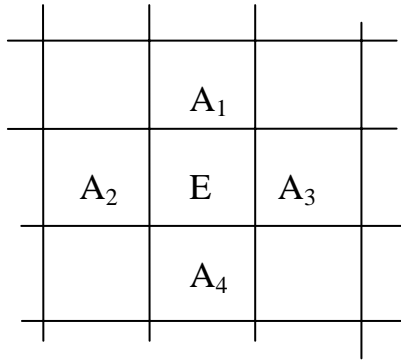
Squares identify actors with positive desires. Circles identify actors with positive beliefs. Black dots identify actors with positive desires *and* positive beliefs; they are the ones who act because they believe that the action will bring about the desired outcome. The white areas of the graph consist of actors who neither believe in the efficacy of the action nor desire the result, and therefore do not act. In the figure, 40% of the actors have positive desires, 40% have positive beliefs, and about 16% act because they are the ones who have positive beliefs *and* desires.

A social structure is introduced into the analysis by assuming that each actor directly interacts with the four neighbors described in Figure 5. If a majority of these four neighbors have a different belief than the focal actor's belief, the focal actor's belief will change. Otherwise, it will remain the same. The desires of the actors evolve according to the same logic. Thus, there will be two parallel contagion processes at work — one operating on the beliefs of the actors and the other on their desires. Actions are the joint outcome of these two processes.<sup>5</sup>

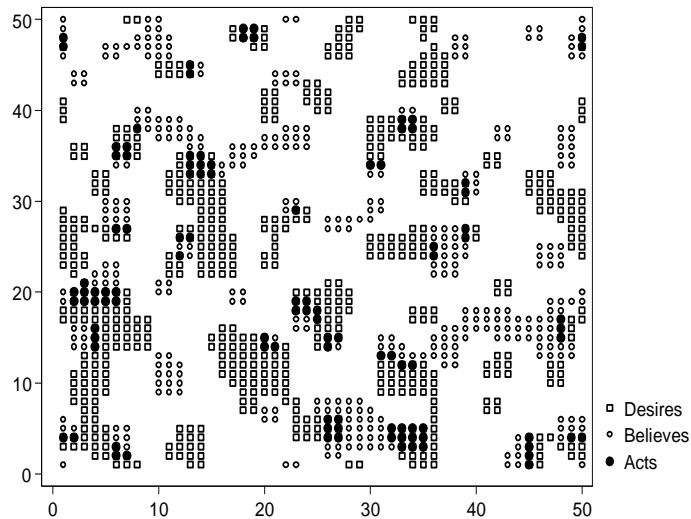
Although the point of departure is an entirely random state-of-nature pattern, the interaction process quickly leads to a lock-in on a highly clustered and segregated pattern. Figure 6 is a typical example of the type of pattern that emerges; in this case, the actors have interacted for 40 rounds.

Running a large number of simulations like these confirms that this pattern is a typical one in the sense that it contains islands of desires and islands of beliefs that occasionally overlap and then lead to actions. Since there are no intrinsic differences between the actors located in

<sup>5</sup> The lattice used here is a so-called torus, that is, a lattice that is wrapped around itself in such a way that actors positioned at the borders of the lattice have neighbors on the other side of the lattice. Hence, all actors have the same number of neighbors. It is assumed that all actors update their desires and beliefs at the same time.



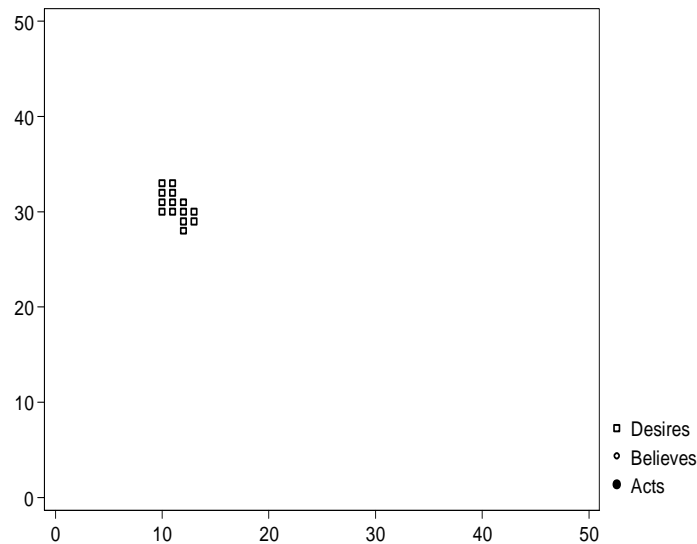
**FIGURE 5** Structure of social interaction between Ego (E) and Alters ( $A_n$ )



**FIGURE 6** Typical patterns of beliefs, desires, and actions in a population of 2,500 actors who socially interact with four neighbors

different regions of this social space, this example shows that social-interaction processes, in and of themselves, can explain social differentiation; that is to say, the tendency of different groups to spontaneously organize themselves into social clusters with different beliefs, desires, and/or actions.

Emergent properties to a large extent depend on how the individual parts (the actors) are interrelated. If, for example, the structure of social interaction is changed in such a way that one of the four neighbors is replaced by a randomly selected actor, the social pattern that emerges then typically looks like that illustrated in Figure 7. The effect of the change in the structure of interaction is rather striking. In the previous simulation, a large number of actors ended up with

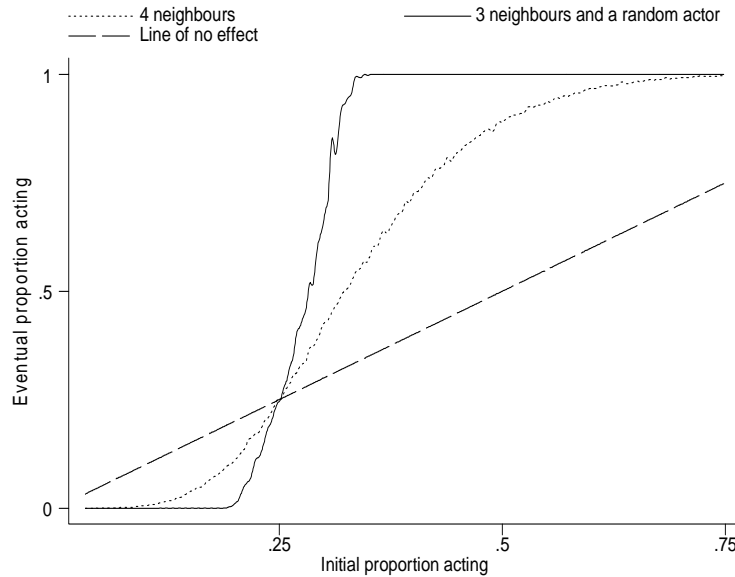


**FIGURE 7** Typical patterns of beliefs, desires, and actions in a population of 2,500 actors who interact socially with three neighbors and one randomly selected actor

positive beliefs and/or desires, and about 1 actor out of 20 acted. In this simulation, however, only a few actors end up with positive beliefs or desires, and no one acts.<sup>6</sup> These differences in social outcomes are exclusively the result of the change in the structure of interaction, since everything else is held constant, including the sequence of random numbers. The reason why this change in the structure of interaction has such a profound effect should be sought in the fact that local belief and desire clusters are much less likely to survive when the actors, through their randomly selected significant other, are exposed to influences from outside their own immediate sphere.

To make sure that these differences between the two interaction regimes were genuine, a large number of simulations were run with different initial values. The results are summarized in Figure 8. The plots in Figure 8 summarize the results of 7,500 simulations and show how the two interaction regimes influence actions. These simulations are based on the same setup as before, that is to say, 2,500 actors who are placed on a lattice with 50 times 50 cells. Their actions were recorded after they had interacted and influenced one another's beliefs and desires for 20 rounds. Normally, a steady state had been reached much earlier; however, typically beliefs and desires locked in on a stable pattern after about 10 iterations. The plots relate the proportion that acts at the (random) outset to the proportion that acts after the actors have interacted with one another. The "line of no effect" indicates when the initial proportion is identical to the proportion that eventually acts.

<sup>6</sup> Had we allowed the simulation to run for a few additional rounds, the isolates with positive beliefs and desires in the middle of the graph also would have become zeros.



**FIGURE 8** Effects on typical actions of two different structures of social interaction

As expected, in both cases the proportion that eventually acts is a positive function of the initial proportion, but there are marked differences between the two interaction regimes. While the four-neighbor structure results in a smooth and gradual relationship between the initial conditions and the final outcome, the three-neighbor structure results in a sharp step-like relationship. In this latter case, the analyses show that no one is likely to act if the initial proportion is below 20%, and that everyone is likely to act if it is above 35%. This means that the two interaction regimes lead to dramatically different outcomes in certain circumstances. If the first interaction regime prevails, the interaction process will lead slightly more than half of the actors to act if one-third of the actors acted at the outset. But under the other regime, that is, when one of the four neighbors is replaced with a randomly selected actor, identical initial conditions will cause more than 9 actors out of 10 to act. These results thus show that there are genuine differences between these two interaction regimes in terms of how they affect actions. If we are to explain differences in the way actors in different groups act, we must pay close attention to the structure of interaction. Even if there are marked differences in how individuals in different groups act, this may simply be due to a small but systematic difference in the structure of interaction.

What I have tried to illustrate with these analyses is how a combination of mechanism-based theories of action and interaction, and agent-based computational models makes it possible to analyze, in a theoretically grounded fashion, how individual desires, beliefs, and actions are the product as well as the producer of large-scale social patterns. As a by-product, some interesting results emerged showing that relatively small changes in the structure of interaction can give rise to large-scale changes at the social level.

## CONCLUDING REMARKS

I have tried to show how the social mechanisms and agent-based communities fruitfully can relate to one another. For sociologists in the social-mechanism tradition, agent-based computational modeling is an indispensable tool for analyzing the relationship between the individual and the social. For agent-based modelers, at least the sociological part of it, I believe that a close integration with the social-mechanism literature also can be beneficial. First of all, computational modeling then could come to have more influence on sociology at large. Secondly, I believe that such a link can help foster a certain theoretically grounded discipline in the way in which action logics are modeled.

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**DISCUSSION:****COMPUTATIONAL SOCIAL THEORY****(Invited Speaker, Saturday, October 9, 2004, 8:30 to 9:30 a.m.)**

Chair and Discussant: *Tom Howe, The University of Chicago  
and Argonne National Laboratory*

**Social Mechanisms and Social Dynamics**

**David Sallach:** I'm very pleased to introduce one of our invited speakers, Peter Hedstrom. Peter and I met about five years ago and enjoyed having an initial discussion about agent simulation and its potential. Peter is an expert in social mechanisms and has made a number of contributions in these areas. From the first, it was obvious that there is a potential for great, fertile interchange between social mechanism work and agent simulation work. As we move toward multi-level, multi-scale models, this interchange will involve the integration of multiple mechanisms. To the extent that competing mechanisms can fill the same kind of niche, it becomes one of the forms that agent experimentation can take. We are anxious to further the dialogue between these two research areas. Nobody is better placed to help us in that regard than Peter Hedstrom. After he speaks, Tom Howe will chair the ensuing discussion and provide some initial comments. Tom is with Argonne National Laboratory. He combined an interest in contributions to social science with development skills, so we'll be interested in his perspective as well.

**Peter Hedstrom:** I'm very pleased to be here. As you understood from David's introduction, when he asked me to come, he asked me explicitly to talk about the relationship between this so-called social mechanism approach that I have been one of the contributors to and its relation to the agent-based modeling community. This is what I will be talking about today.

[Presentation]

**Tom Howe:** This was an important talk to have at this stage in the conference, given some of the discussions that have already occurred, both in terms of agent ontologies and formalistic languages and also in terms of representing agent-based models in terms of empirical data versus simply thought experiments. I want to focus on your discussion of linking agent-based models with the social mechanism literature and with belief, desires, opportunities, etc.

One of the key things that this provides for us is much more of a common language between social scientists and agent modelers. Those of us who have worked with both groups are quite aware that getting either one to talk with the other becomes quite difficult because they are so unaware of the types of language that the other is using. But by using — by structuring — things in this nice, modular, formalistic way, you have the least desires, opportunities, which then, in the proper combination, can lead to action and relation between agents. You provide a nice way to draw or write out a structure in which the two groups can start to talk to each other. And the other piece that is really useful is that by breaking it down into these small, empirical, modular pieces, you really push reuse of the concepts. So this type of dialogue links people from across disciplines a little bit better, in that a concept that might be used in a demographic model

might also very easily be used in a social-movements-type model because the beliefs or the intentions are, at their core, the same. They're just being combined in a different way. This provides a nice language for communication, not just between agent modelers and social theorists, but between social theorists. I want to leave the discussion of mapping the empirical to the agent-based model to the rest of the audience. Are there any questions?

**Claudio Cioffi-Revilla:** Claudio Cioffi of George Mason. I very much enjoyed this presentation because it infuses the design of agent-based models with substantive, rigorous social theory. I think it's high time that we do this in a more direct and explicit fashion.

One question I have is that the DBO [desires, beliefs, and opportunity] model in sociology goes by a different name in political science, where it is known as the opportunity willingness principle. Harvey Starr and I have published a number of formal theorems about that structure, but with a twist. The table that you put up, with ones and zeros, is actually the truth table for the occurrence of action. One way we usually view this is that it is deterministic, as you stated. But then, when you designed the simulation, you rendered things in a probabilistic sense, with the use of a logistic equation. We view the DBO structure probabilistically in political science for the plain reason that for the occurrence of an action, the occurrence of desires, beliefs, and opportunity is never preordained, at least not in general. So our treatment of that is really probabilistic. The complete logic conjunction that must occur for action to obtain ... is something that is governed by some distribution. Would you comment on that because the theoretical foundations that you started out with seemed to be deterministic, but the rendering of the models seemed to be much more probabilistic?

**Hedstrom:** Yes. Thanks. I probably have to give the reference as to the origin of those things. What I talked about today draws upon a book that hopefully will be published in June or July next year. In that book, I discuss probabilistic versus deterministic modeling. My argument is basically that the world is of course probabilistic in some ways, for many different reasons, because there are many things we can't know. If nothing else, it's a way to incorporate our ignorance in modeling things. But I prefer deterministic language because of its economy of expression, its clarity, and so on. However, you think of it as some kind of central tendencies or whatever. So it's not that I want to defend a deterministic language for analysis in principle; rather, it's a convenient way of expressing ideas. Then, being aware of that, there's lots of noise out there that can come in and do things to our analysis. I would very much like to look at what you have written about it.

**Elenna Dugundji:** I'm Elenna Dugundji, from the University of Amsterdam. First of all, I really enjoyed your presentation. It's very much in line with the sort of work that I'm doing, so I hope that you will enjoy my presentation as much as I enjoyed yours.

I have a question regarding the transition from the first part of your talk to the second. In the first part of your talk, you showed how critically important the interaction structure can be, and how just a small change in going from four to three neighbors and one random made a big difference. So I was wondering in the empirical calibration, what interaction structure you assumed among the 59,000 agents. This is a question that I'm also thinking about a lot in my own research.

**Hedstrom:** That's a good question. In the book, it's going to be slightly revised, but here, it's just that I assume that their likely peers are those of the same age in the same neighborhood. So they look on whether they were unemployed or not during the previous week,

and that's what influences it. But in some other papers where I don't use the simulation modeling, I will just do the empirical analysis. I have used other ways of measuring this likely interaction context. And the data things I'm involved in, I've used because we have information about not only where they live, but also what schools they went to, who their families are, where they work, and so on. Of course, those who are unemployed don't work. There are many different alternative interaction contexts that one could look at and then let the data allow the strength of the influence that originates from each of these different contexts. If time allows, I'm going to do that in the book; otherwise, it will be something like this, just to illustrate more how one could do it and to do the detailed analysis.

**Dugundji:** I have a comment. I have a paper that will be appearing next year in *Transportation Research Record* in which I've done exactly this same thing. We looked at a cross-nested logit model and tested different structures, comparing interaction structure with a number of different treatments (a treatment based on a social-demographic group, a treatment based on a small-scale neighborhood, a treatment based on a large-scale neighborhood, and some treatments combining the different small-scale plus demographic and large-scale plus social demographic), and then comparing the influences separately — instead of as one interaction, as two interactions — because maybe people weight the interaction with social network different than their geographic network. I think this may be interesting.

**Roger Burkhart:** In the autonomous agents community, we are coming mostly from the artificial intelligence field, where we actually build working agent systems. They formalize the state of an agent with a similar triplet of beliefs, desires, and intentions (so-called BDI agents). Is it useful to formalize intentions as a propensity to action, whether or not it's blocked from actually being performed? And does your DBO foundation provide a more basic source out of which intentions can arise?

**Hedstrom:** Thanks.

**Michael Macy:** I'm Michael Macy, Cornell University. Thank you very much for a wonderfully refreshing and inspiring presentation. I'm cautiously optimistic that sociology will move in a bottom-up, critical realist direction, and I think your leadership in that process is going to turn out to be really important. I think this is an important paper, and I'm pleased to hear that the book will be coming out soon.

I have three points, two quite small, but one maybe more worth more thought. The first is just on the DBO — that the D, the B, and the O all interact with each other. In cognitive dissonance, opportunities shape desires. John Elster has a book on this subject called *Sour Grapes*. And that is indeed what happens in *Sour Grapes*. With emotions, desires take over and dictate beliefs, or at least ignore beliefs, and ignore opportunities. I think that by adding arrows between the D's, B's, and O's, you can go beyond the sort of instrumental application that you're looking at to include a range of possibilities. So this is really not a criticism; it's actually a compliment, because I think you can extend this in a very powerful way with just a few more arrows between the D, B, and O.

I'll collapse the other two points into one. The second point really is about the calibration. I am very hopeful that agent models can move in the direction that you're suggesting. I would like to see that happen, but I'm not as optimistic about that being successful. My concerns here are not that I wouldn't *want* to do it, but I worry that it isn't so easy to do and can be misleading. Let me just give a couple of instances. I think it's useful for instantiation —

that if we want to instantiate, we should calibrate, and we should calibrate with data that are observed in natural settings. But if we want to test (and this is when I get worried), then when we test I want to go into the lab and do it under controlled conditions, paradoxically, because I'm interested in causal mechanisms and I worry about things like correlation. In the lab I can solve that problem in ways that I just can't do in natural settings. Your focus on mechanisms leads me to be worried about doing this in the field and to want to go into the lab for the data.

Let me just briefly sketch what I'm worried about. I'm worried about two things. One is that wrong models can be proven to be true. The other problem is that true models can be shown to be wrong. Let me quickly sketch how it happens. Let's do this with the Schelling model. I wanted to do it with the unemployment, but I can't think fast enough to do it with a model I don't really understand. Let's assume that Schelling's model is correct. So let's try to calibrate it to London. Let's say we tune it with the correct distribution of preferences from London, the London neighborhood structures and networks, the whole nine yards. What's going to happen is that we know that the process that Schelling is revealing to us is path dependent with a random element. This means that the particular patterns of clusterings are not going to be the same in any two runs of the model. Hence, they're not going to look like what you're going to see in London, so we would reject the model, even though it's true.

Now let's suppose that the Schelling model is wrong. We know that the Schelling model is very robust when the parameters are set in a way that it can be made to work. So we could, in fact, put Houston up there, London up there, New York up there — we could put lots of cities up there and get it to produce the results, even when the model is wrong. And the reason we can do that is that even if we calibrate lots of the parameters, there are always going to be some parameters we don't calibrate — fudge factors, if you will. And you can adjust these things and play around a bit with the functional form, and you can get a wrong model to produce the result you want. So either way it just doesn't work.

**Hedstrom:** As to your first comment [on the DBO], I have actually done that already in my book. In the simulations, I show that I always include a wishful thinking, which is if  $D = 1$ , it leads to  $B = 1$ ; i.e., if you desire something to believe it, it also would be possible. And there is also the sour grapes mechanism, meaning that if  $B = 0$ , it leads to  $D = 0$ . So I've done some simulations along those lines.

I don't think that the type of calibration that I talked about should replace the laboratory or be an alternative to laboratory work. I think one has to do both, in some ways. In that very ideal setting of the laboratory, you have to see if processes actually work out as your theory suggests. That's important in itself. Another thing to see is if they also work like that when you bring them outside the lab. It could be this or that (we have lots of other things going on), or it could be that the lab setting itself frames the actions in such a way that they are different when they are in the lab than when they are out in society. So even if we have a model for which our laboratory experiments in some ways confirm that people in these types of situations behave in a certain way, we still need to check whether they behave in the same way when you move outside the laboratory. You also have to get some sense of the relative substantive importance of these processes because it could be true that this mechanism indeed works as we think, but that in fact it's of trivial importance. We shouldn't attribute any explanatory power to it at all because it just drowns in everything. It could be interesting to know that this works out this way, but we should not exaggerate its importance. To do that, I think we also need to do this real-world experiment and use data outside the laboratory.

I think it's clear. Unfortunately, I think that establishing the strength of these kinds of social interaction effects is exceedingly difficult because you have so many potential selection effects. You mentioned yesterday that birds of a feather flock together. So people in groups may act in the same way, but it has nothing at all for them to influence one another to do it; it's just that they are together. They have self-selected into groups, and it's extremely difficult to empirically separate out this effect. That doesn't mean that one shouldn't try. I think now we are starting to have better and better data on this (like when you actually have population-level data, with fairly rich information, that you can do something, at least). I think it's important to constrain the parameters because, as we can see in these simulations, if you alter a little bit in these agent-based models — oops! You get a totally different result. That's interesting on a theoretical level, but it also means that you have tremendous leeway in explaining anything if you don't have any constraints on the specification of the model or the size of the parameters that you put into the model. So there's dialogue between theoretical specification or models, and calibration is something that is important.

**Burkhart:** Returning to my question on BDI agents (beliefs, desires, and intentions), would it be relatively straightforward to build a formalization that added intentions as an intermediate stage prior to actions, but building on the DBO foundation? And do you know if there have been any attempts to do so?

**Hedstrom:** Certainly that's the way I talk about it in this book. I don't have any model, so intentions are an unobserved construct in these models. But that's the way the model is framed — so that desires, beliefs, etc., make an intention, and the intention is what explains the action.

**Noshir Contractor:** I'm Noshir Contractor of the University of Illinois in Champaign. I'll ditto what others have said in terms of compliments on your presentation. The question I have has to do with the second part, the empirical calibration, as you describe it. Work by Peter Abel and several others argues that when you're trying to use empirical data to calibrate computational models, one of the challenges is whether you used a logit model, which is based on cross-sectional data, to get the probabilities. But you're using the data in a computational model, where you're looking at dynamic processes that these mechanisms are ascribing to. The only conditions under which the dynamic coefficients that you would get from programs like time-series analysis or something along those lines — the only times when dynamic coefficients and cross-sectional regression of logit coefficients are the same is when the data are assumed to be in steady state or stationary. What do you see as the implications of using those cross-sectional coefficients and estimates in running calibrations with longitudinal or dynamic models?

**Hedstrom:** I didn't really explain what I did. It's not cross-sections. It's basically what in sociology goes under the name of discrete-event, time-history models. I follow the individuals week by week, so it's panel data I'm using.

**Mark Fossett:** I'm Mark Fossett of Texas A&M. I really appreciated your talk and am looking forward to your book. I've come to agent-based modeling in part out of frustration with trying to estimate models by using observation or nonexperimental data, even time-series panel data such as you're describing, because establishing the magnitude of causal effects in these systems depends on so many complicated assumptions about which I've become more and more disillusioned. I take a course, then take another course, and the more I understand, the more cautious I am about inferring cause. I turned to agent-based models because I know what's happening and can identify cause within the system, but then I have two dilemmas: (1) going

from a model that I know is not going to map perfectly onto reality, but I know what's going on, and (2) looking at reality in rich detail and not knowing if I know what's going on. You must have wrestled with this. Could you speak to that?

**Hedstrom:** I don't want to be misunderstood. I don't want to argue for some kind of traditional variable-based statistical analysis as a replacement for agent-based modeling. The way I see it is that the ideal way would be to start with stylized agent-based modeling and show on the pure net effect of one particular mechanism that you are interested in, to show that it indeed can generate the pattern that we want to explain, even if we can't understand it completely. When we have done that, the next step is to see what the relevance of this is for the messy world around us, then try to get to things similar to what I did just now. I didn't just estimate the model and make predictions. I estimated the model and then I assumed that this is the decision equation, or this is the way the agents make the decisions. Instead of assuming, say, in your Schelling analysis, that you move if it exceeds a threshold of 30% — instead of having that decision equation — you have the logit equation, and then you run to see what the agent-based simulation model does in normal cases. So the results become very different than if you were just estimating and predicting because you get lots of the kind of social multiplier effects that you would not pick up in a regular statistical analysis.

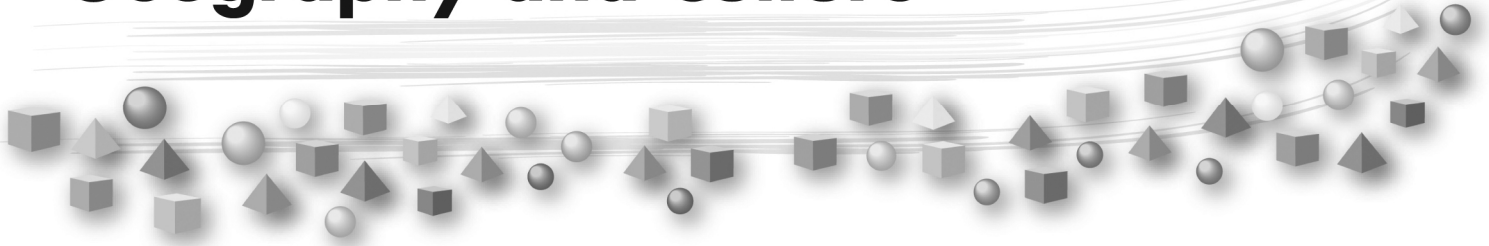
What I'm going to try to do in the book, in some ways at least, is quantitative research to a much larger extent. Instead of believing that they can crank out causal relations directly from the data, they have to start with well-thought-out, agent-base-like models, then use the quantitative data to estimate parameters to put into the agent-based models, and then “round” a bit to simulation models to see what the actors actually bring about in terms of social outcomes — to see some kind of point of contact between agent-based and more traditional quantitative analysis.

**William Lawless:** I think your talk is an important step forward, and I wholeheartedly endorse your comment about the need for experimental data to calibrate against real data. But I also agree with Michael Macy that you need to go back into the laboratory as well. You get these findings, and you've got to go into the lab to test to see just how good the model is. It's at that point that I have problems with the BDI or BU [bottom-up] models. Alice Eagly [Northwestern University] has found very poor correlations with beliefs, desires, and actions, and she's a social psychologist. [Amos] Tversky, the economist [Stanford University], found very poor correlations between the justifications and the actions that had already been taken. And Kelly found virtually no relationship between preferences and choices actually made.

One of the assumptions that you didn't talk about, it seems to me, is that your model is based on no uncertainty. Without the introduction of uncertainty into the model, I'm not sure how far you can go with it. Would you address that?

**Hedstrom:** No, the fact that I didn't add any noise terms or something like that is not that I believe that there are no noises in an individual decision. It was just to explicate the logic of something. I fully agree that if I explore these models further in the future, it would be important to add noise to them. We saw in one of the presentations yesterday afternoon that noise can make a great deal of difference in these kinds of settings. I said that lab work is very important, too, but it can do different things.

# Geography and Culture







## EMERGENCE OF SOCIAL COMPLEXITY IN MESA VERDE BY USING CULTURAL LEARNING IN THE PRESENCE OF BALANCED AND RECIPROCAL EXCHANGE NETWORKS

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T.A. KOHLER, Washington State University, WA

### ABSTRACT

We extend the cultural framework previously developed for the Mesa Verde Village multi-agent simulation in Swarm to include an economic network. Two main social networks are now present: a kinship relation network for generalized reciprocal exchange and an economic network for balanced reciprocity. Agents, or households, are able to procure several resources, including agriculture; the hunting of deer, rabbits, and hares; the collection of wood for fuel; and the acquisition of water. Individuals can exchange surplus goods for needed goods through the exchange network. Currently, agents are only allowed to exchange agricultural produce. We use cultural algorithms as a framework for the emergence of social intelligence at both the individual and cultural level. The knowledge represents the development and use of exchange relationships between agents in both a generalized reciprocal network and an economic network (balanced reciprocal network). The addition of each improves the resilience of the social system. We show that both networks need to be present in order to produce model results that have a good fit with the archaeological data. We also show that both evolved networks are small-world networks but with different parameters. When faced with a drought period, the economic network is depressed more than the generalized reciprocal network and the effects last longer.

**Keywords:** Cultural algorithms, emergence, Mesa Verde, social networks, generalized reciprocal exchange, balanced reciprocal exchange

### INTRODUCTION

Archaeologists excavating the Mesa Verde region in southwestern Colorado stumbled on one of the greatest mysteries of prehispanic history. Many uncovered ruins and settlements scattered in the region reveal the presence of an ancient civilization — the early prehispanic settlers known as the Pueblo Indians, or ancient Anasazi. Scientists scouted the sites and collected detailed information by using the latest geographical information system (GIS) technology, and geological and archeological surveys. As a result, we have ample information on such characteristics as elevation and soil degradation, and on the environment and productivity on the basis of tree ring data (Van West, 1994), to name a few. An important observation of the sites disclosed an event around A.D. 1300, when the settlers abandoned the region. Their disappearance is apparent from the abandoned sites. The Pueblo Indians occupied the region for

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more than 700 years; they farmed the land, built settlements, and domesticated and hunted various animals. Why did these settlers abandon the region?

Many theories have been put forth to answer this question. They include the mini ice age, which made the climate cooler and drier (Dean and Van West, 2002); erosion; the great disease hypothesis; warfare; aggregation activities; and social interaction. A prominent theory tested by Kohler (2000) in a multi-agent simulation model is that environmental factors, especially the long drought in the late eleventh century, caused the inhabitants to move to more sustainable land away from the Mesa Verde region. The model failed, however, to predict the reduction in population associated with known drought conditions in the mid- to late-1100s. Thus, it was suggested that other factors might have played a role.

Follow-up work by Reynolds et al. (2003) and Kobti et al. (2003, 2004) suggests that social and cultural factors motivated the population to evacuate the region, along with environmental variables. The unearthed artifacts and large settlements reveal a sophisticated society rich with language, culture, and community aspects. Kohler's initial model was then extended to weave a social network and embed cultural evolution into the modeled population so as to reflect a more realistic scenario.

Previously, we allowed the population to exchange resources via generalized reciprocal exchange over a kinship network. The emergent network had the properties of a small-world network. In this paper, we add balanced reciprocal exchange into our model, along with the previous network. Our goal is to assess the relative impact of the two emergent networks with regard to their ability to improve system resilience in light of environmental changes.

The current model was developed on Swarm 2.2 (Langton et al., 1995), with environmental data ranging from A.D. 900 to A.D. 1300. Protein resources from deer, hares, and rabbits, and burnable calories from firewood were added. These additional resources increased the complexity of the system and consequently restricted the ability to run the model within a reasonable time on current hardware. Pentium III dual-processor PCs and Pentium IV 3.0-GHz machines would require several weeks to run the model for all the years. The hardware limitations were overcome by porting the model to a high-speed grid computing distributed environment. Twenty independent nodes with dual Xeon processors were configured to compute the simulated model. The model was modified to execute on the grid by implementing the batch mode and to enable parallelization in the model so as to use the Swarm engine's parallel abilities.

In the first section, we introduce the cultural evolution model and the cultural algorithm (CA) framework used to embed social intelligence in the system. Next, we provide an overview of the social network and the composition of the kinship and economic networks. The exchange over these networks is then described. We define the generalized reciprocal exchange as well as the balanced reciprocal exchange that agents can participate in and learn to evolve better exchange choices. Historical, situational, and normative knowledge is collected in the belief space that allows both individual and cultural learning of the exchange networks. In these experiments, we enabled all the resources available to the agents, including maize, deer, rabbits, hares, water, and firewood, but we only allowed maize to be exchanged. In the Methodology and Results section, we describe the effects of using both exchange networks singly and together. The trends generalized from these results are used to show how social intelligence is reflected in population and network volumes.

## CULTURAL EVOLUTION

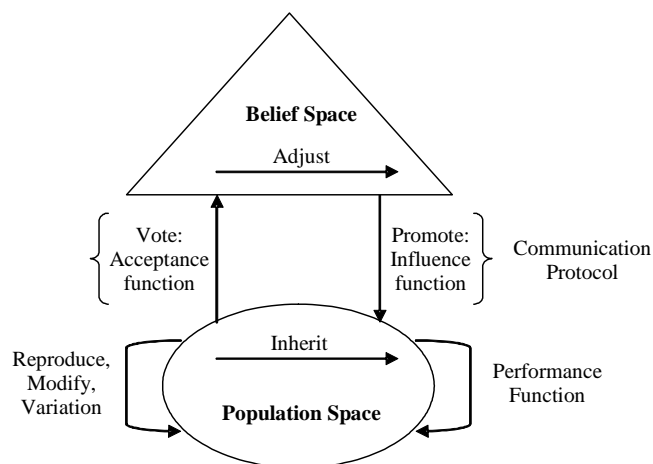
### Evolutionary Adaptation

Holland (1975) developed a formal framework for any generic adaptive system. His framework for adaptation concerns a system that is able to alter its structure and/or behavior on the basis of experience in some set of performance environments (Reynolds, 1979). Adaptability is the capacity to function in an uncertain or unknown environment and to use information to evolve and learn (Conrad, 1983). Adaptation can take place at three different levels: the population, individual, and component levels (Angeline, 1995; Fogel et al., 1966). Cultural algorithms were designed to allow the emergence of social intelligence at all three levels.

Cultural algorithms consist of a social population and a belief space (Reynolds, 1979), as shown in Figure 1. Selected individuals from the population space contribute to the cultural knowledge by means of the acceptance function. The knowledge resides in the belief space where it is stored and manipulated on the basis of individual experiences and their successes or failures. In turn, the knowledge controls the evolution of the population by means of an influence function. A CA thereby provides a framework in which to learn and communicate knowledge at both the cultural and individual levels (Flannery et al., 1989).

### Knowledge Types

There are at least five basic categories of cultural knowledge that are important in the belief space of any cultural evolution model: situational, normative, topographic, historical or temporal, and domain. These knowledge sources were derived from work in cognitive science and semiotics that describes the basic knowledge used by human decision makers (Chung, 1997). In our CA, all of these knowledge sources can be represented and learned. For example, in our current model we assume that agents can acquire knowledge about the distribution of agricultural land as well as wild plant and animal resources (topographic knowledge); the distribution of



**FIGURE 1** Cultural algorithm framework (Reynolds, 1999)

rainfall and water resources (historical or temporal knowledge); agricultural planting and harvesting techniques (domain knowledge); hunting technology; and fuel collection and use. Currently, planting and harvesting techniques are held static. The amount of annual rainfall is also fixed on the basis of tree ring data that are used to estimate the amount of rainfall during each model year.

## SOCIAL NETWORKS

### Kinship Network

The emergent networks in the model are composed of agents. Each agent is a nuclear family or household composed of a husband, a wife, and their children. Household members live together in the same location, share their agricultural production, and are affected by the same environmental conditions. Children can grow up, marry, and move out to form their own households. In our model, their connections to their parent households and siblings are maintained. Similarly, the parents maintain ties to their children. When one of the parents in a household dies, the other can form a new household with an available single agent. The initial structure of the social network here supports the notions of parents, siblings, and grandparents on both sides of the family. The relationships needed to describe the generalized reciprocal network (GRN) from the perspective of a household are shown in Table 1.

The household (agent) rules for marriage and kinship dynamics were described in earlier work (Kobti et al., 2003). The social network is therefore defined as the set of all kinship links.

The simulated model is based on massive amounts of collected settlement and productivity data, with agents initially acting as individual households. The first extension of the model introduced gender, marriage rules, and other localized enhancements to allow individuals to coexist and reproduce. At the next level, the first base network was introduced and known as the kinship network. This is a baseline network that links each individual household to its parents, siblings, children, and other relatives. Over this network, generalized reciprocal exchange was implemented so as to enable the agents to mutually cooperate and exchange resources across the network in order to survive.

**TABLE 1** Connected nodes identified by the kinship social network

ParentHHTagA	A link to the parent from the mother's side
ParentHHTagB	A link to the parent from the father's side
ChildHHTag	One link to each child who moves away from this household and forms its own household
RelativeHHTag	One link to each extended family member

Motivated by individual experience and population norms, an individual, by means of a CA was able to learn and make more intelligent choices in cooperating over the kinship network. For example, an agent can learn to make a better choice when it comes time to decide who to ask for food when in need. Overtime an individual can learn to select more cooperative kin, and indirectly, a population identifies known exemplars and establishes its acceptable norms.

As a result, established individuals became good donors; those in less productive locations needed to depend on the social network for survival. An underlying factor triggered by the dependency on such a social system enabled households to relocate closer to the productive kin and consequently relocated the population to the more productive farm lands. Over time, the clustering of individuals closer together around productive lands was reflected through the hubs in the small-world social network (White and Houseman, 2002). The simulated locations of these hubs were then compared with those community centers known archaeologically, and a good fit was observed. This initial attempt at cultural evolution motivated the notion that culture indeed had a role in population relocations.

## **Economic Network**

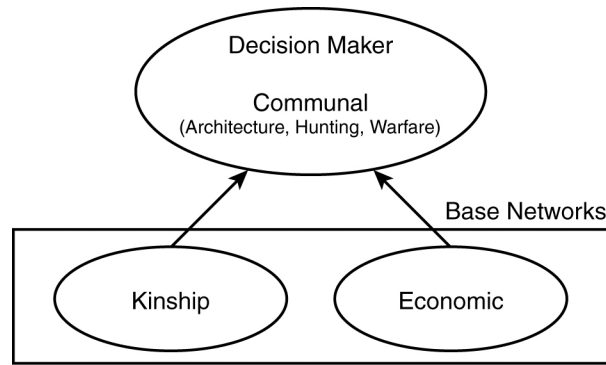
The next phase of development proceeded to implement a second important baseline network — the economic network. Archaeological findings reveal that pottery, tools, and wood, among other artifacts, can be exchanged among individuals. This suggests the potential for economic-based exchange as a mechanism for distributing resources among the agents. To do this, each household essentially maintained a list of trading partners formed mainly from nearby agents who are independent from the kinship network. Individuals adopted a strategy to decide when to exchange and with whom to exchange. In this model, unlike the reciprocal exchange model, individuals needed to keep balances of the amounts owed and traded. The ability of agents to repay their debts reflected their reliability, generalized here as reputation. A well-reputed household is a good producer and without debt, typical of settlers in productive lands or with stronger social ties. Less reliable households resided in less productive lands and had weak social ties. A CA is adopted again in the economic network to guide the decisions that an agent makes in selecting reputable trading partners.

## **USING THE DUAL NETWORKS TO SUPPORT THE EXCHANGE OF RESOURCES**

In this section, we describe how the two networks are integrated together and evolve with the agent population. As shown in Figure 2, agents use both base networks. The performance of agents in these networks can serve as the basis for the formation of community networks at a higher level. We begin with a discussion of generalized reciprocal exchange, followed by a discussion of balanced reciprocal exchange.

## **Generalized Reciprocal Exchange**

The GRN was introduced in previous work (Kobti et al., 2003, 2004) by using a kinship network. The GRN links agents on the basis of their kinship relations and serves to guide the



**FIGURE 2** Overall social network structure, including the two base models and the evolving communal network

flow of resources among relatives on the basis of the states of a giver and a receiver. One individual can request goods from a related individual without the donor expecting explicit payback.

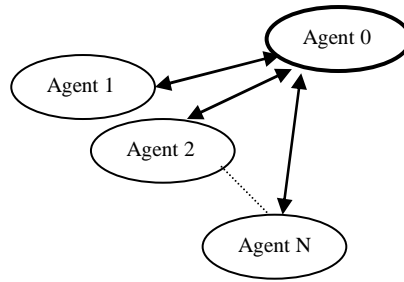
### Balanced Reciprocal Exchange

The balanced reciprocal network (BRN) is an economic network that supports the exchange of goods between neighboring agents. In a balanced reciprocal transaction, the giver expects an immediate payback of an equivalent amount or a deferred payback plus interest. The localization of the exchange between agents in the model is to enforce the physical constraints of travel distance limitations when an agent engages in exchange. This constraint is consistent with what was implemented in the GRN. Each agent maintains a set of trading partners who are not necessarily associated with the kinship network. A trading partner can be any agent within a given radius from the agent.

The overall agent strategy for exchange using both the GRN and the BRN is discussed below. The key idea is that exchange in the current model occurs when an individual is in a state of need in terms of resources. After updating its networks, an agent first tries to satisfy its resource needs by calling in debts from neighbors by using the BRN. If unsuccessful, the agent then requests aid from relatives through the GRN. If there is still a deficiency in terms of resources, the agent goes back to the economic network to acquire them. Figure 3 illustrates the agent connectivity in the BRN.

### Resources

According to archaeological records, the Pueblo Indians were able to harvest maize and hunt deer, rabbits, and hares. In addition, they collected firewood for cooking and heating. Water, of course, was another necessity. In the current model, all these resources are enabled and computed. The household is capable of accessing all of these resources. In this paper, the exchange is limited to maize on both balanced and generalized networks.



**FIGURE 3** Agent connectivity in the BRN; Agent 0 maintains its links with its exchange partners Agents 1 to N

### Integrating Both Networks to Facilitate Exchange

In this section, we provide a brief description in pseudocode as to the two networks integrated together in the current mode. The following actions are performed on each agent by the simulation:

1. Update GRN
2. Update BRN
  - a. Remove dead partners (and nonactive/out of region/expired)
  - b. Search each neighboring cell within a trade radius and get its settlers list and add new ones to the trade list up to a MAX\_TRADE\_LIST
3. Request payback of debt from BRN partners
4. If HUNGRY/CRITICAL
  - a. Request food from GRN (no payback)
5. If HUNGRY/CRITICAL
  - a. Request food from BRN (with payback promise)
6. If CRITICAL
  - a. Agent is DEAD and removed
7. If PHILANTHROPIC/FULL
  - a. (Donate surplus into GRN)
  - b. (Pay back debts owed into BRN)

## METHODOLOGY AND RESULTS

To understand the effect of the balanced reciprocal exchange on the overall population and network resilience, we set up a series of experiments to establish controls and comparison baselines. Table 2 provides the basic levels of cooperation supported by the different sets of experiments. The first step was to execute the model without any exchange. This allowed us to measure the baseline effects of the environment on the population. In the absence of any social cooperation, Figures 4, 5, and 6 illustrate the results of COOP 0 described in Table 2.

Even though the kinship network was not used for exchange, the basic structure of the evolved network was computed. Figure 4 gives the minimum, maximum, and average number of links per agent. The evolved network was again a small-world network with an average of around 4 links per node. The hub nodes, with more but weaker links, were bounded from above by a maximum of 10 to 12 links. Over time, the network volume, which is the product of the degree of the agents in the model, decreased from a maximum of near 2,000 to a value increasingly close to zero, as shown in Figure 5. The corresponding agent population, as shown in Figure 6, also declined to less than 200 agents by the end of the simulation period. This is below what was predicted on the basis of archaeological evidence, which suggests that some type of exchange needs to be present in order to produce more realistic behavior.

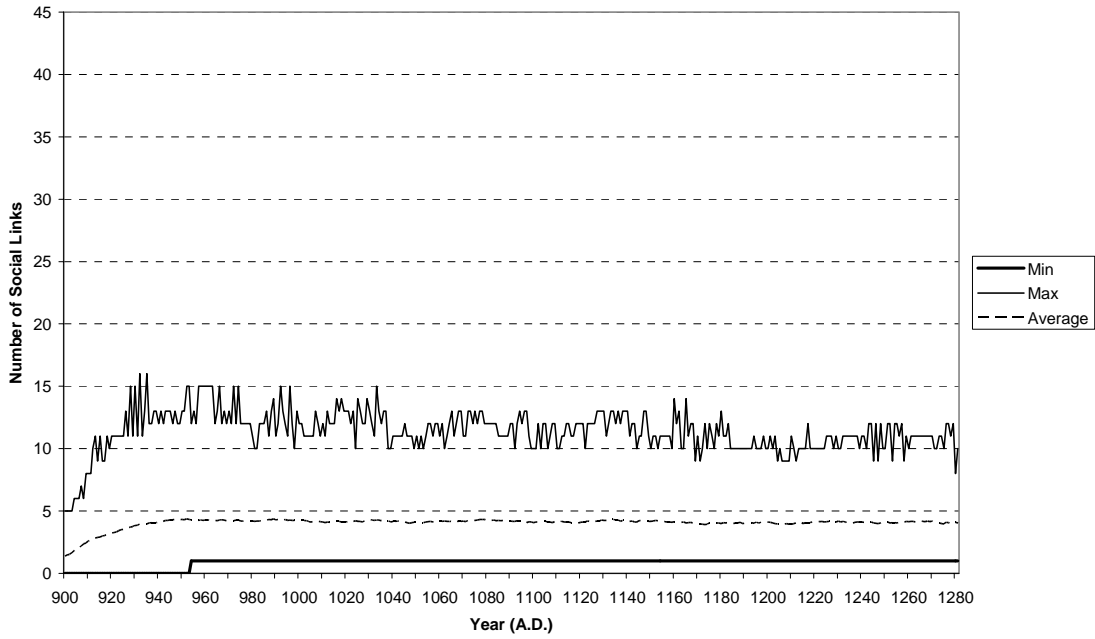
In the next series of experiments, we introduced generalized reciprocal exchange over the kinship network, identified as COOP 3 in Table 2. Figures 7, 8, and 9 illustrate the results of these experiments. By adding in the ability to redistribute resources along kinship lines to the model, the small-world networks produced had an increased average degree, 5, and an increased maximum bound on the size of the hub nodes, around 15. Thus, generalized reciprocal exchange allows the individuals to enhance the kinship network, producing a slightly more complex structure than previously. In Figure 8, we notice that the network volume increased to around 7,000, as opposed to around 500 before. The agent population has correspondingly increased to

**TABLE 2** Description of the different cooperation experiments referenced here

Cooperation Method	Description
0	No cooperation. No exchange of food between households.
1	When an agent requires food, it is allowed to select and request food from within its kinship network in order to survive.
2	When an agent has excess food, above a determined threshold amount, it is allowed to select an individual(s) from its kinship network and donate some of its excess.
3	Both methods 1 and 2 are enabled simultaneously.
4	Full cooperation across the kinship and economic network (generalized and reciprocal exchange simultaneously)

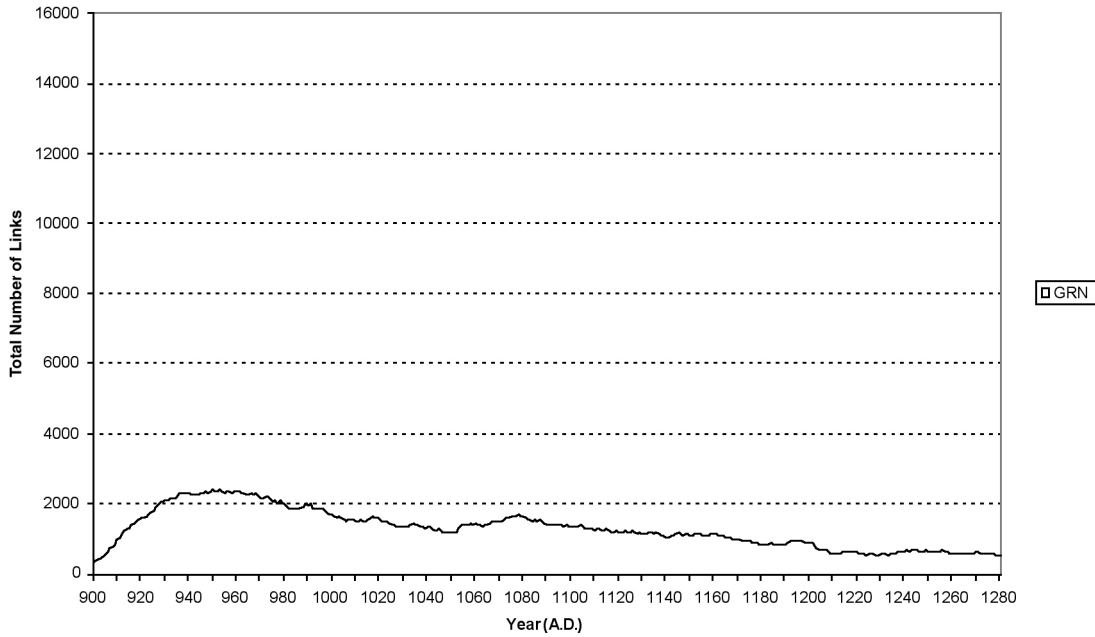


**Social Network Accumulated by Agents Per Year  
(Cooperation 0)**

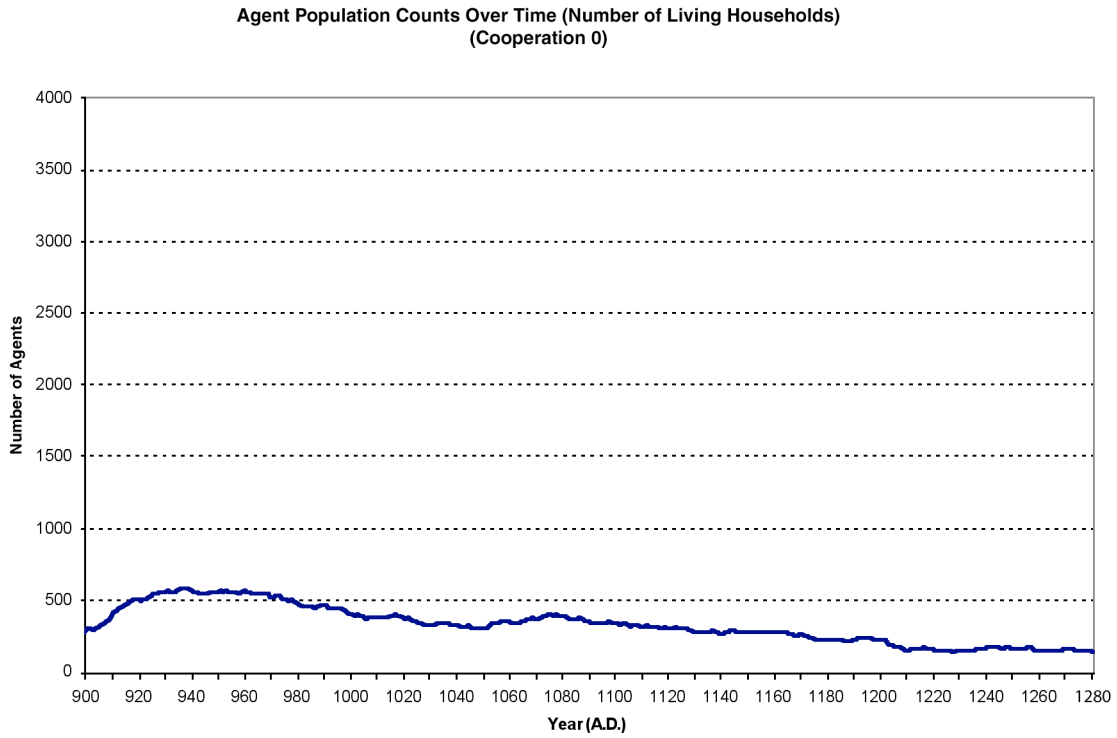


**FIGURE 4** Minimum, maximum, and average node sizes over time, without the presence of cooperation over the kin network (GRN) without any exchange

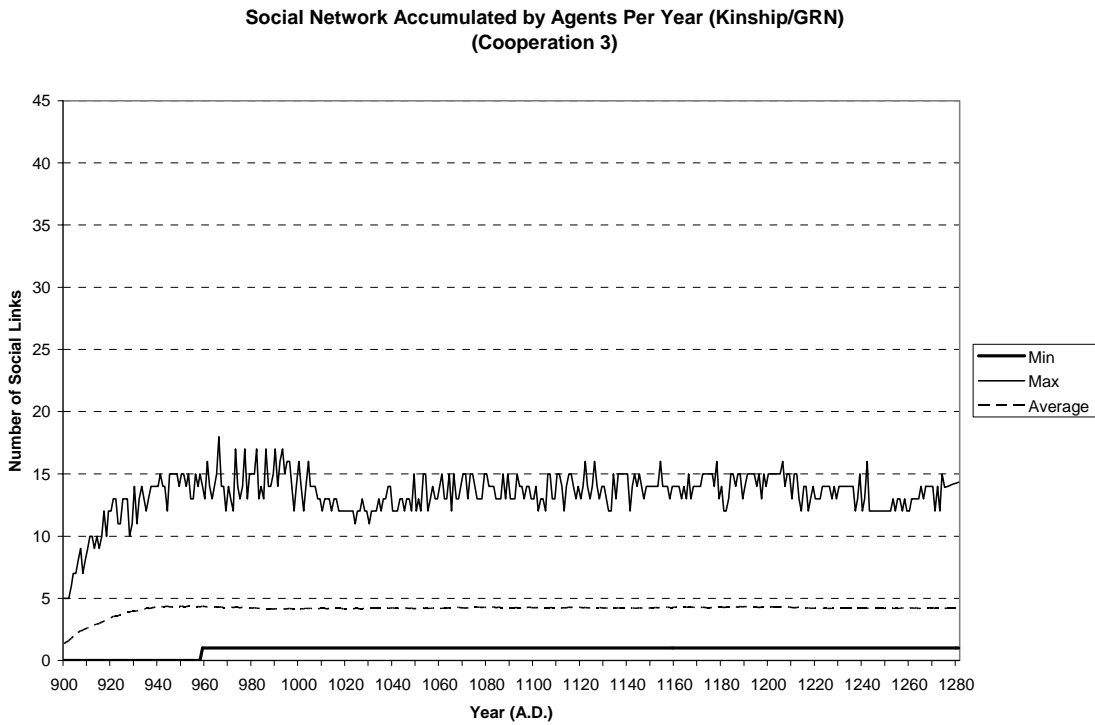
**Volume of Social Network Over Time  
(Cooperation 0)**



**FIGURE 5** Kinship network volume over time, without the presence of cooperation

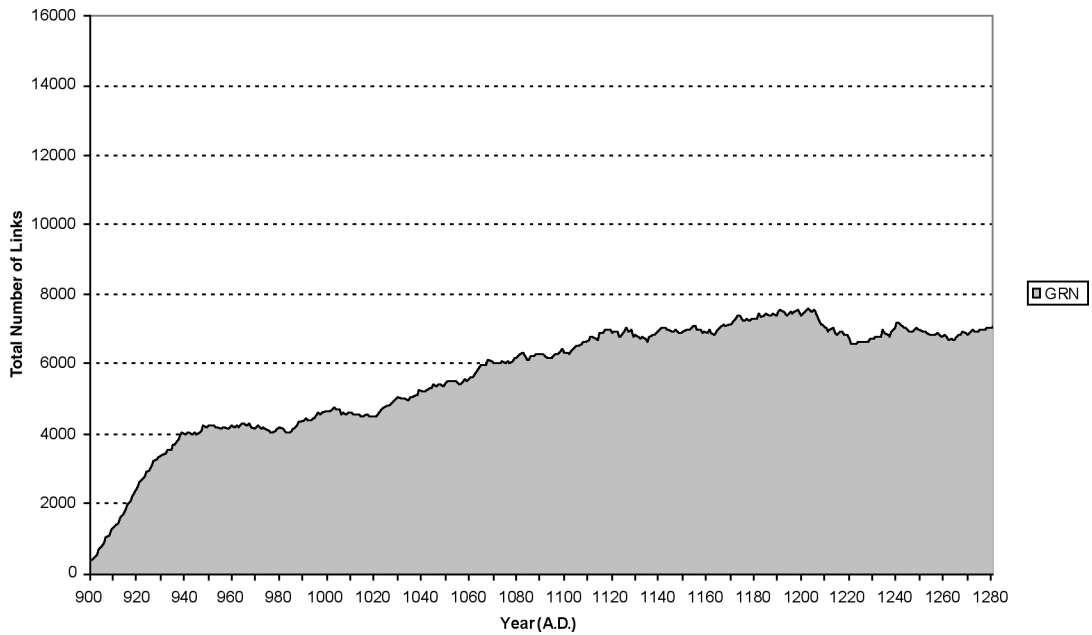


**FIGURE 6** Agent population (number of households) over time, without the presence of cooperation



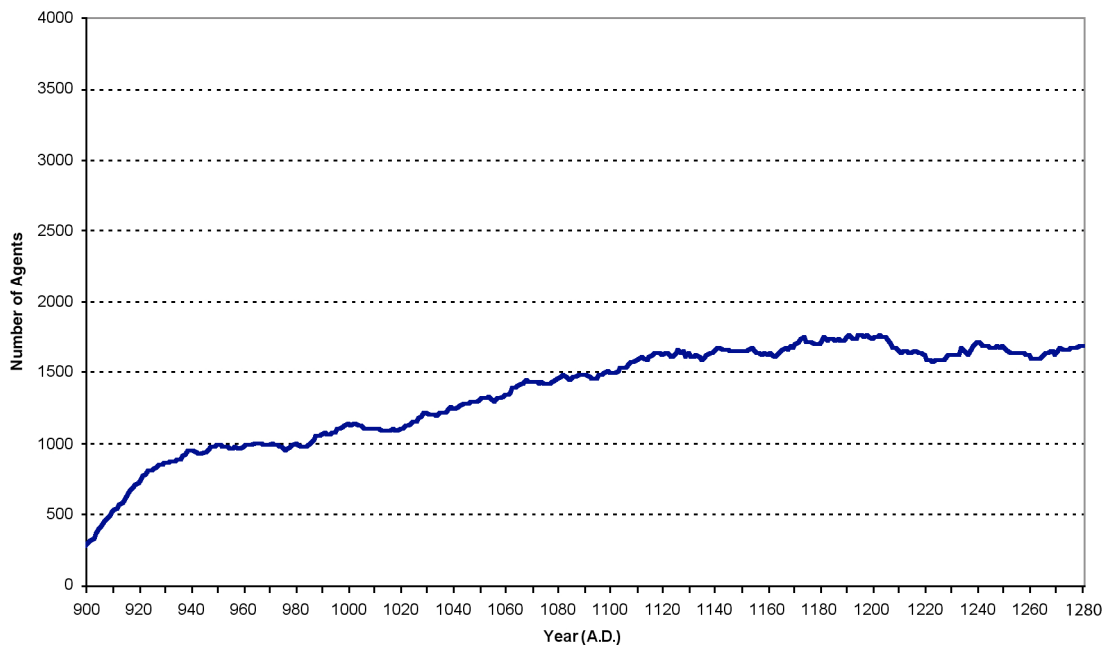
**FIGURE 7** Minimum, maximum, and average node sizes over time, with the presence of generalized reciprocal exchange over the kin network (GRN)

Volume of Social Network Over Time (GRN)  
(Cooperation 3)



**FIGURE 8** Kinship network volume over time, with the presence of generalized reciprocal exchange over the kinship network

Agent Population Counts Over Time (Number of Living Households)  
(Cooperation 3)

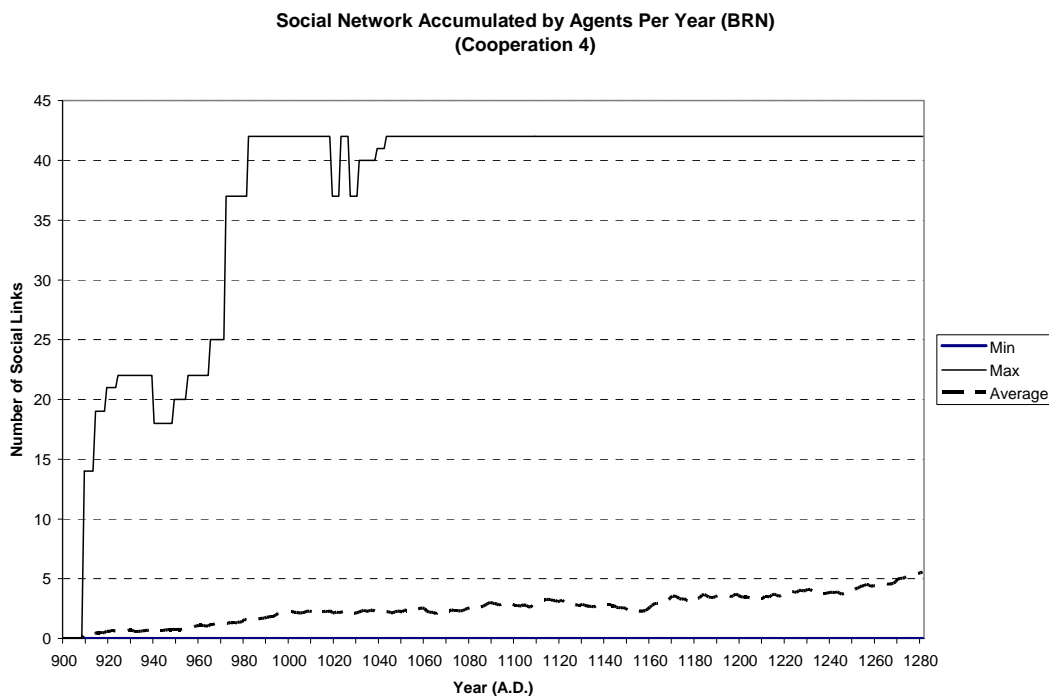


**FIGURE 9** Agent population (number of households) over time, with the presence of generalized reciprocal exchange over the kinship network

around 1,600 agents. This is about 8 times that for the system without any exchange between kin. Still, this is less than the archaeological predictions for the number of agents.

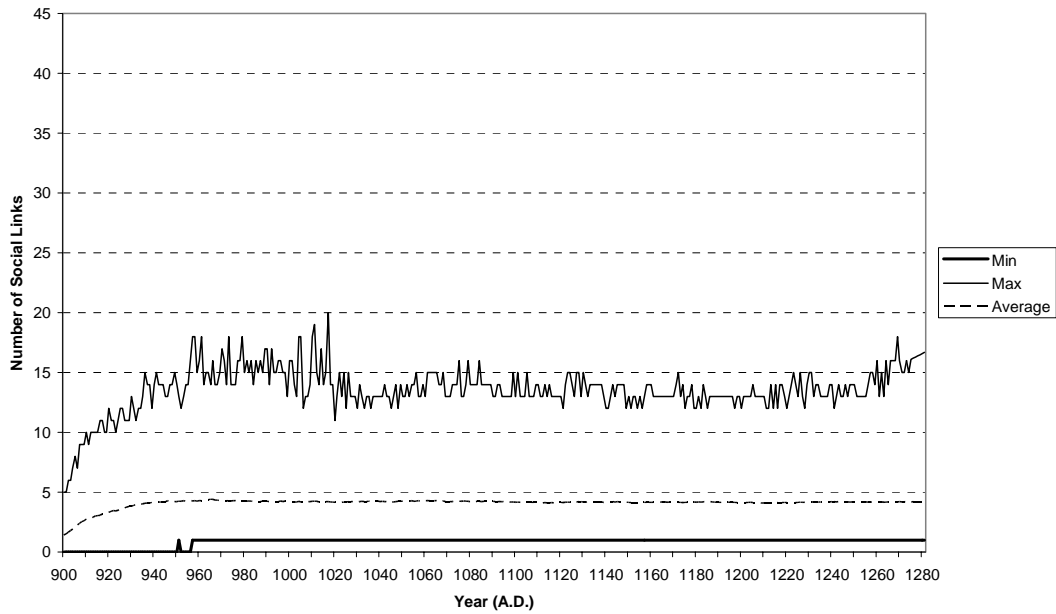
Finally, balanced reciprocal exchange was introduced into the system along with the existing generalized reciprocal exchange. This is described as cooperation level 4 in Table 2. The combined effect of both networks is illustrated in Figures 10 through 13. We can see that the average number of links is still around 5, but appears to be increasing slightly near the end of the simulation period. In contrast, the maximum number of links for the hub nodes has increased to 42, almost 3 times that of the GRN alone. This suggests that the hub nodes for the BRN are linked to more agents, perhaps because the reliability of trading partners in the economic network is less than that for relatives in the kin networks. It also suggests that the network extends and complements the more limited range of the GRN. Figure 11 gives a statistical description of the GRN when used in conjunction with the economic network. The results suggest that the average number of links is the same as previously, although the maximum degree for hub nodes is slightly larger than before.

In Figure 12, the network volume of the GRN and the BRN is given. There, the volume of the GRN exceeds that of the BRN, although the volume of the economic network increases as time goes on. This suggests that there are social needs that are not met by the GRN on its own, and that over time, the groups learn to produce an economic network that gets better at fulfilling those needs. As a result, the population increases to close to 3,000 agents, a much better approximation to the archaeologically predicted number, around 2,800. This suggests that both types of exchange need to be included in order to model real-world patterns produced by the prehistoric system.



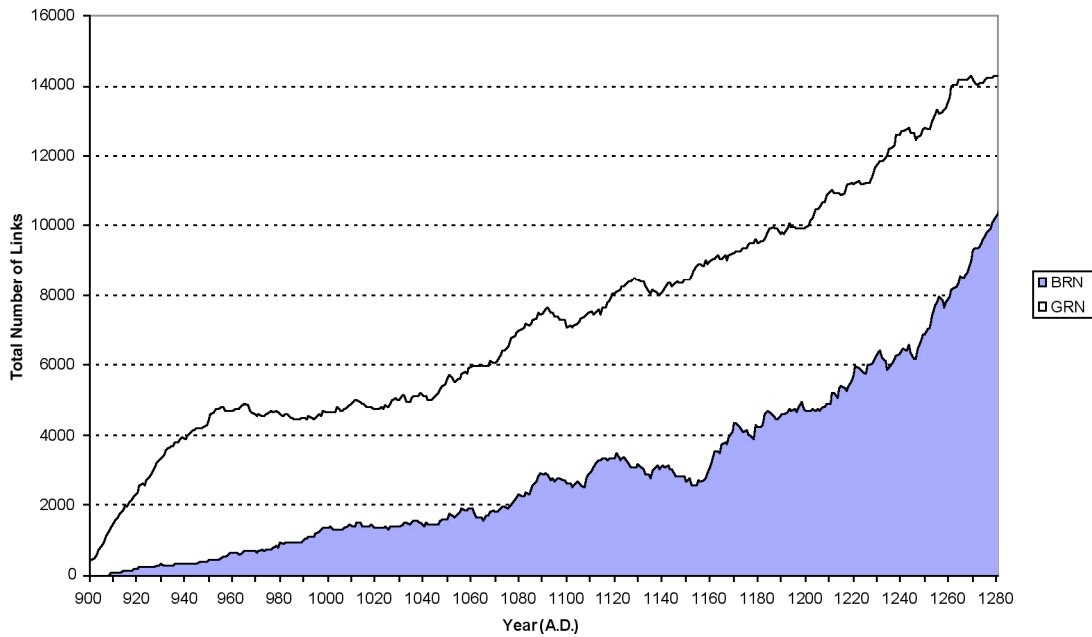
**FIGURE 10** Minimum, maximum, and average node sizes of the BRN over time, with the presence of both generalized and balanced reciprocal exchange over the kin network (GRN+BRN)

Social Network Accumulated by Agents Per Year (Kinship/GRN)  
(Cooperation 4)

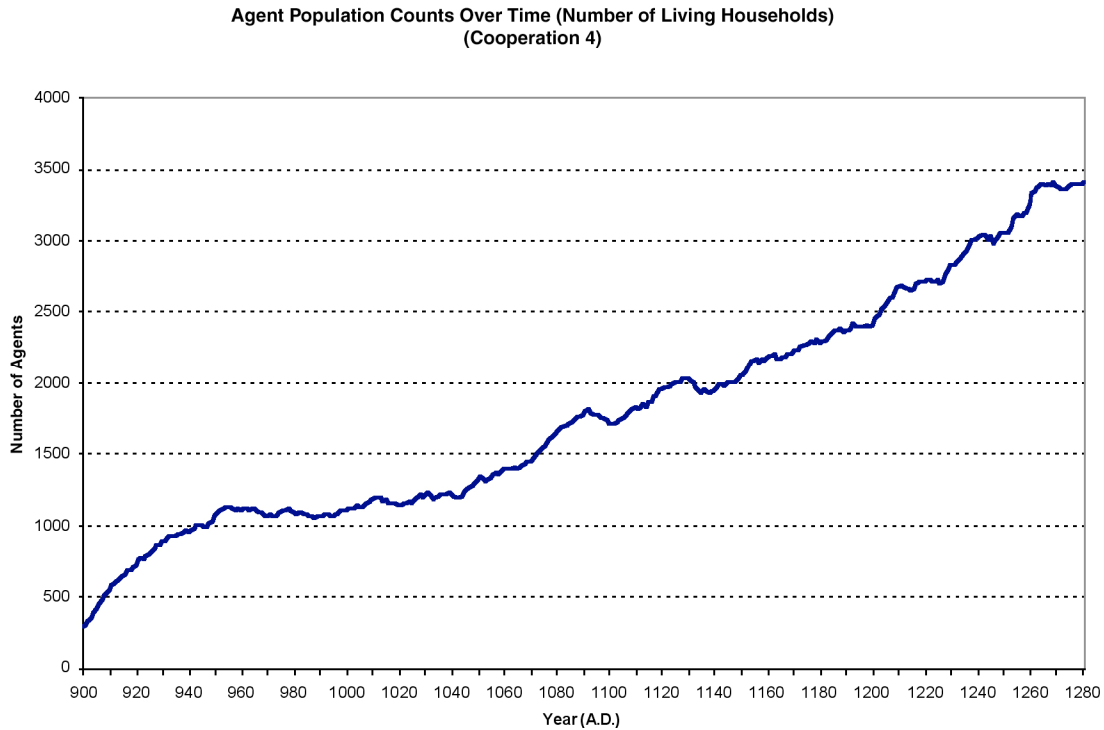


**FIGURE 11** Minimum, maximum, and average node sizes of the GRN over time, with the presence of both generalized and balanced reciprocal exchange over the kin network (GRN+BRN)

Volume of Social Network Over Time  
(Cooperation 4)



**FIGURE 12** Kinship and economic network volumes over time, with the presence of both generalized and balanced reciprocal exchange



**FIGURE 13** Agent population (number of households) over time, with the presence of both generalized and balanced reciprocal exchange

Another issue is that around A.D. 1140, the Little Ice Age reduced available moisture in the valley. This drought impacted the social volume of both networks as shown in Figure 12. Notice that both networks exhibit a dip, but that the dip associated with the kin network is smaller and less prolonged than that of the economic network. The economic network takes more time to recover from the environmental perturbation. It is clear that while the BRN is necessary to improve the distribution of resources among the agents, this network is more sensitive to those situations of environmental stress when it is most needed in order to help out the GRN.

## CONCLUSIONS AND FUTURE WORK

Emergent properties observed in simulated populations of the Mesa Verde Village region reveal a pattern of social intelligence that individual households use to collectively adapt in a CA framework. In particular, the system is able to evolve and to use both a kinship network for generalized reciprocal exchange and an economic network to support balanced reciprocal exchange. The system is not able to develop sufficient social complexity without the inclusion of both resource redistribution networks. Their structures suggest a complementary role for the two networks in which the economic network is adapted by the agents to extend the basic distribution of resources. The economic network's presence is necessary to generate a social complexity that is comparable to that predicted for the real world. However, it also appears that this network is the most sensitive to environmental downturns in terms of the magnitude of its drop and the time it takes for recovery.

In future work, we will extend the range of available productivity data by starting from A.D. 600 rather than A.D. 900. In addition, we will enable agent strategies to exchange all the resources available at once so that we can compare the GRN and BRN networks for each of the resources in order to identify any system fragility with respect to any given resource. This would include all the hunting and firewood collections. Furthermore, communal activities, such as raiding, can be investigated in the model in terms of their impact on the economic network.

## ACKNOWLEDGMENT

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## SOCIODYNAMIC DISCRETE CHOICE ON NETWORKS IN SPACE: IMPACTS OF AGENT HETEROGENEITY ON EMERGENT OUTCOMES

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### ABSTRACT

The reported research treats interactions between households and generated feedback dynamics in the adoption of various transportation mode alternatives. We consider a model where an agent's choice is directly influenced by the percentages of the agent's neighbors and socioeconomic peers making each choice, and which accounts for *common unobserved attributes* of the choice alternatives in the error structure. We explicitly address *nonglobal interactions* within different social and spatial network structures, combining advanced econometric estimation with computational techniques from multi-agent-based simulation, and present an empirical application of the model by using pseudopanel microdata collected by the Municipality of Amsterdam Agency for Traffic, Transport, and Infrastructure. We explore the effects of *additional heterogeneity* introduced into the model through different mechanisms, such as *individual-specific, sociodemographic characteristics* of the agents, as well as *individual-specific attributes of the choice alternatives* and the *availability of alternatives*. We conclude by highlighting the limitations of our present study and giving our recommendations for future work.

**Keywords:** Multi-agent-based simulation, discrete choice, social network, spatial interaction, transportation demand

### INTRODUCTION

A wide spectrum of policy measures has been put forward over the past decade to try to address the infamous rush-hour road congestion in the “Randstad,” the western region of the Netherlands marked by the ring of cities — Amsterdam, Utrecht, The Hague, and Rotterdam. These measures range from flexible work hours to congestion pricing, light rail, facilitation of park-and-ride, and road construction. The research reported here is a small part of a larger work aimed at understanding, measuring, and modeling the combined residential choice and transportation mode choice behavior of households residing in the north wing of the Randstad, that is, the Amsterdam-Utrecht greater region. The focus of the larger work is on the promotion of and facilitation of multi-modal transportation as a land-use transportation planning policy instrument for reducing road congestion (Timmermans et al., 2002; Joh, 2004; Krygsman, 2004; Maat et al., 2004). The contribution of this particular subproject is the treatment of social and spatial interactions between households and generated feedback dynamics in the adoption of various transportation mode alternatives.

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Since the pioneering of Ben-Akiva (1973), Domencich and McFadden (1975), and others in the domain of travel demand, discrete choice analysis has become an industry standard in land-use and transportation planning models. Some subsequent elegant and elaborate operational examples of the development of this methodology can be attributed to Wegener (1996), Waddell (2002), Martinez and Aguila (2004), and Hensher and Ton (2001), to cite just a few. Meanwhile, the field has flourished in the past 30 years, ultimately extending the basic random utility model to incorporate cognitive and behavioral processes, flexible error structures, and different types of data in so-called hybrid choice models (Ben-Akiva et al., 1999, 2002). However, as discrete choice theory is fundamentally grounded in individual choice, an outstanding challenge remains in the treatment of the interdependence of various decision makers' choices, be that via global or local interactions. The formulation of the nature of the interaction in turn raises the issues of networks and network evolution. When considering the domain of land use and transportation, not only social networks but also spatial networks may be relevant (Dugundji et al., 2001).

Some examples of research questions we might like to answer relating to interhousehold networks include spatial coordination/feasibility and social awareness/acceptance in the take-up of various transportation mode choices. If a certain critical mass of households is willing to choose public transit in a particular region or at a particular park-and-ride location, it can become economically viable to provide a high level of public transit service to that region or from that park-and-ride location. Being able to guarantee a high level of service might then in turn attract additional households. On the other hand, lack of a sufficient transit ridership base can be a reason for poor levels of service, which in turn might discourage transit use by segments of the population that have other reasonable transportation mode alternatives at their disposal, which in turn could lead to further cutbacks in level of service and so on. Thus, such interhousehold feedback can have very important implications for predicting (systemwide) results over time. If such feedback exists, it can propel or hinder the adoption of a mode over time. In diverse literature, this dynamically reinforcing behavior is referred to as a social multiplier, a cascade, a bandwagon effect, imitation, contagion, and herd behavior (Manski, 1995). Brock and Durlauf (2001b) give an excellent and extensive literature review.

In the spirit of Aoki (1995), Brock and Durlauf (2001a, 2002), and Blume and Durlauf (2002), we consider a model where an agent's choice to adopt a discrete behavior or buy a discrete product is influenced by the percentages of the agent's reference entities making each choice. An important extension with respect to earlier work is that we now develop results for a case where choice is multi-dimensional or, more generally, where there are common unobserved attributes of the choice alternatives. We revisit a classic approach to statistical prediction in such a situation given an observed sample of decision-making agents in a population, namely the nested logit model. In addition, a key feature of our work is that we explicitly consider nonglobal interactions, with several different social and spatial network structures that we can visualize and analyze by using geographic information system (GIS) tools and techniques.

We present an empirical application of the model to transportation mode choice by using pseudopanel microdata collected by the Municipality of Amsterdam Agency for Traffic, Transport, and Infrastructure (dIVV) in the greater Amsterdam region during the period

1992–1997. Here we combine advanced econometric estimation (Dugundji and Walker, 2005)<sup>1</sup> with computational techniques from the field of multi-agent-based simulation. This paper extends earlier work by Dugundji and Gulyas (2003a,b) by exploring the various effects of social geography and additional heterogeneity introduced in the model through different mechanisms, such as individual-specific, sociodemographic characteristics of the agents as well as individual-specific attributes of the choice alternatives and the availability of alternatives. It is important to note that this additional heterogeneity is beyond the heterogeneity induced by definition through the nonglobal interactions on the socio-spatial network. Finally, we conclude by highlighting the limitations of our present study in any extension for policy considerations on the adoption of innovation in transportation mode choice and giving our recommendations for future work.

## MODEL

Since the early theoretical work of Aoki, Brock, Durlauf, and Blume on binary discrete choice models, a few extensions have addressed both the complexity of the discrete choice model kernel as well as the complexity of the feedback effect and the utility specification. For example, Brock and Durlauf (2002) extended their results on the behavior of binary logit models to multinomial logit models. Dugundji (2003, 2004) makes Brock and Durlauf's multinomial results precise for trinary multinomial choice and extends the results for the case of nested logit with global interactions. Also, while the behavior over time derived in early work assumed that *each* decision maker is influenced by *all* other decision makers (so-called *global* interactions), Dugundji and Gulyas (2003a,b) derived more general behavior for the case where each decision maker is influenced by only a subset of decision makers (so-called *nonglobal* interactions).

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<sup>1</sup> One econometric issue that arises in empirical estimation of such a feedback effect in discrete choice models by using standard multinomial logit or nested logit models, however, is that the error terms are assumed to be identically and *independently distributed across decision makers* (Ben-Akiva and Lerman, 1985). It is not obvious that this is in fact a valid assumption when we are specifically considering interdependence between decision makers' choices. We might reason that if there is a systematic dependence of each decision maker's choice on an explanatory variable that captures the aggregate choices of other decision makers who are in some way related to that decision maker, as considered in the literature referenced above, there might be an analogous dependence in the error structure. Otherwise said, the same unobserved effects might be likely to influence the choice made by a given decision maker as well as the choices made by those in the decision-maker's reference group. In terms of transportation mode choice, for example, accessibility measures for residents in the neighborhood could play such a role to the extent that these are unable to be directly captured through explanatory variables in the utility specification. In this case, the use of transportation mode shares of neighbors living in the same zone as an explanatory variable would be correlated with the unobserved error of the given decision maker, which is a classic case of endogeneity. The results and coefficients of such a model are likely to be biased. To try to separate out effects, it is critically important to begin with a mode as well specified as possible, making use of relevant available explanatory variables. Consequences of omitting significant explanatory variables in the utility specification and improperly accounting for availability of alternatives in nested logit discrete choice models with feedback effects are considered in Dugundji (2004). Dugundji and Walker (2005) continue this exploration of issues in the empirical estimation of discrete choice models with feedback effects by specifically testing for correlation among agents in the error structure in the particular empirical case study of mode choice to work, through the use of mixed generalized extreme value family models.

Importantly, a key to the theoretical results, however, is the assumption that the *only* explanatory variable in the model is the feedback effect. While such a specification may be plausible for a fad, such as the hottest new children's toy, it is much less intuitive for transportation mode choice where other explanatory variables would be assumed to be significant, including both attributes of the alternatives such as travel time, as well as characteristics of the decision-making agents, such as gender, age, and income. Dugundji and Gulyas (2005) thus present initial results using *simulated* data for a binary logit model with nonglobal interactions and other explanatory variables included in the utility with a series of *abstract* random networks. In this paper, we present results for the behavior over time of a nested logit model with nonglobal interactions, using *empirical* data and empirical treatments of which decision makers influence each other defined on the basis of socioeconomic group and spatial proximity of residential location.

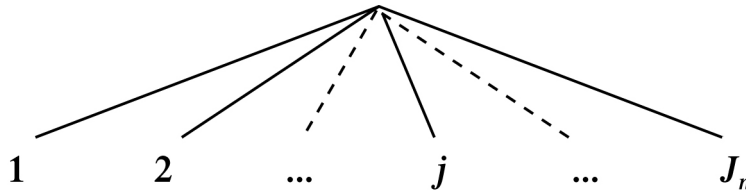
## Multinomial Logit

Discrete choice theory allows prediction based on computed individual choice probabilities for heterogeneous agents' evaluation of alternatives. Individual choice probabilities are aggregated for policy forecasting. In accordance with notation and convention in Ben-Akiva and Lerman (1985), the so-called multinomial logit model well known in econometrics is specified as follows. Assume a sample of  $N$  decision-making entities indexed  $(1, \dots, n, \dots, N)$ , each faced with a choice among  $J_n$  alternatives indexed  $(1, \dots, j, \dots, J_n)$  in subset  $C_n$  of some universal choice set  $C$  (see Figure 1).

Let  $U_{in} = V_{in} + \varepsilon_{in}$  be the utility that a given decision-making entity  $n$  is presumed to associate with a particular alternative  $i$  in its choice set  $C_n$ , where  $V_{in}$  is the deterministic (to the modeler) or so-called "systematic" utility and  $\varepsilon_{in}$  is an error term. Then, under the assumption of independent and identically Gumbel-distributed disturbances  $\varepsilon_{in}$ , the probability that the individual decision-making entity  $n$  chooses alternative  $i$  within the choice set  $C_n$  is given by

$$\begin{aligned}
 P_{in} &\equiv P_n(i | C_n) = \Pr(V_{in} + \varepsilon_{in} \geq V_{jn} + \varepsilon_{jn}, \forall j \in C_n) \\
 &= \Pr\left[V_{in} + \varepsilon_{in} \geq \max_{j \in C_n} (V_{jn} + \varepsilon_{jn})\right] \\
 &= \frac{e^{\mu V_{in}}}{\sum_{\forall j \in C_n} e^{\mu V_{jn}}},
 \end{aligned} \tag{1}$$

where  $\mu$  is a strictly positive-scale parameter that is typically normalized to 1 with the multinomial logit model.



**FIGURE 1** Multinomial choice structure for a given decision making entity  $n$

### Nested Logit

The natural logarithm of the denominator in Equation 1 plays an important role in discrete choice theory when we advance from the basic multinomial logit model to the so-called *nested logit model*. Suppose that the choice set  $C_n$  faced by decision-making entity  $n$  is in fact partitioned into  $M$  mutually exclusive and collectively exhaustive nests  $C_{mn}$  indexed  $(1, \dots, m, \dots, M_n)$ :

$$\begin{aligned} C_n &= \{C_{1n}, \dots, C_{mn}, \dots, C_{Mn}\} \\ C_{mn} \cap C_{m'n} &= \phi, \forall m \neq m' \\ \bigcup_{m=1}^M C_{mn} &= C_n. \end{aligned} \quad (2)$$

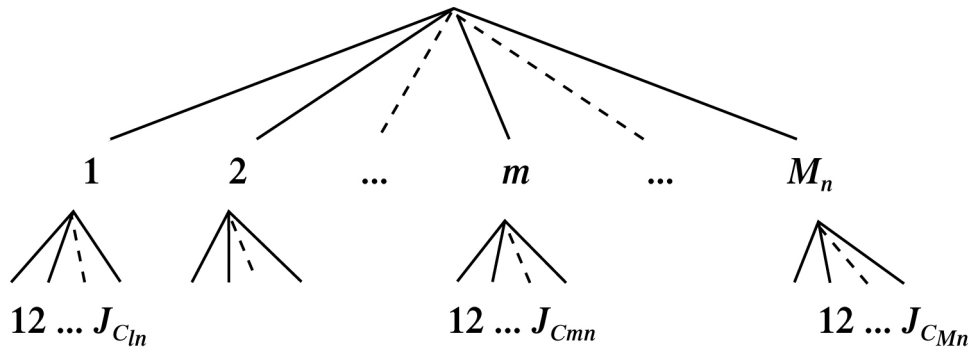
Each decision-making entity  $n$  is faced with a single choice among the mutually exclusive elemental alternatives  $i$  in the composite choice set  $C_n$ . Such a “nested” choice structure is depicted schematically in Figure 2.

Let  $U_{in} = V_{in} + \varepsilon_{in}$  be the utility that a given decision-making entity  $n$  is presumed to associate with a particular elemental alternative  $i$  in its choice set  $C_n$ , where  $V_{in}$  is the deterministic (to the modeler) or so-called “systematic” utility and  $\varepsilon_{in}$  is an error term. Now similarly, let  $U_{mn} = V_{mn} + \varepsilon_{mn}$  be the composite utility that a given decision-making entity  $n$  is presumed to associate with a particular choice subset  $C_{mn}$ . As derived in Ben-Akiva and Lerman (1985), under the assumption of Gumbel-distributed disturbances  $\varepsilon$ , the joint probability that the decision-making entity  $n$  chooses alternative  $i$  within the nest  $C_{mn}$  among all possible alternatives in its choice set  $C_n$  is given by

$$P(i | C_n) = P(i | C_{mn}) \cdot P(C_{mn} | C_n), \quad (3)$$

where the probability of choosing alternative  $i$  within nest  $C_{mn}$ , conditional on having chosen that nest is

$$P(i | C_{mn}) = \frac{e^{\mu_m V_{in}}}{\sum_{\forall j \in C_{mn}} e^{\mu_m V_{jn}}}, \quad (4)$$



**FIGURE 2** Nested choice structure for a given decision making entity  $n$

and the probability of choosing nest  $C_{mn}$  among the set of  $M$  nests is

$$P(C_{mn} | C_n) = \frac{e^{\mu V_{mn}}}{\sum_{\forall m' \in M_n} e^{\mu V_{m'n}}} \quad (5)$$

Each nest  $C_{mn}$  within the choice set  $C_n$  is associated with a “composite systematic utility” given by

$$V_{mn} = \tilde{V}_{mn} + \frac{1}{\mu_m} I_{mn}, \quad (6)$$

where we have the inclusive value  $I_{mn}$ , otherwise known in diverse literature as the “logsum” or the “accessibility”<sup>2</sup>

$$I_{mn} = \ln \sum_{\forall j \in C_{mn}} e^{\mu_m V_{jn}}. \quad (7)$$

The second term in the expression (Equation 6) gives summary information from the lower nests.

## Interaction Mechanism

To make an effort to classify different types of demand-side interaction *mechanisms*, a distinction is hypothesized between social versus spatial interactions and between identifiable versus aggregate interactions (Dugundji and Gulyas, 2003a,b). We speak of interaction between “identifiable” decision makers when the links in the network are well-known and explicitly defined on an individual decision-maker-by-decision-maker basis. We speak of interaction between “aggregate” decision makers when interdependence is assumed to take place only at an aggregate level with links being defined, for example, more generally on the basis of decision-

<sup>2</sup> The term “accessibility” has its origins in the early applications of nested logit models to travel demand analysis.

maker characteristics. We speak of “spatial” network interactions when the interdependence represents a confluence of decision makers in geographic terms. For example, decision makers may be linked on the basis of spatial proximity of residential location, work location, or some other geographic point of reference, such as school, childcare, shopping, healthcare, leisure/recreation, or other relevant location. We speak of “social” network interactions when decision makers are linked on the basis of social circles. The decision makers need not be proximally or tangentially situated in geographic terms, and the interaction is not necessarily centered at a particular geographic point of reference; interaction may take place at a distance, so to speak. Table 1 provides examples of such interactions along these dimensions in the context of transportation mode choice.

The research reported here explores interactions between a decision maker and the aggregate actions of other decision makers proximally situated in a spatial network, and interactions between a decision maker and the aggregate actions of other decision makers associated in a socioeconomic network (mechanisms II and IV in Table 1). Technically, however, interactions between identifiable decision makers (mechanisms I and III in Table 1) may also be modeled by using the approach described here, given the *availability of suitable data*; thus, methods reported here may prove to be useful in those areas as well, up to a point.

Typically, survey data for interaction between identifiable decision makers would include explicit information on the relevant networks for each decision maker for the decision of interest. The members of the networks might then in turn be surveyed. In travel demand data collection, sometimes households from the population are sampled, and then all members of that household above a certain age are surveyed. As of yet, however, the authors are unaware of travel demand datasets that would take, for example, a *snowball sampling* approach, thereby collecting explicit information on interhousehold networks of decision makers. As suggested in Table 1, some examples of research questions we might like to answer related to interhousehold networks include spatial coordination/feasibility and social awareness/acceptance in the take-up of various transportation mode choices. In the absence of survey data on interaction between identifiable

**TABLE 1** Interaction mechanism framework — illustrative examples

Interactions between...	Identifiable decision makers	Aggregate decision makers <sup>a</sup>
Spatial network <sup>b</sup>	I. Coordinating carpooling with neighbors	II. Feasibility of high level of public transit service
Social network <sup>c</sup>	III. Awareness about mode choice alternatives	IV. Social acceptance of cycling/transit

<sup>a</sup> Global interactions between a decision maker and the aggregate actions of other decision makers in the entire sample population (general societal bandwagon effects) may be addressed as the special limiting case of a fully connected network.

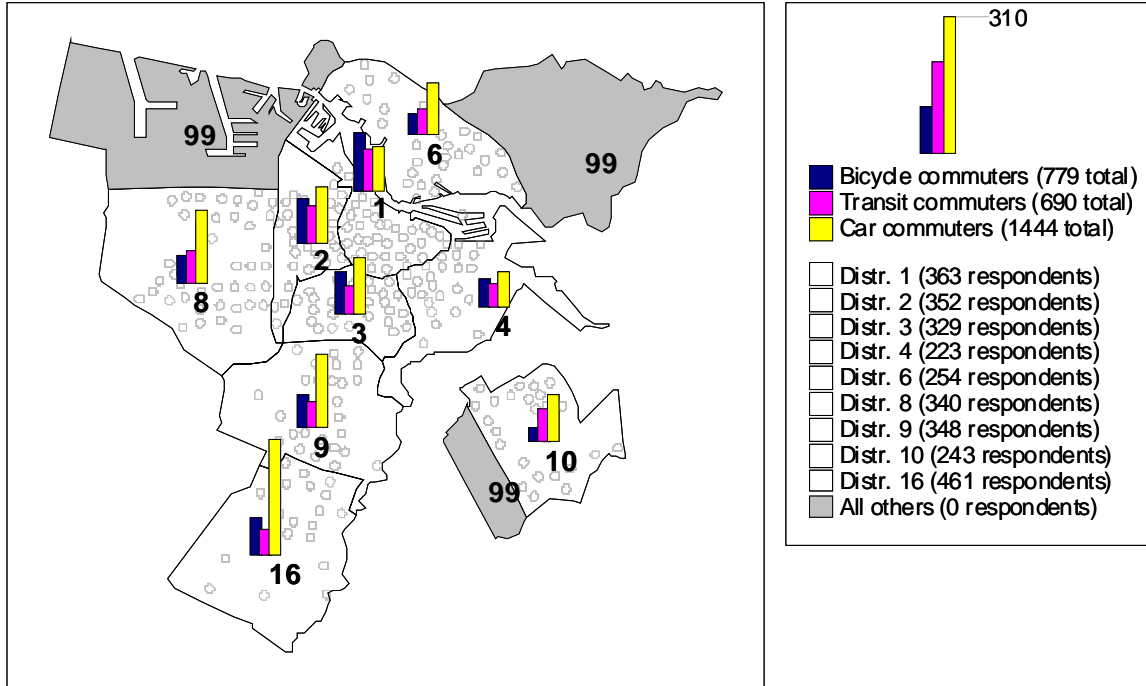
<sup>b</sup> Intrahousehold interactions can be seen as a particular special case of spatial interactions

<sup>c</sup> Not necessarily proximally or tangentially situated in a spatial network; interaction may take place at a distance.

decision makers at the interhousehold level, we turn instead to consider aggregate decision makers and use *a priori* beliefs about the social and/or spatial dimension of interactions to formulate the connectivity of the network.

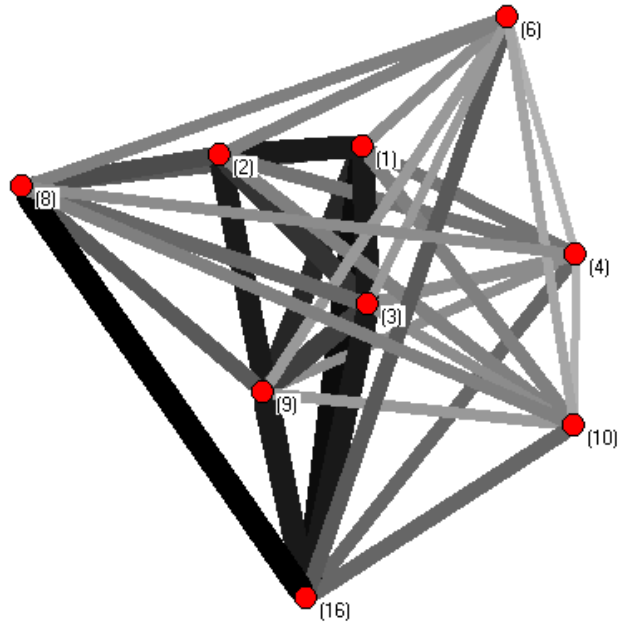
In the case study discussed below, we do not have available data on which identifiable agents influence other identifiable agents' choices. We do, however, have rich socioeconomic data for each respondent as well as the geographic location of each respondent's residence. These data allow us to define aggregate interactions by grouping agents into geographic neighborhoods or into socioeconomic groups indexed (1, ...,  $g$ , ...,  $G$ ) where the influence is assumed to be more likely. In the simplest case, these groups are assumed to be mutually exclusive and collectively exhaustive. That is, each agent  $n$  belongs to one and only one group  $g$ . The agent is influenced by the average choice behavior of his or her group; and the influence by other groups is assumed to be negligible. Figure 3 illustrates the transportation mode shares for decision makers in the sample grouped by residential district.

At a global level, the picture is a fragmented or disconnected network of clustered groups. If we are interested in equilibrium behavior, the consequences of such an assumption are important: influence is not transmitted across groups, and the global picture is a weighted average behavior of the separate clusters. Thus, we consider the case with overlapping groups, with agents, for example, connected by social group as well as by residential district. This leads to a giant cluster for the empirical example under consideration, with the important implication that influence can spread throughout the entire population. Such a network is abstractly visualized in Figure 4 by using the freely available software packet Payek developed by Batagelj



**FIGURE 3** Commuter mode count for decision makers grouped by residential district





**FIGURE 4** Visualization of network defined by residential district plus socioeconomic group

and Mrvar.<sup>3</sup> Red dots represent fully connected residential districts as in Figure 3; the darkness and width of lines give an indication of the number of links between districts induced by socioeconomic group.

## EMPIRICAL APPLICATION

The data used in this paper were derived from activity-based travel questionnaires administered by the dIVV during the period 1992–1997 in Amsterdam and a neighboring suburb to the south of the city, Amstelveen. The dataset made available October 2003 by the dIVV is a subset of the full modal split database containing only the direct home-work trips and direct work-home trips, where the purpose of the trip at the nonhome location is classified as either “work” or “business.”<sup>4</sup> Geographic location is given in terms of the centroid of a traffic analysis zone (TAZ). There are 381 TAZ centroids in Amsterdam and 48 TAZ centroids in Amstelveen,

<sup>3</sup> See <http://vlado.fmf.uni-lj.si/pub/networks/pajek>.

<sup>4</sup> Presumably, there may be a bias in commuter mode choice incurred by only having direct home-work and direct work-home trips in this particular subset of the database. For example, we might hypothesize that there is a potential flexibility afforded by the car in carrying out complex trip chains. If so, the proportion of car users might be underrepresented in the dataset as compared with the population share of all commuters, as the car users may be disproportionately excluded in the set of commuters making stops on the way to and from work. For this case study, we proceeded under the assumption that any extensions to population shares are only made for shares of direct work-home or direct home-work trips, and not for population shares of all commute trips.

with a total of 933 TAZs in the whole of the Netherlands.<sup>5</sup> The subset of data received includes records of trips where respondents indicated the following mode choices: external system public transit or internal system public transit, car driver or car passenger, and bicycle or moped/motorcycle. The data were organized by trip and grouped by respondent.

Development of a tour-based model is beyond the scope of this case study. Furthermore, gaps in the available data because of having only direct home-work and direct work-home trips and thus incomplete and/or ambiguous tour information pose additional challenges. Thus, a trip-based trinary mode choice model is considered here. However, because one of the central research questions to be answered concerns the explanatory power of the average choice behavior in a residential neighborhood on a given respondent's commute mode choice, having multiple trips over the course of the day for one individual in the sample could bias results. That is, the research question could be confounded with and confound decision making, correlation, and constraints of mode choice of trips at the tour level and respondent level, with the research question. It was therefore decided to include only one trip per person in the sample. In practice, the one trip per person was selected on the basis of being the first trip in the day for which there were data for a given respondent. While not a perfect solution (particularly if a respondent happened to travel by different modes on an outward versus return journey), compared with the corrections necessary when including multiple trips per person and treatment of ambiguous information because of having only direct trips, the chosen approach was deemed the most appropriate for this case study. The final sample used in the case study contains 2,913 agents.

### Fully Connected Network: Docking Repast against an Analytical Benchmark

Our first step was to estimate a simple nested logit model with a fully connected network where the only explanatory variable in the model is the network interaction variable (Table 2).

The descriptions of the agents are perfectly homogeneous at this point, since we do not include any sociodemographic information yet about the agents; we do not include attributes of the home-to-work or work-to-home trips yet for each of the agents; we do not take availability of transportation mode alternatives yet into consideration; the network is assumed here to be fully connected; and the model includes self-loops, that is, each agent counts its own choice in

**TABLE 2** Estimation results for a simple nested logit model with fully connected network<sup>a</sup>

Variable	Coefficient Estimate	Standard Error	<i>t</i> -Statistic
Share of respondents in the sample choosing each mode	2.76	0.16	1.78 (against 0)
Scale parameter for transit-car nest	1.03	0.05	0.67 (against 1)

<sup>a</sup> Summary statistics: null log-likelihood: -3,200; final log-likelihood: -3,035; likelihood ratio test: 331.

<sup>5</sup> The samples are stratified by residential location. With the travel mode choice model at hand, we have an exogenously stratified sample and the usual estimation procedure for a simple random sample applies.

evaluating the choices made by reference agents. This is a case for which the steady-state solutions of the sociodynamic system can be solved analytically as derived in Dugundji (2003, 2004).

There are five solutions of this simple nested logit system for the particular given parameter values as estimated in Table 2. Three of these solutions are stable, and two are unstable. Because of the symmetry of the system where transit and car are nested together, at any mode share value for which there is a solution for transit, there will be a dual solution with an analogous mode share value for car, and vice versa. The most stable solution occurs with a mode share for bicycle of 0.700 and mode shares for transit and car each of 0.150 (see Table 3). In practice, we do not expect to see the saddle node solutions. Also, given that the initial starting conditions for the sample are almost 50% car travelers and less than 25% transit users, we might expect in practice that stable solution 2 listed in Table 3 with mode share 0.698 for car and mode share 0.143 for transit will more likely to be reached than its dual solution 3 with the mode shares reversed.

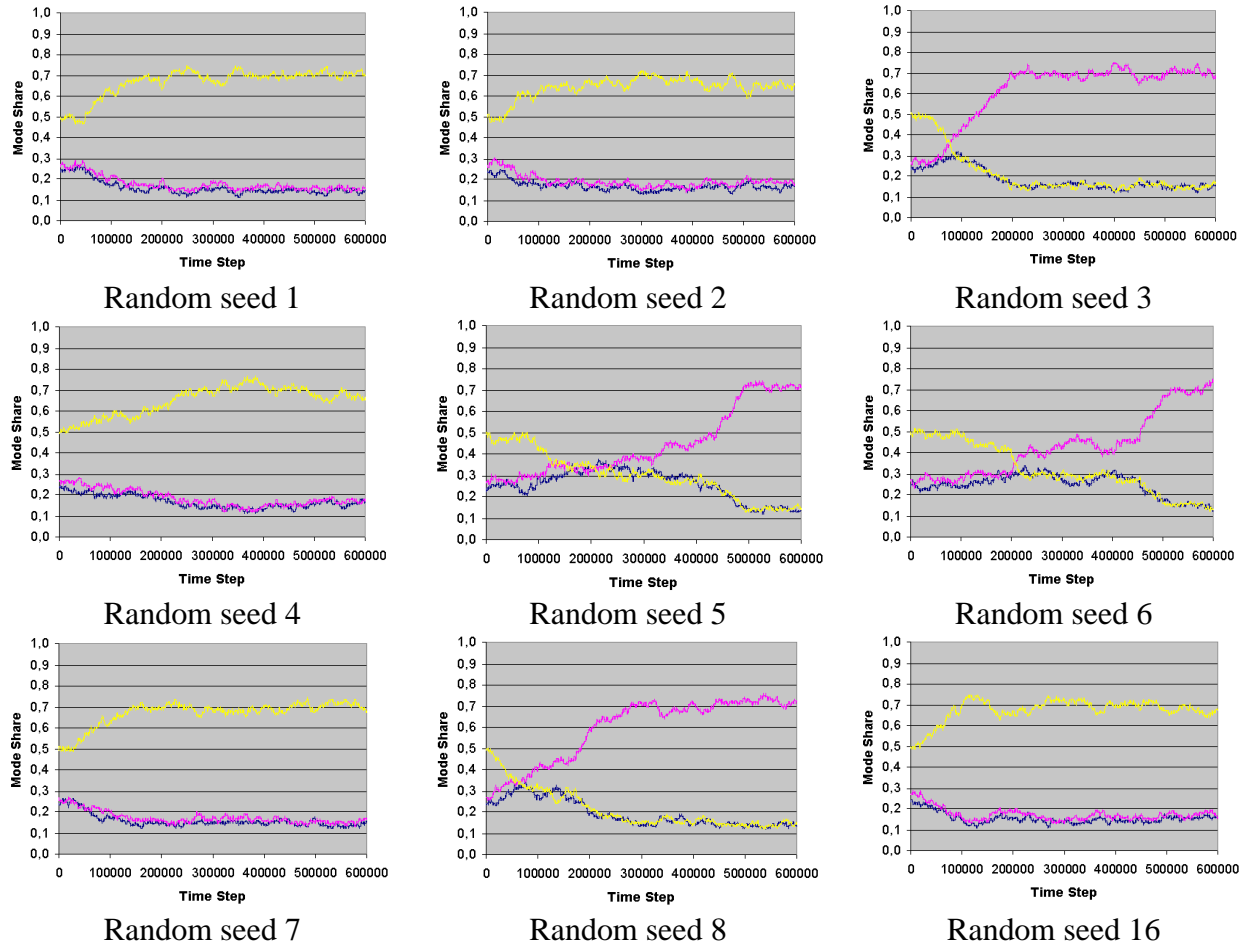
Next, we used the Repast agent-based modeling platform<sup>6</sup> to create a computational version of this model. Example time series results are shown in Figure 5.

In Figure 5, the yellow time series represents agents choosing cars, the pink time series represents agents choosing bicycles, and the blue time series represents agents choosing public transit. Each run is allowed to iterate for 600,000 time steps. This is on average 200 revisions of choices with asynchronous decision making for the sample size of roughly 3,000 agents. We obtain precisely the analytically predicted first two equilibrium solutions in Table 3.

**TABLE 3** Analytical benchmark equilibrium solutions for the simple nested logit model

Stable Solution No.	Stability	Mode Share		
		Bicycle	Transit	Car
1	Most stable	0.700	0.150	0.150
2	Stable	0.158	0.143	0.698
3	Stable	0.158	0.698	0.143
4	Saddle node	0.267	0.237	0.496
5	Saddle node	0.267	0.496	0.237

<sup>6</sup> See Repast Web site (<http://repast.sourceforge.net>).



**FIGURE 5** Example time series for the simple nested logit model with different random seeds

## Heterogeneous Agents

Next, we consider a more empirically interesting case with heterogeneous agents. The model is a trinary transportation mode choice model, with alternatives public transit (pt), bicycle/motorcycle (bi), and car driver/passenger (ca). Raw variables available for use in the model are defined as follows:

availpt	1 if public transit alternative is available, 0 otherwise
carown	1 if <i>decision maker</i> owns a car, 0 otherwise
gender	1 if female, 0 if male
age	Respondent's age category: 12–17 years; 18–29 years; 30–44 years; 45–59 years; 60 years and older
income	Respondent's income category based on Dutch governmental classification: 0–5,000 NLG; 5,000 AOW; AOW social minimum; social minimum zkf; zkf+
education	Respondent's education category: elementary education (LO); lower vocational education (LBO); high school education (MO); post-high-school education (HO); other

ivtpt	In-vehicle-time in minutes with public transit
ovtpt	Out-of-vehicle-time in minutes with public transit (access and egress, waiting, transferring, etc.)
ttbike	Travel time in minutes with bicycle
ttcar	Travel time in minutes with car
parktca	Time in minutes to park car

Various *piecewise* linear specifications of all travel-time-related variables (ivtpt, ovtpt, ttbi, ttca, parkt) as well as age (defined by the midpoint of the age category) were tested against linear, quadratic, and logarithmic forms of these variables. Considering various *a priori* hypotheses of behavior in the region and after statistical comparison of the alternative nonlinear specifications of variables against the linear versions thereof using log-likelihood ratio tests and non-nested tests (Ben-Akiva and Lerman, 1985), the following definitions are ultimately used in the baseline model:

lnage	Natural logarithm of age in years
age4559	Max [0, min (age – 45, 15)]
ivtsqpt	In-vehicle time in minutes with public transit, squared
lnttcar	Natural logarithm of travel time in minutes with car
parktsqcar	Time in minutes to park car, squared
aowmin	1 if income category AOW-social minimum, 0 otherwise

In addition, bicycle availability is defined as follows:

availbi75	1 if travel time by bicycle is less than 75 minutes, 0 otherwise
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## Sociogeographic Network Interdependence

Now we turn to the specification of the network interdependence. We begin with a broad classification by residential district (Figure 3). Nine districts are represented in the sample, ranging in size from 223 to 461 sampled respondents. The mean size is 323 respondents, with standard deviation 74, skewness 0.32, and kurtosis 0.19. Next, using the three variables age, income, and education, 13 socioeconomic groups are defined (see Table 4). The groups range in size from 99 sampled respondents to 385 sample respondents. The mean size is 224 respondents with standard deviation 111, skewness 0.33, and kurtosis –1.8.

Three new variables are then created:

dsdptnsl	Share of respondent's fellow district residents and socioeconomic peers in the sample choosing public transit
dsdbinsl	Share of respondent's fellow district residents and socioeconomic peers in the sample choosing bicycle
dsdcansl	Share of respondent's fellow district residents and socioeconomic peers in the sample choosing car

The designation “nsl” refers to “no self-loops.” That is, the respondent's own choice is not included in the average behavior in the district perceived by a given respondent. The

**TABLE 4** Mode share for direct commute trips and sample count by socioeconomic group

Socioeconomic Group <sup>a</sup>	Mode Share			Sample Count
	Public Transit	Bicycle, Moped, or Motorcycle	Car Driver or Car Passenger	
12–29, LO/LBO	0.31	0.24	0.45	112
12–29, MO/other	0.32	0.27	0.41	385
12–29, HO	0.34	0.30	0.36	329
30–44, LO/LBO	0.24	0.20	0.55	117
30–44, MO/other, 0–z kf	0.29	0.26	0.45	353
30–44, HO, 0–z kf	0.21	0.41	0.37	361
30–44, MO/other, z kf+	0.17	0.11	0.72	115
30–44, HO, z kf+	0.14	0.22	0.63	338
45–up, LO/LBO	0.16	0.23	0.61	175
45–up, MO/other, 0–z kf	0.21	0.27	0.52	175
45–up, HO, 0–z kf	0.20	0.35	0.46	101
45–up, MO/other, z kf+	0.15	0.15	0.70	99
45–up, HO, z kf+	0.17	0.24	0.59	193
Sample count	690	779	1,444	2,913

<sup>a</sup> Defined on the basis of age category in years, education category, and income level. Education is coded: elementary education and lower vocational education (LO/LBO); high school education and other (MO/other); and post-high-school education (HO). Income category is based on the Dutch governmental classification: z kf+ indicates the high-end incomes, 0–z kf is all else. Where income level is not explicitly specified, respondents from all incomes falling in the given age/education group are included.

specification of these variables is generic with coefficient DSDNSL. There are two main motivations for choosing a generic specification, namely, simplicity and identification. The specification could be relaxed with the estimation of three distinct coefficients, but then we would *per se* need to estimate the coefficient as a random parameter.

### Specification of Utility Functions

The systematic utilities for the model are specified as follows for public transit (PT), bicycle/motorcycle (BI), and car driver/passenger (CA):

$$V_{PT} = ASC_{PT} + GEND_{PT} * gender + OVT_{PT} * ovtpt + AGE4559_{PT} * age4559 + LNAGE_{PT} * lnage + IVTSQ_{PT} * ivtsqpt$$

$$V_{BI} = ASC_{BI} + GEND_{BI} * gender + TT_{BI} * ttbike + AOWMIN_{BI} * aowmin$$

$$V_{CA} = ASC_{CA} + CAROWN * carown + GEND_{CA} * gender + LNNTT_{CAR} * lnnttcar + PARKTSQ_{CA} * parktsqcar$$

First, a baseline multinomial logit model is estimated. Next, estimation of three successive nested logit models — first with public transit nested with bicycle, then with public transit nested with car, and finally with bicycle nested with car — shows the first nesting structure to be most significant in terms of the loglikelihood ratio test and in terms of the  $t$  test on the nest coefficient. The third nesting structure was not indicated. The nested logit model thus adds one additional parameter to the multinomial specification, namely, the scale parameter  $\mu$  for the transit-bicycle nest. Table 5 provides estimation results for the multinomial logit and final nested logit model.

### Multi-agent-based Simulation for the Multinomial and Nested Logit Models

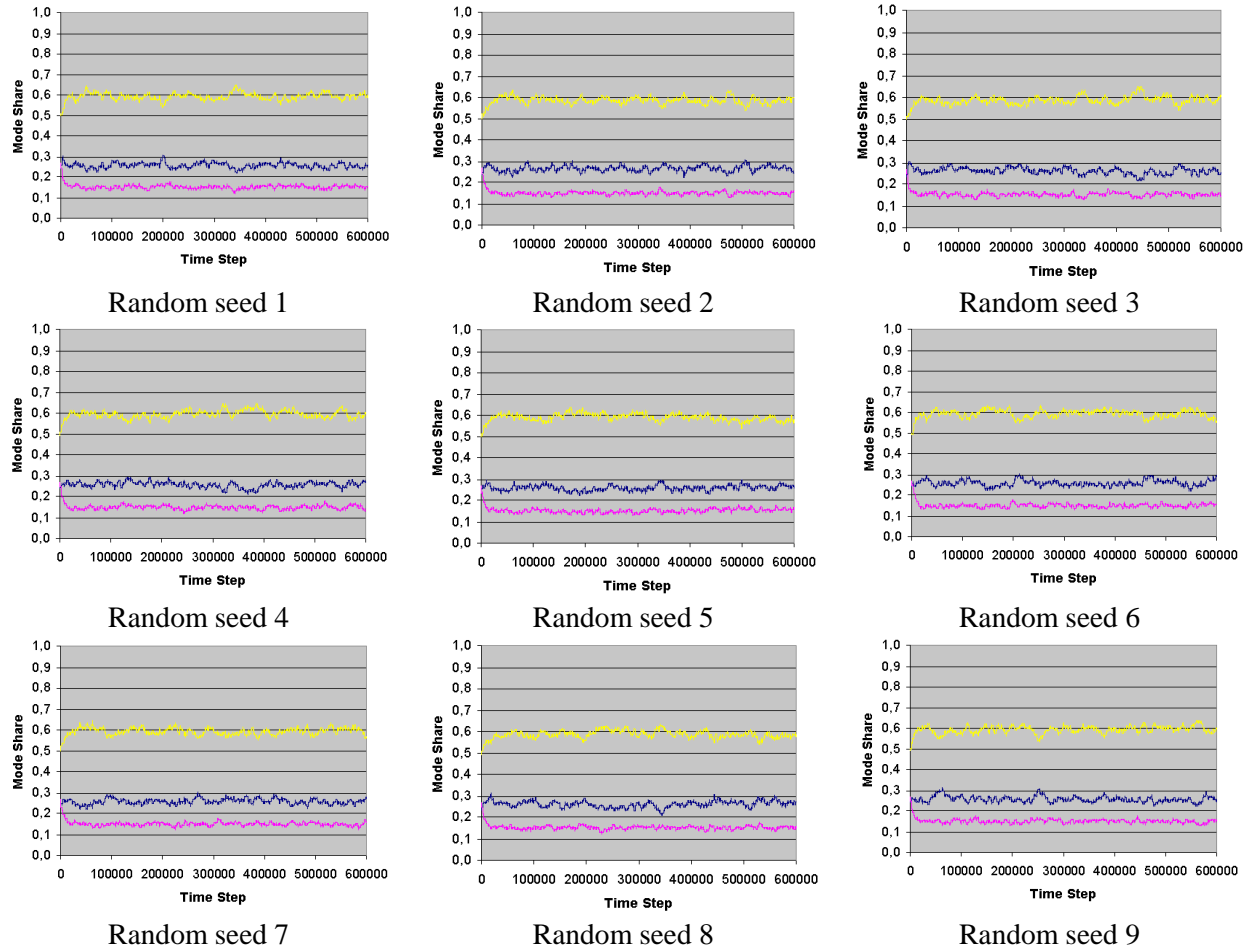
Finally, using the Repast agent-based modeling platform, we created a computational version of our multinomial and nested logit models with heterogeneous agents and sociogeographic network interaction. Example time series results for different random seeds are shown in Figure 6 for the multinomial logit case and in Figure 7 for the nested logit case. As in Figure 5, the yellow time series represents agents choosing car, the pink time series represents agents choosing bicycle, and the blue time series represents agents choosing public transit.

**TABLE 5** Estimation results with sociogeographic network interdependence<sup>a</sup>

Variable Name	Multinomial Logit		Nested Logit	
	Coefficient Estimate	$t$ Statistic	Coefficient Estimate	$t$ Statistic <sup>b</sup>
Share of each respondent's fellow district residents and socioeconomic peers in the sample choosing each mode	1.91	4.54	1.93	5.59
Alternative specific constant defined for transit	0.15	0.18	0.20	0.50
Alternative specific constant defined for car	0.32	0.65	-1.11	-2.14
Car ownership defined for car	2.54	24.68	2.53	24.84
Gender defined for transit	0.56	4.64	0.24	3.12
Gender defined for car	0.45	3.70	0.28	2.46
Low income defined for bicycle	-0.48	-2.92	-0.17	-1.87
Natural logarithm of age defined for transit	-0.72	-3.10	-0.30	-2.12
Age 45–59 piecewise continuously for transit	4.09e-02	2.13	1.94e-02	1.80
In-vehicle time, squared defined for transit	-3.95e-04	-4.42	-2.90e-04	-3.68
Out-of-vehicle time, defined for transit	-2.52e-02	-2.87	-1.91e-02	-3.26
Travel time for bicycle	-8.10e-02	-14.96	-3.75e-02	-4.38
Natural logarithm of travel time for car	-1.40	-7.11	-0.50	-1.97
Parking time, squared for car	-1.17e-02	-7.51	-1.36e-02	-8.35
Scale parameter for transit-bicycle nest	—	—	2.51	2.48

<sup>a</sup> Summary statistics: initial log-likelihood: -2,977; final log-likelihood multinomial logit model: -2,063; likelihood ratio test multinomial logit model: 1,829; final log-likelihood nested logit model: -2,055; likelihood ratio test nested logit model: 1,844. (Note that the initial log-likelihood here differs from the null log-likelihood in Table 2; in order to dock our multi-agent-based simulation results against the analytical benchmark, the availability of alternatives previously had been not taken into consideration.)

<sup>b</sup> All  $t$  statistics are against 0, except for the scale parameter, which is against 1.



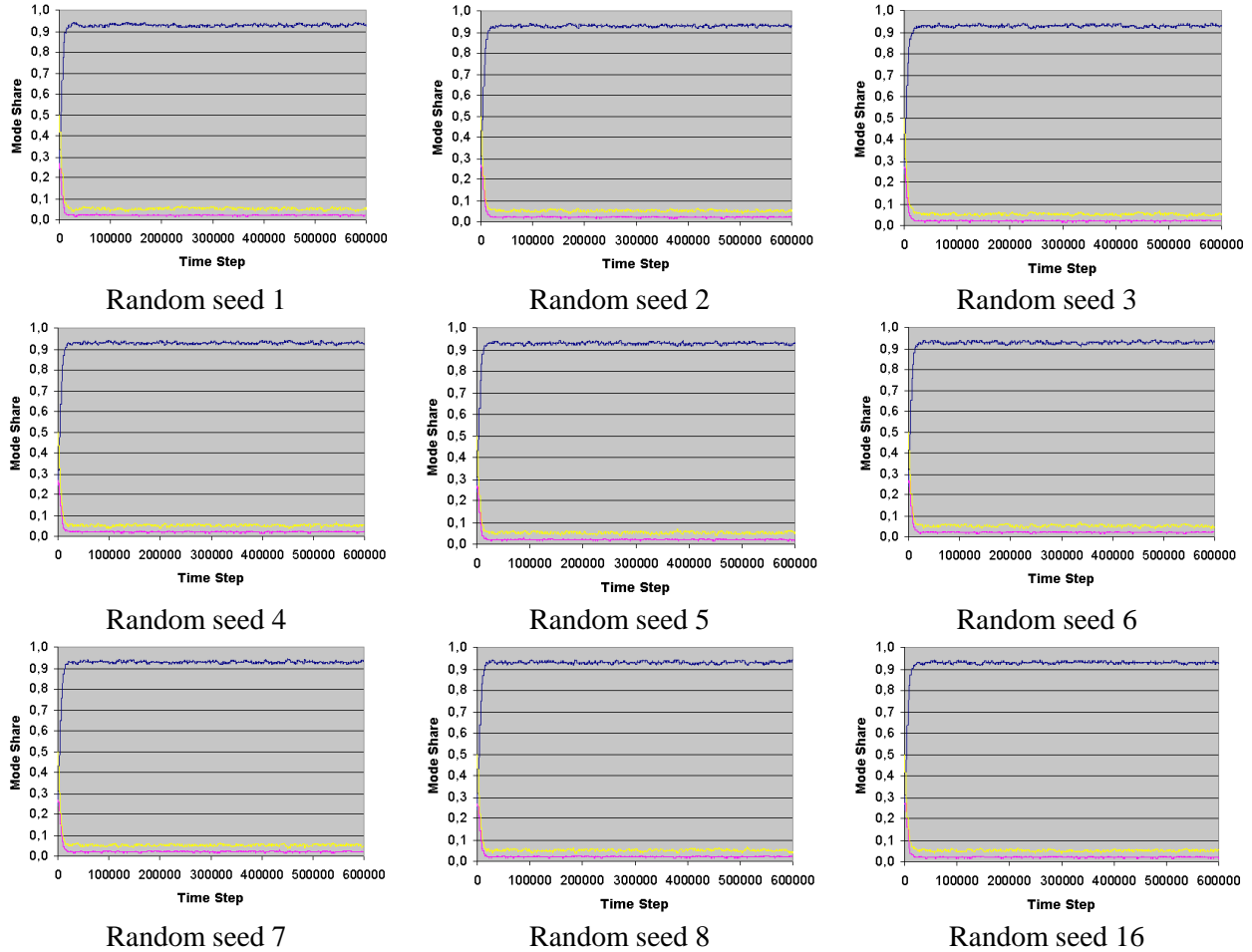
**FIGURE 6** Example time series for the multinomial logit model with heterogeneous agents

Similarly, each run is allowed to iterate for 600,000 time steps, on average 200 revisions of choices with asynchronous decision making for the sample size of roughly 3,000 agents. Comparing the time series for the multinomial with that for the nested logit case, we obtained dramatically different results for the steady-state solutions of the system. This result is particularly significant when we realize that all estimated coefficients for the multinomial logit versus the nested logit model are within two standard errors of each other, except for the scale parameter estimated for the nested logit model and the travel time for bicycle. Thus, the effect of considering unobserved heterogeneity through the introduction of the scale parameter and the effect of common unobserved attributes of the choice alternatives in the error structure is something that clearly cannot be ignored in an empirical application of a discrete choice model with network-dynamic interactive feedback.

## CONCLUSIONS

We have extended previous work on discrete choice with social interactions in important ways. First, we presented a framework for conceptualizing the interdependence of decision





**FIGURE 7** Example time series for the nested logit model with heterogeneous agents

makers' choices, making a distinction between social versus spatial network interdependencies and between identifiable versus aggregate agent interdependencies. In our empirical application, we considered a model where an agent's choice is directly influenced by the percentages of the agent's neighbors and socioeconomic peers making each choice; given the availability of appropriate data, our approach in principle is directly extendable to the identifiable agent case. We introduced additional heterogeneity in the model through different mechanisms, such as individual-specific sociodemographic characteristics of the agents as well as individual-specific attributes of the choice alternatives and the availability of alternatives. Finally, we introduced unobserved heterogeneity by accounting for common unobserved attributes of the choice alternatives in the error structure. We observed that these extensions generate dramatically different dynamics and thus cannot be ignored in any empirical application.

To separate out the effects, more research is needed to explore systematically the effects of different model configuration treatments, for example, the effect of sociogeographic network interaction, the effect of excluding self-loops, the effect of alternative specific constants, the effect of availability of alternatives, the effect of various explanatory sociodemographic agent characteristics, and the effect of various agent-specific attributes of alternatives.

Also very important for any policy application, particularly for transportation mode choice, would be introducing into the model not only positive feedback, but also negative feedback, to account for congestion effects in addition to agglomeration effects.

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<sup>7</sup> See <http://www.sara.nl>.

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## SIZE DISTRIBUTIONS OF LAND HOLDINGS IN AN AGENT-BASED MODEL OF RURAL LAND USE

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### ABSTRACT

This paper reports on investigations of the size distribution of rural land holdings in Scotland and on the output of two simulation programs: (1) a simple numerically based simulation of the partition and repartition of a fixed-size resource between a fixed set of entities and (2) an agent-based model of rural land use and land ownership change, FEARLUS. The work reported in this paper began with the expectation that the sizes of land holdings in Scotland might show a power-law distribution. In fact, the distribution appears to be intermediate between an exponential distribution and a power-law distribution, approaching a power-law distribution toward the upper tail. No simple mechanism has been found that would be expected to reliably produce power-law distributions of land holding sizes. The simple nonspatial simulation program readily produces distributions close to a power-law distribution, while some parameter settings of FEARLUS produce distributions that resemble the empirical findings. Results over a range of parameter settings indicate that the distribution is shifted toward an exponential distribution by the ability of the owners of large holdings to reduce risk by diversifying land use, as well as by the tendency of farmers to buy only land close to their existing holdings.

**Keywords:** Socio-spatial simulation, power laws, agent-based model

### INTRODUCTION

Any set of items or events to which sizes can be attributed can be considered in terms of the distribution of those sizes. In many cases, this distribution approximates to the Gaussian, with the greatest number of entities being intermediate in size and having roughly symmetrical tails. Indeed, the fact that the alternative name for this distribution is “normal” indicates that this has traditionally been considered the default. However, when we consider the size distributions of physical entities such as islands in an archipelago, of more abstract entities such as firms (Axtell, 2001), or of events such as earthquakes (Bak, 1997) or wars (Richardson, 1960), we find a fundamentally different kind of phenomenon: most of the set’s members are small, with numbers decreasing more or less monotonically as larger sizes are considered. This paper focuses on another domain in which this phenomenon of asymmetric size distribution occurs: the division of land holdings among different owners. In particular, this paper focuses on the size distribution of rural land holdings in Scotland.

The Framework for Evaluation and Assessment of Regional Land Use Scenarios (FEARLUS; Polhill et al., 2001; Gotts et al., 2003) is an agent-based modeling system,

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developed primarily to study the processes underlying land use change. One aspect of the system is a simple mechanism for transferring land from unsuccessful *Land Managers*<sup>1</sup> to their more successful neighbors or to new agents entering the simulation. The purpose of including this mechanism in FEARLUS models is to (1) allow the study of the competitive properties of different approaches to selecting land uses under different circumstances and (2) provide a feedback mechanism that increases over time the proportion of land to which the more successful approaches were applied. The actual size distributions of holdings produced is an outcome that was not initially of particular interest. However, when we began to exchange ideas about the size distributions of areas or parcels of land that arise in land-use-related contexts, it became clear that FEARLUS might be a useful investigative tool. Moreover, such use could potentially provide feedback for the design of more sophisticated versions of the FEARLUS system that would have more realistic mechanisms for the exchange of land. As Chattoe (1996) notes, the existence of such “emergent data,” which are not part of the simulation design but can be compared with real-world data, is an important methodological advantage of agent-based simulation, since the data can provide an independent way of checking whether a model is capable of reproducing aspects of the world that have not been, so to speak, “put in by hand.”

As we continued our investigations, it appeared useful to develop a simpler, purely numerical and nonspatial simulation modeling system (R-SG) to elucidate the processes that could produce different kinds of size distributions. This paper, together with Gotts and Parker (2004), reports on our first investigations of size distributions of land holdings by using FEARLUS and R-SG.

### LEPTOKURTIC SIZE DISTRIBUTIONS IN SOCIAL AND SOCIO-SPATIAL CONTEXTS

Among asymmetric size distributions, perhaps the most commonly found are exponential distributions, in which the number of a set of entities or events of different sizes declines with size in such a way that the probability of a randomly selected member of the set  $X$ , being at least a given size  $X_0$ , can be calculated from a formula:

$$P(X \geq X_0) = \exp[(a - X_0)/b], \quad (1)$$

where  $a$  and  $b$  are constants. Asymmetric distributions for which the number of entities decreases more slowly with size are frequently called *leptokurtic* (fat-tailed). Two classes of leptokurtic asymmetric distributions that are important here are the lognormal distribution (for which, as the name suggests, the logarithms of the entities’ sizes are normally distributed) and the power-law distribution. The formula for the power-law distribution is:

$$P(X \geq X_0) = a - X_0^b, \quad (2)$$

where  $b > 0$ . If  $b < 2$ , a power-law distribution has no defined variance, while if  $b < 1$ , the mean also fails to be defined; the larger the sample gathered, the greater the expected sample mean. Of course, for any finite set of entities, the distribution of sizes must eventually fall below the power-law distribution, since there will be some largest member of the set; thus, a power-law

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<sup>1</sup> Terms that refer to FEARLUS model entities are in initial upper-case letters; they are also italicized when they first appear.

distribution (like any other continuous distribution) can only be an approximation to the messiness of the real world.

Nonetheless, a power-law distribution can be closely approximated over several orders of magnitude. Such distributions have been reported from a wide range of social and socio-spatial contexts in research going back more than a century. Among relatively recent literature, Carroll (1982) reviews extensive work on city size distributions, while Axtell (2001) provides evidence that firm sizes in the United States are power-law distributed. Strong empirical evidence has been found for the existence of fractal distributions of density-radius relationships and patch sizes (a patch is a contiguous area given over to the same land use) across many European and North American cities (White and Engelen, 1993; Batty and Longley, 1994; Rand et al., 2003). Because fractals are self-similar across spatial scales, fractal distributions are a special case of power-law distributions. (White and Engelen [1993] has an excellent discussion.) Authors have generally found empirical power-law coefficient estimates (fractal dimension) between 1 and 2. The results related to patch size are most relevant for the research presented here, since the area-scaling relationships depend on decreasing parcel density as distance from the transport center increases. Fractal distributions of patch sizes, however, may reflect industrial as well as spatial structure.

The results of several cellular and agent-based land use models have been tested for the existence of power-law distributions of parcel sizes. These models focus primarily on urban and ex-urban development. Batty and Xie (1994, 1996) use both a diffusion-limited aggregation model and cellular automaton techniques to generate fractal urban growth patterns. White and Engelen (1993) use cellular automaton techniques to generate similar patterns. Rand et al. (2003) construct a model of ex-urban residential location, where agents' location decisions are influenced by a desire for natural amenities (dispersion incentive) and a desire for proximity to service centers (agglomeration incentive). In comparisons of simulation results to real-world patterns, all authors found strong evidence for a power-law distribution of parcel sizes. It is notable that these patterns persisted as the models developed and became more complex and potentially realistic with respect to the number of land uses they represent, their interactions, and the complexity of landowner decision making. The generality of results implies that fractal patterns may result from many combinations of spatial dispersion and agglomeration forces.

The theoretical justification for the existence of power laws in rural land use comes from two sources. The first is the literature on industrial structure. Axtell (2001) reviews evidence for power laws in this realm and demonstrates how these distributions can emerge as the result of decentralized interactions. Moss (2002) similarly argues that power-law distributions will be generated in time series by models with agents that are influenced by, but do not (slavishly) imitate, other agents known to them. The second justification, which suggests a different form of explanation, comes from models concerned with scale-independent growth. Gabaix (1999) demonstrates that a very simple growth process can generate a lognormal distribution and claims that slight modifications to this process can turn the lognormal into a power-law distribution. Specifically, Gabaix observes that if the members of a set of entities grows and shrinks in such a way that the expected *proportional* growth, and the variance of that proportional growth, are independent of entity size, then whatever the initial distribution of sizes is, an approach to a lognormal distribution of sizes will result (assuming that the variance is nonzero; if it is zero, the initial size distribution will be preserved). Growth processes like this are said to obey "Gibrat's law." The lognormal distribution produced will not be stable; rather, the range of sizes will tend

to increase without limit, so that given a large enough population of entities, the distribution will approach uniformity over any given range of values.

Gabaix proceeds to argue that if some mechanism is introduced that prevents members of the set of entities from shrinking indefinitely, the result will be a power-law distribution. Perhaps the simplest such mechanism is to impose a positive lower limit on permitted sizes, restoring any entity that shrinks below this size to this limit. Gabaix states that if this mechanism is applied, the value of  $b$  in Equation 2 approaches 1 as the size of this limit approaches 0.

However, Gabaix's reasoning has been severely criticized by Blank and Solomon (2003). These authors, citing Malcai et al. (1999), claim that Gabaix overlooked a key assumption: the accuracy of an approximation that they claim is required in Gabaix's calculation depends on the number of entities in the set being large compared with the ratio between the mean and minimum sizes in their distribution. (Specifically, it is necessary that  $\ln(N) \gg 1/c$ , where  $N$  is the number of entities, and  $c$  is the ratio between the minimum and mean sizes.) Differences in terminology and in the precise mechanisms employed in the models, as discussed by Gabaix on one hand and by Malcai et al. on the other, make it difficult to assess this claim. Blank and Solomon (2003) appear to be mistaken in claiming that the model described by Gabaix (1999) makes  $c$  liable to decrease without limit over time. (They interpret Gabaix as holding the lower size limit for cities constant as the sum of the sizes of all cities increases, which would lead  $c$  to shrink indefinitely. In fact, Gabaix states that he is working with a limit that is a proportion of the mean size.) However, Gabaix (1999) does not appear to consider the effect of varying the relationship between  $c$  and  $N$ .

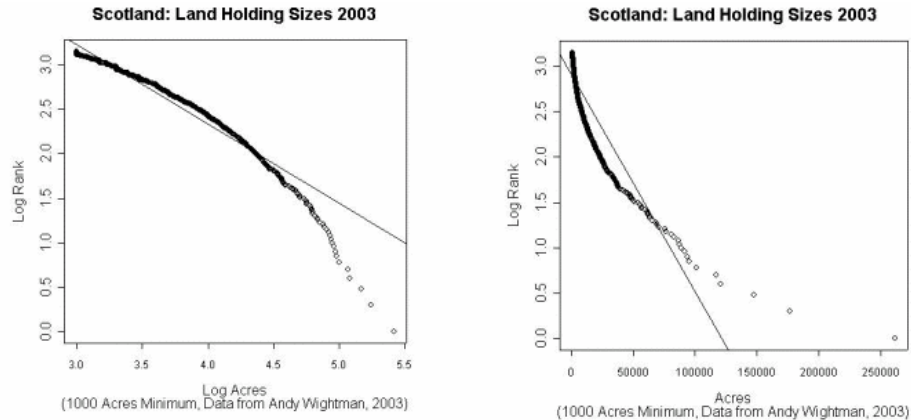
Malcai et al. (1999) analyze a model in which one randomly selected member of the set of entities at a time is resized by a factor  $\lambda$  drawn from some distribution  $\Pi(\lambda)$  (they assert that the details of this distribution turn out not to be important), subject to a lower limit  $c$  on the resulting size relative to the mean entity size before the resizing. They argue, and confirm numerically, that when  $1/\ln(N) \ll c < 1$ , the resulting size distribution tends toward a power-law distribution with a slope of  $-1/(1-c)$  as  $N \rightarrow \infty$  and will approximate a power-law distribution with a slope of  $-\ln(N)/\ln(N/c)$  for any finite  $N$ , when  $c \ll 1/N < 1$ . More generally, the steepness of the slope (given by its absolute magnitude) increases with the number of entities and with  $c$ . We report below on the outcomes of simulations that used a slightly different process; they are generally compatible with these results, but they also indicate the importance of another feature of the process — the rate at which entity sizes change.

In sum, the empirical findings and theoretical background described in this section are sufficient to reasonably hypothesize that land holding size distributions might follow power-law distributions, but they do not suggest a specific hypothesis about slope. It was with this preliminary hypothesis in mind that we examined the size distribution of land holdings in Scotland.

## SIZE DISTRIBUTION OF SCOTTISH LAND HOLDINGS

The main source of data on size distributions of land holdings in Scotland used in the work reported here is Wightman (2003). (See also Wightman [1996, 2004].) Figure 1 shows the most recent available size distributions of Scottish land holdings of 1,000 acres (approximately



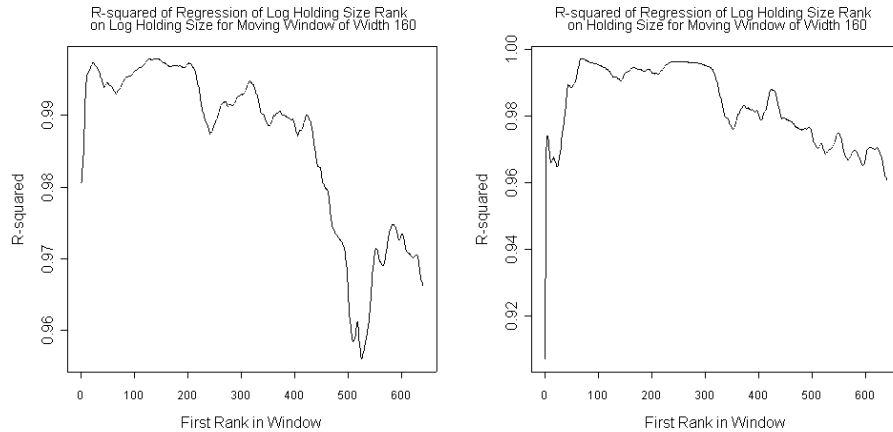


**FIGURE 1** Scottish land holding size distribution ([Left] Power-law distribution would produce a straight line. [Right] Exponential distribution would produce a straight line.)

400 hectares) and over. These plots were produced by ranking the 1,411 holdings concerned and pairing each ranking with the corresponding size in acres to produce a data point. This method is called the “rank-size” approach to plotting or measuring size distributions. In the left side of the figure, a log-log plot is used; a straight line would indicate a perfect power-law distribution, with its slope giving the value of  $b$  in Equation 2. Similarly, a straight line in the right figure, where the logarithm of the rank is plotted against the untransformed size values, would indicate an exponential distribution.

Results from regression analysis are as follows. For the best-fitting power-law distribution found by the analysis,  $R^2$  is 0.9465, the  $t$ -ratio for the slope estimate is  $-157.8$ , and the slope estimate itself is  $-0.89002$ . Both  $R^2$  and the  $t$ -ratio for the slope estimate are less favorable for the best exponential found: 0.7474 and  $-64.58$ , respectively. This suggests that the real-world distribution is closer to a power-law distribution than to an exponential distribution. (The appearance of the two plots is enough to indicate that it is intermediate between the two.) However, a Kolmogorov-Smirnov test (NIST/SEMATECH, 2004) shows that the distribution is not a pure power-law distribution with the slope and intercept given by the straight line on the left figure. (The value of the  $D$ -statistic  $\approx 0.1616$ , giving a  $p$ -value  $< 10^{-15}$ . The  $p$ -value here is the probability that a sample of this size drawn from a power-law distribution with that slope and intercept would give a result at least as far from the ideal as the actual data.)

We can give a more detailed description of the distribution of land holding sizes in Scotland by considering the characteristics of proper parts of the upper tail of 1,411 holdings plotted in Figure 1. First, we can consider shorter upper tails. As shown in Gotts and Parker (2004), the value of  $R^2$  obtained from log-log regression analysis (which would be 1 for a perfect power-law distribution) generally declines as the tail length increases, but it initially rises to two peaks (Figure 2). (These peaks are at values of  $\approx 0.9884$  when the largest 31 holdings are considered and  $\approx 0.9804$  when the largest 160 holdings are taken. The peaks occur in the same



**FIGURE 2**  $R^2$  values for a “moving window” of 160 holdings (left) log-log regression (right) log-untransformed sizes regression

places if the adjusted  $R^2$  is used.<sup>2</sup>) Corresponding values for  $R^2$  when the logs of the ranks are regressed against the untransformed sizes are lower for every length of tail, decline more smoothly, and have a single peak at  $\approx 0.9225$  when the largest 81 holdings are considered. We can thus suggest that the curve moves away from a power-law distribution and toward an exponential distribution and then back toward it as we consider longer tails, but it always remains closer to the former.

We can take this descriptive approach one stage further by considering a “moving window” of 160 holdings, beginning with the largest 160, then considering those of ranks 2 through 161, then 3 through 162, and so forth. Figure 2 shows the  $R^2$  values produced for log-log regression (left) and for log-untransformed value regression (right). It can be seen that for the log-log regression, the values are at first considerably higher, but they fall to similar values by the time ranks 500 through 659 are considered. Again, this suggests that the distribution is more power-law-distribution-like toward the upper tail than it is farther away from that tail.

## R-SG: NONSPATIAL MODEL OF ALMOST SCALE-FREE COMPETITIVE GROWTH

Real-world size distributions of land holdings are the product of complex historical and ecological processes, so it should not be surprising that they do not follow mathematically simple patterns. Nonetheless, as a step toward understanding them, it is important to discover what relatively simple mathematical and computational models can do. This section and the next one examine the results of models developed within two modeling systems: one is a simple numerical system, and the other is a pre-existing, spatially explicit, agent-based system.

R-SG is so named because it is written in the programming language R (The R Foundation for Statistical Computing, 2003) and implements a process of Shrinkage and Growth

<sup>2</sup> The adjusted  $R^2 = -(k - 1)/(n - k) * (1 - R^2)$ , where  $n$  is the number of observations and  $k$  is the number of independent variables.

of a set of abstract entities. This set is fixed throughout a simulation. In the experiments carried out so far, all members of the set are initially the same size. The purpose of building and using R-SG was to illuminate the issues raised in Gabaix (1999), Malcai et al. (1999), and Blank and Solomon (2003), concerning whether simple stochastic growth processes applied to fixed sets of entities can give rise to power-law size distributions, and, if so, what values the slope parameter can take under what circumstances. We compared and contrasted this relatively simple, nonspatial simulation model with the agent-based model described in the next section.

In an R-SG run, the initial set of entities is put through a three-step process, repeated as many times as desired:

1. Each set member is independently grown or shrunk by a factor of  $2^p$ , where  $p$  is drawn from a normal distribution with mean 0.
2. A fixed increment  $f$  is added to the size of each entity.
3. The entire set is rescaled so that the sum of entity sizes remains constant.

Note that in Step 1, as in the process described by Gabaix (1999), but in contrast to the process described by Malcai et al. (1999), all members of the set are processed simultaneously. Step 2 has the function of “repelling” sizes from zero in a way that appears to be more statistically convenient than setting a common minimum size for all entities: in early trials, the latter produced a large number of entities of the same size after most cycles, raising problems in applying graphical and statistical techniques.

In the runs discussed in detail here, three R-SG parameters were varied:

1. Their initial size  $s$  (1,024 or 2),
2. The fixed increment  $f$  (1 or 0.1), and
3. The standard deviation  $\sigma$  of the distribution of  $p$  (1 or 2).

The number of cycles used was 8,192, but examination of the output showed that the system passed through a phase of directional change lasting less than 10 cycles (as the initially equal sizes dispersed), after which further change appeared to have no secular trend. Subsequent analysis was therefore limited almost entirely to the first 1,024 cycles. Each of the two values of these three parameters was combined with each value of the others, giving eight runs; however, only the ratio between  $s$  and  $f$  and not their absolute values should affect results, if it is assumed that floating point errors do not make any substantive difference (see Polhill et al., 2005).

The resulting size distributions appear to be closer to power-law behavior than exponential behavior for the vast majority of cycles, according to visual observation and judging by the results of regression analysis and subsequent Kolmogorov-Smirnov tests.

In addition to a measure of the slope drawn from a log-log regression, three measures of distance from a power-law distribution were used in comparing the eight runs; they were recorded after each cycle. Two of these were produced directly by the log-log regression: the  $R^2$  statistic, and the  $t$ -ratio for the slope estimate. The  $p$ -values, produced by applying the

Kolmogorov-Smirnov test to the actual distribution, and a perfect power-law distribution, constructed by using the slope and intercept produced by the regression analysis, were also measured. The values of each measure for the first 1,024 cycles of each run were then ranked in terms of (absolute) magnitude. (The lack of any apparent directional change after the first few cycles prompted this procedure.) Ranks 1, 256, 512, 768, and 1,024 for the slope estimates,  $t$ -ratios of those estimates, and Kolmogorov-Smirnov  $p$ -values are given in Tables 1 through 3. Each column in a table deals with one of the five ranks; each row gives results for one parameter combination, but the row labels identify the values of  $\sigma$  and  $s/f$ . Values are given to six significant figures. The cells also show the position that the value in that cell holds within the column (italic numbers 1 through 8). Results for the  $R^2$  statistic have been omitted, since they produced orderings within all columns identical to those for the  $t$ -ratios.

The order of values for slope (Table 1) is the same for each column, except that for rank 1. In the other columns, both a smaller  $s/f$  ratio and less variation in growth or shrinkage between entities ( $\sigma = 1$  rather than  $\sigma = 2$ ) produced a steeper slope, with the former having the greater effect. The  $s/f$  ratio will be closely correlated with the ratio between the mean and minimum size, so a decrease would indeed be expected to produce a steeper slope (i.e., a faster fall-off of number of entities with increasing size). Increasing  $\sigma$  will tend to disperse sizes further, increasing the mean/minimum ratio and so producing a shallower slope. For rank 1 only, increasing the value of  $\sigma$  appears to give a steeper slope (it may increase the change between cycles and hence produce a wider spread of values), but the  $s/f$  ratio has the same effect as it does in the other columns.

In Tables 2 and 3, higher values indicate a distribution closer to a power-law distribution. The value of  $\sigma$  is by far a more important parameter than the value of  $s/f$  in these tables. In both, the first three columns (ranks 1, 256, and 512) have the four highest values in the lower half of the column (where  $\sigma = 2$ ), so the value that has produced more dispersion of sizes and more rapid change from cycle to cycle has also produced a nearer approach to a power-law distribution. In the last column (rank 1,024), however, the higher values are in the upper half of each column; a higher value of  $\sigma$  thus increases the greatest deviations from a power-law distribution, presumably because of the greater cycle-to-cycle variability that widens the spread of values over the entire simulation. The rank 768 columns resemble the first three in Table 2, while in Table 3, this column appears transitional: both the highest and the lowest values of Kolmogorov-Smirnov  $p$ -values occur when  $\sigma = 2$ . The effect of variations in the  $s/f$  ratio is somewhat more complicated. The clearest pattern occurs for ranks 256 and 512, where a greater  $s/f$  ratio results in a closer approach to a power-law distribution in both Tables 2 and 3 when  $\sigma = 1$ , but the opposite is true when  $\sigma = 2$ . This pattern remains to be explained, but because of the apparent importance of the value of  $\sigma$ , a number of simulations were run by using both higher and lower values than those in the tables (4, 0.5, 0.25, and 0.0625). Increasing  $\sigma$  consistently decreased the slope, while both the higher and lower new values of  $\sigma$  appeared to take the distribution farther from a power-law distribution. Thus the effects of changes in  $\sigma$  on nearness to a power-law distribution also appear to be more complicated than their effects on slope. Finally, in this section, Figure 3 is a plot of the size distribution that results after 8,192 cycles of the run with  $\sigma = 2$  and  $s/f = 2$ . Visually, this indicates a very close approximation to a power-law distribution, in agreement with the figures produced by the regression analysis and Kolmogorov-Smirnov test.

**TABLE 1** R-SG initial experiments: values of slope estimate (obtained by regression of log holding size rank on log holding size)

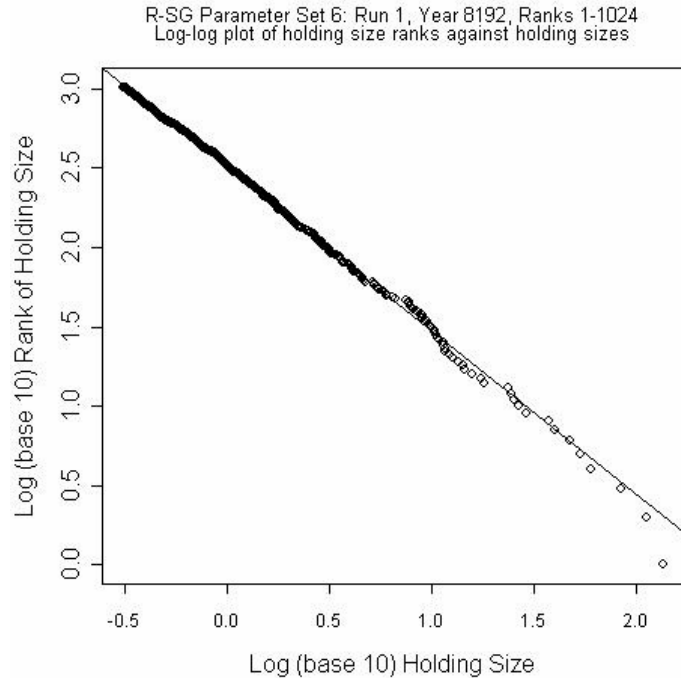
Value for $\sigma$ and $s/f$	Rank 1	Rank 256	Rank 512	Rank 768	Rank 1,024
$\sigma = 1, s/f = 2$	2 -2.09794	1 -1.72147	1 -1.69195	1 -1.66360	1 -1.55482
$\sigma = 1, s/f = 20$	4 -1.46120	3 -0.895743	3 -0.855912	3 -0.834851	3 -0.786376
$\sigma = 1, s/f = 1,024$	5 -1.30373	5 -0.588202	5 -0.529235	5 -0.495024	5 -0.431431
$\sigma = 1, s/f = 10,240$	6 -1.28002	7 -0.510262	7 -0.445979	7 -0.414442	7 -0.352196
$\sigma = 2, s/f = 2$	1 -2.13153	2 -1.14165	2 -1.09618	2 -1.05633	2 -0.968117
$\sigma = 2, s/f = 20$	3 -1.89855	4 -0.798696	4 -0.732043	4 -0.687595	4 -0.600086
$\sigma = 2, s/f = 1,024$	7 -1.22332	6 -0.575801	6 -0.499385	6 -0.460567	6 -0.375413
$\sigma = 2, s/f = 10,240$	8 -0.944702	8 -0.481219	8 -0.423064	8 -0.378591	8 -0.302925

**TABLE 2** R-SG initial experiments: values of  $t$ -ratio for slope estimate (obtained by regression of log holding size rank on log holding size)

Value for $\sigma$ and $s/f$	Rank 1	Rank 256	Rank 512	Rank 768	Rank 1,024
$\sigma = 1, s/f = 2$	8 -305.475	8 -214.074	8 -193.448	6 -175.852	1 -113.542
$\sigma = 1, s/f = 20$	7 -420.519	7 -235.437	7 -205.882	5 -181.272	2 -78.6294
$\sigma = 1, s/f = 1,024$	5 -909.333	6 -287.276	6 -218.758	7 -174.598	4 -56.2555
$\sigma = 1, s/f = 10,240$	6 -753.409	5 -319.692	5 -226.911	8 -170.360	3 -64.6916
$\sigma = 2, s/f = 2$	1 -1239.22	1 -603.047	1 -460.326	1 -342.269	5 -45.3581
$\sigma = 2, s/f = 20$	3 -1117.14	2 -530.117	2 -375.305	2 -265.840	7 -30.3374
$\sigma = 2, s/f = 1,024$	4 -1061.55	3 -436.637	3 -301.583	3 -208.988	8 -22.5185
$\sigma = 2, s/f = 10,240$	2 -1193.04	4 -405.799	4 -273.885	4 -190.816	6 -35.2038

**TABLE 3** R-SG initial experiments: Kolmogorov-Smirnov  $p$ -values (obtained by comparing actual distributions with perfect power-law distributions constructed by using the slope and intercept estimates produced by regression of log holding size rank on log holding size in simulation runs; the numbers in brackets after the zeros in the last column indicate the rank of the lowest nonzero value)

Value for $\sigma$ and $s/f$	Rank 1	Rank 256	Rank 512	Rank 768	Rank 1,024
$\sigma = 1, s/f = 2$	8 0.00450945	8 2.48681e-06	8 6.02319e-07	6 1.35980e-07	1 7.67781e-10
$\sigma = 1, s/f = 20$	7 0.142582	7 1.47649e-05	7 1.97300e-06	4 2.88714e-07	2 1.74865e-10
$\sigma = 1, s/f = 1,024$	6 0.868725	6 2.46820e-04	6 9.57023e-06	3 3.69632e-07	4 0 [1021]
$\sigma = 1, s/f = 10,240$	5 0.972127	5 0.00123282	5 2.78823e-05	4 2.88714e-07	3 4.05231e-13
$\sigma = 2, s/f = 2$	3 0.999997	1 0.551489	1 0.0366311	1 7.73624e-05	5 0 [995]
$\sigma = 2, s/f = 20$	1 1.00000	2 0.384530	2 0.00951858	2 3.92762e-06	6 0 [954]
$\sigma = 2, s/f = 1,024$	3 0.999997	3 0.059457	3 1.14782e-04	7 3.72839e-08	8 0 [915]
$\sigma = 2, s/f = 10,240$	1 1.00000	4 0.0322953	4 5.17362e-05	8 1.27847e-08	7 0 [928]



**FIGURE 3** Log-log plot of size distribution of R-SG run with  $\sigma = 2$  and  $s/f = 2$ , after 8,192 cycles

### FEARLUS: AGENT-BASED SPATIALLY EXPLICIT SIMULATION OF RURAL LAND USE AND OWNERSHIP

A number of agent-based models of rural land use have recently been developed. These models explore a variety of questions. Several explore structural change in agriculture (Balmann, 1997; Berger, 2001; Balmann et al., 2003). Other contributions investigate boundedly rational decision making by rural landowners in developed countries (Gotts et al., 2003; Hoffmann et al., 2003). To the authors' knowledge, however, the work reported on here and in Gotts and Parker (2004) is the first to specifically investigate size distributions of holdings in rural land.

The FEARLUS agent-based modeling system (Gotts et al., 2003) is used to model rural land use and ownership. Each Land Manager chooses *Land Uses* for the *Land Parcels* in its *Estate* every Year, using a *Land Use Selection Algorithm*. This may take into account recent *Returns* gained by the Land Manager and its *Neighbors* (who counts as a Neighbor can be varied). Returns in the Environments used in the work reported here depend only on the Land Use and *External Conditions*, which represent climatic and economic conditions and are homogeneous across space but vary over time. Land Managers in financial deficit at the end of a Year sell enough Land Parcels to clear their deficits, leaving the simulation if this leaves them landless. Such Parcels can be bought by a Neighbor (the definition of "Neighbor" is a model parameter) or by a new Land Manager entering the simulation. (Currently, there is a fixed price, and a lottery decides which Manager gets the Parcel.) A *Break Even Threshold* determines how hard it is to make a profit: interesting size distributions result only if this threshold is neither too high (when most agents go bankrupt and are replaced each Year) nor too low (when the

distribution freezes immediately). The *Land Parcel Price*, which determines how much the seller receives and the buyer gives, can also be varied.

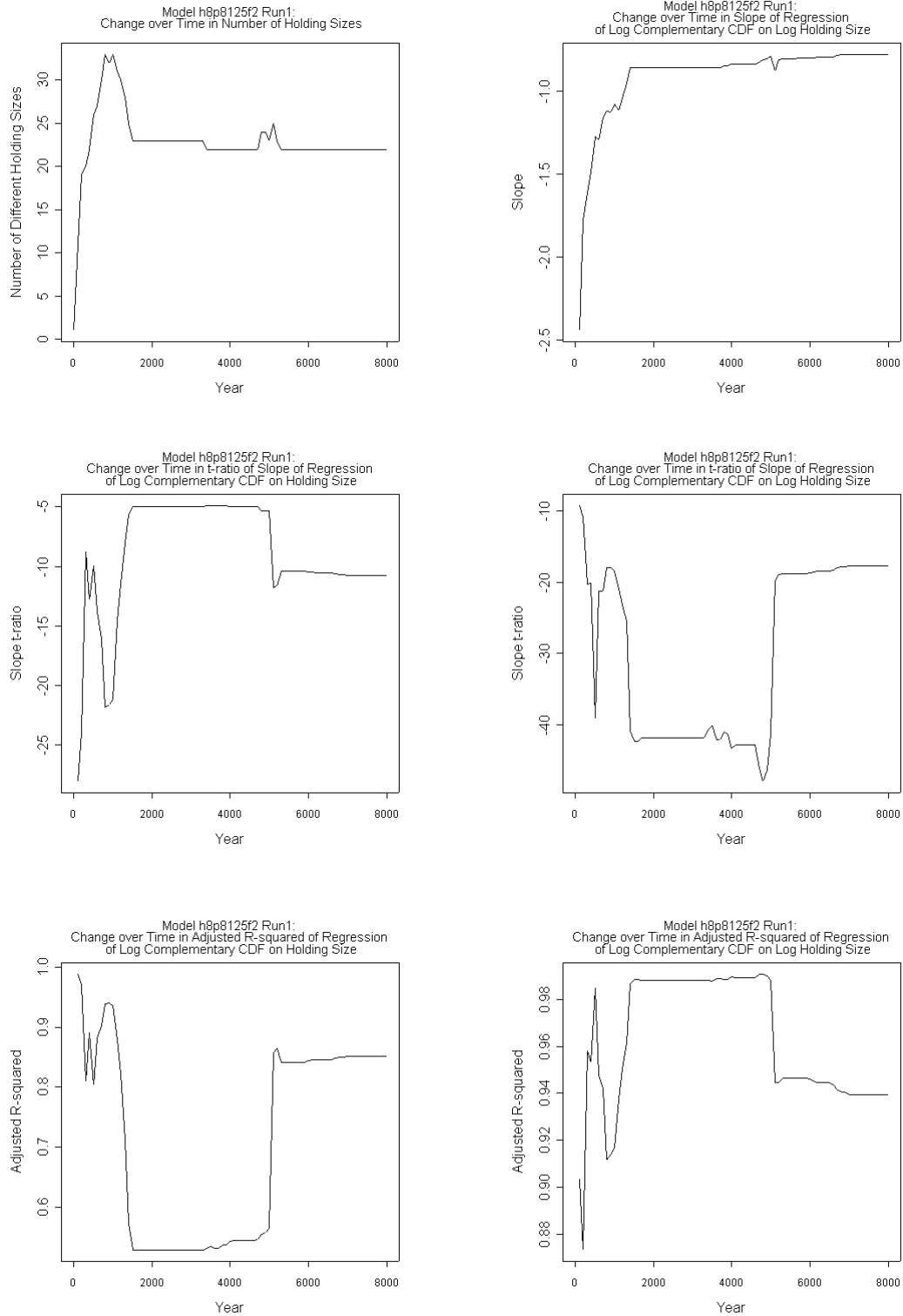
The *Environment* used here is a  $40 \times 40$  toroidal grid of Land Parcels and runs for 8,000 Years. The output from the FEARLUS simulations differs from the R-SG output in that it generally shows a “historical” directionality, presumably because FEARLUS allows the number of Estates to change. In the simulations reported here, the number of Estates begins at the maximum of 1,600, but if, at any point, it declines, it may increase again. The Land Parcel distribution sometimes becomes stable and sometimes continues to change; but in the latter case, it usually appears to be going through size distributions roughly similar to those that have already been encountered by the end of the run. A second general point is that two runs with the same parameters can produce markedly different size distributions; the results reported here generally use the first run made with each parameter set. The comparisons reported must be regarded as provisional until more extensive work is undertaken and statistically significant results are produced.

No parameter settings yet found consistently give size distributions that are as close to power-law distributions as some found for R-SG, but many give distributions that resemble the real-world distribution (i.e., in being intermediate between power-law and exponential in form). The parameters that most influence the size distribution of Estates are the Break Even Threshold and the parameters that determine the Managers’ Land Use Selection Algorithms. The simplest used were *Random Selection* (RS) and *Fickle Selection* (FS): both choose Land Uses randomly each Year, but RS does this independently for each Parcel, while FS applies the same Land Use to the entire Estate. The latter produces ownership patterns closer to power law distributions.

Most of this section reports on results from simulations involving somewhat more realistic Land Use Selection Algorithms, in which the current Land Use is retained if the Return reaches the Manager’s *Aspiration Threshold*, while either RS or FS is used on any remaining Parcels. These Algorithms are called HR (Habit-Random) and HF (Habit-Fickle). The former has turned out to be fairly robust in performance if the Aspiration Threshold is set neither too high nor too low. (At or near the Break-Even Threshold is usually best [Gotts et al., 2003]. In the runs reported here, it was always set at that point.)

In this section’s figures, the line above each subfigure identifies the set of parameters used. Each subfigure shows the temporal evolution of some statistical measure over an 8,000-Year run. Figure 4 plots results from the first run using an “H8P8125F2” parameter set. (This is the second set of parameters investigated in which the Land Managers used HF, and the Break-Even Threshold was 8.8125 and the Aspiration Threshold was 8). This set has produced distributions as close to power-law distributions as any tried so far. It will be used as a reference point through the remainder of the section. The Land Managers here followed an HF Algorithm, and because all Land Managers are “Neighbors” of each other, a Manager with the necessary cash can buy a Land Parcel anywhere in the Environment. The Land Parcel Price is 16. (The units are arbitrary: 16 is also the maximum Return in the runs discussed here.)

The top left subfigure shows the number of different Estate (holding) sizes (Estate size is always an integer number of Parcels), which begins at 1 and, in this case, rises quickly before settling between 20 and 25. The top right subfigure shows the slope estimate produced by a log-log regression of the complementary cumulative density function (CCDF) of the distribution

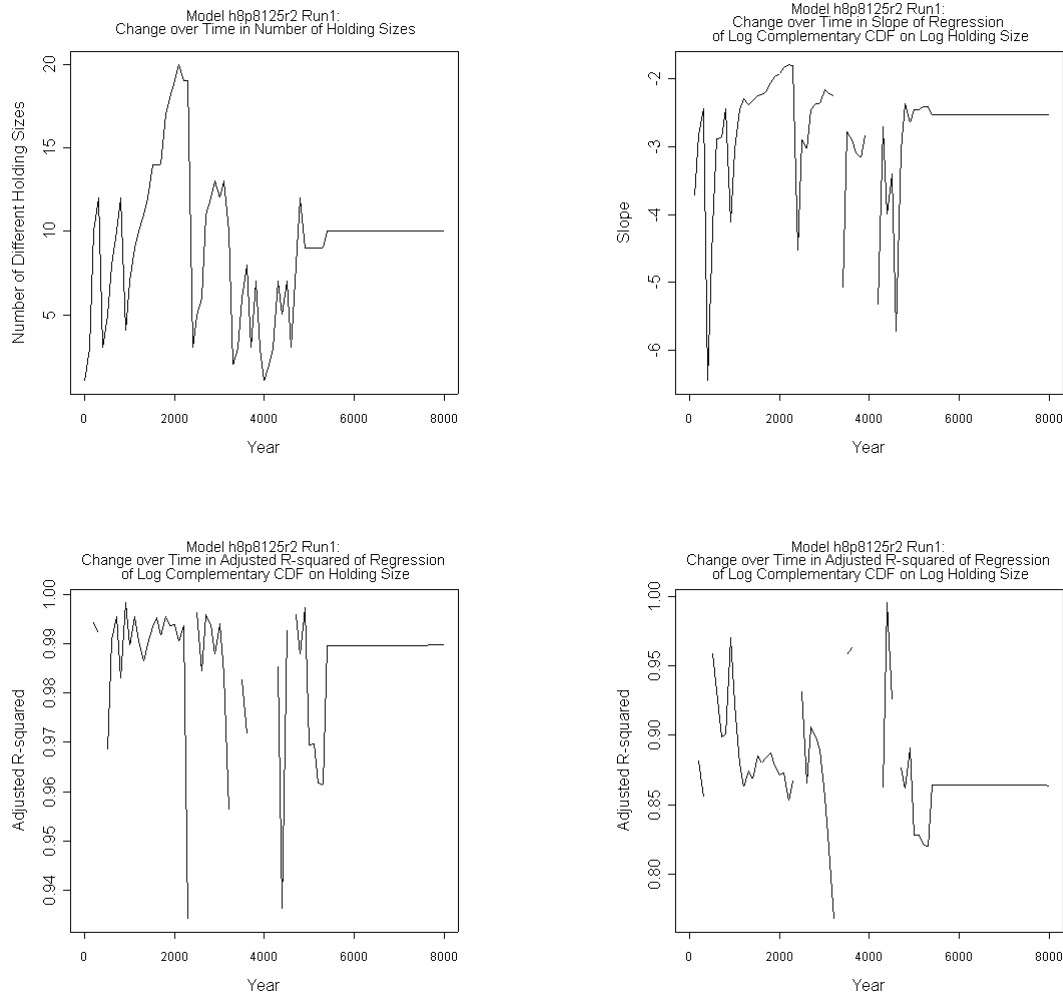


**FIGURE 4** Diachronic plots of output from run 1 with parameter set H8P8125F2



against Estate size. (The CCDF is the fraction of entities at or above a given size.) The CCDF is used instead of the rank-size approach because the integral values of size produce multiple ties when the latter is employed.) The remaining four subfigures contrast the outcome of this regression (on the right) with a regression of the log CCDF on the untransformed Estate sizes (on the left). The middle row shows  $t$ -ratios of the slope estimates, and the bottom row shows adjusted  $R^2$  values. As can be seen, with these parameters, the size distribution appears to be closer to a power-law distribution than an exponential distribution throughout, but there seems to be some movement away from a power-law distribution toward the end of the run.

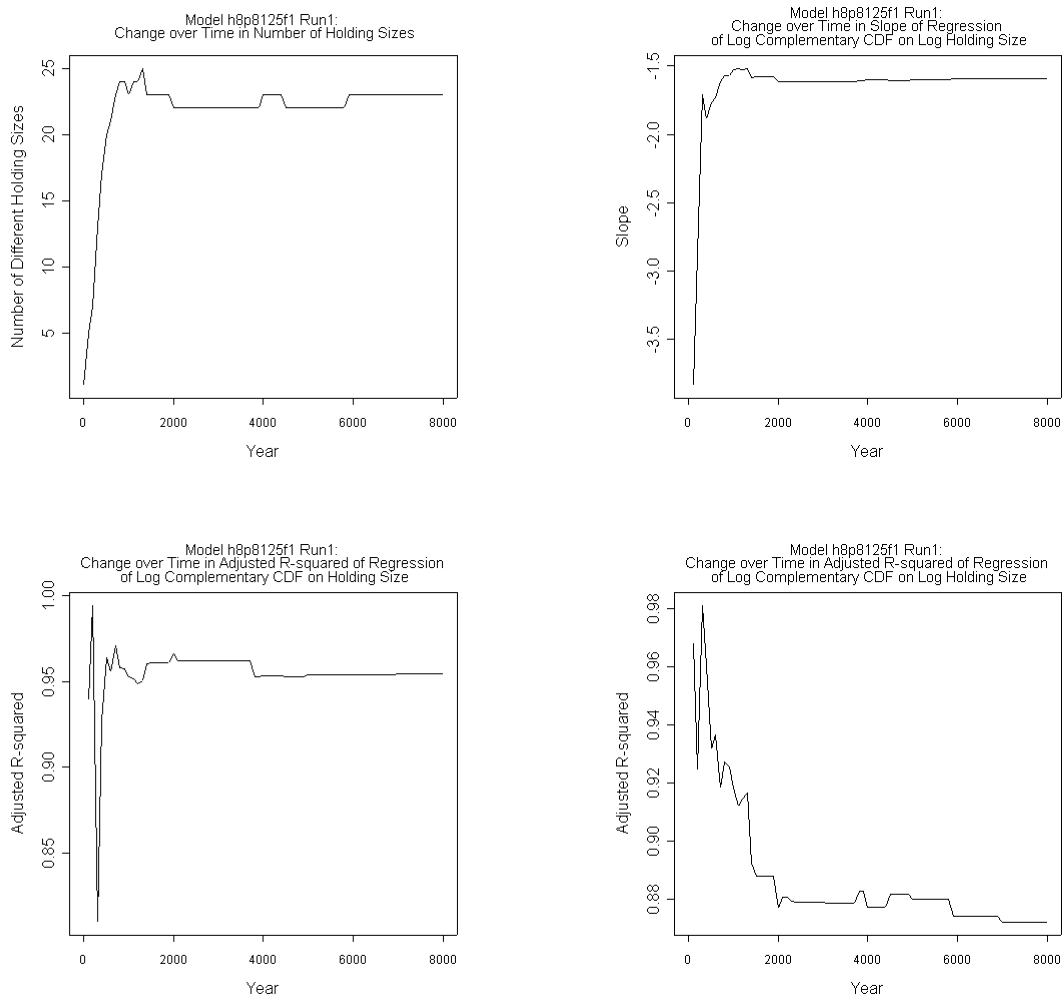
The remaining three figures make it possible to contrast this run with the first runs undertaken with three different parameter sets, each differing from H8P8125F2 in just one respect. In Figure 5, the contrast is with H8P8125R2, which uses Random rather than Fickle Selection on Parcels where the Aspiration Threshold is not met. As can be seen in the top left subfigure, the number of different sizes of Estates is considerably lower. There is, in fact, considerably less consolidation of Estates. The resulting slope estimate from log-log regression



**FIGURE 5** Diachronic plots from run 1 with parameter set H8P8125R2

of CCDF on Estate Size is steeper, and the way in which the number of Estates decreases with Estate size is much closer to an exponential distribution than to a power-law distribution, as can be seen in the lower two subfigures, which show adjusted  $R^2$  values. (The gaps in these plots occur when the number of different Estate sizes falls too low for the regression analysis to be undertaken.) A possible explanation for the difference between H8P8125F2 and H8P8125R2 is that Land Managers using HR spread their risks more once they have multi-Parcel Estates (the Land Uses they employ are, on average, less uniform in any one Year), which will decrease the rate of change in the Estate size in both directions. Hence, there are likely to be fewer large Estates.

In Figure 6, the parameter set concerned differs from H8P8125F2 in the way Neighborhood is defined. In the parameter set H8P8125F1, two Land Managers are Neighbors if, and only if, their Estates share a common boundary point. This change also shifts the resulting size distribution away from a power-law distribution and toward an exponential distribution. In this case, the shift may be due to a reduction in the speed with which Estates can expand. Since they can add new Parcels only at their boundaries, a large Estate cannot expand at as great a proportional rate as a small one, if neither is limited by the availability of cash.

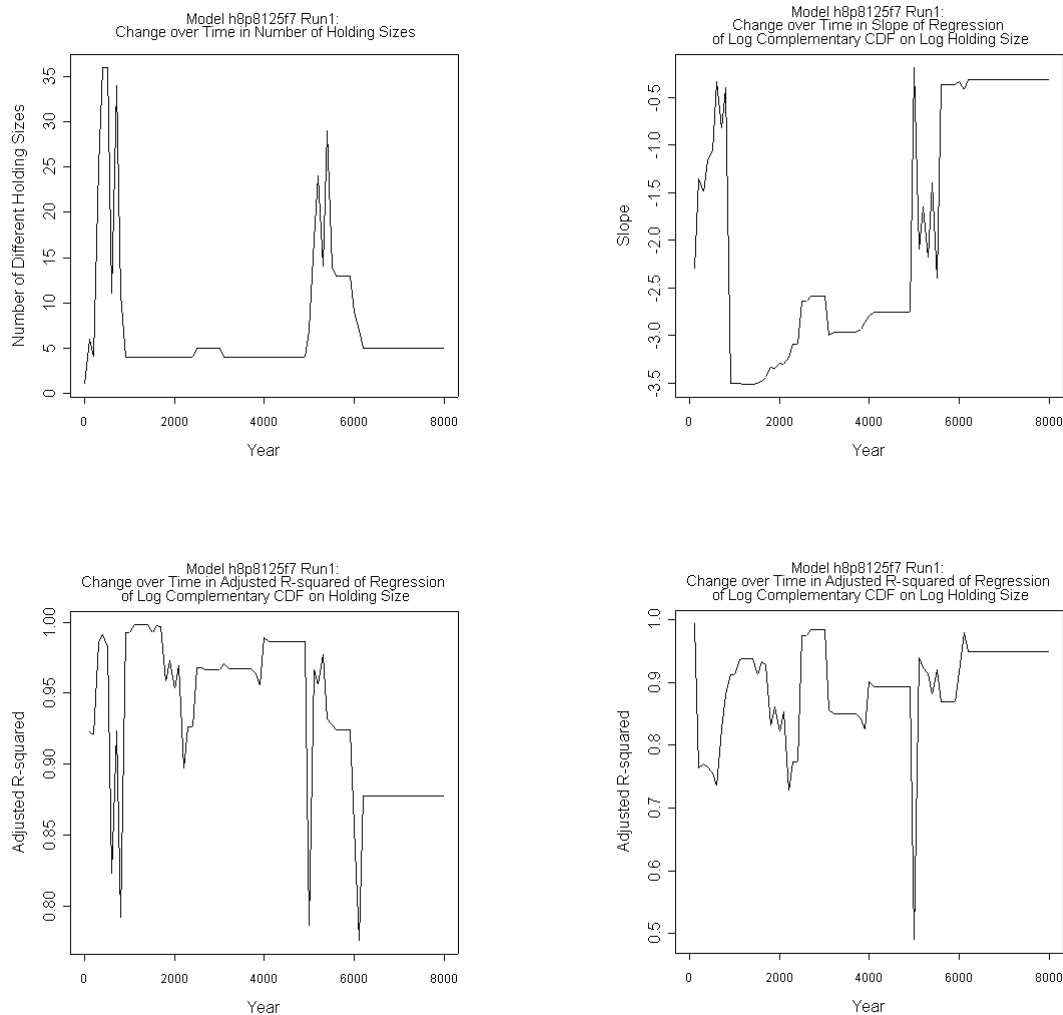


**FIGURE 6** Diachronic plots from run 1 with parameter set H8P8125F1

Finally, Figure 7 shows output from the first run with the parameter set H8P8125F7, which differs from H8P8125F2 in having a lower Land Parcel Price of 1 rather than 16. Here, what has actually happened is that for much of the time, a single Estate controls more than 1,200 of the 1,600 Parcels; therefore, the number of different Estate sizes is small. Note that the slope is now quite shallow. As occurs when R-SG is used, it appears that speeding up the rate of change across the board (by making it easier to buy and by requiring more Parcels to be sold to settle a debt of the same size) resulted in a shallower slope.

## DISCUSSION

Power-law size distributions are reported from a wide range of types of data in the natural and social sciences. However, the simple theoretical model that is claimed by Gabaix (1999) to produce power-law distributions with a slope of  $-1$  in a set of growing and shrinking entities does not do so *in general*. It is not in itself surprising that the measured distribution for Scottish



**FIGURE 7** Diachronic plots of run 1 with parameter set H8P8125F7

land holding sizes does not follow a straightforward power-law distribution. However, we can ask why land holdings appear not to resemble other sets of socioeconomic entities such as cities, firms, and market shares, and why R-SG parameter settings that generate distributions close to power laws are easier to find than their FEARLUS counterparts.

Some specific reasons for the latter difference have already been hinted at in relation to particular FEARLUS parameter sets. The set H8P8125F2, which gave the closest approach to power-law size distributions, has two features that are unlikely to be found in real-world contexts and are not present in most FEARLUS models. First, Land Managers with multi-Parcel Estates choose the same Land Use for all Land Parcels on which they change Land Use in a given Year. Second, a Land Manager is equally as likely to buy a new Parcel remote from its current holdings as a neighboring one. Removing either of these two features appears to shift the distribution away from a power-law distribution and toward an exponential distribution, plausibly by reducing the speed at which large Estates grow (and, in the first case, shrink) in proportional terms. Slowing the speed of change can be expected to produce a steeper fall in the number of large entities, as seen in the R-SG results using different values of  $\sigma$ : if the slowing occurs in only part of the range of sizes, the result will be a local steepening. Blank and Solomon (2003) state that “power laws, as opposed to other functional forms, have no fixed scale and their emergence implies that the system behaves self-similarly over many orders of magnitude.” Where we find deviations from power-law distributions in spatially distributed systems, we may therefore conclude that in some way, different mechanisms are operating at different scales. In this connection, it is interesting that the sizes of the largest 160 estates in Scotland apparently do fall very close to a power-law distribution and fall much farther from an exponential distribution. This suggests that the processes primarily determining the size distribution have been different for different size ranges.

Even H8P8125F2 does not produce perfect power-law distributions in FEARLUS. One possibility of current interest is that the main reason for this is that successful Land Managers can buy more land only when other farmers are financially obliged to sell. If this constraint on growth was important in the real world, long-settled areas might show size distributions very different from those of regions where there has been recent expansion into uncultivated land or regions where land has been taken by force from a weaker ethnic or social group by a dominant group. Furthermore, even in long-settled areas, different institutional systems might produce marked differences. This constraint on growth could be seen as an example of a broader tendency for socioeconomic systems involving interacting adaptive agents to evolve both individual and collective responses that buffer change (Ormerod and Mounfield, 2001). In the near future, we intend to compare the size distribution of Estates in FEARLUS with the distribution of total Wealth, including the “cash” that Land Managers can accumulate if unable to buy more Parcels. The latter distribution may be considerably closer to a power-law distribution, since it is not subject to the same constraints on its growth. We hope to report this work in Gotts and Parker (in preparation).

## ACKNOWLEDGMENTS

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## PUBLIC GOODS THEORY OF THE OPEN SOURCE DEVELOPMENT COMMUNITY USING AGENT-BASED SIMULATION

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### ABSTRACT

Creation of open source software (OSS) can be considered a collective action by individuals with the mutual self-interest of creating and maintaining a public good. We explain the OSS development process in terms of public goods theory, including the notions of connectivity and communality for interactive communication systems. We add a feature — the characteristics of the environment as it interacts with the OSS development community. OSS is more than a simple, classical, physical good; it is a complex, socially constructed, informational good that has heterogeneous resource requirements and provides heterogeneous benefits to its users. Critical mass occurs not at a singular point in time but is an ongoing, adaptive process, and the notion of success for a project depends both on the group's cognitive purpose of the software and each member's cognitive belief in the project's success. We describe in detail the connection between the OSS development community and public goods theory, and we explore the hypothesis of OSS as a public good by using agent-based modeling and simulation.

**Keywords:** Open source software, public goods theory, agent-based simulation, computational social theory

### INTRODUCTION

Creation of open source software (OSS) can be considered a collective action by individuals with the mutual self-interest of creating and maintaining a public good. Public goods theory (Samuelson, 1954) attempts to explain the factors that encourage people to contribute to a public good. Four such factors include (1) identified features of the public good, (2) characteristics of the individuals, (3) characteristics of the group, and (4) the action process of contribution (Marwell and Oliver, 1993; Monge and Contractor, 2003). We add a factor — the characteristics of the environment. For an OSS project, the software itself can be considered the public good, but it would be more accurate to extend the good to also include the project's Web pages, discussion forums (e-mail lists, newsgroups), and management tools (bug/feature tracking, source control) because they provide communality (Fulk et al., 1996). These features are mechanisms for people to collectively share information and knowledge related to the public good. OSS projects generally have full communication connectivity because of the discussion forums. Each individual can easily communicate with every other individual by posting a message, but this does not mean there is full social connectivity, because individuals may not read the forums or may ignore messages on those forums. An important notion in public goods theory is that of critical mass (Marwell et al., 1988), which refers to a point in time when enough

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individuals have committed resources to make the public good a realization. For OSS, such a critical mass is one but not the only criterion for a project to be successful.

In this paper, we describe in detail the connection between public goods theory and the OSS development community. We discuss the various factors of public goods in relation to OSS projects and examine how OSS diverges from the classical theory both in its interaction with the environment and how critical mass and project success are defined. We describe an agent-based model and simulation, especially the challenges involved with correlating social theory with empirical data into a valid simulation. Finally, we offer some conclusions and directions for future work.

## **OPEN SOURCE SOFTWARE AS A PUBLIC GOOD**

### **Characteristics of an Open Source Software Project**

Open source software projects have all of the features of a public good. First, a digital product, it can be easily and inexpensively copied for each individual, which allows for a shared supply; that is, multiple individuals can be using the public good at the same time, and use by one individual does not limit use by another. Second, OSS projects prevent exclusion because each user has his or her own copy with the right to modify and to distribute. The OSS licenses disallow a single user to take away usage rights from other users. Third, OSS projects have the “free-rider” phenomena in that many individuals download and use the software without contributing to the software project. Finally, OSS is developed through collective action by numerous individuals. These four features are the core characteristics associated with classical physical public goods, as described by Marwell and Oliver (1993). However, Fulk et al. (1996) put forward that communality and connectivity are additional characteristics of public goods for interactive communication systems; OSS projects have these additional features.

Connectivity refers to the ability of any member to communicate with any other member. This capability is supplied for OSS projects by such features as e-mail lists and discussion forums, so there is a very low cost to communicate directly to any and all members. Communality is the notion of a shared body of information or knowledge held by the members, so for OSS projects, this shared knowledge pertains to the project’s Web pages, frequently asked questions (FAQs) documents, user and reference documentation, wiki’s, discussion archives, and other such features. The availability of these additional features means that the computer software code alone is not the public good. Instead, all of these communal artifacts that surround the software are encompassed by the definition. The broadening of what is included in the public good definition for OSS projects has the implication that the good is more than a simple, classical physical good; it is in fact a complex, informational good. By complex good, we mean that the good provides a heterogeneous set of benefits to its users in contrast to the often homogeneous benefit supplied by classical public goods. The concept of OSS as a complex good is put forward by Bessen (2001) as a hypothesis for why OSS provides functionality that is not provided by proprietary software companies. As a complex good, OSS provides multiple features whereby individuals have interest in different subsets of those features; we expand upon individual interests and benefits in the next section.



The life cycle of software differs from that of physical goods. Early in the software life cycle, few features are available to users, and little or no benefit can be obtained from the software. As the software develops, other features are added that broaden the potential users of the software. Also, the communality aspects increase as contributors, who are not software programmers, enhance the public good by writing Web pages and FAQ documents, reporting bugs, and suggesting new features. This middle period of the life cycle sees an increase in software complexity as features become interdependent; this change causes a corresponding increase in heterogeneous resource requirements for the project. Besides programmers, the project needs testers to find and report bugs and writers to draft FAQs and other documentation. When resources are scarce, competition appears to determine what features to implement. It is during this period that the critical mass arises or not, determining if the project receives sufficient resources to grow into a successful and self-sustaining project. Later periods in the life cycle are marked by maturity and maintenance tasks; the resource requirements of the software diminishes as few new features are added and most software development deals with fixing bugs or porting the software to different environments.

### **Characteristics of an Individual**

One of the key characteristics of OSS projects is the heterogeneity of the individuals involved. Heterogeneous interests play both cooperative and competitive roles. Individuals cooperate to attract and to accumulate resources for a particular OSS project, but within a project, individuals compete for which features to implement, the architecture and design of the software, the specific license to use, and the technology. Each individual holds beliefs about these issues and communicates them publicly to enforce or to direct these beliefs onto other members of the group. The resource capability, be it time or skill, is also heterogeneous for individuals. Some people have the skills to write software code, while others have skills in Web design, graphics, or the ability to install and use the software. Besides having these skills, individuals must also have the time available to contribute to the project, and that time must match the temporal resource requirements as the project evolves. Resources are generally considered fungible (Marwell and Oliver, 1993), which means that they can be reduced to a single metric (like money). This assumption is not valid for OSS projects, however, because resource interdependencies play an integral part in the evolution of the project. Finally, the benefits that individuals gain from using the software, as well as the costs they incur from contributing to a project, vary from individual to individual. All of these factors play roles as positive or negative feedbacks that attract or repel individuals.

Current research by Xu et al. (in press) has categorized individuals into project leaders, core developers, co-developers, active users, and passive users according to their role and type of contribution to the project. Passive users are the free riders who use the software but do not contribute to the public good in any way, whether it be software contributions or just posting messages to the discussion forums. Active users participate in discussions, report bugs, and request features, but they do not contribute code. Co-developers, core developers, and project leaders contribute source code, but only the core developers and project leaders can commit code into the source repository. Therefore, co-developers must communicate their code to someone in one of the two other categories. Project leaders have the additional authority to perform administrative duties, such as adding or removing core developers, but they can also delegate some administrative duties to the core developers.

## Characteristics of the Group

The group is defined as the set of people associated with an OSS project. The group's communication is characterized by full connectivity and one-to-many messages through the project's mailing lists and discussion forums. One-to-one private communication exists, often for functional purposes like sending patches to maintainers, but the public forums are considered the primary communication medium. Group norms come into play regarding acceptable usage of these forums for both the form and content of messages. These norms are heterogeneous across projects. Some projects may consider posting patches to the forum as acceptable, while others do not, or responsiveness to newbie Help requests may provoke a detailed answer or a blunt response to read the documentation. These norms also extend to the source code for formatting standards and naming conventions. Each project enforces its norms through an often undocumented and informal action process of correcting an individual whenever they have violated a norm.

Of particular interest are group norms that appear to be shared across many projects; one such norm is the maintenance of ownership responsibility for code a developer has written. When new code is committed into the project's source code, the author of that code is expected to respond to bug reports and features requests related to that new code. Developers who do not follow through with their responsibilities may be looked upon with disfavor, and project maintainers may be less inclined to accept code submissions from that developer in the future. This norm is enforced by many open source licenses, which legally require that authors and their modifications be clearly documented with the source code. Such a norm also appears to act as an implementation of division of labor for the project; instead of a manager dividing and assigning tasks, individual developers acquire responsibility in a decentralized and self-selecting manner.

Just as an individual can have cognitive beliefs about an OSS project, the group has a cognitive understanding of the purpose of the project. Such a cognitive structure is inherently dynamic, changing over time as users join and leave the project and inject new ideas into group discussions. Constraints imposed by this group cognitive structure feeds back to individuals' self-interests as they compete among themselves for features to implement in the project. This competition can also be viewed as attempts to shift the group's cognitive goals so that they align more closely to individuals' interests.

## Action Processes of Open Source Software Development

In keeping with our definition of OSS as a complex good, the action processes of contribution undertaken by individuals display considerable heterogeneity. By action process, we refer to any action undertaken by an individual that translates into collective action for the public good; such actions alter the public good by adding, removing, or reallocating resources. An individual can contribute to an OSS project in many ways, and each way requires differing resource commitments of skill and time by the individual. Actions can be categorized as either individual or project actions; however, a project as a socially constructed informational good cannot actually perform an action, so an individual is required to perform the actions on behalf of the project. The type of project action performed by an individual often signifies the role or authority that individual has within the project. Conversely, only individuals with the right authority can perform project actions. Project actions include creating a project, adding or removing core developers, committing source code, and releasing file distributions. Individual

actions include writing source code, writing documentation, posting messages, reporting bugs, and requesting features. Many more individual and project actions exist, but not all can be listed here, and all are considered collective actions for the public good.

An individual's position within the group is not fixed; in time, a person can acquire more responsibility and authority for the group or can become more distant with less interaction and contribution to the project. The evolution of an individual's role in an OSS project is a key action process. A current hypothesis is that a project that can increase the responsibilities of members (which implies increased resource commitment) and can retain those members is more fit and has a better chance of success. Likewise, the disengagement of individuals with a high level of responsibility from the project signals a significant loss of resources and diminished survival prospects for the project.

## **Characteristics of the Environment**

Although not generally considered as part of the theory of public goods, the environment is one of the central concepts in agent-based modeling, and it plays an important role in the OSS community. By environment, we refer to everything external to our unit of interest — the OSS project. Included are such things as proprietary software companies; political and economic climate (both nationally and globally); legal issues, especially with regard to intellectual property rights and the difference of those rights between nations; and technological advances and standardization efforts of technologies. Of interest are commercial organizations that are injecting resources into the community either by hiring programmers to work on OSS projects or investing money in organizations that develop OSS. Included is the trend of proprietary software companies to support their software on OSS systems, as well as to bring OSS internally as components of their proprietary software or as part of their information technology infrastructure. These activities have given endorsement and validity to OSS, which has enabled customers to seriously consider open source alternatives to proprietary software. Most of this activity has occurred after the relevant OSS projects have become successful; while they can help stabilize those projects, such environmental effects are not the cause of the projects' initial success.

Technology plays an important role in determining how desirable an OSS project is to potential developers and users. Such technologies include the programming language, supported operating systems, integration with other tools and libraries, support for standard data formats and protocols, and even the "look and feel" for graphical programs. For OSS projects, technology is part of the environment, and projects may have to adapt to different technologies if they want to attract and retain a larger user base. The environment is not static for OSS projects; it is dynamically changing through introduction of new programming languages, new architectural paradigms, new software engineering practices, new standards and protocols, and new modes of communication. Such a changing environment leads to the development of new software features and makes some existing features more or less desirable than others.

## **Critical Mass and Project Success**

Critical mass is the point when a public good has received enough interest and resources to be self-sustaining. For a classical public good, critical mass indicates a success point when the

public good is realized. For software, the notion of critical mass as a specific event is not so clear because the definition of success is not homogeneous for all software projects. Each project has its own definition of success that is a subjective rating by users of the software; it cannot be computed with a simple numerical measure. The potential user base of an agent-based simulation toolkit is significantly smaller than that for a Web browser or a word processor, so direct comparison between projects is not possible. In addition to projects having a heterogeneous definition of success, each member within a project has a different cognitive belief in the project's success. This situation stems from the fact that OSS is a complex, socially constructed informational good that evolves through interactions between its members and the environment. Critical mass is not a singular point in time; rather, it is an ongoing, adaptive process. Projects that have attained a critical mass can lose it later in time, not just from people leaving the project, but also from people joining the project, shifting the group's cognitive purpose or goal of the software and increasing the resource requirements to make the project successful.

Data mining research (Gao et al., 2004) has indicated that five temporal factors are significant for clustering projects into categories of success: (1) number of developers, (2) number of file releases, (3) number of help requests, (4) number of tasks opened, and (5) number of tasks closed. All of these factors are expressed as rates of change over time. K-means clustering by these factors partitions the projects into failed, normal, and good projects with decreasing confidence, and the remaining unclustered projects are categorized as excellent projects. The significance of these results is that while standard metrics can accurately categorize failed projects, excellent projects are outliers in the dataset. So while these factors offer a good description of what excellent projects are not, they offer little description of what excellent projects are. Our focus on agent-based simulation is then to produce outlier scenarios. Analysis of the time evolution and dynamics of those outlier projects should provide hypotheses as to why the projects succeed, and we expect that empirical surveys can test those hypotheses.

## **AGENT-BASED MODEL AND SIMULATION**

We explore the hypothesis of OSS as a public good by using agent-based modeling and simulation. Individuals and projects are modeled as agents interacting in a virtual environment, specifically a social network. The environment is also an agent in our model, and the social network is dynamic because both individuals and projects appear and disappear from the network, and network links appear and disappear as people join and leave projects. We focus on the time series and evolutionary aspects of the community as individuals join and leave projects as their interests and resource commitments change, and projects are created, abandoned, and allowed to mature through a software life cycle.

We currently are designing and implementing an agent-based simulation for our public goods theory of the OSS development community. Serious challenges are associated with such a simulation for input modeling, parameter estimation, and validation. The primary set of empirical data available to us is a database dump of the SourceForge community, and while this dataset is large, it is missing key attributes of individuals that can usually be obtained for smaller communities through surveys. Likewise, the database dump is a snapshot in time of the community, so not all necessary temporal information is available to enable us to understand the evolution of the projects and the individuals. We do, however, have very good data analysis about the project and developer networks indicating the existence of scale-free and small-world network properties.

Input modeling refers to the process of developing an analytical distribution for empirical data that can be used to synthesize input data for a simulation. Parameter estimation is determining appropriate values to use for the parameters of those analytic distributions like mean and standard deviation. For our model, we need input distributions for attributes of individuals, projects, and the environment. The primary individual attributes are interest, skill, and time. No information on those attributes is directly available in the empirical data, but we can infer skill and time distributions on the basis of the quantity and type of activities performed by individuals, and interest of individuals can be inferred from project attributes. Information on the environment is more difficult because the Sourceforge data have no real measurement of outside influences; however, we can estimate the flow of people in and out of the OSS community. More research is needed on the effect of singular events, such as Oracle supporting Linux, or advocacy events, such as the announcement of a project on Slashdot. Besides the attributes of the agents, the rates for action processes must be estimated. The rate of new projects being created, the membership rate of people joining projects, and the activities within a project (such as posting messages, reporting bugs, committing source code, and releasing files) are all relevant action processes. As mentioned, data mining results have shown some factors to be more significant than others, so we will initially focus on actions related to those significant factors in our implementation.

Validation is the process of comparing the simulation's behavior to the behavior of the real system. Here lies the greatest challenge because it is not possible to acquire complete information about the real system in order to perform extensive statistical testing. The approach we take toward validation uses global network properties and data mining. If the social network created by the simulation has the same network properties (e.g., statistically comparable clustering coefficient and scale-free parameter) as the empirical social network, then we claim that our social network structure is similar to the real social network. Of course, many processes can produce a scale-free network, so we cannot claim we have found the correct process, only that we have found a social theoretic process that produces the correct structural properties. Data mining offers a novel validation technique because we can perform the same data mining and clustering algorithms on the simulation data, and the algorithm tells us what are considered the most significant factors. Therefore, if the algorithms produce the same factors and the same clusters for the simulation data as for the empirical data, then we claim that the trends and patterns within the simulation correlate to the same trends and patterns in the real system. Data mining provides us with a validation technique, not just on the raw data but also on the meta-data. We must be cautious about this claim because data mining of incomplete information in the empirical data may produce incomplete factors. Therefore, our simulation may just be duplicating significant factors in the empirical data instead of representing the truly relevant factors in the real system.

## **CONCLUSIONS**

Public goods theory offers a rich social theory framework for studying the OSS development community. We described OSS in terms of the four theoretical features of classical public goods: (1) characteristics of the good, (2) characteristics of the individuals, (3) characteristics of the groups, and (4) action processes of contribution. We also described OSS in terms of communality and connectivity as additional features for public goods that are interactive communicative systems. Likewise, we extended public goods theory for OSS by incorporating the characteristics of the environment as a new feature and by redefining critical

mass as an ongoing, adaptive process. Transformation of the conceptual model into an agent-based simulation poses numerous challenges for input modeling, parameter estimation, and validation. We described some of these challenges and suggested that data mining algorithms offer a novel form of validation that operates on the meta-data instead of the raw data. As we progress, we look to complete our agent-based simulation and to provide additional insight about the open source development community.

### ACKNOWLEDGMENT

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**DISCUSSION:****GEOGRAPHY AND CULTURE****(Saturday, October 9, 2004, 10:15 a.m. to 12:15 p.m.)**Chair and Discussant: *Pam Sydelko, Argonne National Laboratory***Emergence of Social Complexity in Mesa Verde by Using Cultural Learning in the Presence of Balanced and Reciprocal Exchange Networks**

**Pam Sydelko:** My background is in ecological modeling. Ecologists are brethren with sociologists because we are in a field that isn't a physical science. We often interact with people from the physical sciences who have equations for things that describe something in the real world. Ecology is like sociology. We can't observe things. We often have to come up with models. So stepping out into applications in that area, I have a lot of scars. That's what I do; I'm an application scientist.

When I take a simple model (like some theory out of the literature) and take that first tentative step in making a model that might actually answer a question, I'm left without a hand to hold. That's because basic scientists have the opinion that once you've done that, they'll have nothing to do with you. I would say that culturally, some of what we can get over with when we are trying to come up with something like that very nice graph of Chick's [Macal] is the concept of iterative development—you go back, do experimental modeling, then step out and try it, then go back, and then have that be a team effort and more of a handholding effort. If you're going to try to apply this, that's one of the things I've noticed.

The other thing that I would like to say is that coming from the other end—where decision makers want their models to say black or white or yes or no, it's really frustrating for us applied scientists because we know we can never tell them black or white or yes or no, even though they want that so badly. So there's a role for visualization here. We need to be able to get decision makers to accept a landscape or a surface of outcomes. We need to look at more alternative futures or alternative outcomes analysis, where we can say that we don't know exactly, but it seems it looks a little bit like this. There tend to be more outcomes that look more like this than this. Something along that line gives them at least some ways of making decisions better, without telling to tell them exactly what decision they should make.

Our first talk is a very lead-in to geography and simulation applications. I guess that Bob probably had this happen when he first started stepping out of the literature and doing some applications in this area; in fact, two things probably happened. One was that a lot of people suggested that you forgot this, you forgot this, and you forgot that. But you have to start simple in some ways to get your feet wet. I'm interested that you had a path for extensibility, and now you're adding some of these things you knew we had, that we were ignoring at first and are now trying to put in. I think it's a great example of an application trajectory that can occur if you're lucky enough to have the time and funding to actually step more into the details over time.

Let me now introduce Bob Reynolds, from Wayne State, with a talk on “Emergence of Social Complexity in Mesa Verde Using Cultural Learning in the Presence of Balanced and Reciprocal Exchange Networks.”

**Robert Reynolds:** Wow. I have a notepad to write down all the extensions that I need to add to this. My co-author, Ziad Kobti, is sitting here. This work is part of his Ph.D. thesis, which he is completing this term at Wayne State. In fact, in approximately two weeks, I will be giving a talk on the results to land managers in the city of Cortez. They are, in fact, in charge of dealing with issues there. Here’s one of the architectural remains of the ancient Anistazi, and there’s a story here. In fact, there’s a mystery. This area contains one of the great mysteries of the prehistoric world. There is a civilization, the ancient Anistazi, who occupied this area from around 600 A.D. to 1300 A.D. and built very elaborate architectural structures. All of a sudden, around 1300 A.D., they disappeared. They left. Many of the Native American tribes in the area claim ancestry with these ancient ones. It has raised a number of questions that archeologists, anthropologists, and sociologists have been asking and thinking about for decades. One of the goals of our approach is to figure out or suggest some possible solutions to the mystery or unravel the riddles of what they left behind.

The overall approach for the talk is to motivate this mystery in the geographic and ecological context in more detail. Then we’ll talk about the framework in which we’re going to be developing the agents, and the intelligent agents, and their population. Next we’ll look at the kinds of social intelligence that will be evolving in these agents within that framework. Finally we’ll look at some of the results, and we’ll try to deal with the issue of model validation. In fact, we’re working with ecologists, archeologists, and anthropologists who have a lot of data and who are not reluctant to validate the model. So it’s definitely a constant process.

[Presentation]

**Sydelko:** We have time for one question.

**Craig Stephan:** I’m Craig Stephan of Ford Motor Company. I’m interested in the fact that your population continues to increase. If you had simply let the model run without bringing in drought or climate change or whatever, would you ultimately reach a peak and a population crash?

**Reynolds:** We’re not looking at any of the density-dependent factors that would take place because the population is growing, and there are obviously some areas in which people are more likely to collect. That’s going to create issues of, for example, strife and stress, and none of that is included, but once we start to deal with community issues, then we will. It’s a “to do.”

This is a suggestion for further reading. This is another application where we look use multi-agent-based systems to do design. We’re looking at agents that interact to develop large-scale software systems. So we have a collaboration, but it’s in terms of design knowledge and not the ancient application. This is a brand new book that just came out. Buy it. Done.



## Sociodynamic Discrete Choice on Networks in Space: Impacts of Agent Heterogeneity on Emergent Outcomes

**Sydelko:** Our next speaker is Elenna Dugundji, and the application is transportation. Most of the models we're looking at in this session are probably what Chick calls the insights type of model. It's looking at the theory behind transportation mode choices and how that plays out in a specific place in the Netherlands.

**Elenna Dugundji:** The topic of this presentation is socio-dynamic discrete choice on networks. This is a collaborative work with colleague Lazlo Gulyas in Budapest, Hungary, at the Computer and Automation Research Institute of the Hungarian Academy in Sciences. He is responsible for the code, which is written in Repast. I will go through motivation, then touch very briefly on the literature because there's quite a bit. I'll show you one table. I'll show the model, some analytical results so far, and the empirical application, and finally open the session to questions.

[Presentation]

**Dugundji:** My colleague Lazlo Gulyas would like to thank his thesis supervisors, and I would like to thank mine. This work funded by the Dutch National Science Organization. Also we'd like to thank the people who helped us with the data from the municipality of Amsterdam.

**Reynolds:** I'm Bob Reynolds from Wayne State University and the University of Michigan Museum of Anthropology. On the simulation, you had over 300,000 time steps. What are your units of time? Three hundred thousand is long. What unit does this mean in terms of agent decision making?

**Dugundji:** Very good question.

**Weimo Zhu:** I'm from the University of Illinois. Amsterdam is a city unlike many others in that cycling is very popular. You have an excellent support in the city, and it's a very unique part of your culture, and so that environment support is such an important factor. I was also wondering if the weather plays a role. I know certain times of year are very cold. Do the people still carry out the same behavior?

**Dugundji:** There are several questions. With regard to the questions about Amsterdam, the modal split is actually fairly constant throughout the year. There is indeed a tendency for more bicycles to be used in the summer and fewer used in the winter, but it's not as different as you might expect, so this model is not looking at seasonal effects. I actually could have done this. The data are at a level so that I know at which month they have done this because this is a rolling pseudo-panel over a five-year period. This could have been something to have taken into account. We haven't done this at this level. What's the next question?

**Zhu:** Can you speak a little about the accuracy of the model?

**Dugundji:** With regard to the empirical estimation, I have not shown you these results. We've done a very extensive estimation of these 15 different model treatments for dozens of different model specifications. A paper that will appear in the *Transportation Research Record*

in 2005 explains and goes through the details of the empirical estimation of these effects. And I can show you the rows squared for each model and the fit and how they compare to each other.

**Zhu:** Do you have specific results, and can you mention something about the simulation validation?

**Dugundji:** I don't remember them off the top of my head, because it's hundreds of models that we've compared, putting all these things together. But I can refer you to the paper. Regarding the multi-agent simulation, it's a much more complicated question because we don't have statistical validation techniques that I'm aware of yet that can validate the implications of the dynamic effect on the model. So that is an open question.

**Kostas Alexandridis:** I'm Kostas Alexandridis, from Purdue. I didn't understand one point because the nature of the utility function is that no negatives. ... So how can you account for some kind of learning or intelligence of the agent? How do they account for the fact that some choices draw some kind of negative reinforcement?

**Dugundji:** We do not have negative feedback in this model yet. It is one of the extensions that would be interesting to add. But we're just building it up, step by step, to make sure we understand what the positive feedback looks like before we throw in the negative feedback. We have not added negative feedback. It would be a very important thing to add. That's why it was on that "to do" list that I showed at the end of the slide. Obviously, with regard to transportation issues, such as traffic jams and congestion, you would certainly want to have negative feedback. It's just the positive effect right now.

I should add that the negative is actually a much more complicated question than the positive, which is why we began with the positive feedback. For any physicists in the audience, you would immediately know that this is the case. Adding the negative feedback is sort of a spun glass situation, which is much more complicated than just the regular straight magnetism.

## Size Distributions of Land Holdings in an Agent-based Model of Rural Land Use

**Sydelko:** Our next speaker is Nick Gotts from Macaulay Institute in Scotland. The title of his talk is "Size Distributions of Land Holdings in an Agent-based Model of Rural Land Use."

**Nick Gotts:** This is work that I'm doing with Dawn Parker at George Mason University. It was prompted very largely by Claudio Cioffi from George Mason, who invited Dawn and me to write a chapter in a book on power laws in the social sciences, which he's editing.

[Presentation]

**Brian Pijanowski:** I'm Brian Pijanowski from Purdue University. Great work. We've also developed a land-use change model. We're working in Swarm. I've got a couple of questions for you, but in the interest of time, I'll just ask one. Some of our work suggests that parcel sizes are a function of the distribution of biophysical resources and other types of amenities across the landscape. For example, if you're near a road, your parcel sizes are smaller, or you could be near a river or a lake. To what extent can you introduce that into your power law assessment?

**Gotts:** That's a very important point. It's not one that we've looked at systematically yet. We can vary the biophysical properties of the land. Up to now, we haven't been able to tie that up very effectively with the economics because, for one thing, we've had this sort of fixed break-even threshold, where every bit of land costs the same amount. This, of course, isn't anything near being true. So that's certainly something that's on our list of things to do.

I think it may be so in Scotland, for example. An obvious thing to do is to try separating the highland and lowland regions, where you get quite different types of land use. I believe there are mathematical results showing that if you combine two different power laws, you'll get another power law. If you have two separate regions divided according to different power laws, and you then amalgamate the two sets of data, you will find yourself with another power law. That's certainly something that ought to be looked at.

**Greg Madey:** I'm Greg Madey from the University of Notre Dame. There was something I didn't understand in two different slides. One slide was where you plotted the data on the straight line — the log/log; it was at the tail where it stopped looking linear, but you also said that the top 160 were linear.

**Gotts:** Yes. In fact, the bit of the tail you saw that looks nonlinear only represents something between 10 and 20. Because it's a log/log scale, that represents about the top 10 or 20. So it's rather misleading. You can't go purely on visual appearance, unfortunately. You're right to point that out. There is also a little dip at the very largest, which is perhaps a finite size effect. You can't have estates larger than the whole of Scotland, obviously, yet, it's also worth looking at. However, there were deviations at both ends, and, at the moment, it seems to be the lower one that's in some ways more significant.

**Madey:** So then the failure to fit the straight line was only the top 10 or 20?

**Gotts:** At that end it is, but there's also a failure to fit the straight line at the lower end.

**Madey:** Then is it possible it would be log-normal? You compared it against — I forgot which way it dipped. Did it dip on the other side? That might suggest log-normal.

**Gotts:** There are a couple of complications there. One is that as you go down the scale of estates, the data are less good. Andy Wightman is confident that he's got pretty much all the data for estates that are 1,000 acres, but under that acreage, data start to get less and less complete. So you may get artifacts there. The other thing is that it's not obvious where to stop if you look beyond the large estates. I own a few square meters of Scotland that my house stands. Do we go down that far? I'm not sure. I suspect that sooner or later, you would come to an area where you got into a different regime of behavior. I did. I have tried matching it to a log-normal. It doesn't look log-normal, but since I'm only looking at the upper tail, that's not conclusive.

**Craig Stephan:** I'm Craig Stephan of Ford Motor Company. I wondered if you've tried comparing the relations that you get with physical systems. One thing that comes to mind is, for instance, grain size distribution in metals. A grain can only grow by gobbling up its neighbors, and I'm just wondering whether they would follow similar size laws.

**Gotts:** That's a good question. I don't know. I've done some work with Claudio on comparing models of competition for territory across domains. That's one we haven't looked at.

We have looked at international relations and plant ecology. With international relations, you tend to get log-normal. Is that right? In some simulations you get a power law, but if you look at the size of actual countries, it comes out something like a log-normal.

**Claudio Cioffi-Revilla:** Country size is log-normal.

**Gotts:** Yes. So I think it will vary according to the mechanism that is responsible for the gobbling up. In Scotland, certainly since the clearances, there hasn't been a lot of forcing people off the land by the threat of violence. In the last 150 years, that hasn't happened, but it may be that that still had an effect on the distribution. I don't know. I suspect that we're getting something a little further from a power law because there is this constraint on actually taking land from your neighbors.

### **Public Goods Theory of the Open Source Development Community Using Agent-based Simulation**

**Sydelko:** Our next speaker is Scott Christley. His talk today is titled "Public Goods Theory of the Open-source Development Community Using Agent-based Simulation."

**Scott Christley:** Thank you. I am a first-year graduate student at the University of Notre Dame. Understanding and looking at the open-source development community have been part of an ongoing project at Notre Dame. My colleagues Jin Xu and Yongqin Gao have been working on this for the past couple of years. My adviser is Dr. Greg Madey.

I have to apologize. Some of the presentations [given today] have had lots of simulation results and nice graphs. I'm right at the beginning of the process, so I have a lot of conceptual models and words. But hopefully, my presentation will stimulate some thought and give you some perspective on this phenomenon that we're trying to understand.

[Presentation]

**Sydelko:** I find this work to be quite interesting. I started my career as being part of a group that was doing open-source GIS work. I'm going to suggest one thing. I know we talked about somebody always saying, "Okay, that's great, but *here*, you need to put this in it, too." One thing I noticed in this particular software — in this open source — was that there an ability to lower the constraint to belonging to the group by having the stepped-in alpha-beta contributions. So you could contribute in an alpha way, which says, basically, that I'm not responsible, don't call me. Throw it out there, and people can work with it. Then, at some point in time, that can migrate more into a beta way by having the group give it some validity by saying that this is good; it meets with the goals of where we want to go. It moves into beta. Then, finally, it comes into official release. But at least it lowers the barrier in the first place, so people feel a little less responsibility if they want to start playing. I just throw that out as a suggestion because it seemed to work really well in this particular software development.

**Christley:** Yes. There are two points to that. There's actually getting users to use the software and then there're people who want to contribute. One thing that's known from some surveys that have been done by the Boston group is that increasing your own skill in programming and computer technologies is one of the big motivations for why people get

involved. They want to increase their skills, so they get involved in something, and they write some little programs, and as they get more response, they get more familiar and more involved in it. So, yes, it's hard to say that there's one path. I think there are a lot of different paths, and that's a very difficult thing. Is there ever going to be a way to generalize that, or is that going to be highly path-independent for a lot of projects?

**Cioffi-Revilla:** I'm Claudio Cioffi from George Mason. I'm really fascinated by this project. I think this community needs a project like this. I applaud you, and I can't wait to read more about it in print or preprint. I have a question for you. You're probably the person most familiar with what the dynamics of this movement look like. Are we still on the exponential side of growth, or is there an inflexion point, or are we past that? Can you say anything that would characterize the growth regime as of now?

**Christley:** Yes. I don't know if we have data on it, but my sense is that it's growing. I don't know if it's exponential or not, but I don't think it's reached a peak or plateau yet. The reason for that, if you look philosophically, is that some of the developers have a utopian notion that all software in the world should be open source. As far as they're concerned, it isn't until every piece of software is .... They see big growth there. If you ask any of them, they can list a handful of things, such as we need to do this, we need to do this, we need to do that. So what's going to matter more is the influx of people. Right now, from statistics like SourceForge, there are — I forget the actual numbers — hundreds and hundreds of thousands of registered users. And that's just one site. Many other sites are popping up. So I think it's still in a growth phase.

**Pijanowski:** I'm Brian Pijanowski from Purdue with a quick question and then a comment. How do you introduce what I would call the 'I hate Microsoft behavior' into this? You don't have to answer. The comment is whether you will be looking at determining whether or not the tools are cross-platform — the types of functionality. In other words, it's different to have a Microsoft Word-type program versus agent-based modeling, and the life cycles of those are different as well. The specialty of that application....

**Christley:** I'm sorry; I rushed through both of those in my slide. Yes, when I talk about the environment, I think this 'I hate Microsoft' behavior is actually very important. It almost acts as a driving or forcing function on the community because it coalesces them. We have this enemy to go against. I hate to use the analogy, but it's the Cold War communists. We have this common enemy that we all have to fight against.

The response to your comment is that yes, in our data set, there are a bunch of different things — like what operating system it works on, what programming language it is, what general category of software it is. When you talk about the success of a project, you can't go with simple measures, such as the number of downloads. The reason is that something like Repast, which we consider successful right now, does not have the same size audience as do an open office or word processor or many other tools. So that makes it difficult as well, because that definition is different for each project.

**Gotts:** I'm Nick Gotts from Macaulay Institute. I think this is a great project, and, as several people have already said, it really needs doing. One thing that interests me is the different motivations people have for using open-source software, and one in particular. I've become increasingly convinced that you can't do science unless you do it in an open source because part

of what is producing your results is not public. Therefore, to me, it's not real science. I wonder how far that view has spread, particularly among our community.

**Christley:** Well, there is research on open content. At the previous NAACSOS meeting, David Heinz talked about open content, which are things more like Wikis. In a way, when you look at the research community and conference proceedings, etc., you want to make them as available as possible. To go along with that, I would say that yes, when we're talking about wanting to share models and replicate things, it's excellent to have open source and transparency. Even if we don't want to look at the Java code, the fact that we actually *can* gives us a little bit more transparency. At least you can have your computer science graduate student look at it for you and interpret the code.

**Sydelko:** Sometimes when people are looking for a specific tool on the Internet, they may find something that's open source. There is a tendency by some users to say it's free, so it's not worth as much, whereas if they look at something that costs \$4,000, they think this must be better. I think a little bit of that goes on, too.

**Kathy Lee Simunich:** I'm Kathy Simunich from Argonne. What were some of the hoped-for results of your modeling of the OSS community? Do you hope to discover the emergence or the dominance of, for example, an Apache-type project or the Big 100 projects? You said you had 800 or 80,000 SourceForge projects, which surprises me. Some of them have to just be little blips. Is that what you hope to see?

**Christley:** Yes. The previous data analysis has shown quite a few power laws in the data. If you look at the distribution of, say, the number of developers on each project, there's a huge amount. Of those 80,000 projects, almost 60,000 have only have a handful of developers on them. The other part of the curve is that there are a very few projects that have a lot of developers.

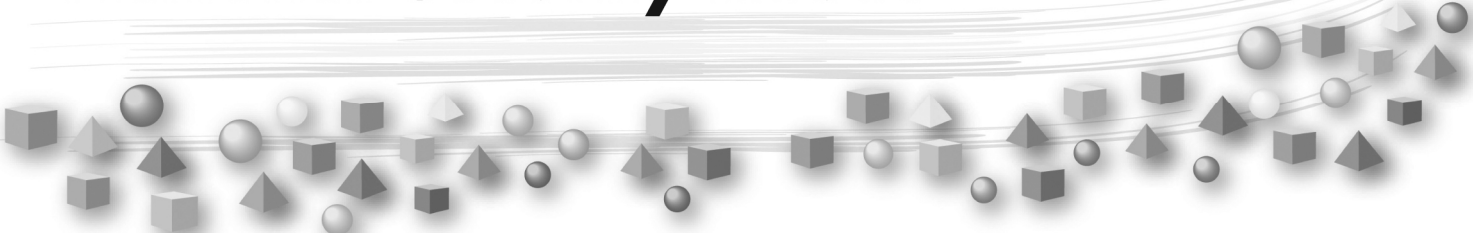
So the real hope is that when we run this social theory, which is motivating the individual actions and behaviors, in a large simulation, it will show the global properties that we're seeing in the real phenomena. That's what I indicated as a weak validation because we've talked a number of times about how different models can still have the same result, especially if we're looking at global things. The second point is that we want to find some techniques for looking at local structural changes and dynamic networks. What kind of techniques can we come up with to do that?

**Sydelko:** Will you come back next year and let us know where you're at on that?

**Christley:** Yes. Thank you.

**Sydelko:** I'd like to finish by thanking all our very brave application modelers.

# National Security Issues







## EPIDEMIOLOGY OR MARKETING? THE PARADIGM-BUSTING USE OF COMPLEXITY AND ETHNOGRAPHY

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### ABSTRACT

On the basis of ethnographic work with youth in Baltimore County, an agent-based model was developed to test the finding that the stories that circulated about a drug (heroin) explained the rise and fall in the curves showing data on heroin epidemic incidences. This paper features the use of design of experiment approaches to evaluate the parameters in that model. Results of the analysis suggest that drug epidemics can be better understood as the diffusion of a commodity rather than an infectious disease, which is the view of the medically dominated substance abuse field. Policy implications of this change in view are sketched in the conclusion.

**Keywords:** Design of Experiment, substance abuse, ethnography, agent-based model

### INTRODUCTION

As we listened to interviewees telling us about illicit drug epidemics in which they had participated, we noticed that they often offered a “folk explanation” of how and why a particular illicit drug took off. The folk explanations, although partial, typically resembled stories about the diffusion of a consumer product more than the diffusion of an infectious disease. People described how early experimenters told stories about experiences they had with a new drug and how, if the stories were positive, they would circulate through social networks and encourage further experimentation as time went on. With truly dangerous drugs, however, the effects of continual use would eventually become apparent, so negative stories would increase and experimentation would diminish.

Simple as it sounds, this shift from “epidemiology” to “consumer diffusion” is a major and fundamental change in how illicit drug use is viewed, and it is a change with implications for drug policy and intervention. It is a change in paradigm, in the classic Kuhnian sense of the term.

In this paper, we describe an illicit drug case to support this paradigm shift — what we tongue-in-cheek call “paradigm-busting.” We also use the case to exemplify a more general argument. That argument lays out a research strategy for paradigm-busting — for setting out to change the framework for viewing a human health problem. The first step is to explore the phenomenological experience of those close to the problem. In the second step, one uses recent computer modeling techniques from complexity theory, specifically agent-based modeling techniques, to explore the alternative framework for viewing the health problem that ethnography (which investigates those nearest to the problem) always generates. In the third step, one returns to the world of the health problem with fresh eyes, looking at things through a

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different paradigm. If the exercise is found to have no real-world consequences for action and if it does not clarify actual cases in new ways, it was pointless.

## **ETHNOGRAPHY**

Ethnographic research is often thought to be simply a matter of data collection carried out to learn about and document some social world. Most people, including many of its practitioners, ignore its paradigm-busting function. The “what-if” question that can “bust” a paradigm comes from conceptual systems and social practices learned in the field rather than from the inspiration of genius. It occurs when a “local” way of thinking and acting suggests a what-if alternative to an established paradigm for describing and explaining a particular group. By investigating local ways of making sense of things, ethnography can show that an official outsider expert framework is paradigms apart from local concepts. In fact, ethnographic results usually offer candidate what-if paradigm-busting questions.

## **AGENT-BASED MODELS**

What in the world does this subject have to do with agent-based models (ABMs)? Such models are derived from complex systems research, a field that studies nonlinear dynamic systems (i.e., systems with multiple interactions moving through time), which can produce surprising results. In the human realm, ABMs allow us to model emergent results of social dynamics, if we can strip these dynamics down to a few features whose interaction we believe to be critical on the basis of our ethnographic work.

What links paradigms, ethnography, and ABMs is the paradigm-busting question mentioned earlier: “What if?” Axelrod (1997), for instance, describes ABMs as a cognitive laboratory, a way to try out ideas, and the computational version of the “thought experiment.” In their pioneering book on artificial societies, Epstein and Axtell (1996) note that their approach is neither “deductive” nor “inductive” but rather “generative.” Both of these foundational views support use of the what-if question.

Given a particular phenomenon, the question arises, What if we modeled it in a different way? In fact, that is exactly the exercise we present in this paper. In the case presented, a consumer product model generates illicit drug epidemics as well or better than does a biomedical model, so the following question gains more credibility: What if drug epidemics are more like marketing than disease? It also gains some rather interesting applications; more on that subject is provided in the conclusion.

## **THE DRUG FIELD**

Let us shift to the “drug field,” that collection of researchers, clinicians, law enforcement officials, and policy makers and users who focus on the use of illicit drugs. Within that field, two competing paradigms have coexisted since the early 20th century: the law enforcement paradigm and the medical model paradigm. The competition between the two goes back to Supreme Court interpretations of the Harrison Narcotics Act of 1914. Subsequent court disputes centered on whether a physician could legally “treat” an opiate addict. The conflict between “legal” and

“medical” remains a centerpiece of drug policy today. In this paper, though, we focus only on the medical paradigm, which is the one that prevention and treatment rely on (along with research that explains drug use as a result of social and psychological deficiencies).

The medical paradigm subsumes drug use under the category of disease, as terms like “prevention” and “treatment” already imply. Physicians provide the relevant expertise, and biomedical research provides the appropriate way to develop knowledge. Root causes are, in the end, a matter of universal human biology. Diffusion of a drug among its users is a matter for epidemiology, with the infected parties transmitting the disease to susceptible parties. The relevant empirical unit is the “case,” which is the infected individual who has been classified according to “diagnostic criteria” and whose “cure” is the goal of the field.

Even though the term medical expanded during the previous century to include nonbiological personal and social factors, the staffing patterns and funding priorities at centers of the drug field, such as the National Institute on Drug Abuse, show that the medical paradigm remains dominant in all the ways implied above. A glance at the drug field in most other countries would show a similar hegemony in the medical arena.

The problem is that many aspects of drug use do not fit a medical paradigm in any straightforward way. What kind of disease do some people want to catch, while others don’t? What kind of disease has portals of entry and exit and vectors that are group-specific and symbolic rather than biological? What kind of disease consists of positive effects? What kind of disease is encouraged if the social and political positions of those who manufacture and distribute the psychoactive drug are mainstream? Think of Valium, Prozac, Ritalin, and Oxycontin.

What if...? What if illicit drugs were more like consumer products than a disease?

## ETHNOGRAPHIC BACKGROUND

We now describe our specific paradigm-busting case. The first step for research in human worlds, as outlined at the beginning of this paper, is ethnographic work, with the purpose being to generate what-if questions on the basis of local concepts and practices. It is actually embarrassing how easy it is to do this. The *official* frameworks of experts are typically distorted by distance and expert interests. It is amazing that any policy works at all. In fact, when policies do work, it is probably more often testimony to the adaptive ingenuity of the represented population rather than to any accuracy in the representation.

The ethnographic part of the paradigm-busting process is given short shrift in this paper because much of our ethnographic and historic research on illicit drug epidemic cases is published elsewhere (for example, see Agar and Reisinger, 2000, 2001). For now, we state that both our research on illicit drug epidemics and numerous other studies suggest that the stories circulating through social networks drive the increases and decreases in illicit drug use. Specifically, in one study of white suburban youth involved in heroin experimentation in the Baltimore suburbs in the late 1990s, youth described the “buzz” around heroin; these stories changed over time as early experiments by risk takers evolved into widespread experimentation and then turned more complicated as negative stories about physical dependence worked against those early positive accounts.

This sounds more like a product evaluation by consumers than a disease being transmitted from infected to susceptible parties. While the biological basis of a drug experience is relevant, the critical issue for the youth was the phenomenology of the experience: good, bad, or both. Those experiences — whether one’s own, or witnessed, or simply heard about — were, in turn, conveyed to others. The dynamic that explained an epidemic of use, in other words, was driven by interactions among good and bad stories, with good stories appearing initially and bad stories increasing in number over time.

It looked like the dynamic circulation of narratives among agents would generate an epidemic incidence curve (the classic S curve) all by itself. In fact, most illicit drug epidemics show a flattening incidence curve well before any policy reaction takes place. Perhaps drug use increases and decreases “naturally” as a result of interagent dynamics rather than externally imposed sanctions. What if the experts failed to make much difference? What if they took credit for a decrease in drug use that was already over and done with?

On the basis of these what-if ethnographic conclusions, we moved to step two, that is, working with ABMs. A model based on circulating narratives does indeed generate incidence curves like those observed in epidemiological graphs based on data sources, such as number of arrests and treatment admissions. It is this part of the paradigm-busting research process that we feature in this paper. We show the importance of three model parameters (learned from youths as important) that force the old medical paradigm to break. Using Design of Experiment approaches, we show that the Design of Experiment analysis does, in fact, support the need to rethink the medical paradigms used as the basis for understanding, explaining, and intervening in illicit drug use epidemics.

## **AGENT-BASED MODEL**

First, we describe the agent-based model, called DrugTalk, which has gone through several incarnations. Common to all iterations is a simple idea born of what which youths taught us in our Baltimore research. The model gives each agent a risk and an attitude. “Risk” is the willingness to try something new and unknown. “Attitude” is the degree of aversion to illicit drug use. Risk is fixed, but attitude can change, depending on what an agent experiences and hears from other agents. Whether or not an agent uses a drug depends on whether or not risk is greater than attitude.

At first heroin is made available at one location on a torus, on which agents move at random. If an agent uses the drug, it evaluates the experience, communicates with its primary social network, and offers them the drug. All agents, at all times, check the attitude value of the agents that surround them as they move about.

In an earlier article, Agar (2005) described the details of the program, and we now borrow and include that description here. Each agent must have a risk and an attitude value at the beginning, since the comparison between the two determines whether an agent will try a drug. All agents are assigned the same attitude value initially. This represents a general orientation to use on the part of a particular population, a “norm,” if you will. The attitudes of individual agents will change during a simulation run, sometimes dramatically.

Risk, on the other hand, differs for each agent. In contrast to attitude, an agent's risk does not change during the simulation. The assumption is that risk is a fairly stable and pervasive characteristic of an agent. There are risk takers and risk avoiders, and those proclivities hold up across different situations. *Diffusion of Innovation* (Rogers, 1995) reports on numerous studies across many different domains. A robust result of those studies is that people's willingness to take a chance on an innovation is normally distributed. With this body of work as background, risk values are assigned to agents by using a random-normal distribution.

Barabasi (2002) argues that social networks show an inverse power law distribution; that is, a few agents have numerous social links, and many agents have just a few links. After simple trial and error, an exponent of 1.5 produced a reasonable-looking distribution for a 500-agent world. There are no restrictions as to which agents might be assigned to a network. The same agent might be selected at random more than once, several times, or perhaps never. And it does not matter what the selected agent's network looks like. The resulting network, if graphed with number of agents on the Y axis and size of network on the X axis, looks like an inverse power law distribution. But the overall network, expressed as a digraph, looks very different from time to time.

Each agent moves at random. First, it "checks-the-buzz." If it has become an addict, it does not bother to check, because it no longer matters what other people are saying about heroin. Check-the-buzz corresponds to what youth often told us: you pick up on stories about drugs wherever you go, from people other than those in your personal network. At a party, a club, an event, school, a part-time job: drug stories are often "tellable" in these settings, since they can be dramatic and surprising — something out of the ordinary.

How does the buzz get checked? Each agent keeps a record of how many positive and negative experiences it has had with the drug. To check the buzz, an agent adds up the total number of positive and negative experiences among the agents on its own patch or within a radius of two patches. The agent who is doing the checking then adjusts its attitude by these numbers, subtracting the positive total from its attitude to make drug use more likely and adding the negative total to make it less likely.

At this point, we introduce a bias based on Tversky et al.'s (1982) prospect theory. The hundreds of studies that have now been performed conclude that people want to minimize loss more than they want to maximize gain. Therefore, an agent puts more emphasis on the negative total than on the positive total. So the negative total is multiplied by two to represent this effect.

The overall effect of checking-the-buzz is low when compared with the procedures to come. This is as it should be, since hearing things from strangers you just happen to run across has less effect than a story from a trusted and long-term friend. However, one buzz-checking experience can have a major effect on attitude. If an addicted agent is also in buzz range, the attitude of the agent who is checking rises by 20. (An addict is defined by a certain number of uses — a parameter — set to five in this case). Twenty is a substantial change, since the range is 0 to 100. (By the way, the range is always kept between 0 and 100. It cannot go higher or lower.)

There is some justification for this number (not this exact number, but for a number that represents a "big" difference). For one thing, youth reported such reactions: I was experimenting, or thinking of trying it out, and then I ran into so-and-so who'd turned into a junkie, and it really turned me off. Other evidence comes from Musto's concept of "generational forgetting"

(Musto, 1999): after an illicit drug epidemic impacts one generation, the next generation tends not to use the drug, since they have seen use go from pleasant early on, to devastating for addicts and communities down the road. Recent observations in Baltimore and other cities suggest that African-American youth, having witnessed the crack epidemic, will have nothing to do with the drug, although a few will sell it as a lucrative niche in the underground economy. For many such youth now, a “drug-related problem” means dealing, not using.

Next comes the moment of truth. If an agent is on a red patch, meaning heroin is available there, it compares its risk to its attitude, and if the risk is higher, it uses the drug.

Immediately following use of the drug, an agent evaluates the experience with a function called “how-was-it,” unless the agent is already an addict, in which case, it no longer matters. To understand how this function works, we first look at two more parameters that play a major role in the analysis to come: (1) goodStuff and (2) badStuff. Each can vary between 0 and 100. Broadly speaking, this number represents a kind of quality evaluation. For the moment, we ignore problems of individual variation and context and assume there is some kind of average that makes sense. Overall, does the drug produce a pretty good or a pretty bad experience? Notice that both things can be true; in other words, a user might have an experience that he/she would describe as both good and bad.

The rest of how-was-it is simple. After an agent has used the drug, it generates a random number between 0 and 100. If goodStuff is larger than that number, the agent records a positive experience. It then changes its attitude in a favorable direction (i.e., it decreases it) by an amount equal to  $(1/\text{positive}) \times 20$ . Notice how the effect of the evaluation diminishes with increased use. The first positive experience reduces attitude by 20, the second by 10, the third by 6.67, and so on.

Independent of the outcome of the goodStuff evaluation, the agent does the same evaluation using badStuff. The difference here, of course, is that if badStuff is larger than a random number between 0 and 100, the value of the agent’s attitude increases to make the agent less likely to use the drug. Another difference also occurs, which corresponds to the prospect theory principle that people are risk-averse, as described earlier: this time the value changes by 40 rather than by 20. The impact changes with experience, just as it did with goodStuff, from 40 the first time, to 20 the second time, to 13.33 the third time, and so on.

The justification for the diminishing impact lies in intuitions about “habit”: that is, the first experience of anything is the most significant, and subsequent experiences show an “I’m getting used to it” effect. A body of literature supports this assumption, which goes back to old-fashioned behaviorist psychology, which we take for granted in this paper.

Immediately after using the drug, agents let their network know, with “tell-the-network.” Recall that the model was set up with an inverse power law social network distribution; that is, a few agents have large networks, and many agents have small networks. An agent who has just used a drug checks its network members. If a network member is already an addict, the agent who just used the drug has no influence on its attitude. But if the network member is not an addict, a couple of things might happen.

First, if the agent who just used the drug is an addict, it will “turn off” the members of its network by adding 20 to their attitudes. Recall that the same thing happened if an agent found an addicted agent nearby when it checked-the-buzz around it.

If the agent who just used the drug is not an addict, something different happens. That agent “pulls” each agent in its network in the direction of its attitude, whatever it might be. It does this by the simple mechanism of assigning to the agent in its network the average of its own attitude and that agent’s attitude.

The agent who used the drug will have an attitude that reflects its history of positive and negative experiences from checking-the-buzz and evaluating its own use. Tell-the-network will move the agent in its network toward its current attitude, which reflects those experiences. The assumption is that if the agent who used the drug is becoming more positive, it will make its network more positive. If it is becoming more negative, it will make its network more negative. Since all agents begin with the same attitude value, the attitude carries the cumulative positive and negative history of an agent with the drug, so its network members should get pulled in the direction of how that history has changed after drug use.

Whatever the outcome of all this influencing (or lack thereof) is, the agent who just used the drug always offers heroin to all the agents in its network, no matter what. If the agents in the network have a risk greater than their attitude, they use the heroin and evaluate the experience, as the original agent did, with the same procedure: how-was-it. At that point, however, the network member stops. In other words, the network member does not, in turn, offer heroin to other agents in its own network. Perhaps it should, not in that particular tick of the program, not immediately but with some time lag.

That is basically the interesting part of the program. Comparisons with actual cases together with observations of how DrugTalk generally behaves show that we are on the right track. The paradigm-busting argument learned from the youth — that a new drug is a consumer product — works as well when we model it as it did when we heard it in interviews. But the classic problem with ABMs occurs: many parameters in the model can vary. One strategy is simply to set up multiple runs to explore the space of possible outcomes by sweeping parameter values with regular intervals, something explored in a preliminary way in an earlier article. We decided to try something different: Design of Experiment approaches.

## **DESIGN OF EXPERIMENT**

The Design of Experiment approach was developed to analyze real-world experiments where there is a practical limit to the number of experiments that can be performed, because they are either expensive or slow. An ABM like DrugTalk, as we saw in the previous sections, has many parameters: attitude, goodStuff, and so on. Ideally, to explore the model, we want to run it under all possible combinations of parameter values. The number of runs would be enormous. The motive for using Design of Experiment is that traditional “parameter sweeps” suffer from combinatorial explosion. Sweeping each of 10 parameters (as in this study) through each of 10 values requires 10 billion experimental runs. If each simulation took 1 minute to run, it would represent a significant investment in time: close to 20,000 years, in fact.

The types of questions that Design of Experiment can answer are slightly different in the context of simulations than in real-world experiments. The latter tend to focus on optimization and prediction, trying to closely specify the input values that produce some desired effect in the output. In contrast, when Design of Experiment is applied to simulations, it answers broader questions:

- It searches for insights for developing a basic understanding of a simulation or system.
- It finds robust configurations, decisions, or policies.
- It compares configurations, decisions, or policies (Kleijnen et al., 2004).

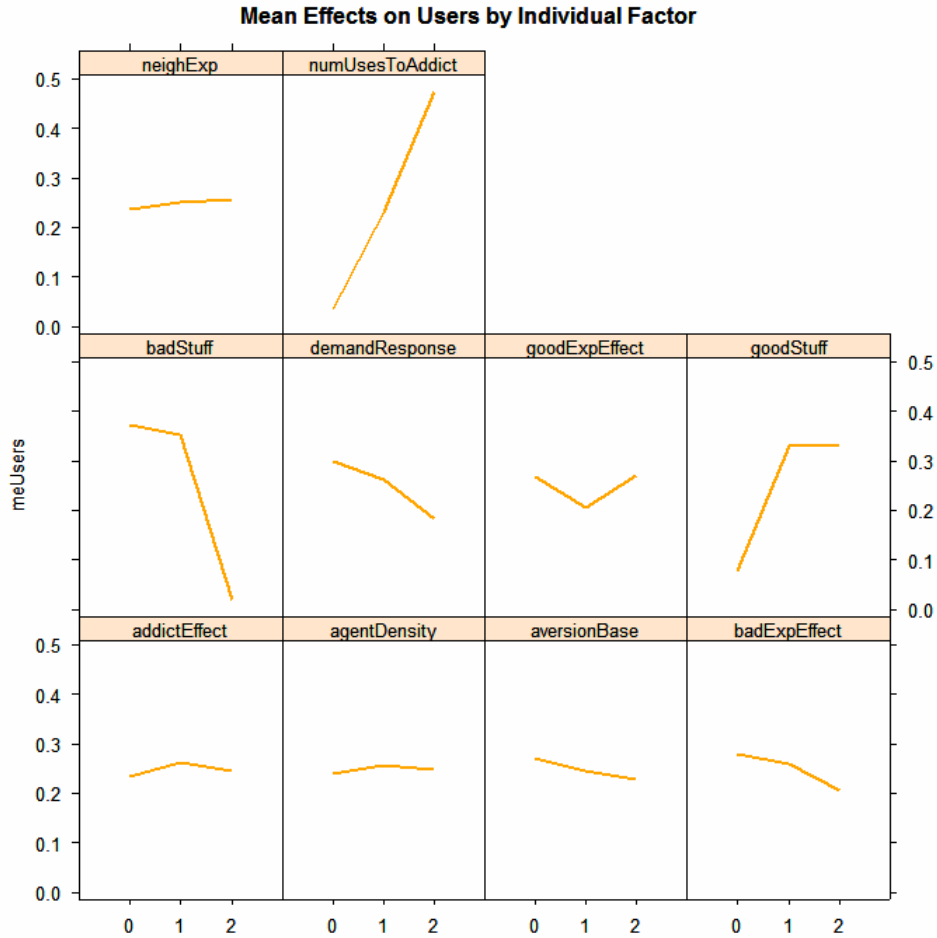
Typical Design of Experiment designs involve specifying a series of experiments that take place at the maxima and minima of the various parameters (in a two-level design) or at the maxima, minima, and midpoint (in a three-level design). The experimenter selects maxima and minima that represent the range over which he/she wants to study the simulation. However, instead of running all possible experiments with these two or three values per variable (because again,  $2^n$  and  $3^n$  explode with  $n$ ), a limited subset of experiments is carried out. This subset is balanced so that the values of any variable are equally represented. For example, in the three-level experiment used in this study, one-third of the experiments were run with goodStuff at its minimum value, one-third were run with it at its midpoint value, and one-third were run with it at its maximum value. Depending on how restricted the subset is, combinations of variables show the same balance (e.g., the nine possible combinations of goodStuff and badStuff appear the same number of times in the experiments). It is this balance that gives Design of Experiment its validity.

The current study uses a three-level design of 81 experiments that evaluates the “main effects” of 10 variables. (In terms of the “balance” concept above, the three values of each of the 10 simulation inputs are equally represented in the experiments.) Main effects are a simple way of finding out what the important variables are. For a particular input variable, the 81 experimental results are divided by high, average, and low values into three groups of 27, and the mean of each of these three groups is calculated. This process is repeated for each input variable. The three means for each input are then plotted in graphs. These graphs show which input variables have a large impact on the simulation output (i.e., there is a big difference between the smallest and largest values in that variable’s plot).

## DESIGN OF EXPERIMENT RESULTS

The Design of Experiment analysis contains one small and one large surprise, both of which suggest the parts of the medical paradigm that need “busting” for the drug field. Examine Figures 1 through 3. Each figure shows the results for a different key outcome variable from the model. Figure 1 shows the effect of the 10 parameters on the total number of users. Figure 2 shows effects on the total number of addicts. Figure 3 shows effects on the way agents become more or less at risk.



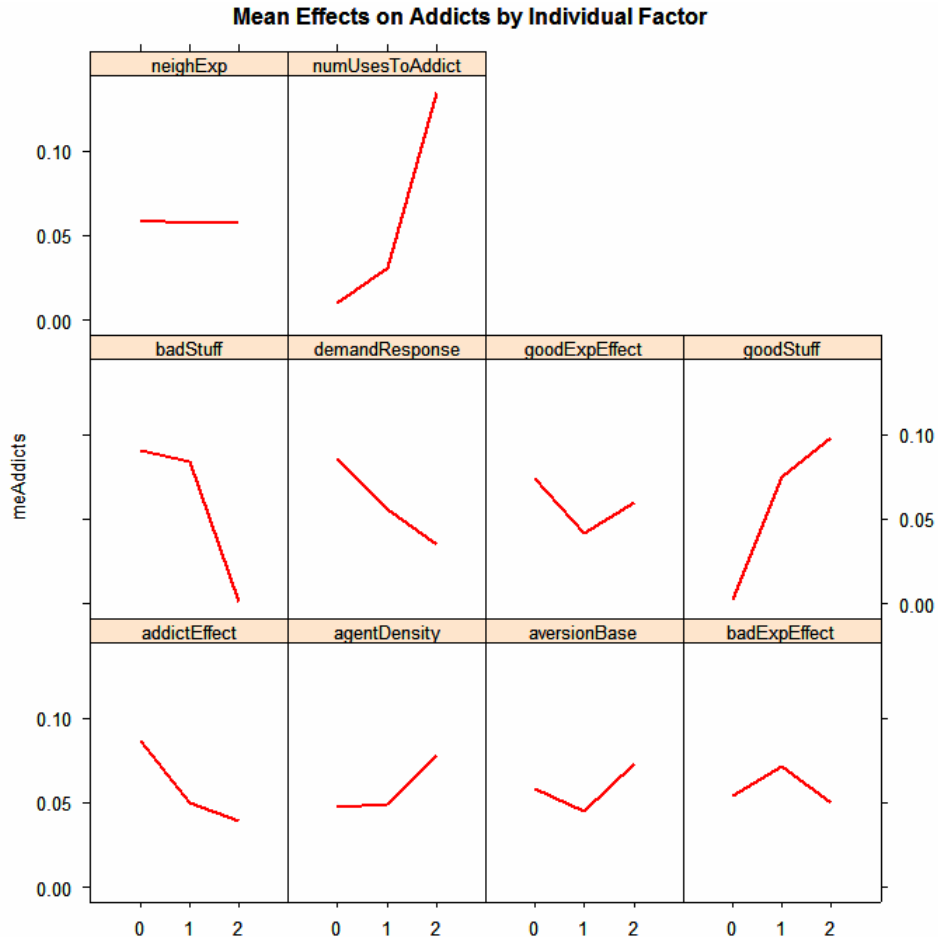


**FIGURE 1** Parameter effects on number of agents that used the drug at least once

Each figure, in turn, contains 10 charts, one for each of the parameters we looked at. Each chart shows an angular line. The more sharply vertical the line is, the stronger the effect that parameter has on that outcome. Limitations of space prohibit a full discussion of all the parameters tested, although we will be happy to provide additional information upon request. But most should be familiar from reading the model details in a previous section.

Listed below are the seven parameters we tested that are not already discussed above. The abbreviations refer to the titles in Figures 1 through 3:

- *neighExp*: the exponent that defines the initial network distributions,
- *demandResponse*: the speed with which additional heroin patches are created,
- *goodExpEffect*: the strength of a particular good experience,
- *addictEffect*: the effect of having an addict in the neighborhood,

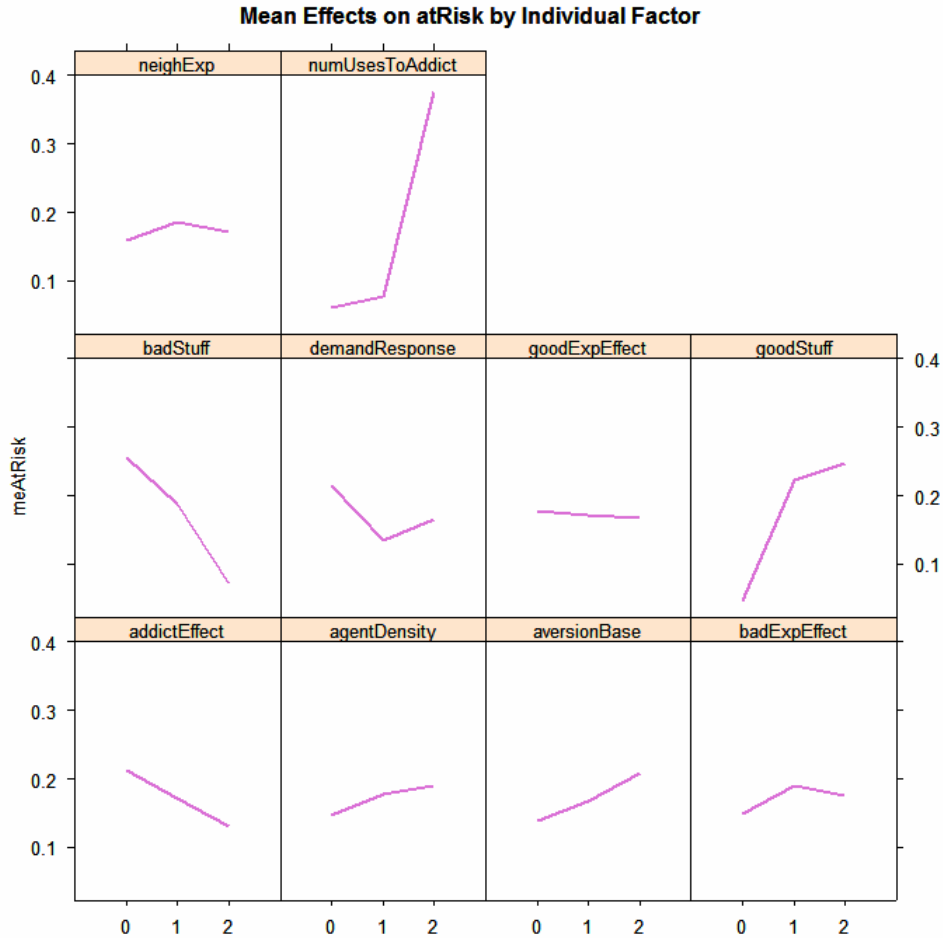


**FIGURE 2** Parameter effects on number of addicts

- *agentDensity*: the density of agents in the model,
- *aversionBase*: the initial setting of attitude, and
- *badExpEffect*: the strength of a particular bad experience.

There is some vertical angularity in many of the charts. But if the reader looks across the figures and scans for repeated extreme angularity for the same parameter, three stand out in striking fashion.

First is the small surprise. It is actually two parameters, but they are two sides of the same coin. They are *goodStuff* and *badStuff*, informal labels that echo ordinary conversation. They represent the quality of the drug as the user experiences it. Recall that *badStuff* has a stronger impact, reflecting the findings of prospect theory. Also recall that the effect of *goodStuff* and *badStuff* on agent attitude declines with the number of uses. Beginnings are most important.



**FIGURE 3** Parameter effects on number of users at risk

GoodStuff and badStuff collapse many things into a single number. Drug effects on a particular person at a particular time can change with biochemistry, setting, and the particular biographic and historic situation. These parameters are complicated. In the end, though, they are appropriate at a phenomenological and social-interactional level because, in the end, a new user is a person who tries something and tells stories to other people about how good or bad it was.

The Design of Experiment analysis highlights the importance of these parameters. It makes the hidden fact explicit, because the fact was invisible in the medical paradigm. For an experimenter, an illicit drug is a commodity to be evaluated, not a disease to be caught or avoided. Ironically, when an earlier version of DrugTalk was presented at the University of California at Los Angeles (UCLA) conference on agent-based modeling in the social sciences (Agar and Wilson, 2002), the organizers put it in a session called “Marketing.” Untainted as they were by a medical paradigm, they immediately saw the model in a different way.

The idea that a drug is a commodity that behaves like other commodities is not an alien concept in the drug field, but it is not a frequent one either. The idea just does not fit the medical tradition. In that tradition, any use is to be discouraged, so any use must be negative. At times, it

seems like an implicit guideline operates: there can be no reason why anyone would want to use an illicit drug (i.e., to catch a disease), so its use must be caused by pathology in the biological, psychological, or sociological system.

This change in how illicit drugs should be understood — as a commodity, not a disease — surely counts as a paradigm shift, and a problematic one, given the mainstream U.S. “War on Drugs” policy. Would the concept allow for more effective intervention? Before considering that question, let us describe the second surprise, the large one.

One parameter in DrugTalk is how many uses have to occur before addiction sets in: *numUsesToAddict* in the figures. Addiction is a loaded and ambiguous term, since the original meaning was the actual physical addiction produced by opiates. Now the drug field uses the more general DSM-IV concept of “dependence.” That concept defines dependence in psychological and sociological terms, that is, in terms of how an individual’s behavior changes.

The critical changes basically show a shift from personal control over use of the chemical to chemical control over much, even most, of what a person does. Smoking a joint on Saturday night is one thing; needing a joint six times a day is another. When most of what you do with your time is getting the chemical, using the chemical, figuring out how to get money to buy the chemical, and thinking and talking about the chemical, etc., you obviously are dependent on that chemical. That is, in fact, a problem for you, your nondependent family and friends, your studies or work, and your community.

Dependency should certainly make a difference in outcomes, so the fact that it did make a difference in the Design of Experiment analysis is not a surprise. A product that makes you dependent should literally capture market share. As Warren Buffet explained when speaking about a legal drug, “I’ll tell you why I like the cigarette business. It costs a penny to make. Sell it for a dollar. It’s addictive. And there’s fantastic brand loyalty” (Field, 2003). The Design of Experiment, in fact, showed that dependence is the most important parameter of all.

The large surprise, though, is this: intuitively one would think that the faster a drug produces dependence (i.e., the fewer uses it takes), the more addicts it will produce in the end. Get them quick and you’ll get a lot of them. As it turned out, however, the Design of Experiment supported the opposite conclusion. The more uses it took before an agent became dependent, the more addicts it produced in the end.

How could this be? What in the model explains this peculiar result? Once again, the model makes a hidden fact clear. Recall that it builds an event into an epidemic, something youth often talked about when we interviewed them. Once dependent persons appear in an agent’s friendship network or in its neighborhood, those visible examples of what that particular drug can do to a person have a negative effect. In fact, such events produce the strongest increase in attitude that ever occurs in the model. So that is probably the explanation: if no dependent agents show up for a long time, attitude will increase more slowly and less dramatically than if dependent agents do appear quickly.

Colleagues in the drug field sometimes joke after a presentation of this model. The best thing to do for a new wave of heroin experimentation would be to fly in dozens of addicts and distribute them throughout the social world of the group that is experimenting. The Design of Experiment analysis explains the joke. It’s not funny.

So another bit of the medical paradigm encounters difficulties. First, Design of Experiment results suggest that a new drug that makes a big splash is to be less feared than a stealth drug that can be used for substantial periods of time before dependency appears publicly and deters use.

Second, if a drug seldom causes dependency in a way that will publicly deter use, it will not go away once it gets going, if there is no draconian punishment. Consider marijuana as the classic case.

Third, and most devastating for the medical paradigm, is this. The old notion of addiction as a matter of biological dependence is clearly inadequate. This is not news, as already noted, since the field now talks in terms of DSM-IV. But the notion of dependence as being primarily an individual problem with intrapsychic causes is inadequate as well. It might be important for clinical work, but it will not explain the shape of an incidence curve. The negative effect comes from social impact. This is a robust theme of ABMs in general: that individual-level properties will not explain system-level phenomena.

Critical to the power of the addict parameter in DrugTalk is what the agents *see* around them as the social consequences of use become public. A biologically addicted psychopath who behaved in public would not have an impact on other agents' attitudes. Without being aware of it, we told the model that what counts under dependence is the observation by other agents that continual use of an illicit drug can have a negative impact on their social world. That's the theme of many of the stories that the youth told us: "And then I saw so-and-so; he was a junkie, and what a mess."

## POLICY IMPLICATIONS

As a result of ethnographic research, the ABM, and the Design of Experiment analysis, we see that drugs can be viewed as a commodity like any other. And we test the idea that the major deterrent to dependence is personal experience and/or stories from networks that dependence is a socially destructive condition. The implications of this paradigm change are massive and beyond the scope of this presentation. Let us just outline a few here:

1. In a social world that is open to illicit drug experimentation, any drug that is high on goodStuff and low on badStuff will be tried if the market can provide it. A wave of experimentation will occur. Trying to prevent this wave is futile.
2. Credible drug education must recognize the positive quality of the product, something it seldom does, as far as we are aware.
3. Many drugs can produce traumatic results upon first use, and these results should be a topic in prevention. But they must be presented so that they correspond with actual experiences with which the population already is familiar. And they must not be presented as the inevitable, or perhaps even likely, outcomes of experimentation, nor must they be overemphasized by way of comparison with positive effects.

4. The most critical part of prevention is to prevent dependence. Educational materials should feature what life is like on the other side of dependence, realistically, with examples.
5. Group sessions can serve as “story amplification” devices. Assuming dependence has already occurred and given the time lag between an epidemic and policy response, it is likely that potential and actual users will already be familiar with the drug’s effects. Program time should be dedicated to permit participants to tell stories about themselves and people they know. Material for prevention is, in fact, available in the worlds of both experimenters and nonusers. This only amplifies what naturally happens anyway, as reflected in ethnographic interviews and in DrugTalk. Group sponsors must accept that some of the stories that will be told about experimentation will be positive.
6. The most important programs will deal with early intervention, something that is rare at this time. By this is meant that if an experimenter shifts to a user and a user shifts to a frequent user, he or she is “at risk” for dependence. Early intervention is an effort to intervene with a serious user on the edge of dependence and pull him or her back. Such serious users are typically identified by the friends, family, organizations, or communities with whom or where they spend their time. Early intervention referral may be a productive use of law enforcement mechanisms, such as drug courts.
7. Dependence will occur, and dependent users will require treatment. Part of their treatment could be community service, where they could serve as speakers (assuming they are peers of the experimenting population), telling stories of the line between use and dependence, how they crossed it, and what the personal consequences were. We have found that often former addicts who are brought in as speakers are not peers. A 40-year-old ex-heroin-addict addressing a high school group is less credible than a session with a peer.

There are other implications, but the list above is already controversial when measured against traditional War on Drugs practices. As far as we know, suggestions such as those in the list above have not been tried extensively or consistently. They might not work, of course, but they should be tried. We are at a juncture where it is widely recognized that the War on Drugs has failed. New alternatives are in order. The problem with the medical paradigm (not to mention the legal paradigm, which we have not dealt with here) is that it has not generated any new ideas.

While our primary purpose has been to demonstrate an ethnography/ABM collaboration as a paradigm-busting device, we also want to emphasize that both the old and the new paradigms that define a particular application may well have massive social and political consequences. They certainly do for DrugTalk. The opportunity for real change in social practices is enormous, and implementation raises political issues that go well beyond the research framework suggested here.

## ACKNOWLEDGMENT

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## CASE STUDY: USING AGENTS TO MODEL STABILITY AND SUPPORT OPERATIONS

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### ABSTRACT

The 1st Marine Expeditionary Force has begun examining questions of interest with the Data Farming methodology developed by Project Albert. This methodology employs agent-based modeling and high-performance computing to gain insight into questions that legacy models and current methodologies have trouble generating. This paper deals with one of these questions: What are the effects of a coalition stability and support operation on civilian populations? To examine this question, we developed two agent-based models in NetLogo that focus on social interactions. The first model explores the dynamics of social interactions among and the effects of “good” and “bad” events on the contentment of civilians. The second model explores different social networks and the effects they may have on the dynamics of civilian contentment change.

**Keywords:** Stability and support operations, agent-based modeling, data farming, NetLogo

### INTRODUCTION

In January 2004, the 1st Marine Expeditionary Force (I MEF) held a workshop with the Marine Corps Warfighting Laboratory’s Project Albert to explore ways by which the Project Albert methodology of Data Farming (Fry and Forsyth, 2002) might be leveraged to assist I MEF with its missions throughout the world. One of the projects that came out of that workshop, and the focus of this paper, is a model examining how such events as coalition stability and support operations (SASO) affect civilian populations. This paper discusses the SASO model and how the Data Farming methodology will be used for verification and validation.

Data Farming is a methodology pioneered by Project Albert (Horne, 2001; Brandstein and Horne, 1998). It is a broad term that encompasses not only developing the model but also running the model and analyzing the results. Data Farming starts with a complex multivariate question, such as the dynamics of a civilian population, that does not lend itself to a closed-form analytic solution. Once the question is formulated, it must be distilled so that it can be modeled. This distillation is usually accomplished by a collaborative team made up of modelers and subject-matter experts. The utility of Data Farming lies in the ability to create the models quickly, run them many times, and easily analyze and interpret the results. This approach requires relatively abstract models with very fast run times (usually less than one minute). Of course, the use of abstract models increases the importance of the subject-matter experts because

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they must be able to distill the situation, as defined by the question, to its essence. Once this distillation is created, it is put into the Data Farming environment and run many times.

Execution of the model within the Data Farming environment has two aspects. First, large parameter space is explored in either a full factorial experimental design or a sampling approach, such as a Near-orthogonal Latin Hypercube (Lucas et al., 2002). Second, because of the sensitivity of the models to slight perturbations in the initial layout of the agents or the random number stream during the run, they are run many times with the same parameter combinations but with different random seeds. Alternatively, the parameter combinations may not be set initially but may be created by using one of a number of different evolutionary or natural algorithms to find near-optimal parameter combinations on the basis of a user-defined fitness function.

Finally, when the runs of the model are completed, the output data are analyzed to determine if the model was created correctly and if it adequately captured the essence of the question. Once the modeler and subject-matter expert are satisfied that the model represents the question at hand, the analysis enters the Operational Synthesis (Horne, 2001) cycle. The Operational Synthesis cycle involves placing the Data Farming methodology in a decision-maker support context. The results from the Data Farming development and analysis loop are used to inform traditional operations research and other analytic methods with particular emphasis on risk analysis and decision support. The insights generated from the Data Farming can be used to inform other aspects of the analytic processes, be they legacy models, traditional decision support, or even a war game.

For this effort, we have developed an SASO model that focuses on agent interactions and the effects that “good” and “bad” events of varying intensity and scope have on civilian contentment and the attitudes civilians have about a coalition performing SASO. Civilians are defined in terms of a series of fixed parameters: sex, marital status, religion, ethnic group, wealth, and social influence. Furthermore, civilians have a number of internal dynamic states, such as Contentment, Orientation, and Predilection. The parameter Contentment is used as a measure of an agent’s (civilian’s) perceived quality of life. Orientation is a measure of how congruent the agent’s views are with the coalition forces. Predilection describes how the agent will interpret the “goodness” or “badness” of events. Finally, although good and bad events affect an agent’s Orientation, the changes in Orientation are generally small relative to Contentment.

The modeling approach described herein is consistent with the work of Silverman et al. (2003) that models the cumulative effect of good and bad events on an agent’s stress level. Future events are then interpreted by a “construal filter” on the basis of the cumulative effect. This result also directly affects the agent’s choice of subsequent actions. Unlike Gillis and Hirsch (1999), we did not consider the frequency of events in determining the cumulative effect, but simply the number and magnitude of events. This approach seems reasonable for stability and support operations where the timeframes are long and events occur infrequently. The work herein is also consistent with Jager’s (2004) recent work that formalizes social judgment theory to incorporate processes of assimilation. Jager’s results have demonstrated that the attitude structure of agents can determine whether those agents will assimilate into a group. He postulates that the assimilation then can cause a group to reach consensus or develop a number of subgroups. However, the model was not created with specific theoretic underpinnings. The

dynamics and structure found in this model are based on the knowledge and opinions of subject-matter experts. Now that the issues involved in the subject matter are well defined, we are researching and experimenting with relevant sociologic and computational theories, such as the aforementioned studies.

## GENERAL MODEL DESCRIPTION

At its heart, this is a model of agent interaction, a screen shot of which is shown in Figure 1. We have removed most aspects of the environment and even of coalition, nongovernmental organization (NGO), and insurgent action. Instead of modeling specific actions, such as blocking a road, building a school, or distributing food, we aggregate the actions into generic good and bad events. In this regard, the model is “effect based.” We do not attempt to model actions; rather, we model their effects on the civilian population. Good events are defined as events that increase the standard of living. Conversely, bad events are those that decrease the standard of living. There are three general types of good and bad events: local, regional, and national. The spatial coverage and frequency of events are both adjustable parameters. For example, currently the model represents a notional three-month period of time, with each time step of the model representing six hours; therefore, if a local good event should happen once a day, on average that event will occur once every four time steps. More detail can be found in Section 3 of the appendix.

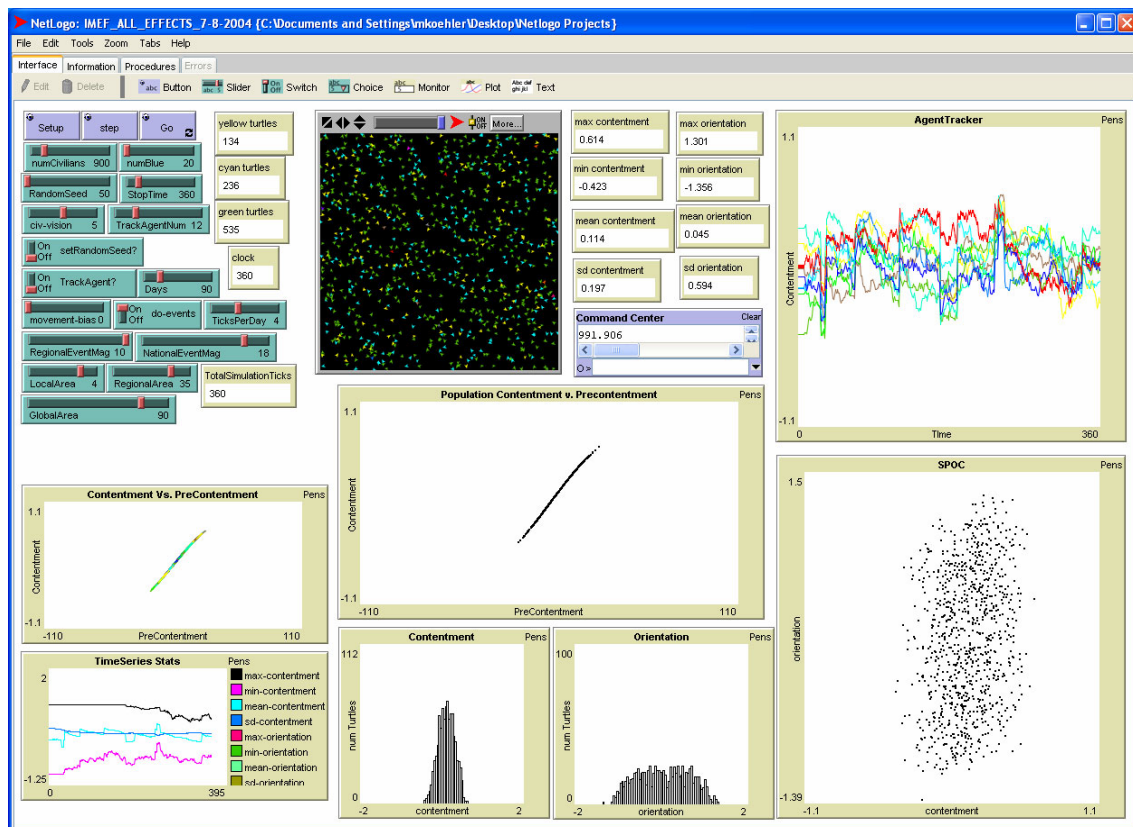


FIGURE 1 Screen shot of the model

Although the actions of the coalition, NGOs, and others are highly abstracted, the modeling of the civilians is relatively rich. Civilians have four canonical types: married female, married male, unmarried female, and unmarried male. Each civilian type is further subdivided into religious groups, clan groups, economic class, and social influence. Finally, each agent has some endogenous, dynamic parameter values, including preContentment, Contentment, Orientation, and Predilection. The user states the percentages of agents assigned to the four types (married/unmarried, male/female). We make the simplifying assumption that on the time scales considered within this model (months), no significant change will occur in the structure of the society. Hence, the values of type (married/unmarried, male/female), clan, religion, and economic status are held stationary throughout a simulation run. Similarly, Predilection and social influence do not change during the run. On the other hand, Orientation, Contentment, and preContentment (see appendix, Sections 2 and 3) do change during the course of the run as agents interact and are affected by good and bad events.

Contentment is modeled as a logit curve (see appendix, Section 3, Equation 5) to provide bounding without arbitrarily forcing Contentment values within a given range. This is accomplished by giving agents an unbounded preContentment score that is then transformed via a logit equation into a score that is tangentially bounded by  $-1$  and  $1$ . We selected this methodology because it allowed us to create a population of agents with a simple memory of past experience and dynamics that fit with subject-matter experts' input. Specifically, it will take a very happy individual a significant period of time to become unhappy when faced with small-scale bad events. After a certain period of time, however, it will take relatively few additional bad events to make the happy individual unhappy. This is similar to the dynamics of a well-buffered solution — an acid or base can be added to the solution, creating little change in the pH until the buffer is overwhelmed, at which point there is a nonlinear change in pH.

Along with Contentment, agents have Orientation and Predilection. These parameters are used to explore the effects of good events (those that increase the standard of living) on individuals who do not want the SASO to succeed. For these individuals, coalition success is a negative event, even though they are benefiting from it — their standard of living is improving. Therefore, it is necessary to affect Orientation as a function of an agent's Predilection (its tendency to be swayed toward the coalition's values as quality of life improves) and the agent's Contentment (its quality of life). In this way, agents with a Predilection that is in between Orientation and Contentment can become more anticoalition as their quality of life increases. This occurs because Predilection is an axis for the line connecting Orientation and Contentment. If the Predilection line is in between Orientation and Contentment, a change in Contentment will cause an opposite change in Orientation (there may be a difference in size, as well). A graphical representation of the above discussion can be found in the appendix, Section 4. If, on the other hand, Orientation was in between Predilection and Contentment, a change in Contentment would cause a similar change in Orientation (there may, of course, be a change in scale).

In a sense, the Orientation can be defined as how vehemently an agent works with or opposes coalition action. As the coalition becomes successful, an agent with a low ( $<1$ ) Predilection will become more opposed to the coalition, even though his individual quality of life is increasing. Conversely, as bad things happen for the coalition and quality of life decreases, agents with a low Predilection will become less severe in their opposition. In a sense, they will not have to be as active since the coalition is “doing their work for them” by being ineffective.

The agent can use one of two “movement” algorithms. First, the agents can simply move randomly about the torus-shaped landscape. Second, the agents can be gently biased to move closer to the agent within their vision (which can be set by the user) who is the most similar to them in the above-described characteristics. Moving toward similar agents seems to be most congruent with guidance provided by the subject-matter experts. We note that in this context, movement is simply a vehicle for agents to interact and does not necessarily reflect movement in a geographic space.

Finally, the coalition’s interaction with civilians is approximated by biasing the probability of good and bad events. For instance, if the coalition met with a great deal of success providing clean water and maintaining order, that would increase the likelihood of civilians being affected by good events. Conversely, if the coalition was doing poorly and was having a great deal of trouble rebuilding the electrical system or bridges, then the likelihood of civilians experiencing bad events would increase.

## **AGENT INTERACTIONS**

Agents have two general types of interactions — with other agents and with good and bad events (see the appendix, Sections 2–4). The probability of an event occurring at any given time step is an input parameter. The occurrence of an event at any given time step is stochastic with a uniform distribution. When an event occurs, a single “target” agent receives a message describing the event characteristics. For example, this agent may be informed that a regional event occurred with  $x$  scope (or radius) and  $y$  magnitude. This agent then tells the agents in a given proximity ( $x$  radius) that an event of magnitude  $y$  occurred. Those affected agents then adjust their preContentment scaled by their distance from the “epicenter” of the event.

Agents will also influence each other by direct communication. Agents within close proximity of each other will communicate with a probability based on how “similar” agents are. Similarity is based on factors such as clan, religion, and economic status. The more similar agents are, the greater the likelihood they will communicate. Communication affects an agent’s Contentment value in two ways. If agents share a common belief about their quality of life, that feeling will be strengthened. In addition, one agent may influence another to adopt a Contentment value closer to its own, based on its social influence parameter. A slightly richer description of agent communications is given in the appendix, Section 1.

One issue is the importance of Euclidean geometry in this system. Currently, all things that affect an agent are somehow related to “physical” space around an agent. We are developing a second model to act as a prototyping environment for social networks. Social networks are very important for at least two reasons. First, civilian populations have social networks that are important sources of information and influence. Second, social networks decrease the relative importance of Euclidean geometry within the system, mimicking the effects of telephones, newspapers, and so on that allow for the widespread dissemination of information beyond that which occurs within the immediate purview of an agent.

## NEXT STEPS

The models that have been developed have produced “reasonable” answers that have passed informal face validity testing with subject-matter experts. We now plan on formally tuning the models with respect to real-world data to explore whether the models may have utility in a decision support environment. Once the models are tuned, we then can use the Data Farming environment to explore possible effects of various courses of action that a coalition may employ within the context of an SASO. Furthermore, we wish to explore accepted sociological, anthropological, computational, and other theories of social/agent interaction and change to further validate and tune the methodology used for agent interaction.

Of particular interest to this research is the work of Sean O’Brien (2002, 2004) on country instability. O’Brien has collected considerable data relating to citizen unrest and conflict within and between nations. Moreover, his work also provides a derived measure of instability within a country, which we will attempt to relate to an aggregate measure of Contentment and Orientation from our model to begin the validation process of the model and to examine its ability to generalize from one region to another.

The SASO model described in this paper has a significant amount of randomness and interdependence, as well as large ranges for the parameters. To fully understand how the various situations may affect the civilian populace, the parameter space must be thoroughly explored. As discussed above, this step will be accomplished with Data Farming. Currently, NetLogo is integrated into the Data Farming environment at the Maui High Performance Computing Center. By making use of the data from O’Brien (2002, 2004) and parameter space sampling, we will be able to gain insight on the utility of this model, its ability to represent reality, and its ability to generalize to various parts of the world, and, thus, continue development of the model. Another avenue we are pursuing is implementing the model into other agent-based modeling frameworks such as Repast and MASON.

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## APPENDIX

### 1 Details of Agent Communications

Agents can affect each other by “communicating.” Communications are limited to agents in close proximity and only involve discussions about each other’s Contentment values. Communications occur in the following way: every time step, agents look around in their immediate vicinity and if there are one or more agents they grab one at random. Once an agent has picked a partner, the agent determines the probability that they will interact. This probability is based on cultural factors dealing with interactions between types (do single males talk to married females?) and attributes held in common (do both agents have the same religion and clan affiliation?). Once the probability is determined, a random draw is made to see if a communication event will occur. In the current case, the subgroup interaction probability table is set up so that the more characteristics two agents share, the more likely they are to interact (assuming they find themselves spatially close enough).

### 2 Communication-based Changes to Agent Contentment

Communication between agents occurs in the following way. First, the agents check to determine if their Contentment scores are close enough for communication to be possible. If the agents’ Contentment scores are close enough, the agents then check if their Contentment values are beyond a runtime set threshold. If this is the case, the agents will move their preContentment scores farther out, thus reinforcing each other’s feelings. This effect is implemented in Equation 1. Finally, the agents will influence each other, thus moving their preContentment scores closer together (Equation 2).

$$effect\_Agent1 = t1Pre + [t1Pre * (1 - scalar) * commonality], \quad (1)$$

$$effect\_Agent1 = (1 - commonality) * t1Pre + commonality * t2Pre, \quad (2)$$

where  $t1Pre$  is Agent 1’s value of preContentment,  $scalar$  is a value from a defined look-up table, and  $commonality$  is a measure of how many attributes the two agents have in common. Equation 2 describes how agents influence each other. All variable definitions are the same as in Equation 1, and  $t2Pre$  is the preContentment value from the partner agent. This equation provides a great deal of flexibility to this communication dynamic. If the value of commonality is 1, the agents will swap preContentment values. If the value is 0.5, they will meet in the middle. On the basis of subject-matter expert input, the commonality tables are currently set up to produce commonality values between 0.0 and 0.07.

### 3 Event-based Changes to Agent Contentment

The SASO model contains good and bad event types. There are three scales to each type of event: local, regional, and national. The scale of the event determines how much of the population is affected on the basis of spatial distance between an agent and the epicenter of the event. The user can specify the frequency (which is the probability that event  $x$  will affect an agent in a single day) of each type of event by scale.



Equation 3 describes bad events, whereas Equation 4 is used for good events. The parameters *minPreContent* and *maxPreContent* are set at runtime:

$$\begin{aligned} preContentment_{x+1} = preContentment_x & \\ + \frac{minPreContent - preContentment_x}{2 * minPreContent} * EventValue, & \end{aligned} \quad (3)$$

$$\begin{aligned} preContentment_{x+1} = preContentment_x & \\ + \frac{maxPreContent - preContentment_x}{2 * maxPreContent} * EventValue. & \end{aligned} \quad (4)$$

Equations 3 and 4 allow the model to capture diminishing marginal effects of good and bad events on an individual agent. Therefore, repeated good or bad events will have less and less effect on an agent's Contentment. After preContentment is created, the preContentment score is mapped into the Contentment score with a general logit curve equation (Equation 5):

$$f(x) = LB + \frac{UB - LB}{1 + \frac{1}{e^{slope(x - mean)}}}, \quad (5)$$

where

*LB* = lower bound,  
*UB* = upper bound, and  
*slope* and *mean* = parameters set at runtime.

To date, we have set *UB* = 1, *LB* = -1, *slope* = 0.05, and the *mean* = 0. This creates symmetrical movement toward happiness or unhappiness. Figure 2 shows the line created by this equation when varying *slope* from 0.01 to 0.16. In the model, *f(x)* represents Contentment, and *x* represents the value of preContentment.

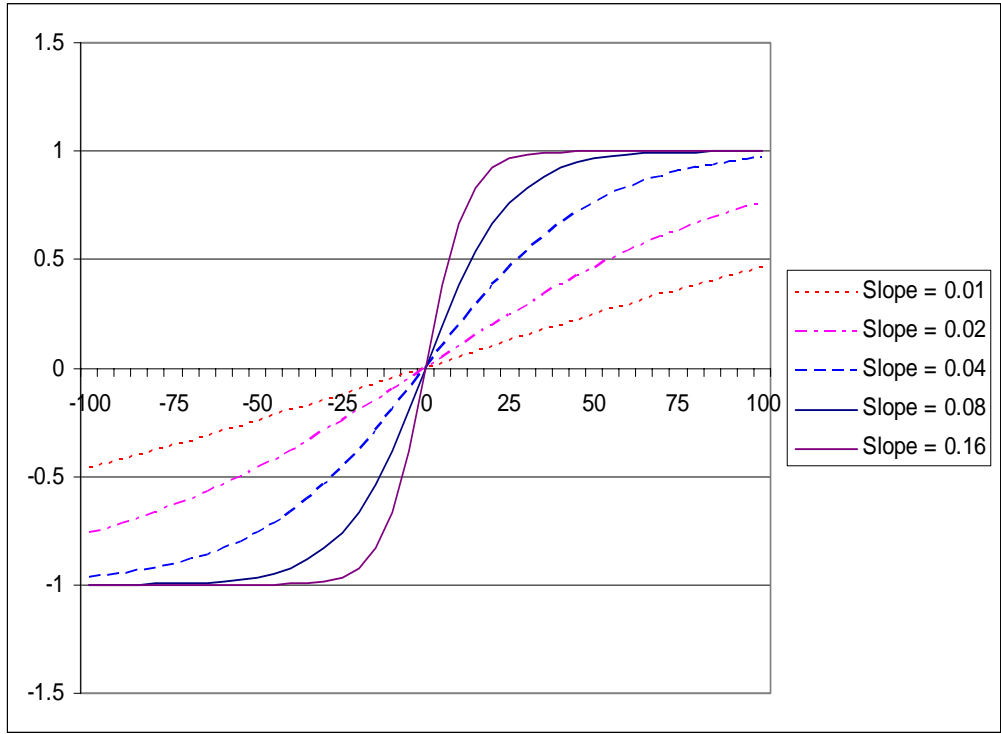
#### 4 Event-based Changes to Orientation

As shown in Figure 3, a given change in Contentment will cause a change in Orientation based on Equation 6:

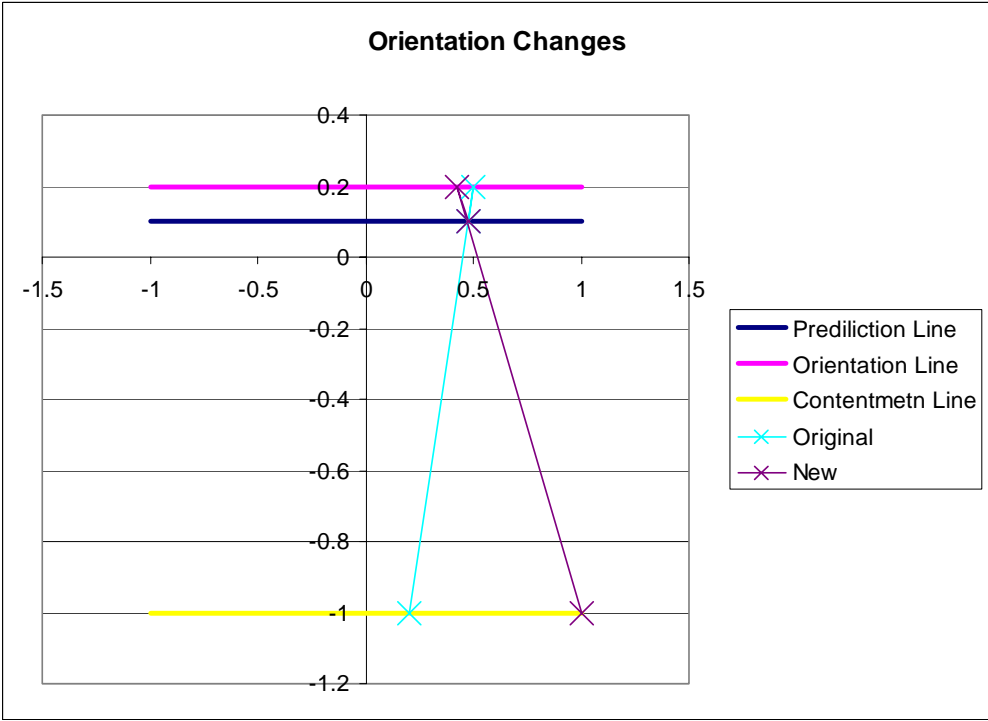
$$O(x_2) = Cx_1 - (Cy_1 - Oy_1) * \{ [(Py_1) * (Ox_1 - Cx_1) / (Oy_1 - Cy_1)] - Cx_1 \} / (Py_1 - Cy_1), \quad (6)$$

where

*O(x<sub>2</sub>)* = new Orientation value,  
*Oy<sub>1</sub>* = Orientation line (here a horizontal line with a y intercept of 0.2),  
*Cy<sub>1</sub>* = Contentment line (here a horizontal line with y intercept of -1),  
*Py<sub>1</sub>* = Predilection line (here a horizontal line with y intercept of 0.1),  
*Ox<sub>1</sub>* = current Orientation value, and  
*Cx<sub>1</sub>* = current time step Contentment value.



**FIGURE 2** Contentment curve



**FIGURE 3** Changes to orientation

## AGENT-BASED COMPUTATIONAL MODEL OF A VIRTUAL INTERNATIONAL SYSTEM

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### ABSTRACT

In recent years, the evolution of a powerful and innovative methodological tool known as agent-based simulation has allowed integration and evaluation of existing theories of international relations by creating a synthetic international and national environment. This virtual system models the interaction of large numbers of heterogeneous “artificial agents” that mimic the behavior patterns of humans or entities. The “emergent macrobehavior” of the effects of the interacting agents can be used experimentally to evaluate strategic and tactical domestic and foreign policy decision making. The computational experimentation approach, wherein human players can participate concurrently with an agent-based environment, offers several benefits. First, it facilitates the seamless and interchangeable integration of human and software agents. Second, it allows a place where the consequences of decisions can be measured and analyzed. Finally, it is a virtual laboratory for testing the efficacy of theories, decisions, strategies, and tools. This paper describes the implementation of an agent-based virtual international system developed for the U.S. Department of Defense to examine how intra-nation dynamics, geopolitical situations, leaders’ predispositions, and citizens’ expectations, goals, and desires for well-being affect a nation’s capabilities and willingness to fight. Specifically, the goal is to understand the conditions that increase or decrease both the leaders’ and the people’s will to fight.

**Keywords:** Agent-based simulation, computational experimentation, emergent behavior, virtual international system

### INTRODUCTION

In the field of international relations, several influential theories have been advanced that aim at understanding the causes of international conflict, regional and state stability, and peace. The foremost contemporary debate that has consumed international relations research for the past few decades is between the neorealist paradigm and neoliberal paradigm. Each paradigm provides an ontologically distinct, sophisticated, and nuanced explanation of states’ behavior in the international system. The neorealists view the international system as being anarchic and thus eschewing cooperation among states. They analyze it in terms of (1) structures and their observable attributes (Waltz, 1979); (2) distribution of power and relative military capabilities of adversarial states (Bueno de Mesquita, 1978, 1981; Thompson, 1988; Huth, et al., 1993); (3) the relationship between a state’s resolve/willingness to take risks and the likelihood of war

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(Snyder and Diesing, 1977; Bueno de Mesquita, 1985; Powell, 1990); (4) trade-offs between domestic ends and military power (Gilpin, 1981; Powell, 1993); (5) alliance structures and their effect on conflict; (6) military alliances and their effect on economic cooperation (Gowa, 1989; Gowa and Mansfield, 1993); and (7) one state's risk propensity for seeking relative gains vis-à-vis those of other states (Grieco, 1988, 1993). Neoliberals, by contrast, argue that anarchy does not eschew cooperative behavior among states. States' mutual interests and concern for future payoffs compel them toward cooperative behavior (Lipson, 1984; Oye, 1986; Axelrod and Keohane, 1993). For neoliberals, states are more concerned about maximizing absolute gains and, as such, are indifferent to the gains of other states (Stein, 1983).

While conspicuous attempts are being made to synthesize the contending theories into single integrated frameworks (Powell, 1991; Sterling-Folker, 1997), few methodological tools to test these contending theories are available. Agent-based simulation (ABS) is a methodological tool that has the capability to integrate and synthesize contentious theoretical frameworks and yield a comprehensive understanding of political, economic, and social systems and processes. In recent years, a significant amount of social science research has been using ABS in various applications, such as the development of synthetic economies (Chaturvedi, et al., 2005) and societies (e.g., ethnic conflict) (Bhavani and Backer, 2000); investigation of conditions for alliance among nations (Axelrod, 1997); conditions for state formation and dissolution (Cederman, 1997); identity development and diffusion (Lustick, 2000); secessionism in multiethnic states (Lustick, et al., 2004); and emergence of ethnocentrism (Axelrod and Hammond, 2003). However, very little of this work has focused on creating a holistic model of the international system. This paper describes the implementation of an agent-based virtual international system (VIS) developed for the U.S. Department of Defense to examine the interrelated effects of intra-nation dynamics, geopolitical situations, leaders' predispositions, and citizens' expectations, goals, and desires for well-being, on a nation's capabilities and willingness to fight. Specifically, the goal is to understand the conditions that increase or decrease both the leaders' and the people's will to fight.

## **AGENT-BASED MODELING OF A VIRTUAL INTERNATIONAL SYSTEM**

In recent years, the evolution of the powerful and innovative methodological tool known as ABS has allowed us to integrate and evaluate existing theories of international relations by creating a synthetic international and national environment. This virtual system models directly the interaction of large numbers of heterogeneous "artificial agents" that mimic the behavior patterns of humans or entities (citizens, leaders, groups, organizations, and institutions). The emergent macrobehavior of the effects of the interacting agents can be used experimentally to evaluate strategic and tactical domestic and foreign policy decision making. Furthermore, ABS allows us to test the relative explanatory value of the various theoretical approaches in international relations such as theories on deterrence, escalation of crisis, conflict, negotiations and bargaining, and peace operations by elaborating, refining, and testing the logically interconnected theoretical claims.

Also known as intelligent agents, artificial agents are "software modules equipped with artificial intelligence mechanisms that are capable — independently or in cooperation with other agents — of achieving specific goals. [Intelligent agents] can autonomously react to unexpected situations and learn from errors (and experts) to improve efficiency" (Boudriga and Obaidat, 2004, p. 35). Tens of thousands of these agents are situated in the artificial environment, and

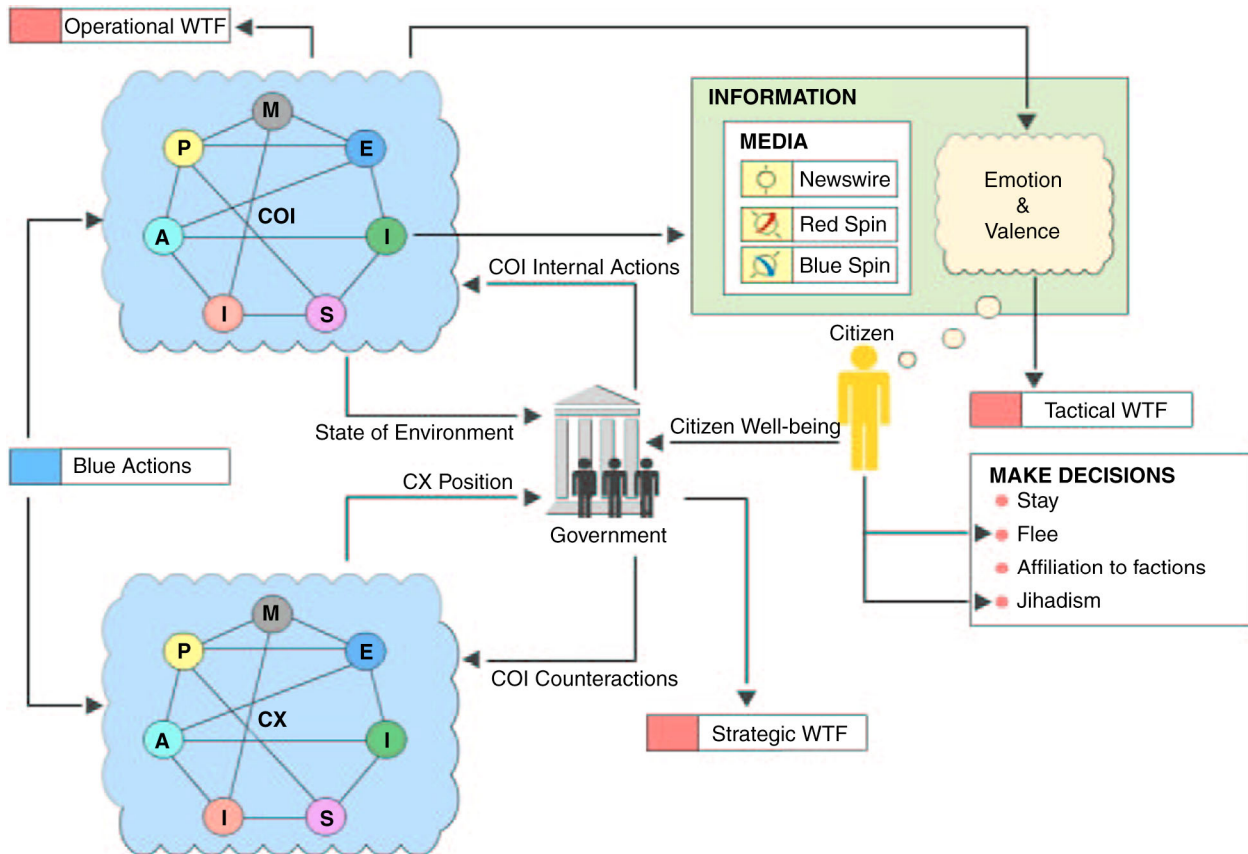
each agent typically represents one or more people in a simulation. The artificial agents can interact with other agents and with the environment; communicate, negotiate, and cooperate with each other; interact with human players; anticipate and adapt to changes in the environment and users' needs; and effectively communicate with user and network resources. There is a distinction between artificial agents and human agents. The behavior of the human players is not predetermined; they are free to act as they wish under prevailing conditions (which might include various capabilities and constraints), and these conditions are very clearly described and presented to them. The roles of the human and artificial agents can be interchanged on the basis of the requirements of the problem domain and the design of the experiment.

The computational experimentation approach, wherein human players can participate concurrently with an agent-based environment, offers the following benefits. First, it facilitates the seamless and interchangeable integration of human and software agents, which allows us to conduct significantly more complex experiments and simulations than are usually possible in the fields of experimental economics, psychology, political science, and epidemiology. Second, it allows a place where the consequences of decisions can be measured and analyzed. This extends the purview of traditional decision support from building models that support human decision making to actually being able to gauge the impacts of decisions as well. Finally, it is a virtual laboratory for testing the efficacy of theories, decisions, strategies, and tools. Experiments can be devised that measure the effects of various decisions against the support tools used to arrive at those decisions (Buodriga and Obaidat, 2004; Chaturvedi et al., 2005).

### **Virtual International System: A Case Study**

In this section, we describe a scenario-based case study in which the VIS is used to analyze the issues involved in coordinating diplomatic and military actions. We used VIS to represent 10 countries in a strife-torn region of the world. Developed by using the Synthetic Environment of Analysis and Simulation (SEAS), VIS comprises an environment containing multiple classes of agents. The SEAS platform allows the creation of virtual societies, nations, organizations, and institutions that “mirror the real world counterparts in all its key aspects by combining large numbers of artificial agents with smaller numbers of human agents to capture both detail intensive and strategy intensive interactions” (Chaturvedi et al., 2005). The virtual environment also provides the rules that govern and guide the actions of agents and interactions between agents. The VIS environment is composed of geographic entities (nations, provinces, cities) and their infrastructures (electricity, telecommunications, transportation), political systems (type of government, political parties/factions), social systems (institutions, group), economic systems (formal and informal sectors), and information systems (print, broadcast, Internet), as shown in Figure 1.

The VIS consists of teams of players — human as well as synthetic. The coalition task force (CTF; Blue team) is represented and played by humans. The other teams are the country of interest (COI; Red team); the other regional countries, that is, Country X (Green teams); and the media (Red-leaning, Blue-leaning, and Neutral teams). They are represented by more than 200,000 autonomous agents. The goal of this experiment is to analyze the COI's will to fight at the strategic, operational, and tactical levels.



**FIGURE 1** Conceptual model of VIS represented in terms of a political, military, economic, social, informational, and infrastructure (PMESII) framework

## MODELING THE COUNTRY OF INTEREST: SOCIETY OF SYNTHETIC AGENTS

We modeled the COI at the provincial level. Each province within the COI consists of five types of synthetic agents: citizens, leaders, organizations, institutions, and states. To represent a synthetic nation, individual citizen agents are constructed as a proportional representation of the societal makeup of a real nation. Each individual agent is encoded with static traits, such as gender, nationalism, ethnicity, race, income, education, and religion, and dynamic traits, such as political, societal, religious orientation, and will to fight.

The agent's well-being consists of six elements or needs: basic, health, security, religious, educational, and freedom of movement. Agents take actions on the basis of their assessment of their perceived state of their well-being. The agent's emotional state is the second psychological parameter that the system tracks. Either a leader or an event reported by the media can affect the agent's emotional state. The role of the emotion is to capture the level of arousal and the intensity of the action in which the agent engages. Allowable actions for citizen agents include joining organizations, leaving organizations, demonstrating, supporting Red or Blue teams or staying neutral, fighting or fleeing, and committing hate crimes.

Leader agents are leaders of various organizations. The leader agent's repertoire is larger than that of the citizen agent and includes traits such as fundamentalism, nationalism, power

base, and stance on domestic, economic, and social policies. Leader agents are categorized as social, religious, and political and are encoded with influence levels that reflect their power within groups, organizations, and institutions. These agents affect the political and social climate within the synthetic environment. They work to effectively impose their stances upon citizens and organizations to promote their goals. The goal of leader agents is to solidify their positions in the environment and to try to persuade organization agents to make decisions that favor those positions. Like citizen agents, leader agents use measures of well-being to access action. However, their actions are based on their position in the synthetic environment with regard to political orientation, freedom of opinion, societal orientation, economic policy, openness to western investment, religious orientation, and power base. A specific leader's perception about these attributes defines his/her stance and will to fight. The value of these attributes may then influence the corresponding organization agent's behaviors. Leader agents can take the following actions: incite agents to take actions, harmonize dissenting views, and persuade.

Clusters of agents form groups, organizations, or institutions. They differ from individual agents with regard to the rules that govern their behavior and intent. Groups can be formal or informal. Formal groups and factions operate overtly in the synthetic environment, while informal groups, such as terrorist cells, operate covertly. Organizations and institutions are legal entities that provide structure to the synthetic environment. Like groups, organizations can be formal or informal, although they differ from the latter with regard to size (larger) and structural development (more refined). An organization's will to fight is constitutive of operational will-to-fight measures.

Institutions are increasingly more formal than organizations with regard to policy development, implementation, and adjudication capabilities. Some institutions have the right to use force. Some specific traits for groups, organizations, and institutions include political orientation, freedom of opinion, societal orientation, economic policy, openness to western investment, control over resources, and power base. The institution's will to fight is constitutive of strategic will-to-fight measures.

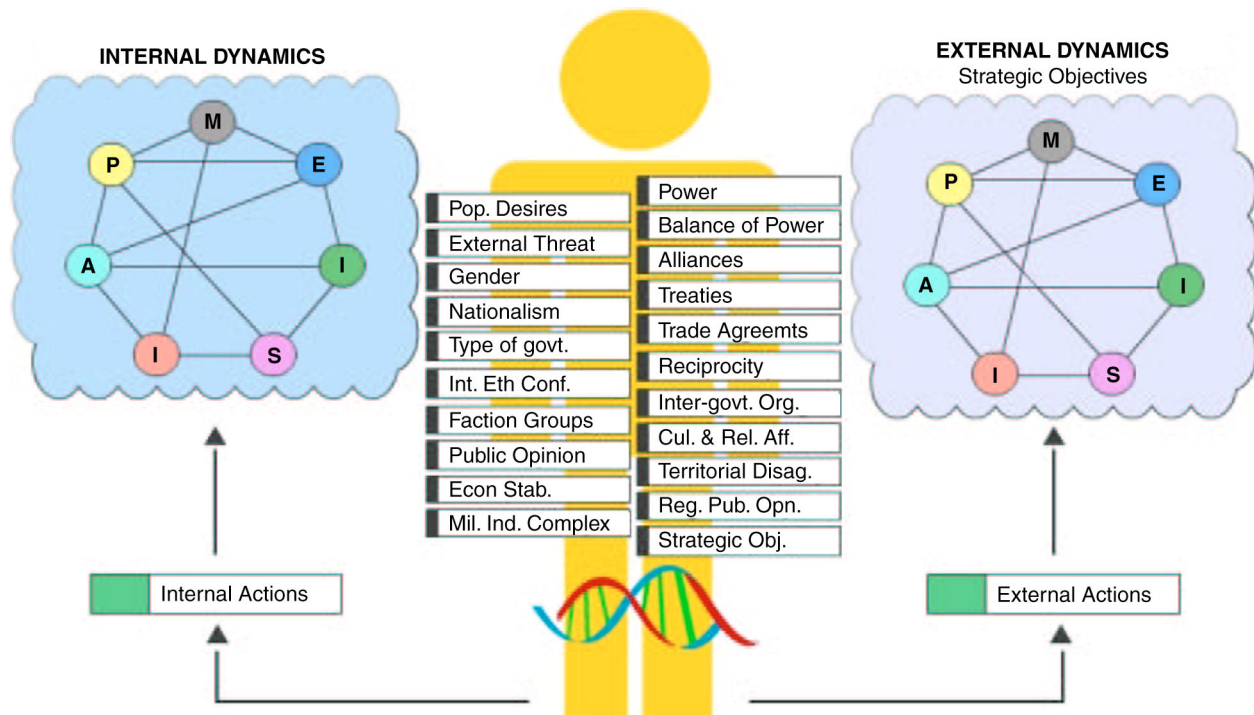
## **Modeling Country X**

Modeling Country X is at the heart of the VIS. Considerable research has been conducted to show the possible links between societal attributes of a state and its foreign policy behavior. According to Zakaria (1992, p. 198), "a good account of a nation's foreign policy should include systemic, domestic, and other influences, specifying what aspects of the policy can be explained by what factors." Waltz (1979, p. 64) further argues that explanations for a state's behavior that emphasized national or subnational interest would be reductionist at best, since "one cannot infer the condition of international politics from the internal composition of states, nor can one arrive at an understanding of international politics by summing the foreign policies and the external behaviors of states."

Nation states in VIS are a cluster of agents representing the legislative and executive institutions.<sup>1</sup> The clusters exhibit intelligent behavior based on internal and external dynamics, as shown conceptually in Figure 2.

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<sup>1</sup> Judiciary institutions are not implemented in the current version of VIS.



**FIGURE 2** Internal and external dynamics of agent clusters

### Internal Determinants

A state's foreign policy reflects the interests and relative power positions of competing groups within the state. For this simulation, we chose seven societal determinants of foreign policy. A brief description of the determinants follows:

1. *Nationalism*: Nationalism is defined as the psychological attachment to the nation-state, and this attachment, in turn, gives the nation-state its legitimacy. *Nationalist sentiment* is the feeling of anger aroused by the violation of the principle or the feeling of satisfaction aroused by its fulfillment (Gellner, 1983).
2. *Type of government*: There is an important distinction in policy-making functions between a democratic and an authoritarian system. In democratic systems, periodic elections give people a chance to shape policy through the selection and rejection of key policymakers. In authoritarian regimes, military councils, hereditary families, or dominant political parties choose policymakers. Hence, the contribution from citizens is negligible. In anocratic states, however, opportunities to affect policies are extended to certain segments of society, such as the elite and the intelligentsia (Almond et al., 2002).



3. *Internal ethnic conflict*: Most scholars agree that ethnic conflict has a detrimental effect on a state's stability and is strongly correlated with terrorism, guerilla warfare, and civil war. Linkage of groups might cause domestic conflict to "spill over" to neighboring countries or to the international arena. Domestic turmoil is often seized upon by traditional enemies to further destabilize the nation by providing incentives, finances, and revolutionary ideology (Horowitz, 1985; Gurr and Harff, 1994).
4. *Public opinion*: Public opinion provides legitimacy to a state's foreign policy goal. Hence, states and substate actors seek to influence the range of views held by the citizens of a state on foreign policy. They attempt to influence views because, in the end, policies are carried out by ordinary people, such as soldiers and bureaucrats. Public opinion has a greater influence on foreign policy in democracies than it does in authoritarian governments (Herrmann et al., 1999).
5. *Economic stability*: Resource availability makes a difference in how active a policy a state can pursue. It also has an important impact on military and economic strategies. Conversely, a state with limited resources can ill afford to pursue a global foreign policy (Gasiorowski, 1995).
6. *Military-industrial complex*: The military-industrial complex tends to have considerable influence on a country's foreign policy decision making. Since it is the most modernized and skilled sector of the society, it has the ability to influence decision making and mobilize support through glorification of past and present military strength and through its association with all segments of the elite and the nation's leadership (Millet et al., 1986).
7. *External threat*: Decision makers use external conflict to unify their population and galvanize support for foreign policy decisions. External threat is also used to foster alliances, especially in the military domain (Huth et al., 1993; Bueno de Mesquita, 1997).

### **Systemic Determinants and Strategic Objectives**

Although states are sovereign entities in the international arena, they are not autonomous. Their relative position in the international structure is determined by their relative power position, distribution of power regionally as well as globally, political and economic alliances, cultural/religious affinities with other nations, and regional public opinion.

- *Power*: A state's power is determined by its relative capabilities, which, in turn, determine its position regionally and globally. A state's capabilities are the combination of its industrial, military, and demographic power (Singer et al., 1972).
- *Balance of power*: To manage insecurity, states try to balance themselves against other states and, in the process, make rational and calculated

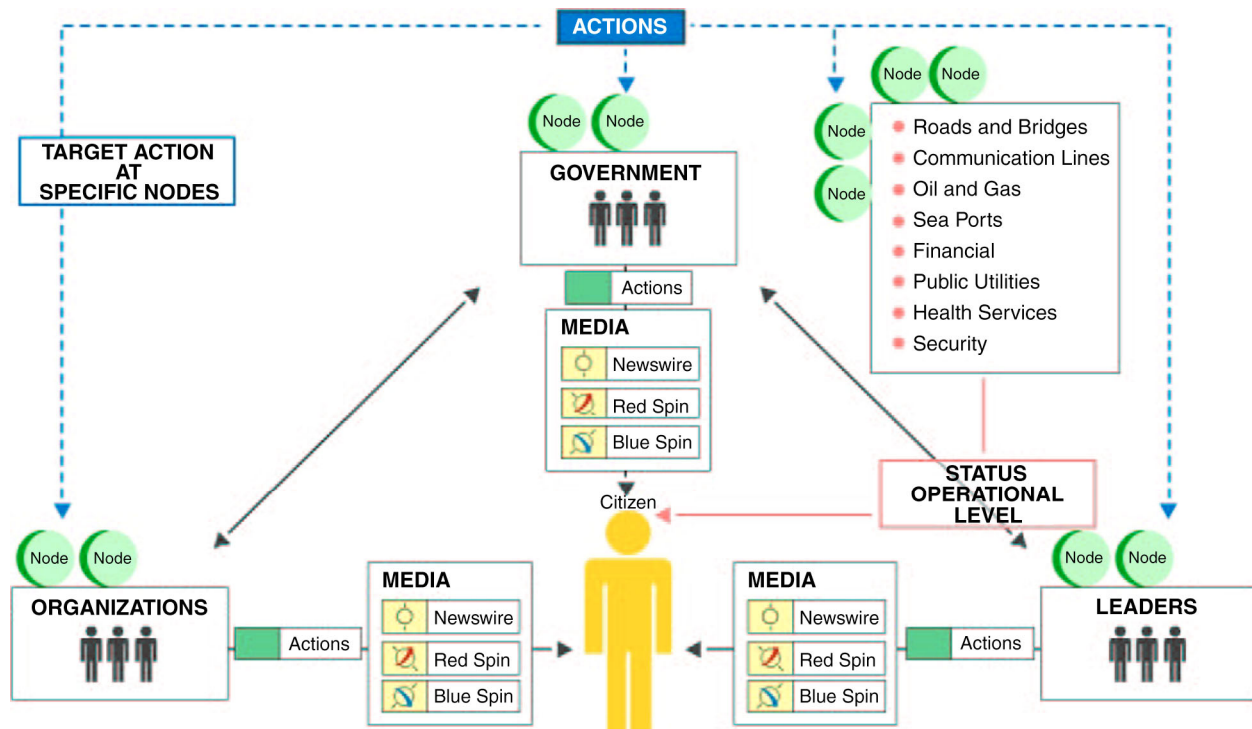
evaluations of the costs and benefits of particular policies that determine their role in the system (Waltz, 1979; Walt, 1987).

- *Alliances*: States form alliances to prevent possible aggression from other states. Alliances have a significant impact on foreign policies of allied countries and provide the basis for power projection. Two main factors are important to the formation of alliances: (1) an idealistic factor that is a national commitment to alliances based on shared values and ideas and (2) a realistic factor based on cost and benefits. The assumption is that alliances can save costs and multiply benefits through division of responsibility, sharing of common assets, and protection of a stronger country (Walt, 1987; Gibler, 2004).
- *Treaties*: Bilateral and multilateral treaties between states are reciprocal arrangements and facilitate cooperation, which, in turn, affects the power structure of the region (Jervis, 1988).
- *Trade agreements*: Trade agreements are economic strategies that states adopt to maximize their own wealth and economic power in the process of carrying them out. Trade agreements can promote cooperation by increasing reciprocity and linking various issue areas (Keohane and Hoffman, 1991).
- *Reciprocity*: States use reciprocity as a strategy for achieving cooperation in a situation of conflicting interests. Reciprocity is a specific bargaining strategy that a state adopts to enhance its own goals and to induce other actors to take the actions it desires (Lebovic, 2003).
- *Intergovernmental organizations*: International organizations set the norms and rules of behavior for their member states. They provide conditions that are conducive to greater cooperation and interdependence among states, thereby regulating interstate conflict (McCormick, 1980). According to Ruggie (1992), multilateral norms and institutions “appear to be playing a significant role in the management of a broad array of regional and global changes in the world system today.”
- *Culture and religious affinities*: According to Axelrod (1997, p. 82) states have “some interests that affect their behavior toward other countries, such as the desire to be militarily secure, but also have specific conflicts and affinities with particular other states based upon ideological, ethnic, economic, or prestige values.” Similarities or dissimilarities in culture and religion across states affect their strategic calculations accordingly.
- *Territorial disagreements*: Bilateral territorial disagreements significantly increase the probability of war, which determines a state’s policy regionally as well as globally. States tend to increase trade relations and alliances with the adversary and/or neighboring states; increase their military capability vis-à-vis their adversary; and/or negotiate, bargain, and follow other diplomatic channels, such as cultural exchange, with the adversary to balance their position in the region (Vasquez and Henehan, 2001).

- *Regional public opinion:* Globalization and information technology contribute extensively to a state's foreign policy objectives. Information sharing can galvanize the masses, compelling states to adjust their foreign policy choices accordingly (Robinson, 1999).

## PUTTING IT ALL TOGETHER

Figure 3 depicts the interaction between the CTF and COI and the role of the media. As mentioned earlier, the COI is composed of citizens, leaders, organizations/institutions, and infrastructures. A user interface was designed to allow the CTF to interact with VIS. The CTF has diplomatic, information, military (actions limited to information and psychological operations), and economic (DIME) action sets.<sup>2</sup> Each action has intensity levels on a scale of zero to six. Zero implies a "status quo" level of effort, and six represents an extremely high level of effort. Each of these actions can be directed toward any entity in the system, such as one or more persons, organizations, infrastructures, or governments. While only the logical actions have effects on targeted entities, no constraints exist in VIS on what actions can be taken or to which entity they can be targeted. In this way, VIS does not eliminate certain types of errors committed by the players.



**FIGURE 3** VIS environment

<sup>2</sup> Attrition-based simulation ran in parallel to SEAS runs. The output of that model was entered in SEAS, and SEAS output was entered into the attrition-based model.

Agents in VIS can either directly sense the state of the environment or receive the news from the media. Three types of media are modeled: neutral/news wire, red-leaning, and blue-leaning. The role of the news wire is to present the “ground truth” to the red- and blue-leaning media. The red- and blue-leaning media bias their messages to meet their respective agendas and goals. Agents subscribe to the media on the basis of their own beliefs. In the starting condition, about 20% of the population subscribes to the red media, 20% subscribes to the blue media, and 60% subscribes to both. The media report on the well-being parameters of all agents. Agents can subscribe or unsubscribe to the media on the basis of their pattern of believability in reporting.

Before the model was used in the experiment, a lengthy process of calibration was performed. In our agent-based model, each agent is a microsimulation, and the entire system is a society of simulations. Therefore, we validate each class of agent against theory and calibrate the emergent behaviors of the system against empirical data (if available) and/or experts’ opinions regarding the subject matter, as shown in Figure 4. Typically, a third party performs the validation and verification of the model before it is made available for experimentation.

## **Experiments and Results**

This section presents partial results of an extensive set of experiments with subject-matter experts. The experiment has two parts. The first part entails actions taken during the period D – 90 to D-day. D-day represents the day of the start of major military intervention. The goal of the D – 90 to D-day simulation is to use diplomatic, informational, and economic means to bring the COI to the negotiating table.

The second part of the experiment pertains to the use of diplomatic, informational, and economic interventions in conjunction with a major military offensive. CTF’s actions (Figure 5) and the corresponding COI’s posture during D – 90 to D + 10 are shown in Figure 6. Results indicate that as the tension in the region increased during the D – 90 to D-day time period, the public mood and employment began to slide downward as a result of the informational and economic operations of the CTF. However, the national pride index remained relatively high.

The states of the strategic, operational, and tactical wills to fight are shown in Figure 7. The tactical (public) will to fight (as a function of public well-being and emotion) continued to rise and the operational (military and militia) will to fight stayed relatively constant, whereas the strategic will to fight (political leadership) fluctuated significantly.

After the breakout of hostilities on D-day, diplomacy, psychological, and informational operations seem to be quite effective. Although the tactical and operational will to fight remained steady, the strategic will to fight decreased, implying that the leadership of COI was willing to negotiate. The strategic will to fight could continue to stay low by providing economic incentives and rapid de-escalation.

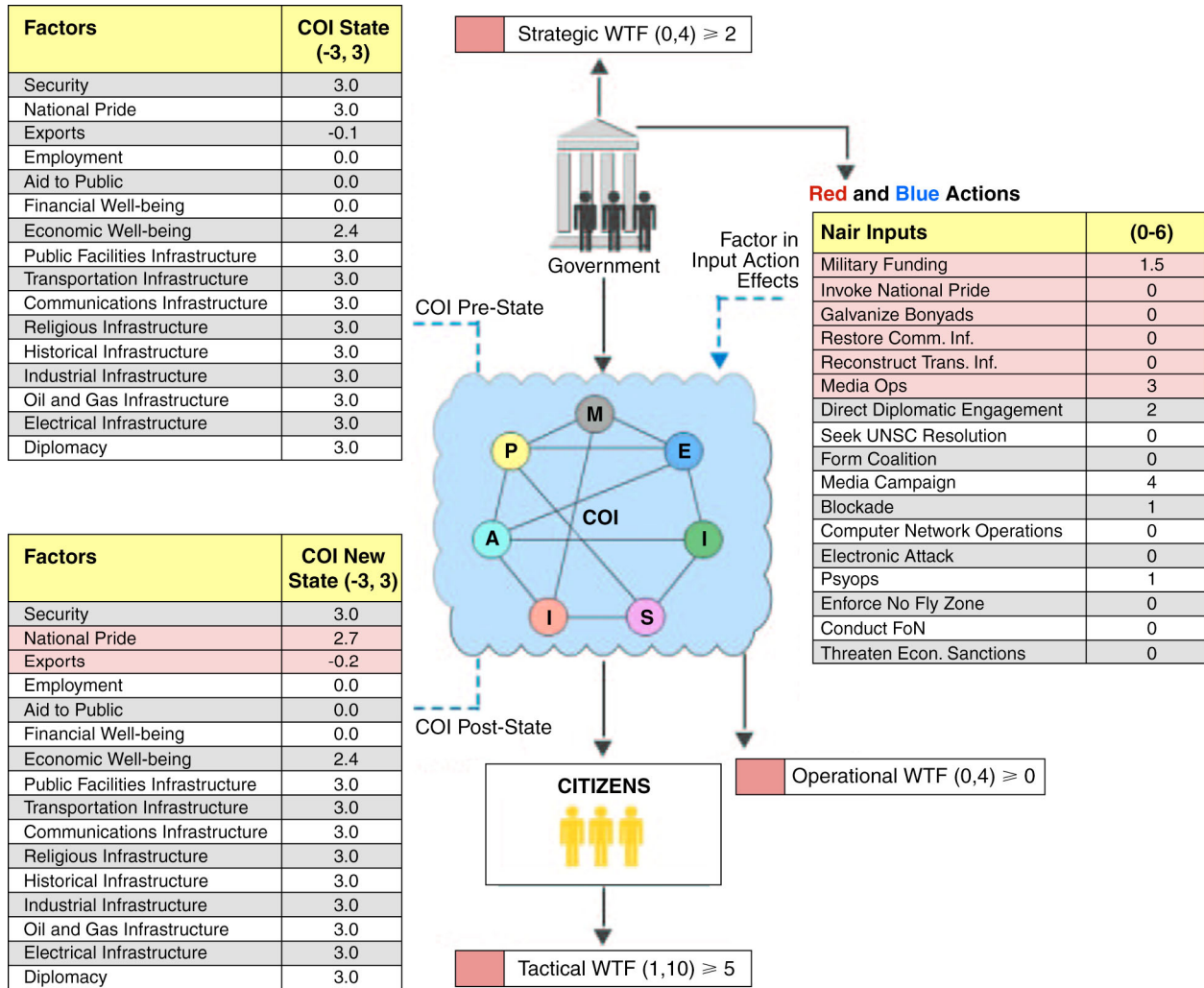
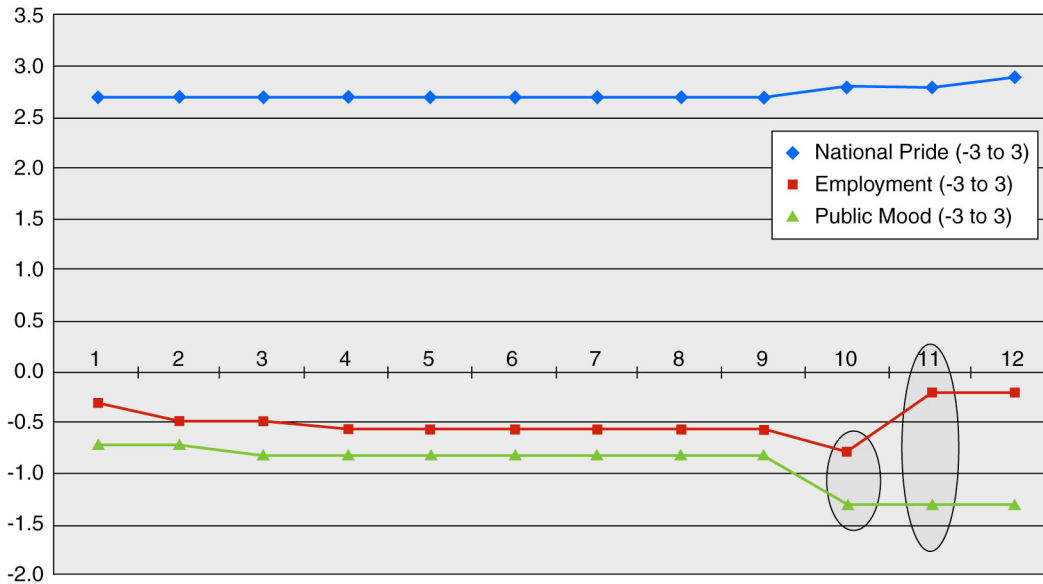


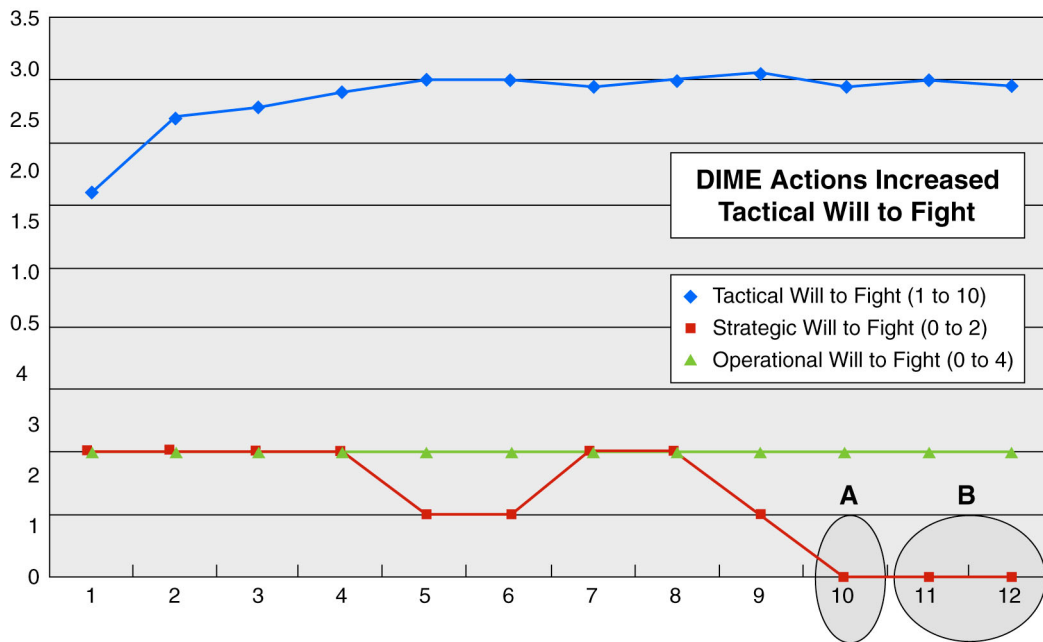
FIGURE 4 COI calibration process for will-to-fight measures



FIGURE 5 CTF actions at times D + 1 (day 91) and D + 10 (day 100)



**FIGURE 6** Public mood, employment, and national pride indicators of COI (Day 9 represents D-day, when the hostilities start. Day 10 represents a major attack with casualties and infrastructure damage. Day 11 represents a reduction in information, military, and economic interventions.)



**FIGURE 7** Effect of CTF's actions on strategic, operational, and tactical will to fight (D – day = day 90; on D + 10 or day 100, CTF achieved the minimum strategic will to fight and sustained it until D + 30 or day 120.)

## Discussion and Implications

Agent-based simulation is a constructivist approach that offers a compelling argument for theoretical convergence, synthesis, and exchange of ideas. According to Lustick (2000), this paradigm “opens wonderful opportunities for complementary application of different approaches to the study of an important set of inter-related phenomena.” ABS allows us to integrate different methodological tools to study individual and state interactions. This research is the first attempt to model micro- and macro-level interactions in a single environment.

Although the model does not yet have the fidelity to be used as a predictive tool, an extended VIS exercise could definitely provide a CTF with insight into the complex linkages between and across a diverse set of entities in the international system. While we were successful in integrating and testing models from a wide range of disciplines, several challenges still remain, as described below:

- *Common representation of knowledge from multiple disciplines:* Although there is reasonable representation from the agent, group, organization, and system levels, considerable work still needs to be done.
- *Extremely large number of causal factors:* An automated method for isolating and validating causal relationships needs to be developed.
- *Difficult-to-perform multiple trials:* It takes about 2-4 minutes each day to run trials on a 4 dual xeon cluster. The processing time needs to be further reduced to accommodate more rigorous experimentation.
- *Human elements:* The outcome of an exercise depends on the human players and their understanding of the problems and issues. A distributed experimentation environment, with nodes at many universities, “think tanks,” and national laboratories, would help us to develop a deep understanding of the intricacies of the international system.
- *Repeatability and reproducibility:* This factor is always a challenge for ABS. A more formal stochastic paradigm is required to repeat and reproduce the results from complex, nonlinear systems.
- *Multiple granularities in space and time:* To deal with the complexities of a large-scale system, such as the virtual international system, a formal paradigm needs to be developed to deal with multigranularity in space and time.

In summary, we described a computational experimentation environment for a VIS. We also presented a case study in which we analyzed the impacts of diplomatic, informational, military, and economic actions on the strategic, operational, and tactical will to fight. This research is a work in progress, and, as such, there are several limitations. The long-term goal of this project is to develop a comprehensive computational experimentation environment in which scholars can contribute their theories, models, and data.

## ACKNOWLEDGMENTS

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**DISCUSSION:****NATIONAL SECURITY ISSUES****(Saturday, October 9, 2004, 1:30 to 3:00 p.m.)**Chair and Discussant: *Keven Ruby, The University of Chicago***Epidemiology or Marketing? The Paradigm-busting Use of Complexity and Ethnography**

**Keven Ruby:** Today we have three very interesting papers, and we're going to begin with Stephen Guerin who will talk on the structure of agent-based revolutions.

**Stephen Guerin:** I have a small consulting company in Santa Fe [Redfish Group]. My collaborators are Michael Agar at the University of Maryland and Robert Holmes and Dan Kunkel. Mike is an ethnographer. Dan and I are software developers and are involved with visualization. Robert Holmes is a mathematician who does analytics for us, funded by the National Institutes of Health and the National Institute on Drug Abuse.

In light of this morning's conversation, what are some possibilities for empirical calibration, and what are some visualization challenges? I want to start by saying that we're an applied company, but this was not an applied project. It was a research project, so it doesn't contain the same kind of customer requirements. This came out of Mike's work as an ethnographer. He's had 20 years in the field studying illicit drug use in the streets of Baltimore. The title that Mike came up with means, "Is There a Paradigm Shift Going on Here That We Can Capture with an Agent-based Model?" As an ethnographer, he's interested in using agent-based modeling as a way of presenting ethnographic hypotheses or ideas, as opposed to producing some kind of written treatise on ethnography that you would put up on a shelf. He's very interested in getting ethnographies that are models that people can play with and iterate after obtaining feedback. So this idea came out of the field work and the desire to feed back to policymakers and the kids in the streets to ask them if this is their reality.

[Presentation]

**Ruby:** Thank you, Stephen. We're going to save the questions for the end of the session, unless somebody has immediate questions.

**Zhian Li:** I am Zhian Li, from Argonne National Laboratory. I would really like to hear something about how you overlap your social and geographic networks.

**Guerin:** We basically had two events, time stamps, and you're moving between the two geographically. I'm thinking about putting a radius around the destination and increasing that radius interactively, so that once people are inside that radius, they are no longer trying to get to the destination, but now interact more socially, like embedded springs at that point. Once they're inside that, they're random walkers, repelled by other people that they're not connected to and attracted to the people that they are connected to. So if you want to go purely geographic, you'd

make that radius zero, and if you want to go purely social, you would make that radius go all the way out so that it has no geographic influence. I can show you examples.

**Li:** So you can turn off some stuff purposely.

**Guerin:** Right.

## **Agent-based Computational Model of a Virtual International System**

**Ruby:** We move on to Alok, who's going to be talking about a virtual international system. Something to think about during his presentation is how the models that have been presented so far have been advancing in complexity.

**Alok Chaturvedi:** Thank you, Keven, for giving me the opportunity to speak to you. Sitting through several presentations has been a fascinating experience. What I'm going to present is an effort that we have been working on for over 10 years. You'll see a certain maturity in some of the modeling, especially the computer science aspect of it.

I'll go over the building blocks very quickly, the calibration, validation, and experimentation capabilities, and then talk about all of the challenges. Support for our effort is primarily from the National Science Foundation through a medium ITR grant, Indiana State 21st Century for Department of Defense, and Simulex, Inc., which is a company. I am the principal investigator of this effort, and several other people are involved from Purdue, Naval Post-Graduate School, and Indiana University, as well as from the company.

[Presentation]

**Ruby:** I have a few framing comments for the discussion. We've heard three very interesting presentations that address some important topics under the heading of national security, including how to approach the question of occupation and conflict dynamics, as well as how to rethink the drug problem and the impact that may have on drug policies in the so-called 'War on Drugs.' Methodologically, we've seen at least two very different approaches. The first two papers used a more standard agent-based modeling approach in which all of the action takes place within the model; whereas, the presentation we just heard, which is very interesting in developing a more realistic model of the world, has added considerable complexity and has created, in a sense, a double laboratory in which the first is the model itself and then the second is the interaction between the model and the human decision makers as they try out different strategies and test them against model results.

The questions that I have are very general and apply across the presentations. But the main one involves correspondence or external validity, particularly with respect to the last presentation. As the complexity goes up, the model becomes somewhat more of a black box, and it's not clear to what degree policymakers can be sure that what's actually driving the results corresponds to actual mechanisms in reality.

Also in many of the cases, a lot of parameters are included that are not fully explained, such as in the Marine support operations model. It's not clear why, for example, sex and marital status are incorporated into the model. The distributional effects of parameters would also be an

interesting thing to at least include briefly in the papers. So with that, I will open the discussion to questions from the floor.

**Cioffi-Revilla:** I'm Claudio Cioffi, from George Mason. My question concerns the last presentation. I'm at a loss for words. I'm baffled. The reason I'm baffled is that modeling international systems has been my business for the last 30 years. You said you've been working on this model for the last 10 years?

**A. Chaturvedi:** Yes.

**C. Cioffi-Revilla:** On the international system?

**A. Chaturvedi:** No. Not on the international system, but on this whole framework, the computer science end of it.

**Claudio Cioffi-Revilla:** This international system model is completely new and unpublished, as far as I know. I go to these meetings, and I've never heard any colleague who works in this community ever mentioning this model — not Barry Hughes, not the late Stu Bremer. I mean, the theories that you're referencing here, about balance of power and so forth, are extremely unsettled; they lack tremendous efforts in validation. And the field that studies these things in IR [international relations], quantitative IR — as I said, I'm at a loss for words because you're portraying a tremendous amount of positive science that in fact does not exist in that area. The construction of international models has been a very challenging thing for a long time. I'm not saying that it is an impossible feat to achieve, and perhaps you have done it, but I get very nervous when results from this type of work are going to high councils to help decide on policy without really a whole lot of scientific diffusion and peer review and validation and publication and so forth; I'm just shocked.

**A. Chaturvedi:** Okay. Thank you for your comment.

**Cioffi-Revilla:** I hope you got it right.

**A. Chaturvedi:** I've been working on the computer science end of it for 10 years. I mean the modeling. We started working on SEAS back in — I mean, my personal background is in machine learning in a multi-agent system, right from the beginning, from distributed AI to multi-agent systems. We started by looking at the deregulated telecommunications industry, by working on synthetic economies. From that point onward, we started looking at terrorism. The Virtual International System [VIS] is a new phenomenon for us; we were approached by the Department of Defense to develop a political, military, and social information infrastructure model. We have been working with the Department of Defense (DoD) for about a year, and this VIS is a new phenomenon about which we are just beginning to publish.

Now, as to the questions you raised about being scientifically validated, none of our assumptions are black boxed. When we work with our colleagues and policymakers, we are working with intelligence communities; we are working with many people who know exactly what is going on in the parts of the world we are trying to model. One of the things we have been able to achieve is to make the model totally transparent; you can see whatever assumptions we use. We are saying that these are the theories on which we are basing our models. So if there are accredited people who tell us that these are not valid models, then we can change that. Our goal

is to develop a paradigm, a method whereby people can put in their theories, put in their assumptions, and run and test them. As far as individual models are concerned, the psychology of people or the hedonic psychology of people, the sociology of peoples — we have experts in different areas who are helping us out.

**Unidentified Speaker:** Can you talk a bit about the IR construction?

**A. Chaturvedi:** Several people have worked in the IR construction, so we have our own experts. At Purdue University, we have worked with people like Michael Stoll. Michael Stoll used to do a lot of work on terrorism when he was at Purdue; now he is at Santa Barbara.

**Cioffi-Revilla:** Terrorism is one subject. International systems dynamics is a very different field.

**A. Chaturvedi:** Yes. Oh, absolutely.

**Cioffi-Revilla:** It's like saying biology and chemistry are the same thing.

**A. Chaturvedi:** No. I mean, everything is very difficult. I'm not saying that we have solved all of the problems. You are free to use the system. You can test your theories; you can validate or invalidate them. I'm not a subject-matter expert in that; that is not my thing. I mean, I'm an agnostic. What I'm saying is that if you have an assumption, if you have a theory, we can validate or invalidate the theory; all of those things are open to you. I'm not saying that we are proving certain axioms or certain theorems. All we are saying is that this is a framework, a mechanism whereby you can test these things. That's all.

**Unidentified Speaker:** I'm from Argonne National Laboratory. I'd like to approach the subject from the same direction, more or less, as Claudio, but with a slightly different focus. Some of the problems you face are problems that we all face, but your research program is particularly ambitious; therefore, it seems more vulnerable to these kinds of issues.

For example, you just said that you're not saying you solved all of the problems. But the question is whether you have a methodology that seems likely to solve the necessary problems. I have two questions related to that. One is that social science theories are notoriously fragmented, and if you are using some default theories, then when you have outliers going and are finding other theories to explain the outliers, how do you avoid radically overfitting the particular circumstances of the case? That's the first question. The second question is more specific to the example you used of the will to fight. You were calculating the will to fight. Well, this is one of these examples that is inherently complex. Sometimes an attack demoralizes; sometimes it enrages. In the Revolutionary War, the soldiers had to go home in the spring to plant their crops. You could continue to point out examples of that, where these are inherently complex dynamics that are (a) hard to capture by a single theory, and (b) if you create a pastiche of a number of theories, you're explaining one thing, but without the ability to generalize. So my second question is, do you think that you can achieve your goals without substantive progress in social theory per se?

**A. Chaturvedi:** Oh, these are wonderful questions, so let me take the second question first. I cannot do it by myself. One of the reasons why the National Science Foundation has funded us is to make this computational experimentation paradigm available to the wider

community. So one of the things that we would like to do is have the wider community contribute their own thoughts and their own models to this arena.

As for the first question, yes, what we are trying to do is orders of magnitude more complex than anything else. So in terms of a paradigm, we are trying to create a virtual society in which we have all of these competing theories. Now, we can say that there are some governments or states that believe in maximizing power, while another state is trying to achieve more balance of power — although these two different types of theories are not very well understood, at least they are certain assumptions.

When we start populating our virtual environments with these types of behaviors, starting from micro- to macro-level behaviors, because one of the bigger challenges in our coming here is that we are taking individuals, the citizens, and attempting to scale to the macro-level behaviors from the government point of view or from the institutional point of view. So these are challenges, and we are not saying that we are already there, but we are developing frameworks in which we can start understanding it, or at least learning about it. We can isolate different regions, different countries, different states, and then we can try and test those theories. It is more of experimentation, so I am not saying that this is policymaking or a solution, but this is an experimental environment in which people can say that it is okay if this group or community behaves in a certain way, but what are the ranges of outcomes that we can get? Once you start getting those ranges, you can have a more rigorous statistical analysis of that. Whether those conform to theories or do not conform to theories are different things that other people will have to interpret.

What we are trying to do is build a set of instruments that can be applied by wider communities in starting to develop certain types of frameworks and metrics to have a much deeper understanding or at least a quantitative analysis of international systems. I mean, international systems are one of the things, obviously the bigger thing, but all of these different building blocks lead to that.

**Nick Gotts:** Nick Gotts, Macaulay Institute. This question is for the last two speakers. I'd like to ask what they feel are the moral implications of modeling ways to invade and subdue other countries. It's a serious question, and I would like a serious answer.

**A. Chaturvedi:** That is a valid question, and we have considered that. Our approach to this problem is to not do the end piece, the military piece. We are trying to see how we can bring about peace, peace in the community. Although we are working with DoD, the thing that we have been able to do is energize the State Department and USAID and others, so that these interagency groups have a better say in what is going on. We are looking more on the peaceful side.

**Gotts:** It didn't really sound like that because you were talking a great deal about the will to fight.

**A. Chaturvedi:** The will to fight, yes. From the State Department and USAID points of view, the will to fight is involved with how you can stop a war from happening.

**Gotts:** Well, one way is not to start it yourself.

**A. Chaturvedi:** Yes, exactly. When we are working with them, we are looking at how to prevent the war. We are at the front end of many of these war games and exercises involving the State Department, USAID, and all of the other interagency groups because we are not modeling attrition; we are not doing shooting wars; we don't simulate that at all.

**Elenna Dugundji:** Elenna Dugundji, from the University of Amsterdam. I just had a technical question. I was very impressed by the large-scale nature of this. You said you had a distributed application of parallel processing. I was wondering if you could comment on some of your experiences and give some advice in the area of the challenges that you had to overcome, or just a few words of wisdom from this experience with a distributed application.

**A. Chaturvedi:** That is my area. I can speak for days on that. But the critical thing is that most of the applications are designed to run on a single machine at first, and then people try to parallelize it and run it as parallel processes. That is the wrong way of doing that.

If you are designing the algorithms on your system, you should parallelize it. An agent-based model is very, very conducive to that. You can distribute different agents, you can break down geographies, and you can run different geographies on different things, or you can run different classes of agents. How you can configure your system is one of the key things. When you're designing your system, make sure that you are not hardcoding or hardwiring to bring the configuration in. You should be able to distribute the agents whichever way you want.

The second thing is the input-output, which is critical, because that is where most of the bottleneck occurs. If you are not designing your system for inputs and outputs, then you are going to have a bottleneck. No matter how large the machine is, you are not going to get the throughput you need. So distributed memory management is one of the critical pieces — how you distribute the memory — then you can build the input and output. Those are two critical things: distributed memory management and configurability.

**Greg Madey:** Greg Madey, University of Notre Dame. I have a few short questions. Who at DoD — what office or branch — is sponsoring your work?

**A. Chaturvedi:** It is coming from OSD [Office of the Secretary of Defense] and several war games that we run for DoD.

**Madey:** On the slide you have there, you say you validate at the individual level and you calibrate at the population level. What does that mean? Why won't you do it the other way around?

**A. Chaturvedi:** If you are developing a true agent-based system, then each agent should be a micro-simulation in itself. It should have its own user interface; it should have its own memory; it should have its own execution and everything. Once you are doing that, you are essentially building a society of simulations. When you are building a society of simulations, then obviously each microsimulation is a lot easier to validate and verify.

To give you an example, we developed an epidemiological model for smallpox and influenza. You can use the epidemiological model, which is essentially a population-level model, and try to look at the individual from the population. If you are studying the epidemiology of STD, which is an individual-level model, and then you try to look at the population, the agent-



based model allows you to do the individual level as well as the population level because you have many individuals.

The reason for validating at the individual level is that the rules and behaviors are a lot simpler. When you put hundreds of thousands of these agents, or tens of thousands of these agents, depending on what you are trying to study, it is a lot easier to calibrate at the population level. Take the field of marketing, for example. I cannot predict what you are going to do, and you cannot predict what I am going to do. But you can segment me in a population, then you can say with pretty good certainty how much of this type of toothpaste this population or group or segment is going to buy. There's a lot more confidence at the small-group or population level than at the individual level. That is the reason why we like to validate at the individual level and calibrate at the population level.

**Ruby:** We have time for two more questions.

**Roger Burkhart:** This is Roger Burkhart, John Deere. A question for Alok. Do you use any standard framework for integrating all of these distributed components, such as the DoD high-level architecture for real-time simulation?

**A. Chaturvedi:** We have an extension of high-level architecture because high-level architecture has many limitations in terms of time management. Some of the things we are doing require more extensive time management, temporal relationships, so we can do things in high-level architecture, HLA, and we can use RTIs, but in the simulation bridge we are building, especially our shared reality engines, we can interoperate very easily with RTIs.

**Zhian Li:** Zhian Li from Argonne. I would like to follow up with a very technical question. In the morning, Dr. Macal gave a speech about complexity and reality, saying that one must occur on the bottom and the other on the top. So when you build this model, how do you justify which way you want to go? If you want to build a system with all of the overhead for distributed simulation, how do you handle the concurrency issues? Or if you build a small, simple model and you do a conceptual or case study, how do you then expand from that?

**A. Chaturvedi:** We do both, actually. Each of our agents is very simple, very elegant models. Whether you are looking at psychological behavior or economic behavior, you can isolate all of these behaviors of an agent and you can run tests to see whether these behaviors conform to the theories that you want to program these agents on. Each individual agent is a microsimulation in itself. It's very elegant, runs very fast, and you can isolate behaviors completely. So whether in terms of hedonics or well being, you can look at basic necessities or security requirements or whatever. You can define all of those based on hedonic psychology, that is, the well being that this agent is trying to meet or maximize. Then you can populate; you can create groups of agents; you can create societies of agents; you can create an organization of agents, so you can very nicely start putting in structures. And then you can start building things, start building bigger blocks. You can put a leader in an organization and specify how the leader interacts with all of the agents. So you can start in a simple, very elegant way at the agent level, and then you can start expanding that to build the synthetic cities and synthetic nations.

**Ruby:** We have time for one final question.

**John Sullivan:** John Sullivan, Ford Motor Company. This is an observation. It's more philosophical and maybe someone, perhaps you, can explain this to me later, if need be. A good tool of the kind that you've just described, one that's available, could be used, not only by us, but also by our enemies, it seems to me. Why are you here, if this thing is as good as it is purported to be?

**A. Chaturvedi:** I'm an academic, and I would like for more people to develop models, more people to understand what is going on because, as was mentioned, social science is very fragmented, whether it involves international relations or sociology or other areas. I'm working with the Department of Defense as a computer scientist. We are also working with several Fortune 500 companies. We have people coming to us to look at virtual product introduction. So promoting this whole notion of computational experimentation, and that is what the NSF is funding us for, serves to create a new paradigm, or at least enhances a certain paradigm that was widely available in engineering and science because, for example, the national labs are big on computational experimentation. The national labs are the ones who are proposing that computational experimentation be a third leg of science, in addition to the analytical and observational legs.

**Unidentified Speaker:** I'm sorry. I have to correct you. That was not something the national labs invented.

**A. Chaturvedi:** Department of Energy.

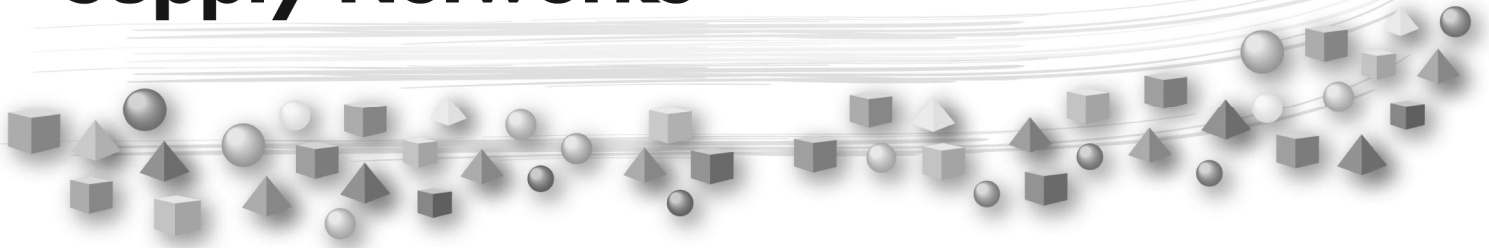
**Unidentified Speaker:** No, that's something Robert Axelrod invented.

**A. Chaturvedi:** Yes, okay. But you're going to see computational experimentation at most of the DOE Web sites. We are just trying to have computational experimentation as a paradigm for social science and business. I'm primarily in business school, so that is what I'm looking at.

**Ruby:** Thank you very much to the presenters and to you for a very great discussion.

**Unidentified Speaker:** Thank you very much, Keven Ruby, for chairing the discussion. John, I think perhaps the short answer to your question is that Alok is here with us because he's 'on our side,' apparently.

# Supply Networks





## LEARNING TO ORDER IN SUPPLY NETWORKS: AN AGENT MODELING STUDY

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### ABSTRACT

As business processes become more streamlined through the use of interorganizational information systems, supply chains have been transformed into supply networks. Key among these processes is the ordering decision process, which has improved over the years through the use of various modeling approaches. The trend is to create systems that reflect the real world; however, the complexity of the models soon reaches the limits of mathematical analysis. Agent-based models, however, have proved to be very useful for studying supply chains. The learning capabilities found in such models form the foundation for our broader study on supply networks. This paper examines an approach in which models are used to explore different operating policies and modes of operation. Two learning methods are explored: Q-learning and derivative following (DF). Briefly, Q-learning involves reinforcement; that is, positive reactions result in positive feedback and vice versa. The DF approach involves continuously acting in one of two directions if feedback is positive and reversing direction otherwise. This study investigates how both algorithms perform as a search mechanism in the context of supply networks. The paper also examines the effectiveness of the learning algorithms in either a low- or a high-competition setting. Results show that both Q-learning and the DF approach are effective in searching for optimal solutions in the low-competition setting. Both approaches fail, however, in the high-competition setting. More sophisticated algorithms are needed to prevent learning failure in the high-competition setting.

**Keywords:** Agent-based modeling, supply networks, competition settings

### INTRODUCTION

As business processes become more streamlined through the use of interorganizational information systems, supply chains are transforming into supply networks. Many decisions need to be reconsidered in light of this transformation. Key among these is the ordering decision (i.e., when to order and how much to order). Various models and solutions have been suggested, from the simple model of economic ordering quantity proposed in the early days, to the more sophisticated news-vendor model and order-up-to policy (Clark and Scarf, 1960; Scarf, 1960), to the complex models of more recent years that take into account such factors as capacity constraints and information sharing (Federgruen and Zipkin, 1986; Cachon and Fisher, 2000; Moynzadeh, 2002). The trend is to incorporate greater reality in the models. The problem with this approach, however, is that the complexity of the models quickly reaches the limits of mathematical analysis.

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Agent-based models (ABMs) have proven to be very useful for studying complex phenomena (Axtell, 2000) and have been applied to supply chains (Macal and North, 2003). In the context of supply chains, ABMs are generally used in two ways: (1) for calibrating the agent models and parameters with real-world data and examining various scenarios that may play out or (2) for devising agent models to explore different operating policies and modes of operation. The latter approach can be useful in several ways. For example, it can be used to examine different supply network configurations for which no real data may be available, to use as a decision support tool in designing supply networks, and to seek good operating policies in different settings. This study adopts the second approach and examines the effectiveness of learning as a mechanism for searching in agent models.

In this paper, learning is studied as a mechanism for searching rather than for adaptive control (Greenwald, et al., 1999). In other words, we examine whether agents can simultaneously learn “optimal” or close-to-optimal decisions. Since optimality can be difficult to discern in complex systems, we are not concerned with achieving strict optimality in an analytical sense but rather with seeking operating policies that are generally good. ABMs will also be useful in evaluating the robustness of policies and decisions, an important criterion in real-world supply networks.

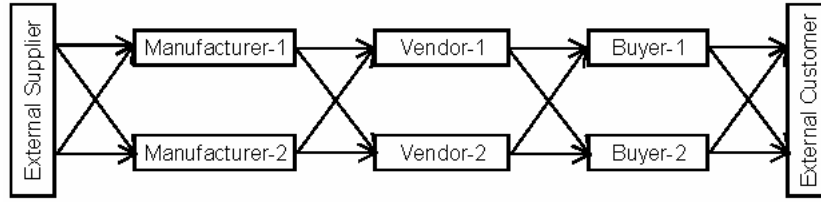
Two learning algorithms are explored in this study: Q-learning and derivative following (DF). Our study investigates how both algorithms perform as a search mechanism in the context of supply networks. Q-learning (Watkins, 1989) is a type of reinforcement learning, in which actions resulting in positive feedbacks are reinforced and more likely to be taken in the future, while actions leading to negative feedbacks are less likely to be taken in the future. Q-learning has been found to be a better adaptive mechanism than other learning algorithms, including DF (Greenwald, et al., 1999). The idea of DF is to continuously act in one of the two possible directions if feedback is positive and to reverse direction otherwise. This learning method has been studied in the context of dynamic pricing in agents (Greenwald, et al., 1999; Kepar, et al., 2000; Dimicco, et al., 2003).

The effectiveness of the learning algorithms is examined in two types of competitive settings. In a low-competition setting, agents randomly select suppliers from an upper tier to place a new order. This setting represents supply networks in which customers are less informed about the suppliers’ status and thus select suppliers largely on a random basis. In a high-competition setting, agents select suppliers on the basis of the suppliers’ inventory position. The supplier who has the largest amount of uncommitted inventory at the time of ordering is selected.

Results show that Q-learning is very effective in searching for optimal solutions in the low-competition setting. DF performs quite well in the low-competition setting, too. Both algorithms fail in the high-competition setting, however. Modifications made to the DF algorithm and related factors show that more sophisticated algorithms are needed to prevent learning failure in the high-competition setting.

## **MODEL**

We model a supply network with three tiers: buyer, vendor, and manufacturer (Figure 1). Each tier contains two agents. In addition to the three tiers, the network contains an external



**FIGURE 1** Three-tier supply network

customer who is responsible for generating end demands and an external supplier who serves as the ultimate source of raw materials. Agents operate in discrete time steps. In each time step, they receive shipments from suppliers, process orders from customers, and place new orders. The model allows both informational and physical lead times. For the experiments in this study, orders are assumed to reach destinations immediately, but shipments are subject to delays. Agents use a standard order-up-to policy as follows:

$$O = (1 + L) \theta + \beta \sqrt{(1 + L)\sigma} - I + B - G, \quad (1)$$

where

$\beta$  = safe stock coefficient (SSC),

$\theta$  = moving average of demand (over a forecasting window of 80 periods),

$\sigma$  = moving variance of demand (over a forecasting window of 80 periods),

$B$  = back order,

$I$  = inventory at hand,

$L$  = lead time,

$O$  = ordering quantity, and

$G$  = outstanding purchase orders (orders placed but not yet received).

Agents seek to learn the value of the SSC in the ordering policy (Equation 1). The action space in the Q-learning consists of 41 SSC values ranging from 0 to 40, with an interval of 1. Each action is associated with a  $Q$  value; these are initiated to some small values and updated every 120 periods, on average (Equation 2). Actions are selected by using Boltzmann selection (Equation 3).

$$Q_{n+1} = \kappa * (P_{n+1} / A - Q_n), \quad (2)$$

$$\rho_i = e^{Q_i / t} / \sum_i e^{Q_i / t}, \quad (3)$$

$$t_n = \max(t_{\min}, t_{\max} * 0.999^{20*n}), \quad (4)$$

where

$\kappa$  = learning rate,

$\rho$  = selection probability,

$A$  = profit scaling factor,

$i$  = action  $i$ ,

$n$  = number of updates,

$P$  = average profit per period since last update,

$Q$  =  $Q$  value, and

$t$  = temperature.

In DF, agents change their SSC values sequentially, as follows:

$$SSC_{n+1} = SSC_n + \lambda_{n+1}(\omega + v * 0.99^{n+1}), \quad (5)$$

$$T_{n+1} = T_n + M + R, \quad (6)$$

$$\lambda_{n+1} = \begin{cases} \lambda_n & \text{if } (P_{n+1} - P_n) / P_n > H \\ -\lambda_n & \text{if } (P_{n+1} - P_n) / P_n < -H \\ 0 & \text{otherwise,} \end{cases} \quad (7)$$

$$\lambda_0 = 1 \text{ (or } -1), \quad (8)$$

where

$v$  = variable change size,

$\omega$  = minimum change size,

$H$  = updating threshold (a small positive number),

$M$  = minimum updating interval,

$R$  = random updating interval,



SSC = safe stock coefficient, and

$T$  = SSC update time.

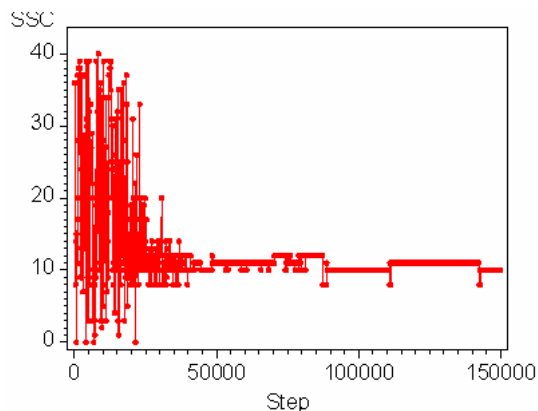
## RESULTS

Results for Q-learning in the low-competition setting are presented first. Three learning scenarios are considered: (1) a single agent learns, (2) two agents learn simultaneously, and (3) all agents learn simultaneously. Performance of the learning is gauged by comparing the learned SSC values with the optimal SSC values. The optimal SSC values are obtained by sweeping over a reasonably wide range of SSC values for corresponding agents. Results for DF in the low-competition setting are presented next. To avoid repetition, only results for the most complex scenario — where all agents learn simultaneously — are presented in this part. Results for high-competition setting are presented last.

### Low-competition Setting

#### *Q-learning*

As mentioned above, agents randomly select suppliers from an upper tier in the low-competition setting. Results show that Q-learning by a single agent (buyer-0) performs very well. The learned value of SSC is very close to the optimal value. Figure 2 shows the learning process. The figure shows that initial learning focuses on the exploration of different SSC values. At about step 50,000, learning starts to converge. To examine the converged values of SSC, a frequency distribution of SSC values between steps 50,000 and 150,000 (sampled every 100 steps) was calculated (Table 1). Table 1 indicates that most of the time, SSC has a value of 9, 10, or 11, with 10 being the most frequent. As a result, the learning can be considered to converge at 10. To test the optimality of the converged value, a sweep-over was conducted on buyer-0's SSC. During the sweep-over, buyer-0's SSC was systematically changed from 0 to 20, with an interval of 2. At the same time, the other agents' SSCs were kept constant at the same



**FIGURE 2** Q-learning by a single agent (buyer-0)

**TABLE 1** Frequency distribution of buyer-0's SSC

Buyer-0 SSC	Frequency
8	19
9	329
10	539
11	112

values as those when buyer-0 learns. Buyer-0's average profit per step was then plotted with the SSC values (Figure 3). Figure 3 shows that buyer-0's average profit increases rapidly as SSC increases from 0, and it peaks when SSC reaches 9. After that, the profit declines gradually. It is clear from the figure that the optimal value of SSC is around 10. This verifies that the learned SSCs (9, 10, and 11) indeed are close to the optimal value.

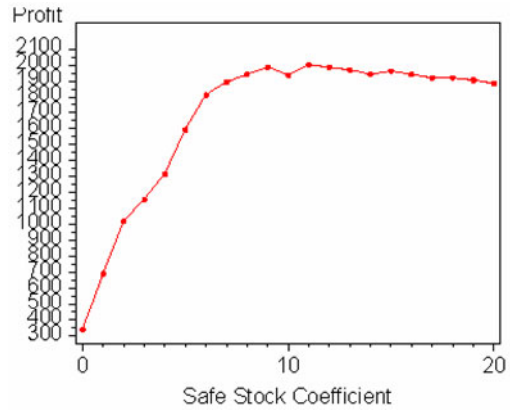


FIGURE 3 Sweep-over of buyer-0's SSC

Results show that simultaneous Q-learning by two agents (vendor-0 and vendor-1) is also very effective. Both vendor-0 and vendor-1 learn close to optimal SSC values. Figure 4 shows the learning process of both agents. It shows that the learning of both agents converges at about step 50,000. To show the converged values, the frequency distribution of SSC values between steps 50,000 and 150,000 (sampled every 100 steps) is summarized in Table 2. Table 2 shows that vendor-0's SSC converges at 3 and 4, and vendor-1's SSC converges at 4 and 5. To evaluate the optimality of these converged values, a sweep-over was conducted for vendor-0's SSC and vendor-1's SSC (Figure 5). Since vendor-0 and vendor-1 were identical, their SSCs were kept the same during the sweep-over. The SSCs start at 0 and end at 10, with an interval of 0.5. Figure 5 shows that both vendor-0's and vendor-1's average profit per time step is highest when SSC is 4. This suggests that the SSC values learned by both vendor-0 and vendor-1 are close to optimal.

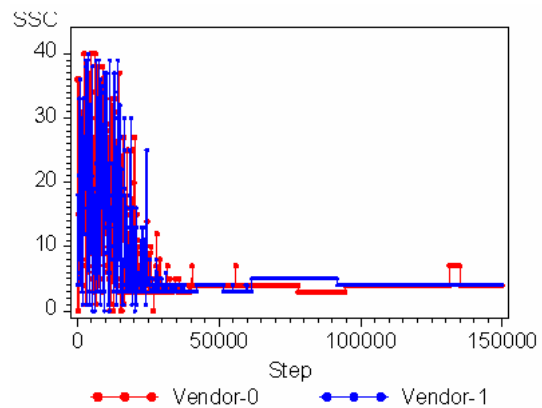


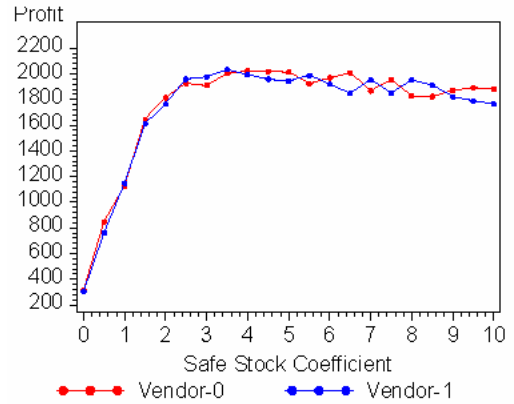
FIGURE 4 Simultaneous Q-learning by two agents (vendor-0 and vendor-1)

Simultaneous Q-learning by all agents also exhibits excellent performance. Figures 6a through 6c show the learning processes of all agents, with each figure showing two agents belonging to the same tier. Learning of all agents converges at around step 50,000. For ease of analysis, the mean rather than the frequency distribution of SSC values after convergence (between steps 50,000 and 150,000) was calculated (see Table 3). To determine the effectiveness of the learning, a sweep-over was conducted on SSCs of the three tiers in order to find "global optimal." The same SSC was used for both agents belonging to a common tier. The buyer SSC starts at 0 and ends

TABLE 2 Frequency distribution of vendor-0's SSC and vendor-1's SSC

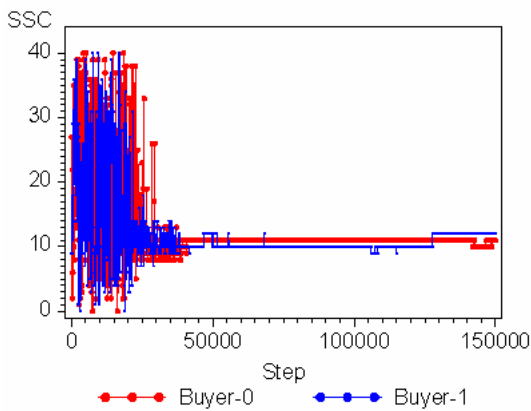
Vendor-0 SSC	Frequency
3	166
4	796
7	38
Vendor-1 SSC	Frequency
3	94
4	602
5	304

at 20, with an interval of 2. The vendor and manufacturer SSCs start at 0 and end at 10, with an interval of 1. Therefore, there are 11 levels of SSC for each tier, and the total number of combinations in the sweep-over is  $11 \times 11 \times 11 = 1,331$ . Figures 7a through 7c show each tier's average profit per step with respect to that tier's SSC, as well as the other two tiers' SSCs. For example, Figure 7a shows that the buyer tiers average profit with respect to buyer SSC. For each level of buyer SSC, there are 11 levels of vendor SSC and 11 levels of manufacturer SSC, which means 121 combinations are possible. Average tier profits for all 121 combinations are plotted at the corresponding buyer SSC. As a result, there appears

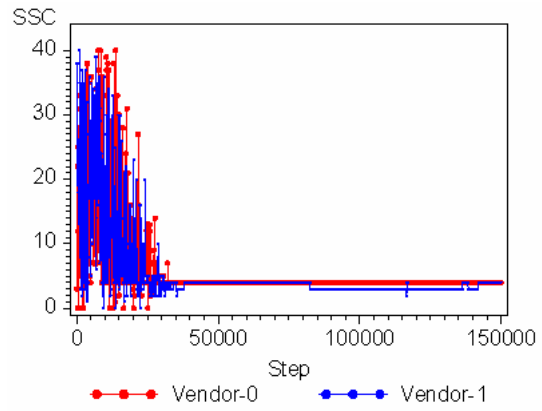


**FIGURE 5** Sweep-over of vendor-0's SSC and vendor-1's SSC

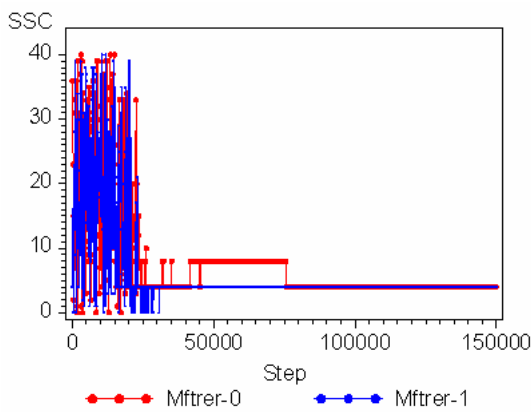
a. Learning of Buyers



b. Learning of Vendors



c. Learning of Manufacturers



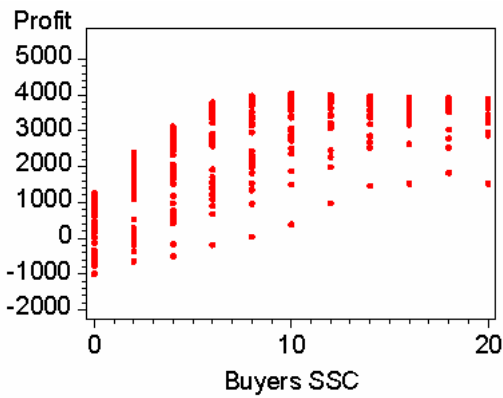
**FIGURE 6** Simultaneous Q-learning by all agents

to be a “vertical bar” for each buyer SSC. Each dot in a “vertical bar” represents profit for a different combination of vendor SSC and manufacturer SSC. Figures 7a through 7c show that the tier profit is affected by both the SSC of that tier and the SSC of the other two tiers. More important, the figures show the maximum profit and the corresponding optimal SSC value for each tier. Figure 7a shows that of the 1,331 combinations of SSC values, the buyer SSC value in the optimal combination that is associated with the highest buyer tier profit is 10. Thus, 10 can be considered a globally optimal value for buyer SSC in the space considered. Similarly, Figure 7b shows that the global optimal value for vendor SSC is around 3.

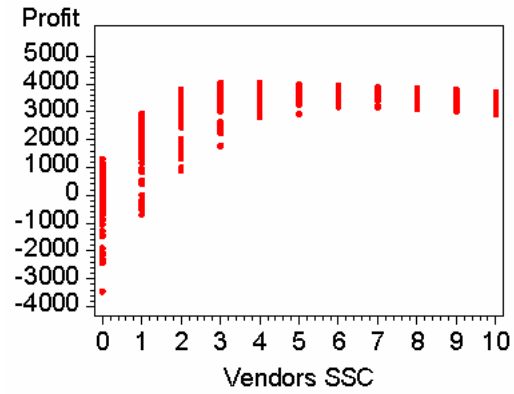
**TABLE 3** Mean values of SSC after step 50,000

Agent	Mean of SSC
Buyer-0	10.9
Buyer-1	10.4
Vendor-0	4.0
Vendor-1	3.4
Manufacturer-0	5.0
Manufacturer-1	4.0

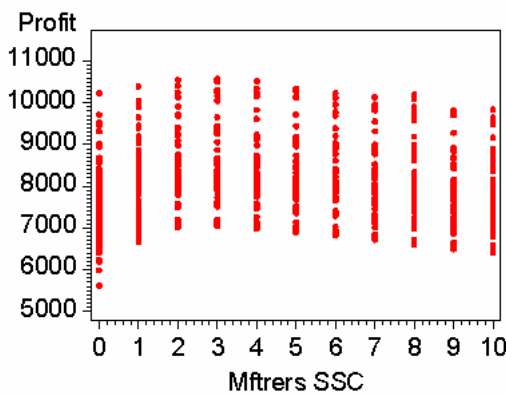
a. Buyer Tier Profit vs. Buyer SSC



b. Vendor Tier Profit vs. Vendor SSC



c. Manufacturer Tier Profit vs. Manufacturer SSC



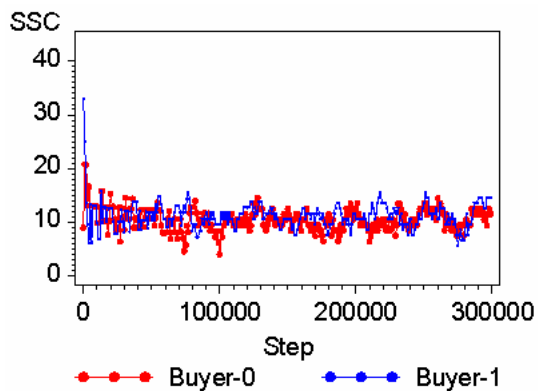
**FIGURE 7** Sweep-over SSCs of buyers, vendors, and manufacturers

Figure 7c shows that the global optimal value for manufacturer SSC is also around 3. A comparison of these global optimal values with those learned by agents (see Table 3) shows that the learned values are quite close to the global optimal, which suggests that the learning is effective.

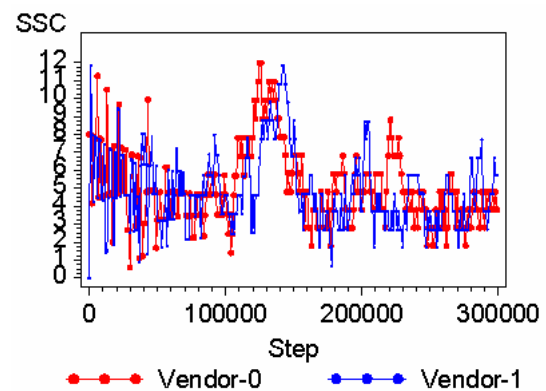
### Derivative Following

Derivative following is also an effective learning technique in our model. To avoid repetition, we report only results where all agents learn simultaneously. Figures 8a through 8c show the learning processes. Apparently, DF's learning course is very different from that of Q-learning. One major difference is that there is minimal exploration of different SSC values at the early stage of DF. For example, one of the vendors (Figure 8a) and one of the manufacturers (Figure 8c) start with a very high SSC value (over 30). Without spending much time exploring different SSC values, both agents quickly lower their SSC values close to the optimal values. However, once the SSC values are close to the optimal, they keep fluctuating, which makes it difficult to discern if or when the learning converges. We consider the learning to have converged when the fluctuation is within a reasonable range for a period of considerable length.

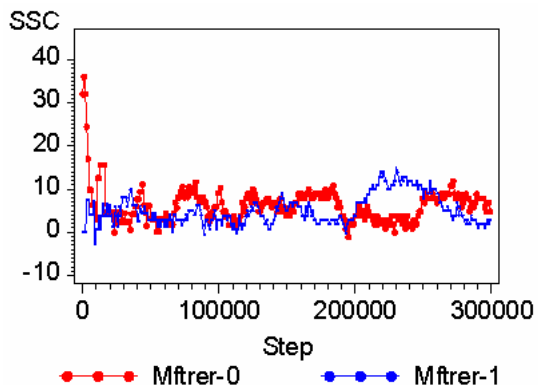
a. Buyers



b. Vendors



c. Manufacturers



**FIGURE 8** Simultaneous learning from using derivative following by all agents

For Figures 8a and 8c, we consider learning to have converged after step 100,000. For Figure 8b, we consider learning to have converged after step 200,000. To evaluate the performance of the learning, the mean of the SSC values after convergence (sampled every 100 periods) was calculated (see Table 4). A comparison of these means with the global optimal values obtained above shows that buyer's and vendors' learned SSC values are very close to the optimal, and that the manufacturers' learned SSC values are a little bit larger than the optimal values.

**TABLE 4** Mean values of SSC after step 100,000

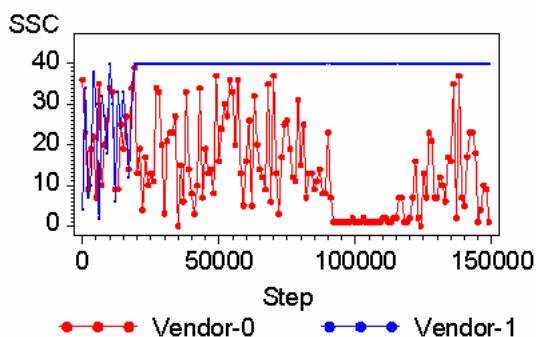
Agent	Average of SSC
Buyer-0	10.3
Buyer-1	11.1
Vendor-0	4.3
Vendor-1	4.2
Manufacturer-0	5.8
Manufacturer-1	5.7

### High-competition Setting

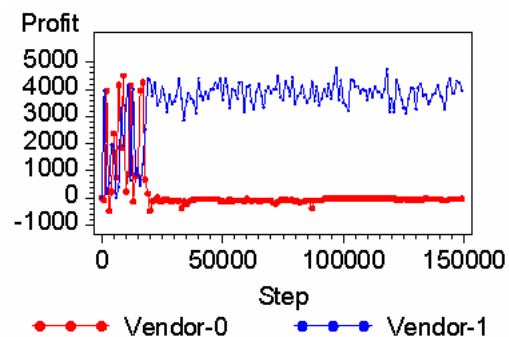
As mentioned in the Introduction, an agent selects the supplier who has the largest amount of uncommitted inventory at the time of ordering in a high-competition setting. Results show that both the naive Q-learning and the naive DF as described in the model section fail in the high-competition setting. Figures 9a and 9b show the process of simultaneous Q-learning by both vendors. Figure 9a shows that one of the vendors learns to set its SSC at the highest possible value, 40, while the other vendor keeps changing its SSC values. Figure 9b shows that the vendor who sets its SSC value at 40 takes over the entire market, with an average profit around 4,000, while the other vendor has a zero average profit. Apparently, the vendor with zero profit is not receiving orders from customers.

The naive DF-learning shows similar failure (Figures 10a and 10b). Figure 10a shows that after a certain time, one vendor consistently sets its SSC value larger than the other vendor's. As a result, the vendor who sets its SSC at the higher values gets all customer orders and enjoys a high profit, and the other vendor receives no customer orders and has a zero profit. Both vendors should have positive profit and continuously receive customer orders for the learning to be considered effective because both their attributes and their behaviors are identical.

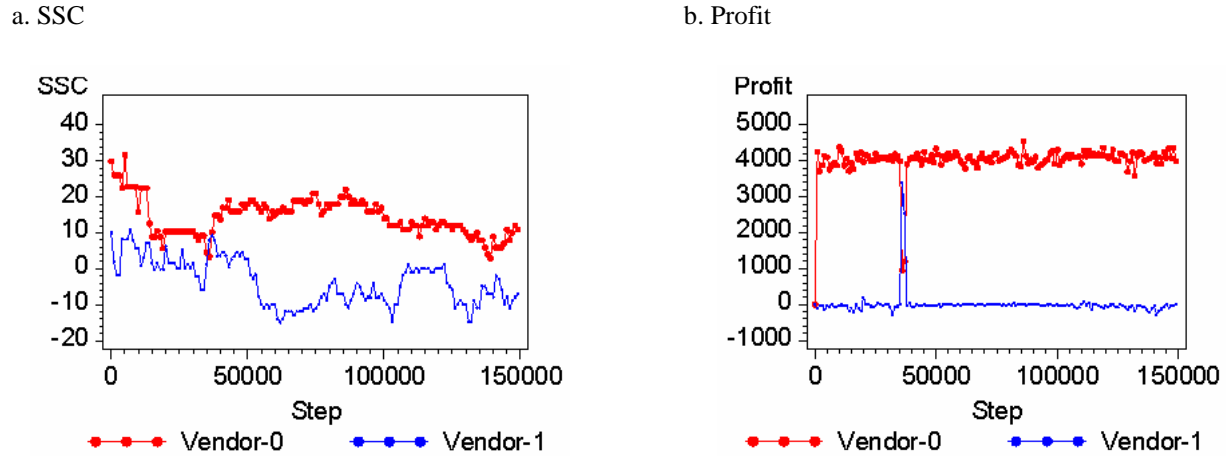
a. SSC



b. Profit



**FIGURE 9** Simultaneous Q-learning by two vendors with inventory-informed supplier selection



**FIGURE 10** Simultaneous learning by two vendors using DF, with inventory-informed supplier selection

The original DF algorithm and ordering policy is modified to explore strategies that prevent the learning failure described above. The DF algorithm is modified as follows:

If average demand since the last update is less than 5% of total end-customer demand,

$$\lambda_{n+1} = 1. \quad (9)$$

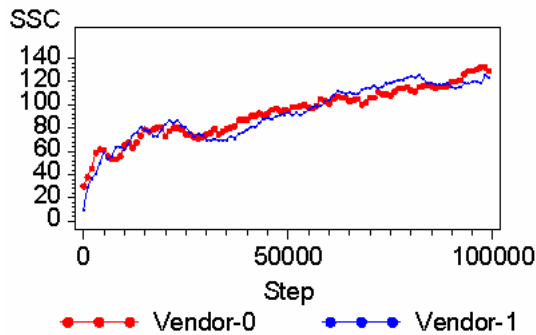
Otherwise, determine  $\lambda_{n+1}$  by using Equation 7.

The ordering policy is modified by replacing the moving average of demand  $\theta$  in Equation 1 with a fixed value of half of total end-customer demand. By using the modified DF algorithm and ordering policy, both vendors stay in operation but engage in an “inventory war” (Figures 11a and 11b). Figure 11a shows that the two vendors gradually and steadily increase their SSC values as they compete with each other for customer orders. However, Figure 11b shows that because vendors overly increased SSC values, the vendors’ profit becomes negative.

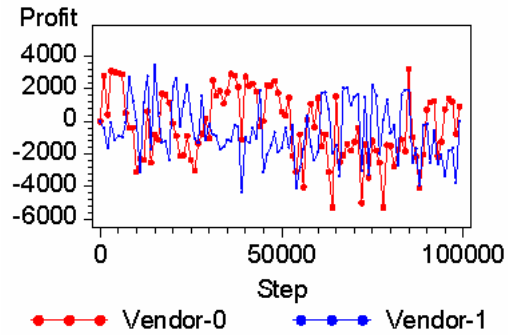
## DISCUSSION

This study demonstrates that Q-learning and DF are two effective learning algorithms for searching optimal solutions in supply networks that have a low degree of competition among agents. Both algorithms find close to optimal SSC values even when all agents learn simultaneously. A comparison of the two algorithms shows that Q-learning converges better, while DF spends less time exploring nonoptimal solutions. Q-learning tends to converge to one or two specific values, while convergence in DF is more difficult to discern. DF’s ability to quickly approach the optimal values can be an attractive attribute for situations where nonoptimal decisions are very costly.

a. SSC



b. Profit



**FIGURE 11** Simultaneous learning by two vendors using modified DF, with inventory-informed supplier selection

Learning capabilities in ABMs form a foundation for our broader study on supply networks. In the absence of a learning capability, models need to prespecify operating policies and parameters, the implications of which may not be apparent in complex environments. Agents that can learn appropriate operating policies in different settings and organizational contexts will be able to examine varied configurations and situations and help in obtaining answers to key issues (e.g., the implications of different modes of information sharing in supply networks, or the propensity of agents to share information in different contexts).

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# AGENT-BASED DISTRIBUTED SIMULATION PLATFORM FOR EVALUATING PRODUCTION PLANNING STRATEGIES IN FOREST PRODUCT SUPPLY CHAINS

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## ABSTRACT

The agent-based simulation approach is discussed for modeling and analyzing various supply chain planning and control strategies and different configurations in the forest products industry. The discussion focuses primarily on how the experimental platform addresses the distributed and agent-based discrete-event simulation. In addition, the discussion examines what is envisioned for the future to ensure that a real system is implemented and used in the forest products industry.

**Keywords:** Agent-based simulation, distributed simulation, distributed manufacturing systems, forest product supply chain

## 1 INTRODUCTION

Organizations can no longer be considered isolated, as evident in the many networked organizational paradigms being discussed. When organizations are seen through a network structure, the problem of planning and control can be considered as being both multi-faceted and intricate. To address this problem, agent-based simulation has demonstrated great applicability and provided significant results.

The use of distributed and independent simulations across a supply chain associated with agent-based simulation can also be considered an interesting approach for achieving better simulation results. Likewise, the use of simulation can be streamlined by obtaining real, updated, accurate, and sometimes on-line and real-time information from a set of dispersed and different planning and control systems employed across a supply chain.

The FOR@C Research Consortium (<http://www.forac.ulaval.ca>), a Canadian research group in e-business and supply chain management (SCM) in the forest products industry (based at the Université Laval, Quebec City, Quebec, Canada), is investigating ways in which these approaches can be combined in what is called the FOR@C Experimental Planning Platform. This system will allow researchers to test different planning and control scenarios across the forest product supply chain (FPSC).

This paper discusses the advances of such an experimental platform. It is organized as follows. Section 2 provides the general context of this research. Section 3 discusses the FOR@C Experimental Planning Platform in general terms and presents the FOR@C experimental planning platform in the future. Section 4 provides some final remarks.

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## 2 GENERAL CONTEXT

### 2.1 Planning and Control in Dynamic Networked Organizations

The concept of collaboration has been discussed at length in both the business and academic world. The topic has emerged as a result of the perception that a company is not an isolated island but rather part of an interdependent world. Enterprises depend on their partnerships and relations with other organizations to reach better competitive levels (Pires et al., 2001). Browne and Zhang (1999) wrote that the traditional view, which treats companies as having well-defined boundaries and relations with other organizations and a focus on internal performance, is no longer valid. This conclusion gives rise to the emergence of inter-firm network concepts, which have led to the generation of a number of related concepts, such as the extended enterprise, virtual organization, networked organization, SCM, and cluster of enterprises (Camarinha-Matos and Afsarmanesh, 1999).

These new requirements have stimulated researchers to propose new concepts and promote the evolution of decision making, coordination, and control structures for networked manufacturing systems. The complexity of the decision problem is of crucial importance in this context. The complexity, which arises from the intricacy of the network of interdependent decisions, consistently relies on the articulation, integration, and coordination of several distributed decision-making units. It is also a result of the characteristics of the information, which can be stochastic, incomplete, inaccurate, delayed, or asymmetric; these characteristics contribute significantly to the complexity of this kind of system.

In practical terms, manufacturing planning and control — when performed in dynamic, open, highly competitive markets and in intricate production systems and supply chains — can be considered to make up a very complex problem. This problem involves several constraints and variables. Also, the unreliable nature of manufacturing, demand, and supply can add to the complexity of the problem (Davis, 1993).

This entire situation makes it difficult to perform analyses of and make strategic decisions about the planning approach and supply chain configuration, especially when the stochasticity of the environment needs to be considered (particularly when one wants to compare distributed and centralized planning strategies). This timely research question requires the full support of simulation technology and of decision support systems. An approach for addressing the integration of these technologies that is getting more popular is agent technology, which is briefly discussed next.

### 2.2 Agent Modeling and Multi-agent-based Simulation in Supply Chains

According to Marcenac and Giroux (1998), the complexity of a system can be treated by using an agent-oriented approach. In such approaches, interactions lead to a global behavior, which helps researchers understand how stochastic behavior can emerge from interactions between agents. Marcenac and Giroux think this agent-based behavior is close to the self-organized criticality used to explain natural phenomena. Marcenac and Giroux (1998) explain that problems are solved by agents using distributed control instead of global controls, as occurs in parallel systems.

Shen (2000) argues that distributed manufacturing (as with a supply chain) concepts can usually be modeled and implemented with agent-oriented technology. Many authors have experimented with this approach, such as Parunak (1998), Parunak et al. (1998), Swaminathan et al. (1998), Fox et al. (2000), Anosike and Zhang (2002), and Frayret (2002). This distributed computing technique is inherently modular and possesses most of the mentioned requirements needed to design intelligent distributed manufacturing systems (Shen and Norrie, 1999; Anosike and Zhang, 2002; Frayret et al., 2004).

Shen and Norrie (1999) and Sauer and Appelrath (2003) wrote that agents represent an interesting approach for treating problems in the domains of manufacturing planning and scheduling because of several characteristics:

- *Social ability.* Agents can work in groups or in communities in order to define a schedule or to solve a problem.
- *Capacity to treat knowledge.* Agents have some knowledge of the problem to be solved, such as a scheduling problem.
- *Autonomous nature.* As independent entities, agents can plan and schedule their own activities.
- *Negotiation capacity.* Agents need to solve problems in a multipartner environment.
- *Reaction capacity.* Agents can react to changes in the environment and adjust their plans and schedules.
- *Proactivity capacity.* Agents can optimize their own plans and schedules.
- *Encapsulation capacity.* Agents can put certain existing compartments and methods in a nutshell.
- *Representation capacity.* Agents are capable of embodying manufacturing resources, such as workers, cells, and machines.

These abilities, capacities, and properties of agents, combined with the concept of simulation, lead to the notion of multi-agent-based simulation (MABS). MABS has demonstrated a large utility when applied in distributed manufacturing environments. “Multi-agent systems are appropriate for modeling SCs because they involve divisible processes with loosely coupled command and control” (Strader et al., 1998). Labarthe et al. (2003a) explain that an MABS focuses on distributed behavioral descriptions and studies in dynamic societies composed of agents. They argue that the concepts of autonomy and cooperation in multi-agent systems have shown promise by providing a modeling and simulation framework for industrial systems, especially supply chains.

The theory and practice of applying MABS in manufacturing and supply chain environments can be considered a powerful instrument to support the SCM paradigm. These concepts are suitable for use in many industrial sectors (specifically, the forest products industry), as discussed in Sections 2.3 and 3.

### **2.3 Gap in the Forest Products Industry**

The forest products industry is facing increasing global competition and is compelled to respond to new requirements. The FPSC is of great importance in Canada because it is one of the largest industrial employers and generates a significant part of the national revenue. This supply chain is defined by the FOR@C Research Consortium (2004) as being the value creation network that includes all the companies and business units involved in the procurement, production, and distribution of a given forest product to the market. This can include companies responsible for forestry operations, sawmilling, value-added production, furniture manufacturing, and pulp and paper.

The FPSC has some particular characteristics that can complicate its SCM practices. These characteristics include the growing market pressure for high service levels and guaranteed volume; the long and variable production cycle times (harvesting and transformation); the stochastic process of “disassembling” trees/logs (due to the very nature of fiber); the growing market pressure for direct delivery (to stores, construction sites, mills); and the growing pressure to reduce operating costs and increase customer value (e.g., quality, new product, e-business) because of the large fluctuations in the demand for and prices of its products (D’Amours, 2004).

All these particular characteristics lead to intricate manufacturing planning and control across the entire value chain. In this way, SCM practices related to manufacturing coordination across the FPSC can be considered an important challenge to address in order to improve the competitiveness of the supply chain. Considering this situation, the FOR@C Research Consortium concentrates on the management of value creation networks of the FPSC and is carrying out a set of research initiatives in order to help supply chain coordination.

The FOR@C Research Consortium is using the concepts of distributed planning to develop an experimental planning platform, thereby making a major contribution toward closing the gaps discussed. The platform is discussed in the following section.

## **3 FOR@C EXPERIMENTAL PLANNING PLATFORM**

The FOR@C Experimental Planning Platform is one of the main initiatives of the Consortium. Its main objective is to test (1) different configurations of the FPSC and (2) what-if planning and scheduling scenarios. The distributed decision is established around planning units, such as a sawmill or paper mill, which are capable of making their own planning decisions and of interacting among themselves in order to find mutually acceptable solutions.

The agent-based platform embodies the concept of distributed planning to integrate multi-agent software in the simulated environment used to test the agent’s behavior when it is faced with different dynamic stimuli. In more specific terms, the platform aims at helping define how the FPSC should coordinate distributed decision-making units and also how it should react to a turbulent environment in a flexible and modular way, while accommodating all possible disturbances (e.g., a consumer demand variation or unexpected product distribution). By using agent-based simulation to evaluate the planning strategies, it is expected that the FPSC will be able to properly synchronize the entire value creation network.

This platform is under development, but many functions have already been implemented. A general distributed architecture has been defined, and some structural components have been developed, such as the supply chain cockpit and supply chain modeler. The supply chain cockpit is a shared software component that enhances global visibility. It provides an integrated view of all the planning units of the supply chain concerning management questions (e.g., inventory levels to allow users to have an overview of the inventory for the entire supply chain). The supply chain modeler is a general software component that allows for system administration (e.g., user management and security). It is also used to manage the supply chain structures to provide a general view of the supply chain. In addition, some agent components of the platform have been created (e.g., the agents' shell, which defines the basic agent's functionalities that are common for the entire agent society and message management). The next section discusses the agent components in more detail.

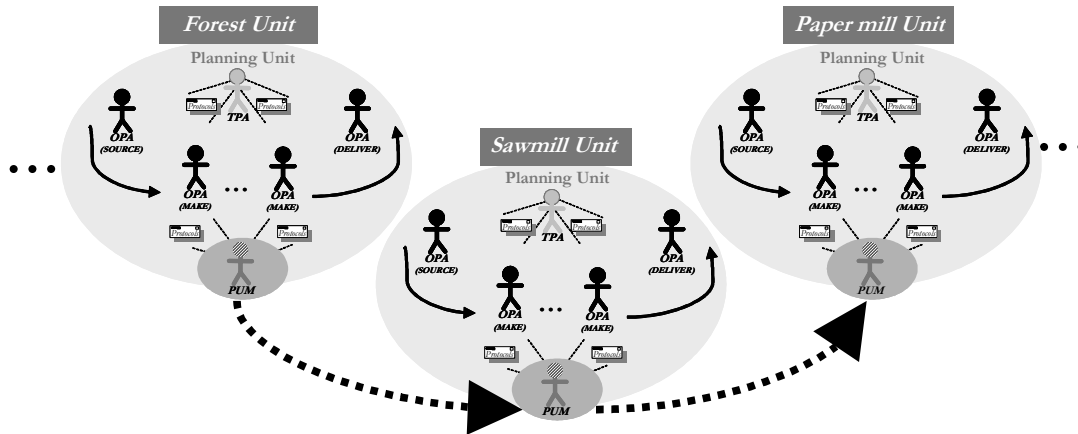
### 3.1 Multi-agent Planning System: Basic Components and Functioning

The first agent-based components of the platform are those that compose what is called the Multi-Agent Planning System, which is responsible for all planning activities at a planning unit level. Table 1 explains these components. Figure 1 depicts an integrated view of the components of the platform related to agents and communications. In Figure 1, a simple model of a basic supply chain composed of a forest unit, a sawmill unit, and a paper mill unit is illustrated.

**TABLE 1** Main components of the Multi-agent Planning System

Components	Role	Description
Planning unit manager	Management of the planning unit's community of specialized agents	The planning unit manager is the basic element of the planning unit. It is from that component that we install and manage all the specialized agents that are part of the planning unit. It is the single face to all external agents; all external messages are sent to it, and it dispatches messages to the relevant agent.
Operational planning agent	Operational planning responsibilities	Inside every planning unit, all planning responsibilities are distributed on the basis of functional specialization, defining a community of specialized agents. Such distribution is based on the SCOR (from Supply Chain Council; see Stephens, 2000), defining the following agents: deliver, source, and make. Each agent receives requests from other agents, analyzes available capacities and capabilities, and establishes commitments to satisfy the requests.
Tactical planning agent	Tactical planning of the planning unit	The tactical planning agent provides a global view of the planning unit and global synchronization and integration of its agents by defining the responsibilities of each specialized agent (e.g., it decides which agent will supply another for a specified product or period inside the planning unit).
Conversation protocols	Communication framework	Conversation protocols define a workflow of potential states in a conversation, guiding all communication among agents by means of a communication protocol.

Source: adapted from Van Horne et al. (2004).



**FIGURE 1** Generic integrated view of the main components (based on Rousseau, 2003)

It is important to highlight the basic mechanisms that manage agent responsibilities. The main responsibilities of an agent are to make requests (send requests and ask for commitments for new or modified requirements for product or processor capacity or receive updates on commitment status); establish commitments (receive requests, provide commitments for new or modified requirements, and update commitment status); and develop a plan (generate a plan to respect commitment, generate requirements for this plan, and maintain the status of the commitment). The agent communication protocol is based on the FIPA (foundation for intelligent physical agents) agent communication language, which has the advantages of being quite rich and well documented and being a standard that is widely employed.

Using these components, a first planning unit was created. It is a sawmill unit composed of specialized agents for planning sawing, drying, and finishing operations.

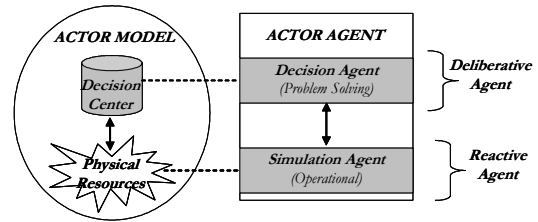
### 3.2 Preliminary Definitions of the Multi-agent-based Simulation Elements

This discussion was inspired by the progress made by Lyonnais and Montreuil (2001) and Lyonnais et al. (1999) in simulations related to the NetMan (Networked Manufacturing) project and in proposing a general conceptual simulation architecture to model, implement, and simulate distributed manufacturing (see Montreuil et al., 2000; Cloutier et al., 2001; Frayret et al., 2001; and Frayret, 2002). It was also inspired by the research of Labarthe et al. (2003a,b) related to behavioral studies of active entities constituting the logistic organization. We provide a preliminary discussion about agents to address MABS in the Experimental Planning Platform.

First, Labarthe et al. (2003a,b) propose an agent-based modeling approach that motivated some important macro initial definitions used in this research. Their approach is based on actor behavior modeling for complex systems, in which company business units are modeled as actors realizing activities in a logistic network. From an actor model (which is a social entity, as an individual or a group), Labarthe et al. created the concept of actor agent (a simplified model of reality permitting behavioral study). They split actor behavior into two classes (deliberative behavior and operational behavior), which creates a dissociation between decision making and



operational activities. Therefore, it is possible to represent the dynamic characteristic of a system. Deliberative behavior represents the decision-making process performed by actors, which transmits decisions to simulation agents. These decision agents allow the representation of rules and knowledge in order to produce decisions (plans) through their reasoning capacities. Operational behavior relates to how decisions are put into operation by reactive agents, reproducing the behavior of an operational activity and transmitting signals to the decision agent to report the results of activities. Actions performed by reactive agents influence decisions of deliberative agents, and vice versa. Figure 2 gives a general schema proposed by the authors.



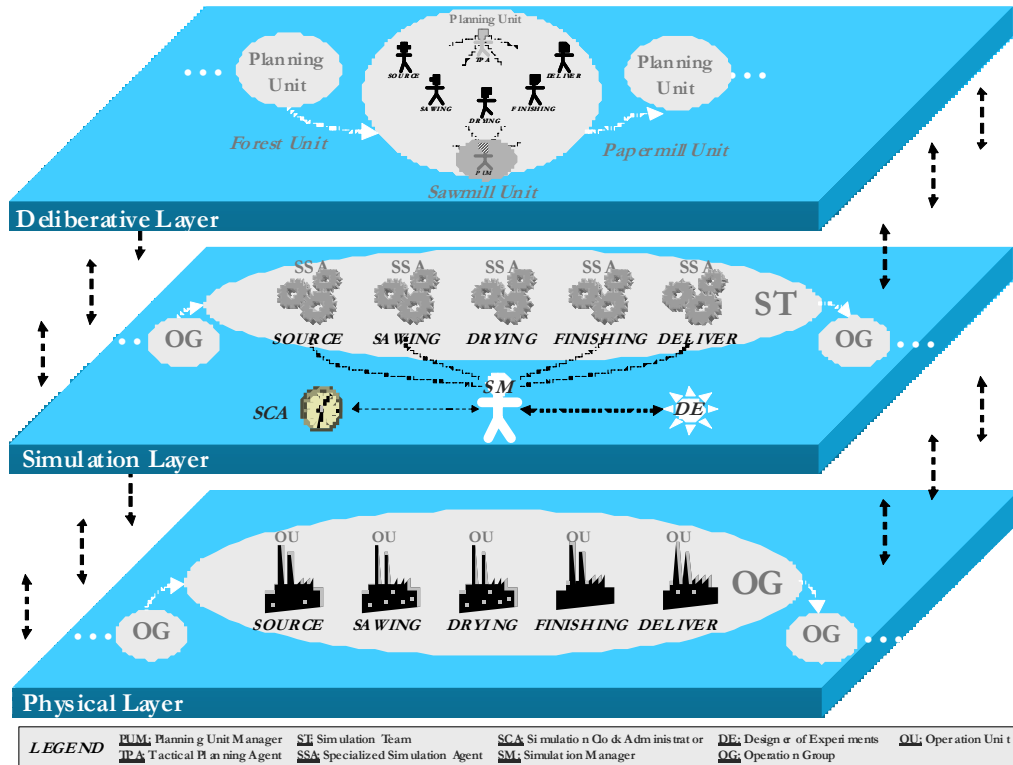
**FIGURE 2** From actor model to actor agent (adapted from Labarthe et al., 2003b)

The elaboration of the simulation model requires identification of entities in a real system and associated activities. When dealing with a community of agents (as a supply chain), it involves specifying the actions, events, and interactions among different actors in the community as well as defining responsibility decomposition and distribution. In their architecture of multi-agent systems for supply chain modeling, Labarthe et al. (2003b) propose a separation into three structural levels: deliberative agent society (implements decision processes), reactive agent society (assumes the behavior of physical resources), and real system (the supply chain of the real world). This influenced the macro structure of our framework.

By using the proposals of Lyonnais and Montreuil (2001) and Lyonnais et al. (1999), we envision an approach that uses discrete-event-based simulation of physical components or resources (representing real ones) that are able to operate in a simulation environment. The authors propose an architecture for distributed simulation in networked manufacturing composed of software agents, physical objects (e.g., machines and workers), and organizational constituents. In this architecture, a set of NetMan units (that perform the planning decision) and a set of simulation agents (that simulate the real objects in a NetMan center, encapsulating the objects' behavior) are used. In addition, the authors propose a global simulator controller responsible for the simulation clock and for synchronizing all events among the simulation agents.

By using all these research advances in MABS and modeling, we propose some essential elements of the simulation platform. Our proposal consists of three layers: deliberative (acts as decision maker), simulation (acts as the reactive agent, simulating the comportment of the physical layer), and physical (encapsulates the supply chain element description). Figure 3 gives a general schema, and Table 2 provides a detailed explanation.

The basic simulation functioning is provided by the simulation layer, a set of specialized simulation agents connected with a simulation manager, which is influenced by the simulation clock administrator and the designer of experiments (see Table 2 for a definition of each component). There is a specialized simulation agent for each operation unit (e.g., a sawing machine), each of which is connected to the simulation manager. As proposed by Lyonnais et al. (1999), the simulation layer does not directly manipulate the deliberative layer. It only sends information that can be used to make new plans or revise the existing ones. By using this



**FIGURE 3** A general schema about the simulation platform

approach, a deliberative community of agents can learn by means of previous real experience about the actual behavior of the supply chain (learning from past experience), as well as by means of experimental behaviors occurring at the simulation layer.

Such approaches allow for a synchronous, deterministic, and stochastic discrete-event simulation, as well as qualitative and quantitative analysis of the experiments. By using these concepts, it is expected that global and local performance of the FPSC can be observed and studied.

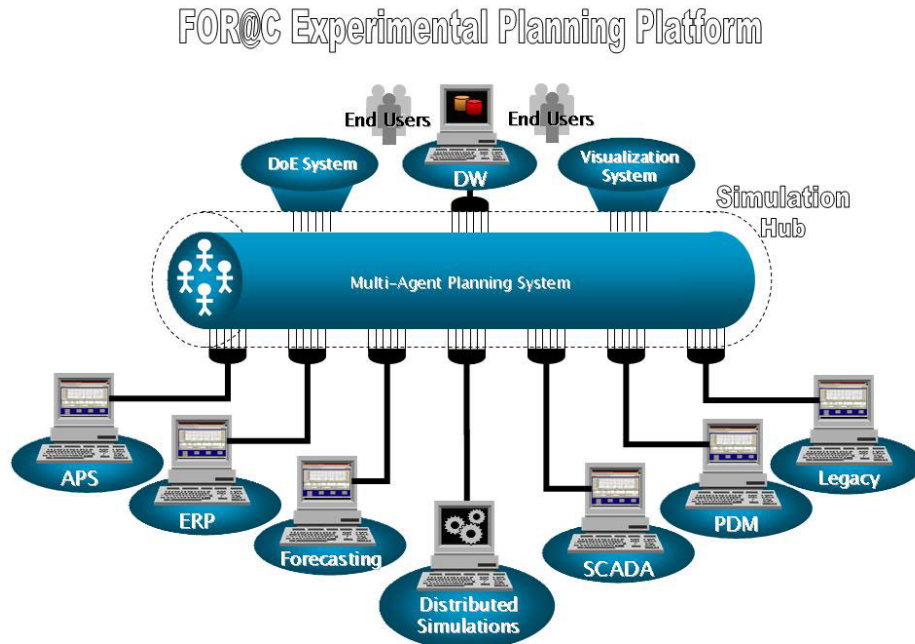
### 3.3 Future Challenge: Simulation Hub

The earlier advances of the Experimental Planning Platform already discussed are the nucleus of a larger concept: a novel approach being envisioned to integrate a set of traditional simulation and related systems by means of the FOR@C Experimental Planning Platform. This approach is called the Simulation Hub and is one of the important future challenges of the Consortium.

The Simulation Hub is a new way of understanding the FOR@C Experimental Planning Platform. New aspects include integration among ordinary distributed simulation and related systems, transactional systems, decision support systems, operational systems, and management information systems. It was inspired by the simulation cloud of Wilson et al. (2000) and is presented in Figure 4.

**TABLE 2** Basic elements of the Experimental Planning Platform

Layer	Structural Organization	Responsibilities Description
1. Deliberative: It represents the decision-making layer. At this level, the plans and schedules are generated.	1.1 Planning unit manager (PUM)	See Table 1 for details.
	1.1.2 Tactical planning agent (TPA)	See Table 1 for details.
	1.2 Operational planning agent (OPA)	See Table 1 for details.
2. Simulation: It is the layer where the reality (production, supplier, customer, ...) is simulated.	2.1 Simulation team	The simulation team is composed of a set of SSAs (see 2.1.1), a simulation version of a given operation unit (see 3.2).
	2.1.1 Specialized simulation agents (SSAs)	An SSA is responsible for generating events that may happen in a resource represented by an operation unit (see 3.2), reproducing its basic behavior. It also calculates the behavioral statistics. Events generated at the SSA level are scheduled in the SSA event list, and messages are sent to the simulation manager (see 2.2) to obtain global synchronization.
	2.2 Simulation manager	The simulation manager (1) synchronizes each SSA when a given event is triggered at the SSA level; (2) generates global events; (3) gathers global statistics; and (4) synchronizes the supply clock administrator (SCA) (see 2.2.2) with all local operation unit status, updating its event list and the event list of all SSAs.
	2.2.1 Designer of experiments	A designer of experiments is an organization structure responsible for parameterizing experiments, such as supply chain configuration scenarios and supply chain operation scenarios. In addition, data collected by the SM are handled and compared here; this includes sensibility and statistical validity analysis based on a pool of statistical methods available at the DE level.
	2.2.2 Simulation clock administrator (SCA)	The SCA controls how time advances during a simulation. When the simulation clock advances in the SCA, it sends messages to the simulation manager informing it that its clock and the simulation team local clock must be advanced to a particular time. The simulation manager thus informs the simulation team and the SSAs to update the time.
3. Physical: It represents the physical resources that compose the supply chain.	3.1 Operation group (OG)	The operation group is composed of a set of operation units (see 3.2) of an entire PUA. The operation group does not behave autonomously, but it supports the other two layers.
	3.2 Operation unit	The operation unit represents real resources (e.g., sawmills) and it contains information about operations (e.g., capacity, lead-time distribution). Information can be deterministic or stochastic.



**FIGURE 4** General schema of the simulation platform

As suggested by the work of Lendermann et al. (2003), input data may originate from a set of individual systems, which motivate the evolution of the experimental platform. The Simulation Hub can be defined as a general neutral structure that is capable of integrating many independent simulations and distinct datasets that can supply information needed for simulated experiments. The integration is accomplished by means of software agents that coordinate distributed operational simulations and efficiently communicate data between simulations and other data sources.

Basically, the Simulation Hub is an environment in which it will be possible to incorporate the planning tools currently being developed by the Consortium (the tube in the center) with a MABS layer (the dotted tube that encloses the planning tools). This layer acts as an architecture that supports simulation according to the design of experiment system, which defines the simulation guidelines initially set by the end users. The simulation execution can be visualized by means of the visualization system, and the results of the simulations can be sent to a data warehouse system. The MABS layer is an evolution of the simulation platform presented in Figure 4.

It is important to emphasize that, in our approach, a set of external, dispersed, and independent simulations is encapsulated as agents (by means of a simulator adaptor). These agents — together with a set of connections with input data systems, such as advanced planning and scheduling systems, enterprise resources planning systems, forecasting systems, supervisory control and data acquisition (SCADA) systems, product data management systems, and legacy systems — form the Simulation Hub, a new way of using the FOR@C Experimental Planning Platform. The simulation adaptor was inspired by the work of McLean and Riddick (2000), which proposes an integration approach for independent simulations based on the concept of a simulation adapter mechanism, which is an evolution of the high-level architecture (HLA). This adaptor provides a method for integrating legacy simulations into distributed simulations while

also providing as many of the capabilities of the HLA as possible. We go further, by allowing the simulation to be encapsulated as agents (using the concept of agentification), so that they can be used directly by the Simulation Hub. This approach is expected to provide the FOR@C Experimental Planning Platform with real, updated, accurate, and, sometimes, on-line and real-time information, as well as the use of external simulations that can act as part of the platform (e.g., a specialized simulation agent).

The Simulation Hub is the final motivation behind this project and the desired end result of this project. To make it possible and real, it is necessary to develop what we call the Simulation Framework, which provides the structure, methods, and organization for the Simulation Hub. This is briefly discussed in the following section.

### **3.4 Simulation Framework**

To make the Simulation Hub possible, a Simulation Framework is envisioned. This framework is composed of a set of building blocks that encapsulate several abstract and concrete classes, features, functionalities, methods, mechanisms, and interfaces for the Simulation Hub. The Simulation Framework is a simplified representation of an intricate process and can be adapted as necessary and is easily implemented.

Following the suggestion of Lendermann et al. (2001), McLean and Riddick (2000), and Wilson et al. (2000), some elements of the Simulation Framework may include (1) distributed computing systems (hardware computing platforms, operating systems, communication systems, database management systems, computer security); (2) simulation components (the process of building, initializing, running, observing, interacting with, and analyzing simulations); (3) modeling requirements (how to model the behavior and data of specific manufacturing organizations and systems, as well as model the entire integration among agents and heterogeneous systems); and (4) agent model requirements (coordination and cooperation, internal agent architecture, general agent behavior, the simulation engine, properties of the environment, and communication protocols).

## **4 FINAL REMARKS**

This paper describes the initial advances made by the FOR@C Research Consortium toward an Experimental Planning Platform that addresses the distributed and agent-based discrete-event simulated behavior of an FPSC in order to analyze different supply chain planning and control strategies and different configurations. Our study led us to some advances in the architecture of the Experimental Planning Platform. An agent-based structure is proposed and is being analyzed and tested by the Consortium.

Nevertheless, the final result of our project, the Simulation Hub, is still a research proposition and requires further discussion. In addition to the advantages cited in the body of the paper, perhaps one of the most relevant advantages of the Simulation Hub concept is that member enterprises of a supply chain do not have to replace their current information systems with a totally new and ambitious technology in order to have a sophisticated, distributed, agent-based, and discrete-event simulation tool across their supply chains. Rather, they can use their current technology and merge it with a flexible and pioneering agent-based integration

approach — the Simulation Hub. The accomplishment of the Simulation Hub approach will provide the FOR@C Experimental Planning Platform with more complete, broad, and refined capabilities.

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## GROWTH OF A HYDROGEN TRANSPORTATION INFRASTRUCTURE

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### ABSTRACT

A transition to a personal transportation system based on hydrogen rather than on petroleum will entail major changes in the supporting infrastructure and in consumers' driving habits. Consumers who adapt such a system early on will incur some inconvenience in making trips because they will likely have to plan ahead to determine if hydrogen stations are available when and where they need to refuel. While this and other potential drawbacks to an individual's decision to purchase and drive a hydrogen vehicle operate on a personal level, the benefits of doing so are almost exclusively societal in nature (i.e., reduction in both the worldwide demand for petroleum and the emission of carbon dioxide). It will be critical to build up the hydrogen support infrastructure in a way that minimizes the hardship to the consumer and creates as strong an incentive as possible for robust early growth of the system. In this paper, we examine the growth of a hydrogen infrastructure by means of a simple agent-based model consisting of a city center, a metropolitan region, suburbs, and a surrounding rural area. Previous studies have shown that a successful transition to a self-sustaining system depends on cost of ownership, community member influence, and vehicle and station densities, and that the growth and ultimate penetration of the hydrogen system may depend significantly on the initial distribution of stations and drivers. We extend the investigation to consider other factors, such as effects of driver preference for refueling near home and effects of changing subsidies.

**Keywords:** Drivers, hydrogen, infrastructure, transportation

### INTRODUCTION

Energy security and carbon emission concerns have stimulated renewed interest in shifting world energy consumption away from fossil fuels and replacing them with alternative energy resources. One approach envisions a transition to hydrogen as a fuel, in particular for use in the transportation sector. A number of researchers have addressed this transition, some from a strategic point of view and others from an infrastructure- or vehicle-centered point of view. All cost-related studies conclude that the development of a hydrogen vehicle and fuel infrastructure (i.e., a hydrogen transportation system) will be very expensive. Ogden et al. (2004) found that most advanced vehicle/fuel options, including hydrogen fuel cell vehicles, would not be cost-competitive with conventional vehicles without internalizing externalities associated with air pollution, climate change, and energy security. They also said that even if such fuel/vehicle systems were available, it would take decades before a meaningful impact on the above-cited issues could be made and that this technology should not be pursued to the exclusion of work on advanced conventional technologies (hybrids, diesel, advanced spark-ignited).

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Mintz et al. (2002) have estimated the cost of hydrogen generated from natural gas by using three different production systems — resource-centered, market-centered, and decentralized hydrogen production. Hydrogen unit costs range between \$18 and \$23 per gigajoule (GJ), much higher than today's gasoline cost, which is about \$7/GJ and not likely to ever exceed \$10/GJ (Mintz et al., 2002). This cost differential is formidable, but perhaps developing a hydrogen fuel infrastructure in some other way could help reduce the differential. For example, Farrell et al. (2003) have argued that selecting a transportation mode like shipping, which represents a few large operating units that move along comparatively few routes, might reduce the cost of introducing and developing a hydrogen infrastructure.

As useful as they are, the above-cited studies and others in the literature base their analyses on some combination of exogenous economic factors about conventional and hydrogen transportation system costs with the inclusion of hitherto unaccounted-for externalities (e.g., climate change). Unfortunately, these studies neither attempt to account for the evolution of a market for such a system nor to elucidate the factors that could emerge to either impede or spur its growth. Agent-based modeling (ABM) can be used for such a purpose and — if done successfully — could provide valuable insight into this important question. Because market supply and demand behaviors (including cost) emerge endogenously in such models, ABM results potentially offer a realistic representation of the evolution of the hydrogen infrastructure.

ABM has been extensively used in traffic modeling simulations. For a sampling of that work, the reader is directed to a recent journal issue (*Transportation Research*, 2002) devoted to applications of ABM in transportation. With the exception of our previous paper (Stephan and Sullivan, 2004), to the authors' knowledge ABM has not been applied to the evolution of any alternative fuel market, let alone hydrogen. It would be misleading to suggest that all one needs to address such an important economic and societal question is to build an ABM. We recognize that ABM is a nascent field. Nevertheless, insights into human and social behavior have already been gleaned from ABM results (Axelrod and Cohen, 1999; Carley, 2000), including interpretation of organizational behavior. It is even being applied to long-term policy analysis (Lempert et al., 2003). Indeed, Ford's interest in ABM is broader than the question of hydrogen transportation system evolution addressed here. For example, the climatic and supply issues cited above concerning fossil fuel use portend changes in world energy use patterns. What form they will take is not known, but they are likely to cause a shift in market preferences, including those for transportation. Anticipating potential shifts in both magnitude and timing has obvious business implications, but it requires more than a casual acquaintance with understanding causes and magnitudes of social trends. Again, ABM could help illuminate discussions around such questions.

## MODEL

The transition from a petroleum- to a hydrogen-based personal transportation system promises to be a difficult and complex one. The technical problems of building hydrogen-fueled vehicles and the infrastructure to support them are formidable in and of themselves. However, a further challenge that must be faced is how such a system can grow from what must, of economic necessity, be a small beginning to one comparable in extent to the present petroleum-based one. It is a classic "chicken-and-egg" problem in that fuel suppliers will be reluctant to invest in hydrogen production, distribution, and fueling facilities until they are assured of a sufficient customer base, and drivers will not purchase vehicles unless the number of

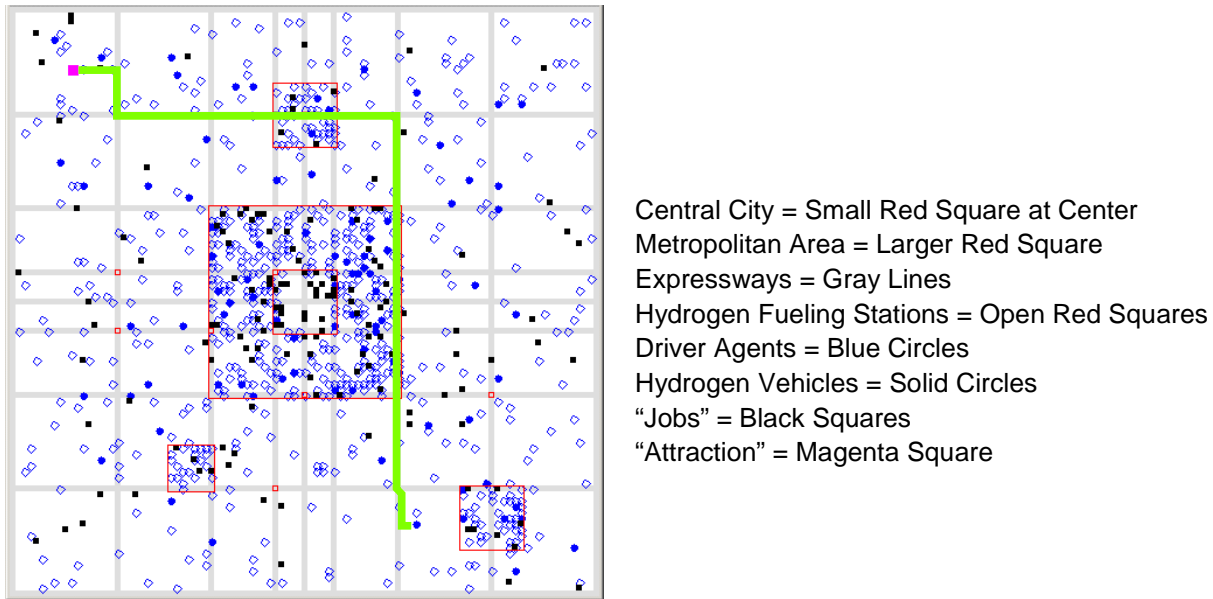
hydrogen stations in existence is sufficient to ensure that they need not worry about refueling. To maximize the chances of a successful transition, it will be vital to have a good understanding of how the various agents involved in a hydrogen-based transportation system — vehicle owners, vehicle manufacturers, hydrogen producers, distributors, retailers, and government bodies — will interact as the system grows.

We have taken a first step toward that understanding by considering a simple system involving just two types of agents, vehicle owners and hydrogen retailers. They interact on a grid representing a central metropolitan area, suburbs, and a rural area. This region is shown in Figure 1, a screen capture of the display from the Repast/Java ABM modeling framework in which the simulation was developed.<sup>1</sup> The grid, which consists of a  $100 \times 100$  array of cells, is considered to represent an area about 100 miles on a side. A number of expressways, shown as light grey lines, crisscross the grid and form a ring around the boundary. Local roads are considered to be ubiquitous and are not shown explicitly on the display. The population of drivers (blue circles) is distributed randomly, but weighted so that density is highest in the metropolitan and suburban areas and zero in the central city district. In the simulations, a driver population of 800 was used; thus, agents can be considered “markers” for a much larger population living in the 10,000-square-mile area. At the beginning of a simulation, most drivers drive conventionally powered vehicles (open circles), but a small percentage have hydrogen-powered ones (solid circles). The grid contains a number of locations (representing jobs, schools, etc., shown as black squares) to which the drivers commute on a daily basis. Each driver is associated with a single such location. The drivers also make less frequent (“weekend”) trips to other locations on the grid. The destination for each such trip is picked randomly, but certain cells on the grid representing “attractions” (sports stadiums, parks, etc., shown as one or more large magenta squares) are weighted to be favored destinations. In driving to a given destination, a driver agent follows a protocol of driving on local roads to the nearest entrance of the first north-south expressway in the direction of his or her destination, following that expressway to the east-west expressway closest to (but not past) the destination, then following that expressway to the appropriate exit, and finally once more taking local roads to the destination. A typical route is shown in the figure. (Entrances and exits to expressways are located at intersections and on each expressway at the midpoint between two intersecting expressways.)

Fuel retailers are the second type of agent in the simulation. Conventional fuel stations are considered to be ubiquitous and are not shown explicitly on the display. At the beginning of the simulation, a small number of cells (open red squares) are chosen to contain hydrogen fueling facilities. These locations can either be chosen randomly (though always at expressway intersections) or placed as desired. As the simulation proceeds, these stations monitor their hydrogen fuel sales; if sales are insufficient, they close their facilities. Every cell on the grid is a candidate location for a new hydrogen fuel station, and if the expected sales volume is high enough, a new station opens. Once opened, a hydrogen station will remain open for at least six months, but then it may close again if the actual sales volume is less than a second, lower threshold. Depending upon its location, a station can have one or two types of sales. Studies of consumer behavior have found that drivers prefer to fuel their cars at stations near their home or work (Kitamura and Sperling, 1987). Reflecting this, our driver agents purchase all their fuel for local trips (commuting and the portions of random trips that are within 50 miles of home) from stations within a specified radius of either home or work, distributing their purchases equally

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<sup>1</sup> For information regarding Repast, see <http://repast.sourceforge.net/>.



**FIGURE 1** Screen capture of the model region, showing a central city, surrounding metropolitan region, three suburbs, and a rural area. (Hydrogen fueling stations have been placed randomly at expressway intersections. A small fraction of the driver agents have hydrogen vehicles. The green line traces the route of one hydrogen vehicle driver making a trip to the attraction.)

among all such stations. A station located in a cell containing an expressway (i.e., a station that is within one-half mile of the expressway) sells fuel both to local drivers and to nonlocal drivers using the expressway. It is expected that two stations located in close proximity to each other on an expressway (e.g., on adjacent cells) will compete for business from such drivers, while one that is relatively isolated will service all passing drivers who need fuel.<sup>2</sup> To account for this, we incorporate a local "proximity factor" that reflects the competition that an expressway station faces from nearby stations. For example, a station with a competitor on an adjacent cell has its sales reduced by one-third compared to what they would be otherwise, and the two stations together sum to  $4/3$  "effective" stations. When an agent makes a nonlocal trip, fuel purchases are apportioned among all hydrogen stations passed on the trip on the basis of their effective ratings. (Obviously, an individual driver would not divide purchases this way, but the procedure reflects the marker nature of the agents.)

During each time step of the simulation (one step representing a time period of approximately 1 month), the actual or potential fuel sales for each cell on the grid during that period are calculated. The sum of sales from all preceding months is multiplied by a factor chosen to exponentially decay and normalize the historical record to reflect a characteristic time period of about 1 year, weighted toward more recent months. For off-expressway locations, sales are local only, whereas expressway locations add the local and expressway sales. If the sum for an empty cell exceeds a threshold, the cell will add a hydrogen station. If the sum for a cell with

<sup>2</sup> A cell is considered to have either 0 or 1 hydrogen fuel station. In reality, there could be more than one station in the cell's 1-square-mile area, but we assume that drivers will treat all such stations equivalently in terms of their location, so that their sales can be combined to represent one "superstation."

an existing hydrogen station (which has been in operation for a minimum of 6 months) falls below a lower threshold, the station will close.

Drivers buy new cars on a regular basis, keeping them for a randomly assigned length of time. When the next purchase time arrives, a driver chooses either a conventional or a hydrogen vehicle on the basis of a “utility function” that takes into account a number of factors. The first is the difference in fixed costs of a hydrogen vehicle compared with a conventional one. This factor includes not only the purchase price of the vehicle but such intangibles as a desire to be “environmentally friendly” or “high tech.” The hydrogen vehicle is assumed to have a lower fixed cost, yielding a positive “fixed benefit” in the utility function. Likewise, there is assumed to be a positive “variable benefit,” proportional to the distance driven, for a hydrogen vehicle. This also includes benefits that are both tangible (fuel and other operating costs) and intangible (e.g., dispensation for unrestricted travel in HOV lanes). In addition, the agent’s purchase decision may be influenced by the purchase decisions of friends and neighbors and the public at large. Also, we expect that the cost of hydrogen vehicles will drop as volume grows. Counteracting this, there may be a purchase-price government subsidy (such as is presently the case for hybrid vehicles), which could decrease as sales of hydrogen vehicles increased. In the present simulation, we incorporate these three factors into a single volume-dependent term, the percentage of all drivers who own hydrogen vehicles. Depending upon its sign, this term can add an element of either positive or negative feedback.

Offsetting these assumed benefits are the two drawbacks of (1) possible lack of convenient hydrogen stations near home or work and (2) worries about running out of fuel on nonlocal trips. The first factor is expressed mathematically as follows:

$$\text{Inconvenience} = [8(0.25 + N_{Home})(0.5 + N_{Work})]^{-1}, \quad (1)$$

where  $N_{Home}$  and  $N_{Work}$  are the number of hydrogen stations within a three-cell distance of the agent’s home and job, respectively. Values for different numbers of home and work stations are shown in Table 1. The term is 1 for no stations at either location and rapidly approaches 0 as the number of stations increases. The different additive terms for home and work reflect most people’s preference to refuel near home rather than work. (In this expression and the one to follow, both the form of the equation and the numerical values of the parameters are arbitrary. We have chosen them only as approximations reflecting our limited understanding of consumer behavior.)

**TABLE 1** Inconvenience vs. number of local hydrogen stations

No. of Stations near Home ( $N_{Home}$ )	No. of Stations near Work ( $N_{Work}$ )	Inconvenience
0	0	1
0	1	0.33
1	0	0.20
1	1	0.07
2	2	0.02

We include a “worry factor” to account for possibly uncomfortably or prohibitively long distances between successive hydrogen stations on extended trips. Drivers (both hydrogen and conventional) monitor the locations of hydrogen facilities that they pass along their random trips. If the stations are spaced close enough together, a driver’s worries about running out of fuel are diminished. The worry factor is calculated as the square of the distances between successive fuel stations passed when the distances exceed a threshold:

$$WorryFactor = \sum_{All\ trips} (\text{distance between successive hydrogen stations} - \text{comfort zone})^2 . \quad (2)$$

(The power of 2 reflects the simple observation that one’s worry about being stranded increases in a more than linear fashion as the fuel gauge approaches empty.) Note that for drivers of hydrogen vehicles, inconvenience and worry are *actual*; for conventional vehicle drivers, they are *potential*. All these factors are summarized in the statement of the driver utility function  $U$ :

$$U = \text{FixedBenefitFactor} + \text{VariableBenefitFactor} - \text{DistanceTraveled} + \text{VolumeFactor} - \text{InconvenienceFactor} - \text{WorryFactor} . \quad (3)$$

Each term can be weighted as appropriate. For example, the weights of coefficients multiplying InconvenienceFactor and WorryFactor would reflect the relative weights of inconvenience and worry in a driver’s purchase decision. The utility function differs from driver to driver, depending upon location and travel distance from month to month. If the utility function is positive at the time when a driver is ready to purchase a new car, he buys a hydrogen vehicle; otherwise, he purchases a conventional one.

The model used in this study differs in some significant ways from the one used for results reported in our earlier paper (Stephan and Sullivan, 2004). We have extended the previous model to include suburban regions of high population and job density, and we have been more precise in specifying to what fuel stations a hydrogen vehicle driver’s fuel budget is distributed. In the earlier model, hydrogen fuel stations were restricted to expressway cell locations (i.e., within 0.5 mile of an expressway), and no distinction was made between sales to vehicles being used for commuting and sales to those being used for “random” trips. A hydrogen fuel station, or potential hydrogen fuel station, was credited with a fuel purchase every time drivers of hydrogen vehicles passed their station. These purchases were discounted based on the proximity of competitor stations in the same way they are here. The actual amount of fuel sold by a given hydrogen station in one time step (1 month) was calculated as follows:

$$Fuel\ Sold = Total\ H2\ Vehicle\ Eff.\ Passes \frac{Total\ H2\ Vehicle\ Miles}{Total\ Passes\ by\ all\ H2\ Drivers\ of\ All\ H2\ Fuel\ Stations} , \quad (4)$$

where *Eff.* (effective) denotes that passes were discounted for local competition.

In this model, in contrast, a hydrogen fuel station can be located anywhere on the grid, although to participate in sales to vehicles on “random” trips the station must be located within 0.5 mile of an expressway. Commuting drivers buy their fuel only at fuel stations near their home or work, not en route. Purchases of fuel in a “random” trip are distributed equally among

all stations (outside the home neighborhood) passed en route. The expressway fuel sold by a given station is:

$$Fuel\ Sold = \sum_{All\ H_2\ Drivers} \left( \sum_{\substack{All\ trips\ of\ a \\ given\ H_2\ Driver \\ past\ Station}} \frac{Total\ Distance\ of\ Trip}{Eff.\# H_2\ Fuel\ Stations\ Passed\ on\ Trip} \right). \quad (5)$$

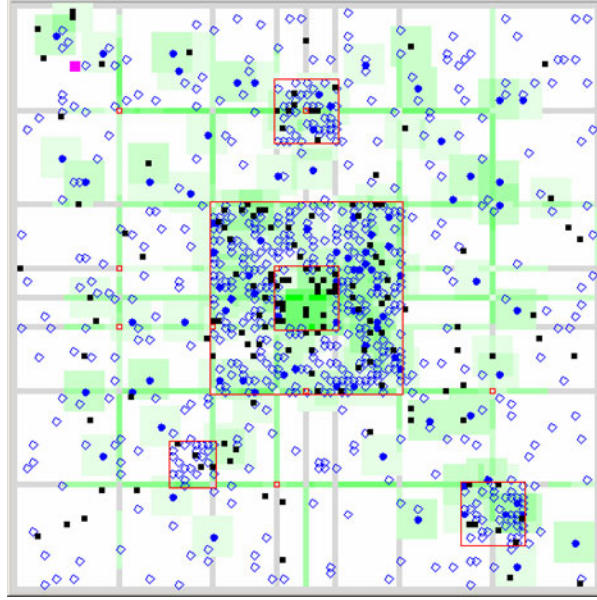
The result is to take into account more precisely the effect of nonlocal competition. A driver following a route with many hydrogen fuel stations (even if spaced far enough apart that there is no local competition) will purchase less fuel at each station than if the route were sparsely populated with hydrogen stations.

## RESULTS

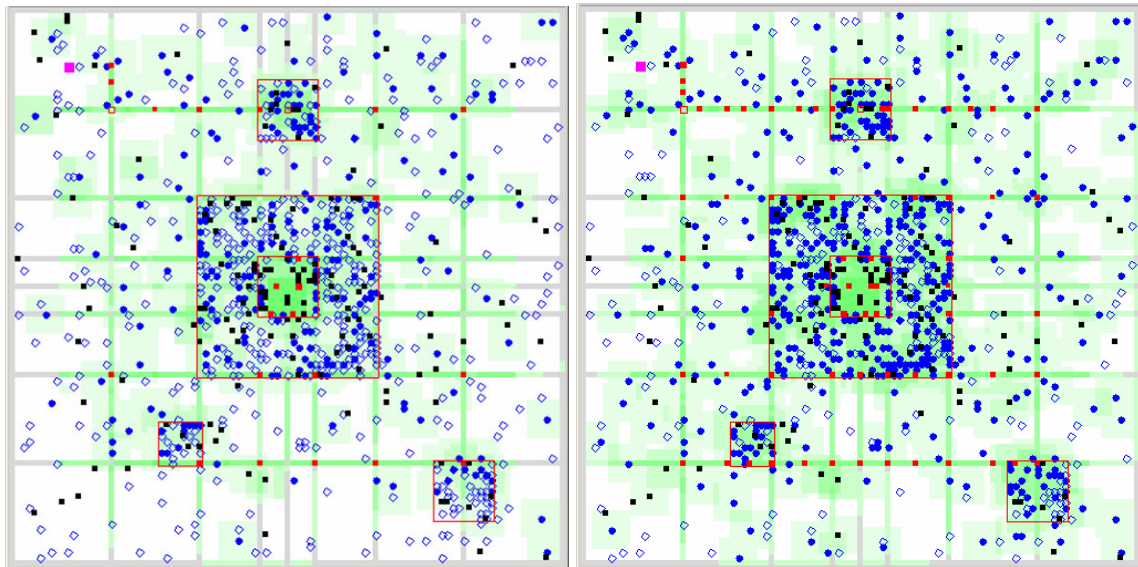
Figures 2 and 3 show a display akin to that of Figure 1, but after 1 month (one step), 3 years, and 15 years of a transition where the net benefits of driving a hydrogen vehicle are substantially positive. Although hydrogen fuel stations can be located anywhere, in this case they have all chosen to locate on expressways to take advantage of noncommuter traffic. There is a particular concentration along the approach roads to the attraction, which is the destination for 5% of random trips. Figure 4 shows the time dependence of the percentage of drivers who have switched to hydrogen vehicles, the number of hydrogen fueling stations, and the fuel sales per station. The transition is substantially complete after about 10 years, with about 70% of drivers having switched to hydrogen and the number of hydrogen stations having grown from a starting value of 11 to 60. There is still slight growth for another 10 years. Note that the sales volume per station remains relatively steady, because in most cases when the sales volume of a station in a given cell (indicated by the size of the square) rises much above average, competitor stations spring up in nearby cells to share the business. The station at the intersection due east of the attraction provides an example of an exception. (A competitor locating north of that station would not get any business from the majority of drivers coming from the south.)

Figure 5 shows the average fixed and variable benefits, worry, and inconvenience for all drivers and for hydrogen vehicle drivers. As expected, the negative factors decrease over the years as more hydrogen stations are built, and they are smaller for hydrogen vehicle drivers than for overall drivers. The latter is particularly true in the case of inconvenience, which has been weighted in this example to be the dominant consideration for drivers.

Figure 6 contrasts the growth of hydrogen vehicles indicated in Figure 4 with that resulting when conditions are changed in two ways. In the “Lower Benefits” case, the benefits to the hydrogen vehicle driver are cut by about 40% (e.g., through lower subsidy of vehicle and fuel purchase costs). Not surprisingly, the ultimate penetration of hydrogen vehicles is lower (60% vs. 74% after 20 years). In addition, the growth rate is much slower at the beginning: after 10 years, penetration in the Lower Benefits case is less than half that in the original case. In the “Judicious Placement” case, we again cut the benefits, but this time we attempted to place the initial stock of 11 hydrogen fuel stations in a “judicious” (though probably not optimal) fashion, on the basis of observing their placement at the end of the previous runs. With this procedure, the

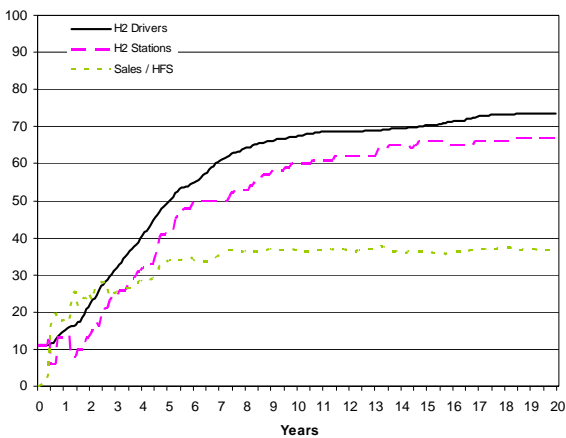


**FIGURE 2** Changes in the distribution shown in Figure 1 after the first step of the simulation (The areas where there is a potential for hydrogen fuel sales are shown in green, with darker shades indicating higher potential.)

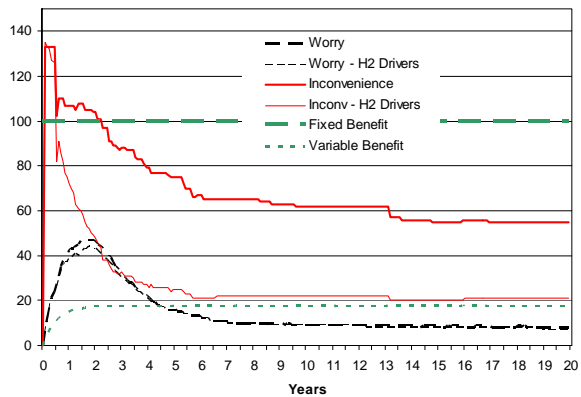


**FIGURE 3** Changes in the distribution shown in Figure 1 after 3 and 15 years

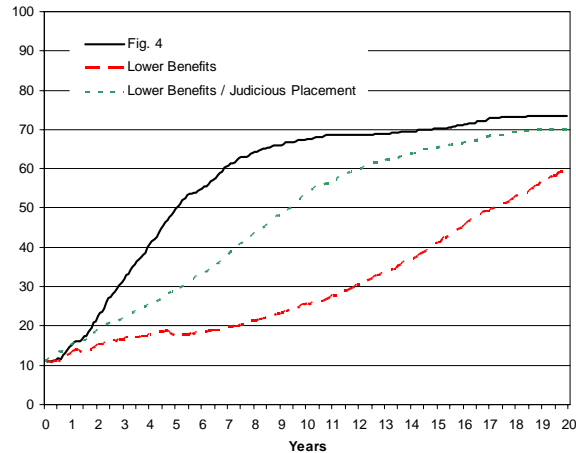




**FIGURE 4** Transition as a function of time<sup>3</sup>



**FIGURE 5** Worry and inconvenience factors

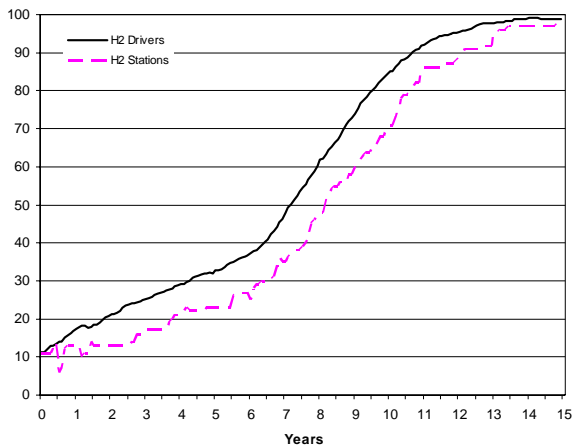


**FIGURE 6** Effect of lower benefits combined with "judicious placement" of initial hydrogen fuel stations

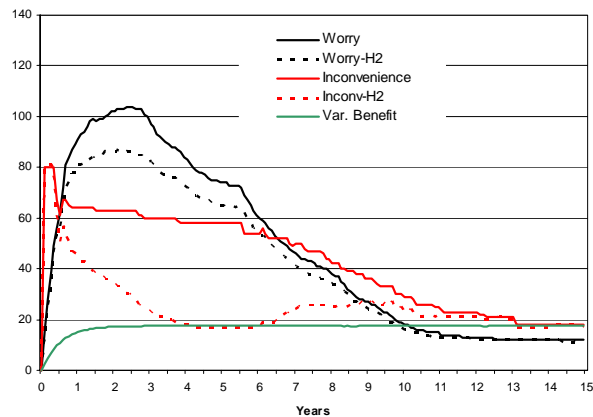
ultimate penetration recovers to 70% and the initial growth rate is much higher than before. Indeed, under some circumstances the initial growth rate can surpass that for a system with ultimately higher penetration. Correct initial placement of hydrogen fuel stations thus appears to be key to a successful hydrogen transition.

Figures 7 and 8 show a simulation run identical to that used to generate Figures 4 and 5, but with the worry weighting coefficient increased and the inconvenience coefficient decreased to make worry the dominant consideration. In contrast to the original case, the transition is complete; virtually all drivers have hydrogen vehicles at the end of 15 years. However, the

<sup>3</sup> In this and all following figures (except Figures 5 and 8), the same ordinate scale represents percentage of hydrogen drivers, absolute number of hydrogen stations, and arbitrary units for fuel sales/station.



**FIGURE 7** Transition as a function of time, with different weighting coefficients

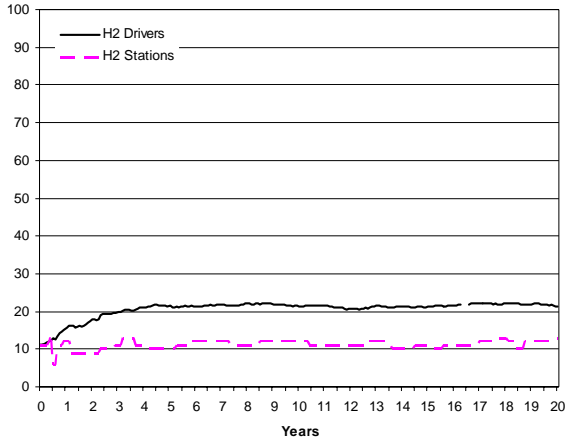


**FIGURE 8** Worry and inconvenience factors, with different weighting coefficients

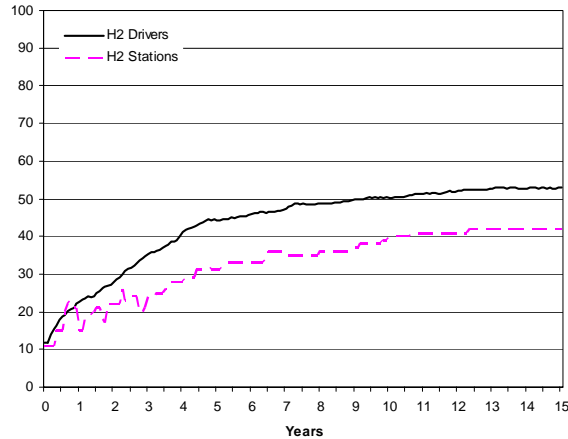
results are very sensitive to the positive benefit factors. Previously, a 40% cut in benefits slowed the transition and reduced penetration by 74% to 60%; here, a 5% cut reduces penetration from 100% to 20% (Figure 9). Why should this be? In the former case, the decision to switch to hydrogen depended markedly on the driver's location. If there happened to be a hydrogen station nearby, then inconvenience was low; otherwise it was high. In the present case, a driver's decision is more heavily weighted in terms of the worry generated in making random trips. Thus, all drivers are in more similar circumstances, and if one driver finds it beneficial to switch, the rest are more likely to reach the same conclusion. Although in reality drivers will have individual situations and preferences that we have so far not taken into account, nevertheless there appears to be a lesson that can be drawn. Hydrogen vehicles marketed to commuters (for whom inconvenience is presumably a prime consideration) may face less risk of an utter failure, but also have less chance of a complete conversion to hydrogen, than those that are marketed to consumers for use in longer trips.

While reducing the benefits at the outset can "kill" a transition (see Figures 7 and 9), gradually reducing a subsidy as the transition gains momentum may be quite tolerable. This effect is illustrated in Figure 10, which is similar to Figure 7 except that the subsidy has been reduced as a function of penetration, reaching zero at roughly 60% penetration. This results in an ultimate penetration of just over 50%. (Had the subsidy been reduced even slightly at the beginning, the transition would have failed, with all the initial seed stock of vehicles and stations quickly disappearing.)

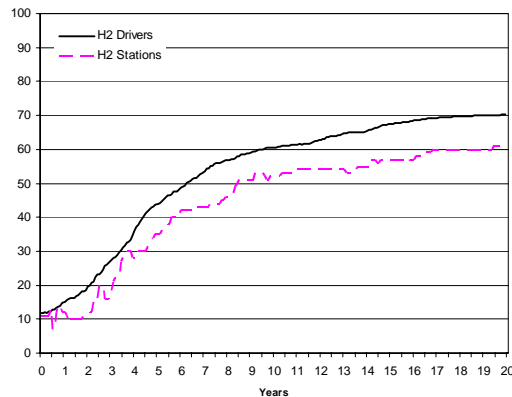
The presence or absence of suburbs does not appear to have a large effect. Figure 11 shows the outcome for a simulation like that of Figure 4, but with no concentrations of drivers in suburban regions. Under these conditions, the same ultimate penetration is achieved, but the transition takes longer. This effect will be explored more fully in future work.



**FIGURE 9** Transition as a function of time with benefit factors reduced by 5%



**FIGURE 10** Effect of a gradually decreased vehicle purchase subsidy



**FIGURE 11** Transition as a function of time for a layout with no suburbs

## CONCLUSIONS

Our work so far cannot be considered a complete picture of reality. The model contains only two types of agents, and the driver agents in particular do not embody the many variations characteristic of real drivers. Also, our model does not approach the level of true economics in describing agent behavior. Nevertheless, we believe that the responses of the model to variations in parameters are of interest and may be helpful in guiding the development of more sophisticated models. We find that the initial growth period of the transition is critical; the ultimate success or failure of the transition is determined in the first few years. Appropriate initial placement of hydrogen fueling stations is important and may make the difference between success and failure. Interestingly, the relative importance that consumers place on being able to fuel their vehicles near home or work, as opposed to concerns about finding fuel on longer trips, greatly influences the sensitivity of the transition to vehicle and/or fuel subsidies.

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## EMERGENT STRUCTURES FROM TRUST RELATIONSHIPS IN SUPPLY CHAINS

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### ABSTRACT

This paper describes an agent-based model of supply chains in which trust relationships between agents emerge as a result of successful and mutually beneficial agent interactions. Repeated, successful social interactions between supply chain agents are self-reinforcing and lead to trust and sustainable cooperative relationships. Various social interaction mechanisms for modeling the establishment of trust are proposed on the basis of reciprocity relationships, such as “tit-for-tat.” The simulation is used to study aspects of trust relationships and how their establishment can be effectively modeled. Agent-based simulation is used as an electronic laboratory to explore the establishment of trust relationships and their impacts on the structure of the supply chain.

### 1 INTRODUCTION

Supply chains touch all aspects of production, distribution, and retailing, linking together networks of suppliers, manufacturers, distributors, wholesalers, retailers, and consumers. Agent-based simulation is a modeling approach that is well-suited to represent supply chains for what they are: collections of heterogeneous, autonomous decision-making agents operating at multiple levels of organization. Agent interaction occurs along several dimensions as business units, companies, and individual decision makers all add to decision-making complexity.

Supply chain agents are necessarily social agents. Issues associated with social interaction and the formation of sustainable relationships are essential aspects of supply chains. Supply chain agents seek sources of supply and seek outlets for their products from among other supply chain agents. Agents negotiate on pricing and delivery. Agents decide to share information when it is mutually beneficial. Trust between agents, negotiations that result in transactions that are acceptable to all parties, and incentives offered to affect agent behaviors are all examples of social interactions relevant to modeling real-world supply chains.

Previous models (including agent-based models) used to understand the evolution and dynamics of supply chains have only considered economic variables. This paper describes an agent-based approach to modeling the dynamic evolution of supply chains in which trust between agents is an endogenous property of the system. Trust emerges on the basis of individual agent interactions. Repeated, mutually beneficial and self-reinforcing social interactions among supply chain agents lead to trust and sustainable cooperative relationships. Trust relationships evolve according to the ongoing dynamic interactions between and among agents. Various interaction mechanisms for modeling the establishment of trust are posited and explored on the basis of reciprocity relationships, such as “tit-for-tat.” The simulation is used to study aspects of trust relationships and how they can be effectively modeled. Agent-based

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simulation is used as an electronic laboratory to explore the impacts of trust relationships on overall supply chain dynamics.

This paper is organized as follows. Section 2 proposes a general model for the calculation of trust on the basis of reciprocity in agent interactions. Section 3 describes the implementation of the trust model into the supply chain model. Section 4 presents an experimental design for the simulation to understand the implications of the trust relationship. Section 5 presents results and draws conclusions.

## 2 MODEL FOR THE ENDOGENOUS GENERATION OF TRUST

*Trust* between two agents is a measure that changes according to the nature of the interaction between the agents. An interaction between two agents consists of an action by one of the agents and a reaction by the other agent. Associated with each action and reaction is a scalar number. For example, in the case of two supply chain agents, the action could be the amount a retailer agent orders from a supplier agent, and the reaction could be the number of items received from the supplier in response to the order. An interaction between two agents is either positive or negative. Positive interactions boost trust. Negative interactions cause trust to decline. A *positive interaction* is defined as one in which a reaction to an agent's action is greater than or equal to an action the agent previously took (i.e.,  $\text{reaction} \geq \text{action}$ , where action and reaction are real numbers assigned to the action response to the action, respectively). A *negative interaction* is one in which  $\text{reaction} < \text{action}$ . Following the supply chain example, if the shipment received meets or exceeds the order, the retailer agent's trust in the supplier increases, and if the shipment falls short of the order, the ordering agent's trust in the supplier is diminished.

### Reciprocal Nature of Trust

We assign a trust measure to the result of an interaction between two agents at any time  $t$ . The trust value of the interchange for an action that is successfully reciprocated ( $\text{reaction} \geq \text{action}$ ) is set equal to the value of the initiating action. For an action that is not successfully reciprocated ( $\text{reaction} < \text{action}$ ), the trust value of the interchange is set to the value of reaction. If an agent reciprocates by providing more than was requested ( $\text{reaction} > \text{action}$ ), the excess provided above the action (request) is not considered in the trust value for the interaction. In effect, credit is given only for what was requested. Each pair of agents that has a relationship has two trust functions, one for each agent, regarding the trust that an agent has for the other agent in the relationship. This allows for the possibility that trust relationships may be asymmetric. Agent  $a$  may trust agent  $b$  at a different level than agent  $b$  trusts agent  $a$ .

Formally, we define the *indicated trust* for an agent  $a$  relative to agent  $b$  at time  $t$  as:

$$\begin{aligned} \text{Indicated Trust}_{ab,t} &= \text{action}_{at}, \text{ if } \text{reaction}_{bt} \geq \text{action}_{at} \text{ (positive interaction)} \\ &= \text{reaction}_{bt}, \text{ if } \text{reaction}_{bt} < \text{action}_{at} \text{ (negative interaction)}, \end{aligned}$$

where  $\text{action}_{at}$  is the action taken by agent  $a$  at time  $t$ , and  $\text{reaction}_{bt}$  is the reaction by agent  $b$  at time  $t$  in response to the action taken by agent  $a$ . Generally, the notion of trust considered here

(with reciprocity building a more sustainable relationship) is similar to the “tit-for-tat” strategies that have been employed in evolutionary game theory (Axelrod, 1997).

Similarly, we define a trust measure for agent  $b$  relative to agent  $a$  at time  $t$ . We may also introduce a delay time between an action and the associated reaction into the above formulation. For example, in the supply chain, the action may be the order placed at  $t$ , and the reaction may be the shipment that arrives later at  $(t + \text{orderDelay} + \text{shipmentTime})$ .

## Trust Decay

Trust between two agents persists over time. However, if two agents do not interact over an extended period of time, trust between them decreases. Trust must occasionally be reinforced with positive interactions to be maintained. Trust decreases over time according to the *trust decay parameter*  $\tau$  ( $0 < \tau \leq 1$ ) that represents the fraction of trust that decreases over each period. The trust decay parameter is a fixed value for the duration of a simulation and is set as part of the scenario parameters. A value of zero for  $\tau$  indicates that trust does not decay and is constant between interactions. A value of one for  $\tau$  indicates that trust decays immediately and completely after each interaction; for  $\tau = 1$ , trust does not carry over from one interaction to the next, and, in effect, trust is ephemeral. The *effective trust* at time  $t$  is the decayed value of trust from the previous time period:

$$\text{Effective Trust}_{abt} = (1 - \tau) \text{Trust}_{ab,t-1},$$

where  $\text{Trust}_{ab,t-1}$  is the trust of agent  $a$  for agent  $b$  at time  $t-1$ , and  $\tau$  is the trust decay parameter.

## Trust Adjustment

We introduce a *trust adjustment parameter*  $D$  to account for the stickiness in how quickly trust is updated in light of recent interactions between agents. Even if an agent’s reaction in response to an action is not satisfactory, all trust is not completely lost. Some trust may remain as a result of previously established goodwill. Similarly, if a positive interaction occurs, we allow for updating trust only partially to the new implied trust level by using the parameter  $\rho$ . A value of  $\rho = 0$  indicates that trust is not lost (bolstered) in light of a negative (positive) interaction. A value of  $\rho = 1$  indicates that trust is adjusted fully and immediately in light of an interaction. This corresponds to a kind of total reinforcement. Values between zero and one indicate partial reinforcement and caution or hesitancy in adjusting trust levels in light of recent experience.

## Trust Heuristic

The *trust heuristic* generates trust values over time between two agents in a relationship. We can summarize the trust heuristic as follows. Trust increases if and only if the reaction is at least as great as the action ( $\text{reaction}_{b,t} \geq \text{action}_{a,t-*}$ ) and the action is greater than the effective trust level ( $\text{action}_{a,t-*} > \text{Effective Trust}_{ab,t}$ ), where  $*$  is a possible time delay factor. Trust decreases as a result of two factors: (1) the assumed decay of the trust measure over time (assuming  $\tau > 0$ , because if  $\tau = 0$ , there is no decay) and (2) if the reaction is less than the action

( $\text{reaction}_{b,t} < \text{action}_{a,t-*}$ ), (assuming  $\rho > 0$ , because if  $\rho = 0$ , there is no impact of the action-reaction interaction on the trust measure).

The trust heuristic combines the indicated trust and the effective trust by weighting the two components. Finally, we define *trust* for an agent *a* relative to agent *b* at time *t* as follows:

*Trust Heuristic:*

If  $\text{reaction}_{b,t} \geq \text{action}_{a,t-*}$ , then:

$$\text{Trust}_{ab,t} = \text{Max}[\text{Effective Trust}_{ab,t}, \rho \text{ action}_{a,t-*} + (1 - \rho) \text{ Effective Trust}_{ab,t}.$$

If  $\text{reaction}_{b,t} < \text{action}_{a,t-*}$ , then:

$$\text{Trust}_{ab,t} = \text{Min}[\text{Effective Trust}_{ab,t}, \rho \text{ reaction}_{a,t} + (1 - \rho) \text{ Effective Trust}_{ab,t}.$$

Six cases can result at time *t* depending on the relative values of the three variables: action, reaction, and effective trust (Table 1, illustrated in Figure 1).

### 3 SUPPLY CHAIN MODEL

The supply chain model used in this study is based on Sterman's "beer game" simulation (BGS) (Sterman, 1987, 1989, 2000, 2001; Mosekilde et al., 1991). The original BGS considered a linear supply chain consisting of a single customer, retailer, distributor, wholesaler, and factory, programmed as a systems dynamics model (Forrester, 1961). The BGS is a classic case of a multi-tiered supply chain model, well-known and well-studied. Although highly idealized when compared to the complexities of real-world supply chains, it nevertheless exhibits important properties of real-world supply chains, such as the "bullwhip effect," in which inventories are typically amplified at each stage of the chain as a result of the effect of uncertainties in supply and demand on ordering decisions (Lee et al., 1997).

**Table 1** Distinct cases for the inference of trust

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*Positive Interaction:*

Case 1:  $\text{reaction}_b \geq \text{action}_a \geq \text{Effective Trust}_{ab,t}$ , implies  $\text{Trust} = \text{action}_a$

Case 2:  $\text{reaction}_b \geq \text{Effective Trust}_{ab,t} \geq \text{action}_a$ , implies  $\text{Effective Trust}_{ab,t}$

Case 3:  $\text{Effective Trust}_{ab,t} \geq \text{reaction}_b \geq \text{action}_a$ , implies  $\text{Effective Trust}_{ab,t}$

*Negative Interaction:*

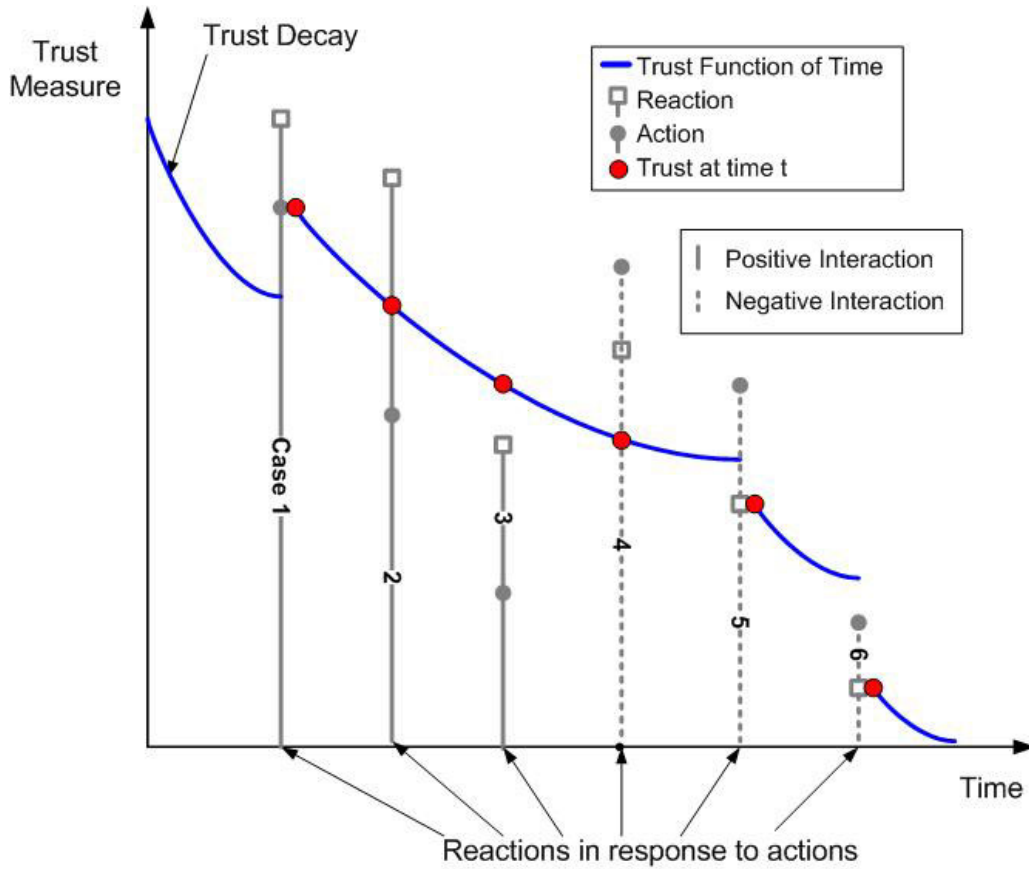
Case 4:  $\text{reaction}_b < \text{action}_a < \text{Effective Trust}_{ab,t}$ , implies  $\text{Trust} = \text{reaction}_b$

Case 5:  $\text{reaction}_b < \text{Effective Trust}_{ab,t} < \text{action}_a$ , implies  $\text{Trust} = \text{reaction}_b$

Case 6:  $\text{Effective Trust}_{ab,t} < \text{reaction}_b < \text{action}_a$ , implies  $\text{Trust} = \text{Effective Trust}_{ab,t}$

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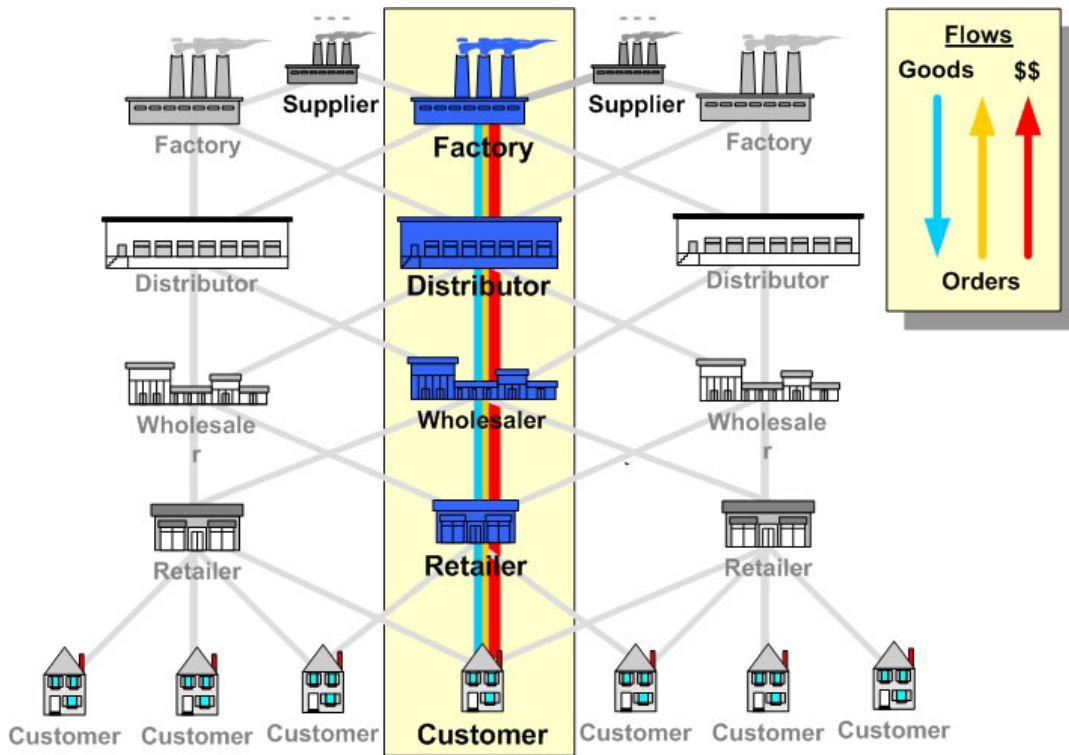




**FIGURE 1** Trust function, assuming that trust adjustment parameter  $\rho > 0$  and trust decay parameter  $\tau > 0$

To add the richness of agent decision-making situations and behavior as well as realism in supply chain dynamics, we extend the standard linear supply chain BGS to a full supply chain network simulation (Figure 2). Each stage of the supply chain consists of an arbitrary number of agents. Agents are the decision-making members of the supply chain. We term our model the Network Agent Supply Chain (NASC) model.

The goal of the supply chain process is to meet consumer demands for goods. The process begins with the manufacturing stage or factory stage and extends through distribution, wholesaling, and retailing. Customers place orders with retailers. A retailer fills the orders if on-hand inventory (stock) allows. Otherwise, the order is placed on backorder, and the retailer places an order with the next upstream stage, the wholesalers. Wholesalers fill retailer orders if their inventories allow. Wholesalers are faced with the same ongoing problem of filling incoming orders from downstream and maintaining adequate stocks. To do so, they order additional items from the upstream stage, distributors. In response to an order, agents receive shipments from the upstream stage after a delay to account for order processing and shipment. The same process is repeated by the warehouse and factory stages further upstream. If the factory cannot fill an order with stock on hand, it places the order into production.



**FIGURE 2** Network Agent Supply Chain (NASC) model

The sequence of stages from manufacturing to consumption is termed *downstream*, and the sequence of stages from consumption to manufacturing is termed *upstream*. Manufactured goods flow downstream, and information in the form of orders (demand) flows upstream. In the original BGS, it is assumed there is a one-period delay in the time between placing the order and the time the order is received by an upstream agent, a two-period delay in items shipped and reaching their destinations downstream, and a three-period production delay. These same assumptions are adopted here for the NASC model.

### Supply Chain Agents

Each supply chain agent decides how many items to order and ship in each time period on the basis of its inventory, outstanding orders in the pipeline, and the orders and shipments it has received. An agent's decision framework consists of five rules:

- *Demand Forecast Rule*: Forecast expected demand.
- *Supply Rule*: Determine total supply to downstream agents.
- *Ordering Rule*: Determine total orders to upstream agents.
- *Supply Allocation Rule*: Allocate supplies to downstream agents.
- *Order Allocation Rule*: Allocate orders to upstream agents.

Together these rules constitute a business process. There are many possible ways that agents could combine these rules to arrive at the requisite decisions, and many reasonable forms of specific rules that an agent could follow. The supply chain agent rules used in the NASC model follow the rules used in the original BGS, with the exception of the allocation rules, and are described elsewhere (contact author for details). The allocation rules for allocating shipments to downstream agents and for allocating orders to upstream agents are unique to the supply network, as opposed to the linear supply chain that was addressed in the original BGS model (Figure 3). The allocation rules are the basis for modeling the emergence of trust in the supply chain and the subject of the remainder of this paper.

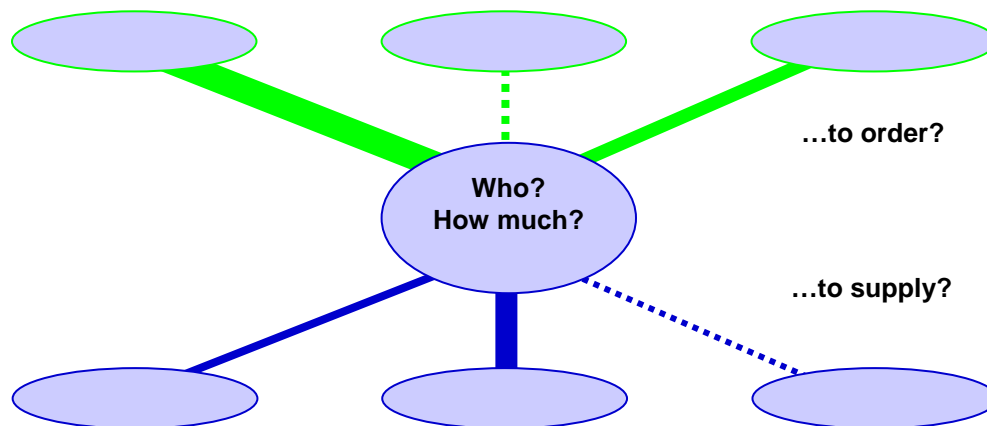
## Allocation Decisions

### *Allocate Supplies to Downstream Agents*

In the supply chain, an upstream agent has shipment decisions to make. The upstream agent has to decide (1) how much to supply in total to all downstream agents, and (2) the share of the supply (shipment) that should be made to the various downstream agents. Consider an agent that would like to allocate a total supply,  $Supply$ , to a downstream agent,  $d$ :

$$\text{New Supply}_d = \text{allocateShipmentToDownstream}[Supply].$$

There are many reasonable heuristics for allocating supplies. For example, one approach is to prioritize the downstream agents on the basis of the largest backorder. The goal would be to supply the downstream agents in order of the largest backorder first (LBF) until all backorders are filled or the supply runs out, whichever comes first. A reasonable alternative approach is to prioritize the downstream agents on the basis of smallest backorder, and supply the downstream



- *Supply Allocation Rule*: Determine who among the downstream agents to supply
- *Order Allocation Rule*: Determine from whom among the upstream agents to order

**FIGURE 3** Allocation decisions of supply chain agents

agents in order of the smallest backorder first (SBF); this scheme would seek to supply as many downstream agents as possible. The LBF rule could be implemented as follows:

$$\text{allocateShipmentToDownstream[Supply]} = \text{Supply}_{ut} \times (\text{Backorder}_{ud,t} / \sum_d \text{Backorder}_{ud,t}),$$

where  $(\text{Backorder}_{ud,t} / \sum_d \text{Backorder}_{ud,t})$  is the relative backorder share for agent  $d$ .

### *Allocate Orders to Upstream Agents*

In the supply chain model, a downstream agent has ordering decisions to make. The downstream agent has to decide (1) how much to order in total from all upstream agents, and (2) the share of the order that should be placed with the various upstream agents. Each agent decides how much of its order to allocate to each of the upstream agents. Consider an agent that would like to allocate a total order,  $\text{Order}$ , to an upstream agent,  $u$ :

$$\text{New Order}_u = \text{allocateorderToUpstream}[\text{Order}].$$

There are several reasonable alternatives for allocating orders. For example, one heuristic is to allocate a relatively larger share of orders to upstream agents having fewer previous orders that have not been filled (backorders, if any) as of the current time. Agents with larger backorders are allocated a relatively smaller share of the order made by the downstream agent  $d$ , as follows:

$$\text{allocateOrderToUpstream} = \text{New Order} \times (1/\text{Backorder}_{d,ut} / \sum_u 1/\text{Backorder}_{d,ut}),$$

where  $(1/\text{Backorder}_{ud,t} / \sum_d 1/\text{Backorder}_{ud,t})$  is the relative backorder share for agent  $u$  and is the inverse of the LBF rule used above for supply. If there are no backorders outstanding, then agents receive an equal share of the order.

## **Application of the Trust Heuristic to the Supply Chain**

We next extend the supply and ordering allocation rules to include trust considerations. Downstream supply chain agents have relationships with upstream agents according to the structure of the supply network. Each agent in the relationship has a trust measure for the other agent in the relationship.

### *Trust Calculation for Downstream Agent*

Calculating trust on the part of the downstream agent for the upstream agent is based on the following notion:

*“We trust them if they deliver on our order, and we don’t trust them if they don’t deliver.”*

For a downstream agent who places an order to an upstream agent hoping to receive a shipment in response some time later,

$$\text{Action}_{at} = \text{Order Placed}_{a,t-F-*},$$

and

$$\text{Reaction}_{b,t} = \text{Shipment Made}_{b,t-F} = \text{Shipment Received}_{at},$$

where  $*$  is the ordering delay ( $*$  is one period in the supply chain example),  $F$  is the shipping delay ( $F$  is two periods in the supply chain example),  $\text{Order}_{a,t-F-*}$  is the order by the downstream agent  $a$  at time  $(t-F-*)$ ,  $\text{Shipment}_{b,t-F}$  is the shipment made by the upstream agent  $b$  at time  $t - F$ , and  $\text{Receive}_{at}$  is the shipment received by the downstream agent  $a$  at time  $t$ .

### *Trust Calculation for Upstream Agent*

Calculating trust on the part of the upstream agent for the downstream agent is based on considerations of reciprocity:

*“We trust them if they continue to order as much as we have shipped, and we don’t trust them if they don’t demand that much.”*

This notion is as close to the reciprocal of the considerations for the upstream agent in specifying trust for the downstream agent as it is for the downstream agent in specifying trust for the upstream agent.

For an upstream agent  $a$  who makes a shipment to a downstream agent  $b$  hoping to receive an order in response some time later,

$$\text{Action}_{a,t} = \text{Shipment}_{a,t-F-*},$$

and

$$\text{Reaction}_{b,t} = \text{Order}_{b,t-*} = \text{Demand}_{a,t},$$

where  $*$  is the ordering delay,  $F$  is the shipping delay,  $\text{Shipment}_{a,t-F-*}$  is the shipment by upstream agent  $a$  at time  $(t-F-*)$ ,  $\text{Order}_{b,t-*}$  is the order made by downstream agent  $b$  at time  $(t-*)$ , and  $\text{Demand}_{a,t}$  is the demand (order) received by upstream agent  $a$  at time  $t$ .

Trust on the part of the downstream agent for the upstream agent need not be the same as trust on the part of the upstream agent for the downstream agent. It is often observed in the supply chain simulation that if the model is set up to allow this, these two trust measures diverge considerably. Since there is a delay between the time a downstream agent places an order and the time an upstream agent receives the order, and there is a delay between the time the upstream agent makes a shipment and the downstream agent receives the shipment, the trust the agents have for each other can be out of phase, especially for highly dynamic situations in which demand is fluctuating rapidly.

### *Order Share Allocation by Downstream Agents*

In the supply network model, a downstream agent has a trust measure for each upstream agent. The trust measures are used to allocate orders among upstream suppliers in a manner similar to the way backorders were used to allocate orders above. Agents that are trusted more (have relatively higher trust values) are allocated a relatively larger share of the order made by the downstream agent  $d$ , as follows:

$$\text{Order}_{du,t} = \text{Order}_{dt} (\text{Trust}_{du,t} / \sum_u \text{Trust}_{du,t}),$$

where  $\text{Order}_{du,t}$  is the order by agent downstream agent  $d$  placed to upstream agent  $u$  at time  $t$ ,  $\text{Order}_{dt}$  is the order by agent  $d$  at time  $t$ , and  $(\text{Trust}_{du,t} / \sum_u \text{Trust}_{du,t})$  is the relative trust share for agent  $u$ .

### *Supply Share Allocation by Upstream Agents*

In the supply network model, an upstream agent has a trust measure for each downstream agent. The trust measures are used to allocate supply in the form of shipments to individual downstream agents. Agents that are trusted more (have relatively higher trust values) are allocated a relatively larger share of the supply and shipments made by the upstream agent  $u$ , as follows:

$$\text{Shipment}_{ud,t} = \text{Supply}_{ut} (\text{Trust}_{ud,t} / \sum_d \text{Trust}_{ud,t}),$$

where  $\text{Shipment}_{ud,t}$  is the shipment by upstream agent  $u$  placed to downstream agent  $d$  at  $t$ ,  $\text{Supply}_{ut}$  is the supply by agent  $u$  at time  $t$ , and  $(\text{Trust}_{ud,t} / \sum_d \text{Trust}_{ud,t})$  is the relative trust share for agent  $d$ .

These heuristics for using the trust measures imply that greater trust between agents ensures that a larger share of an order will be placed to the trusted agents and a larger share of supplies will be shipped to trusted agents. Agents that are not trusted as much still receive a portion of orders and supplies, but it is relatively smaller.

## **5 EXPERIMENTAL DESIGN**

We run three simulation experiments designed to establish a baseline set of simulation results and explore the effects of adding trust to the supply chain model. In effect, the question to address through the simulation is how the consideration of trust as a factor in allocating orders and supplies influences the structure of the supply network. The modeling strategy is to develop a base case having predictable results, then add other cases individually for comparison, as occurs in a controlled experimental framework. All simulation are deterministic and do not consider stochastic elements. There are five agents at each stage of the supply network.

## Base Case

In the first simulation, all agents at each level of the supply chain are identical in terms of their decision rules, attributes, and resources. Since all agents are identical and face identical conditions, we would expect the results for each agent at each level in the supply chain in terms of the decisions made, inventories, orders, shipments, etc., to be exactly the same too. This symmetry in the agent simulation results would be true for whichever criteria were used for allocating orders (whether on the basis of backorder prioritization without trust considerations or with trust considerations) or for allocating shipments (again, whether on the basis of backorder prioritization without trust considerations or with trust considerations) because in the event of ties, both procedures allocate shares equally among all of the upstream or downstream agents.

The original BGS model includes a number of parameters regarding how agents behave in making supply chain decisions (e.g., adjustment to inventory at each step, the weight put on the demand forecast relative to actual demand), and these parameters are carried over into the network supply chain model. The full definition of these parameters is given in Macal (2003). The overall dynamic behavior of the supply chain is driven by these parameters, which can be varied on a scenario basis. The parameter settings for the runs reported on here are assumed to be in the mid-ranges for all parameters and all experiments. The assumed parameter values are shown in Table 2.

## Backorder Case

In this experiment, we introduce a degree of asymmetry in the agents but only in terms of the amount of inventory with which they begin in the simulation. Allocation decisions are based on backorder levels. Parameter values for the Backorder Case are shown in Table 3.

**TABLE 2** Parameter settings for symmetric Base Case

Parameter/Option	Symbol	Value
Adjustment to Inventory Discrepancy	$\alpha_S$	0.5
Adjustment to Pipeline Discrepancy	$\alpha_{SL}$	0.5
Demand Forecast Weighting	$\beta$	0.5
Upstream Agent Supply Rule		Backorder/backorder proportional or trust <sup>a</sup>
Downstream Agent Order Rule	–	Backorder or trust <sup>a</sup>
Agent Inventory–Factory 1 through Factory 5	Inv <sub>FAC</sub>	{12, 12, 12, 12, 12}
Agent Inventory–Distributor 1 through Distributor 5	Inv <sub>DIS</sub>	{12, 12, 12, 12, 12}
Agent Inventory–Wholesaler 1 through Wholesaler 5	Inv <sub>WHO</sub>	{12, 12, 12, 12, 12}
Agent Inventory–Retailer 1 through Retailer 5	Inv <sub>RET</sub>	{12, 12, 12, 12, 12}

<sup>a</sup> Backorder or trust allocation rules produce the same results because of the symmetry of the agents.

**TABLE 3** Parameter settings for Backorder Case

Parameter/Option	Symbol	Value
Adjustment to Inventory Discrepancy	$\alpha_S$	0.5
Adjustment to Pipeline Discrepancy	$\alpha_{SL}$	0.5
Demand Forecast Weighting	$\beta$	0.5
Upstream Agent Supply Rule		Backorder/backorder proportional
Downstream Agent Order Rule	–	Backorder
Agent Inventory–Factory 1 through Factory 5	$Inv_{FAC}$	{14, 13, 12, 11, 10}
Agent Inventory–Distributor 1 through Distributor 5	$Inv_{DIS}$	{14, 13, 12, 11, 10}
Agent Inventory–Wholesaler 1 through Wholesaler 5	$Inv_{WHO}$	{14, 13, 12, 11, 10}
Agent Inventory–Retailer 1 through Retailer 5	$Inv_{RET}$	{14, 13, 12, 11, 10}

### Trust Case

In the Trust Case, we also introduce a degree of asymmetry in the agents (viz. the symmetric Base Case) but only in terms of the amount of inventory with which they begin in the simulation. Allocation decisions are based on trust levels. Parameter values are shown in Table 4.

## 6 RESULTS

The main results for the three simulation cases are presented in Figures 4 through 6. In the figures, blue solid lines indicate maximum trust levels between both agents on a link in the network. Dashed lines indicate a moderate amount of trust between the agents. The underlying yellow lines indicate the relative amounts of material (shipments) flowing on a link from upstream to downstream agents.

### Symmetric Base Case

The Base Case simulation was run for 600 time periods. The results are depicted in Figure 4 in terms of the average trust and shipment levels over the time horizon. As expected, the results indicate that all the agents in a stage trust all of the agents in adjacent stages (upstream and downstream) by an equal, moderate, amount. That is, since all the agents within a stage are identical, all trust relationships are symmetric and equal among agents in adjacent stages. Shipments are also symmetric and distributed across all agents.

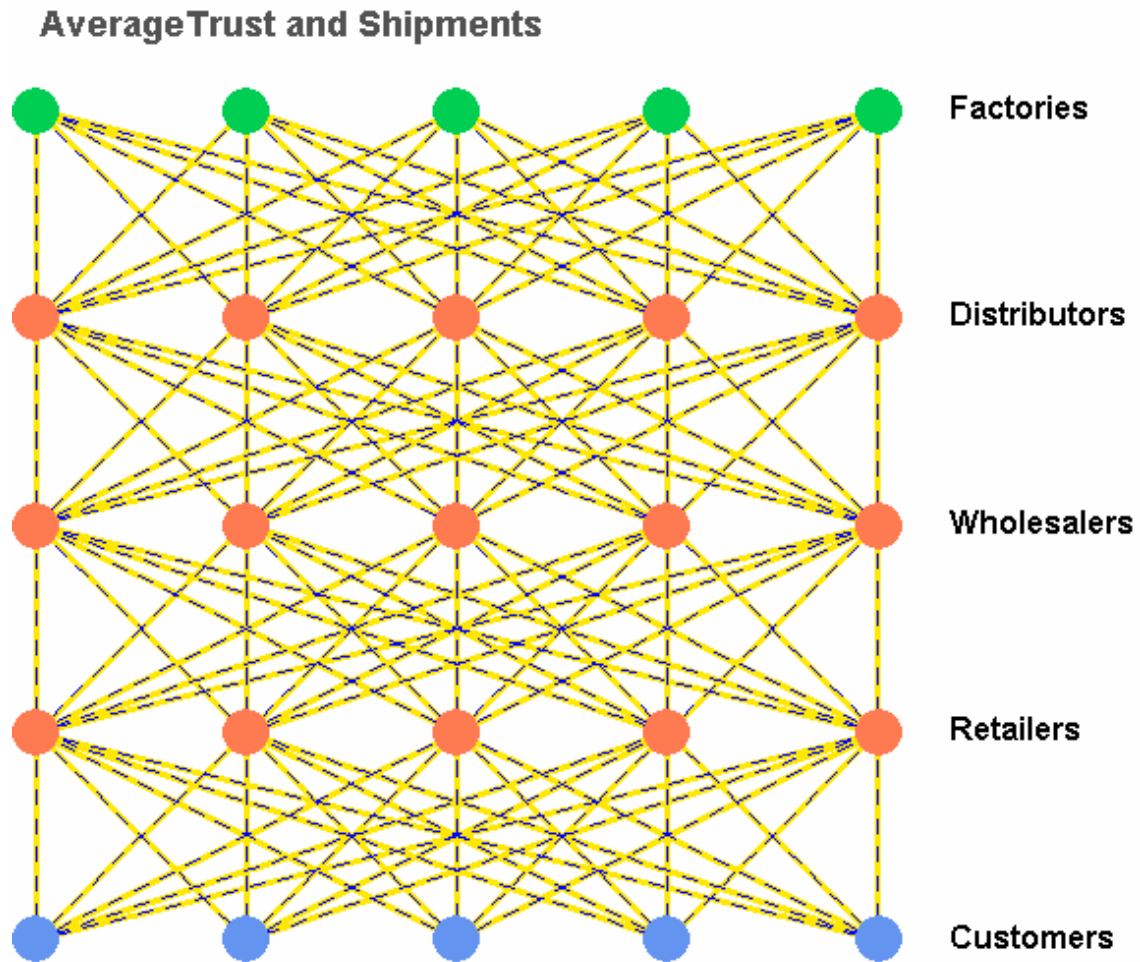
### Backorder Case

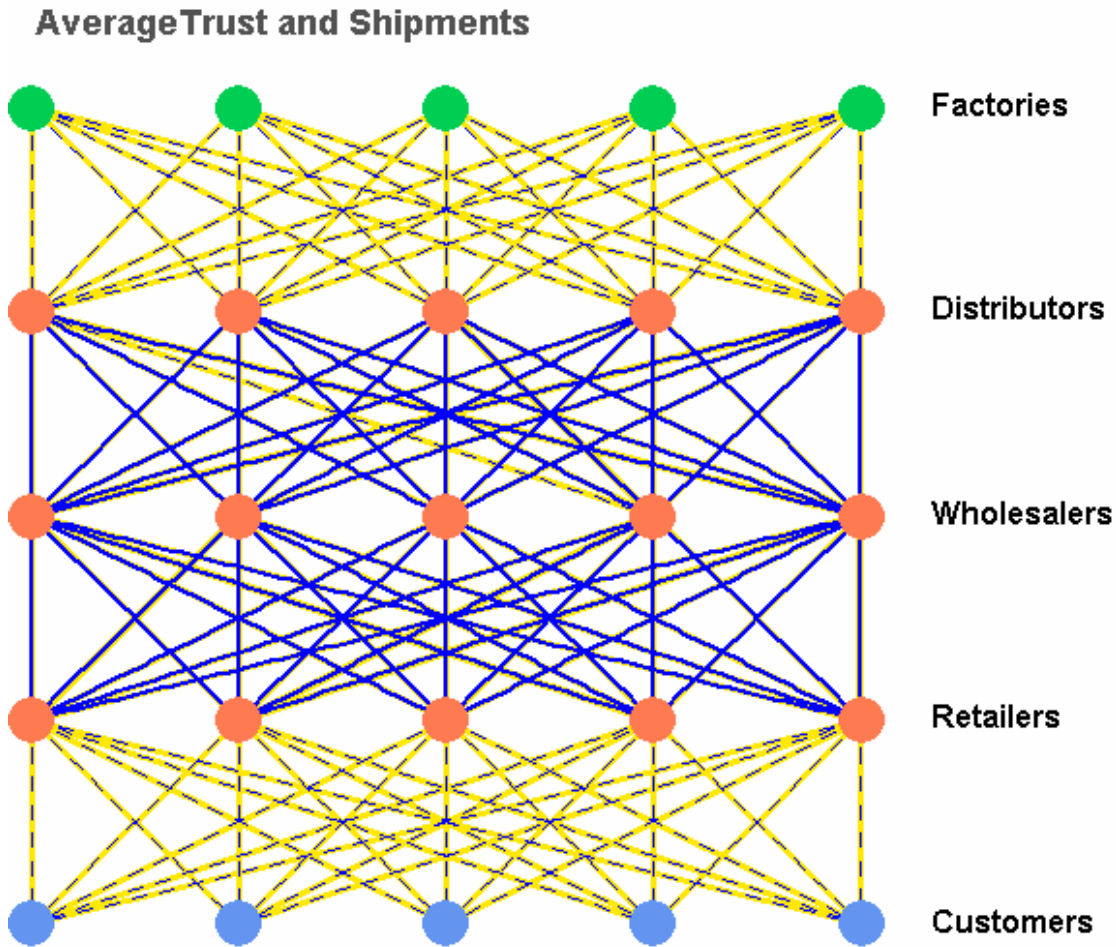
The Backorder Case simulation was run for 600 time periods. In this case, an agent's allocations of orders and supplies are based on backorder levels. The trust levels each pair of agents have for each other are recorded but not used in the allocation process. The results are depicted in Figure 5. The results indicate that the slight variation in the initial agent inventories (all agents are otherwise identical) leads to slight variations in trust and shipment levels between



**TABLE 4** Parameter settings for Trust Case

Parameter/Option	Symbol	Value
Adjustment to Inventory Discrepancy	$\alpha_S$	0.5
Adjustment to Pipeline Discrepancy	$\alpha_{SL}$	0.5
Demand Forecast Weighting	$\beta$	0.5
Upstream Agent Supply Rule		Trust
Downstream Agent Order Rule	–	Trust
Trust Decay Parameter	$\tau$	0.025
Trust Reinforcement Parameter	$\rho$	0.5
Agent Inventory–Factory 1 through Factory 5	$Inv_{FAC}$	{14, 13, 12, 11, 10}
Agent Inventory–Distributor 1 through Distributor 5	$Inv_{DIS}$	{14, 13, 12, 11, 10}
Agent Inventory–Wholesaler 1 through Wholesaler 5	$Inv_{WHO}$	{14, 13, 12, 11, 10}
Agent Inventory–Retailer 1 through Retailer 5	$Inv_{RET}$	{14, 13, 12, 11, 10}

**FIGURE 4** Symmetric Base Case results

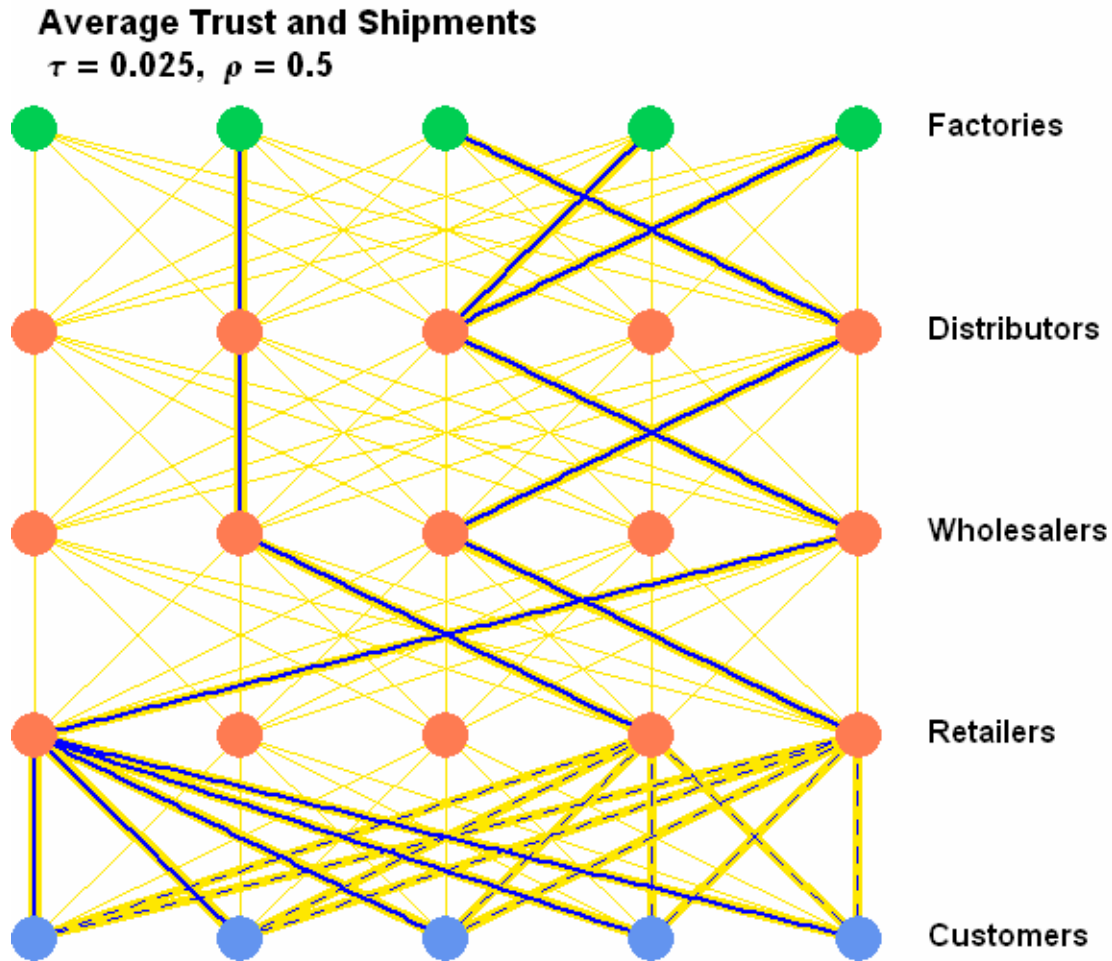


**FIGURE 5** Backorder Case results

agents across adjacent stages. However, there is a significant difference in trust levels observed from stage to stage. For example, only moderate trust levels are observed between consumers and retailers and between distributors and factories. On the other hand, high trust levels are observed between retailers and wholesalers and between wholesalers and factories. This difference is due to the fact that the supply chain inventory levels are continually fluctuating, and the middle stages are better able to smooth out the effects of these fluctuations than are the stages on the end of the chain.

### Trust Case

The Trust Case simulation was run for 600 time periods. In this case, an agent's allocations of orders and supplies are based on trust levels. The trust levels each pair of agents have for each other are used in the allocation process. The results are depicted in Figure 6. Figure 6 indicates that allocating orders and supplies on the basis of trust rather than backorders results in a much different pattern of trust and shipments. Trust relationships develop and sustain

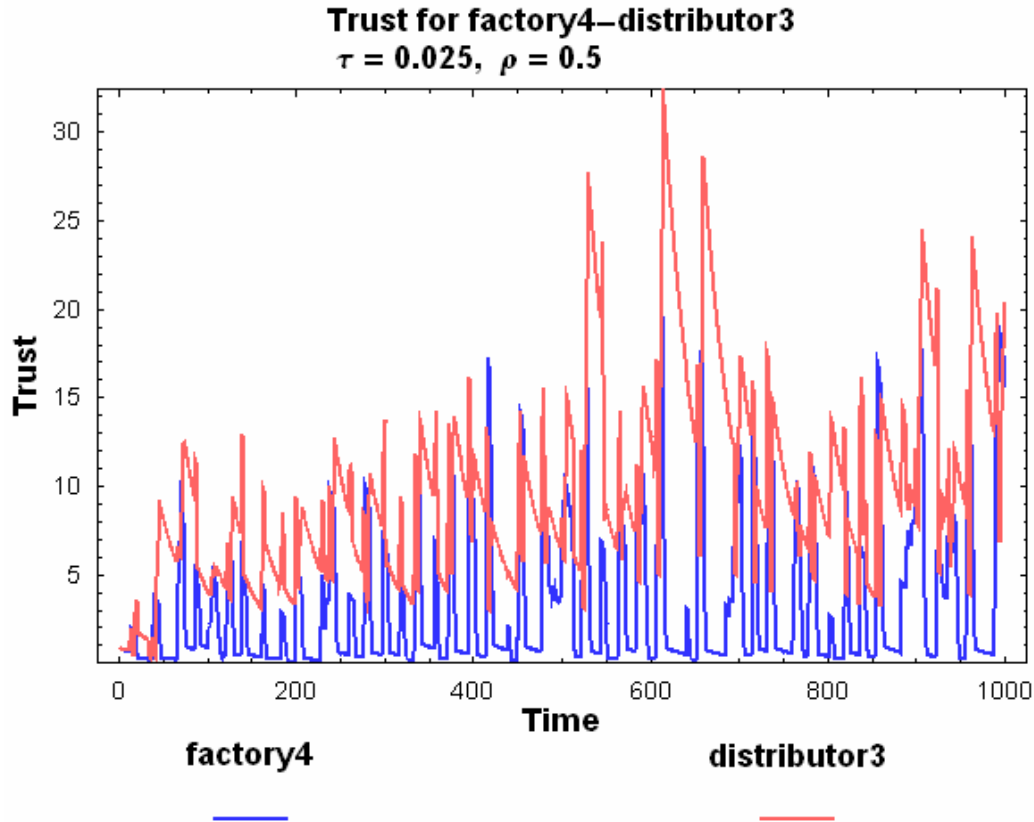


**FIGURE 6** Trust Case results

themselves in a stable way. The effect of trust is the formation of almost exclusive trading relationships between pairs of agents in adjacent stages. Within each stage, three or four dominant agents emerge to the exclusion of the other agents in the stage.

Figure 7 shows the history of one trust agent relationship (between Factory 4 and Distributor 3) over the simulation history. Trust fluctuates over time for each agent in the relationship (Factory 4 trusts Distributor 3, Distributor 3 trusts Factory 4), tracking the supply chain dynamics overall, but the average trust levels over time are maintained at high levels. Figure 7 also indicates that the trust relationships between the agents are symmetric but lag in time, which accounts for the delay between placing an ordering to an agent and receiving a shipment from the agent.

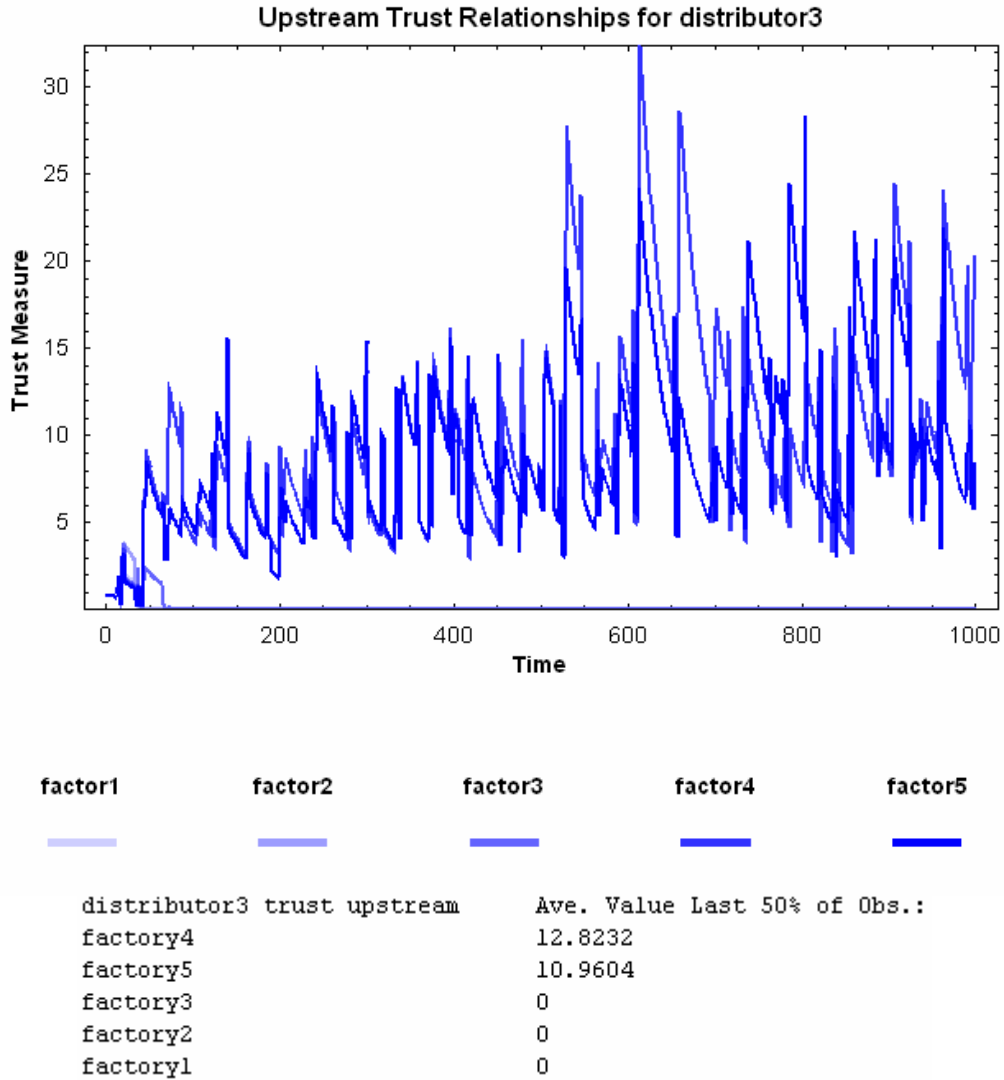
Figure 8 shows the history of one agent's (Distributor 3) trust relationships with all the other agents in an adjacent (upstream) stage (factories) over the simulation history. Trust fluctuates over time for each agent in the relationship, but average trust levels over time are sustained at high levels for a subset of the factories (Factories 4 and 5). The distributor's trust of the other factories (and vice versa) quickly dissipates to zero and remains there.



**FIGURE 7** History of trust relationship for Factory Agent 4 and Distributor Agent 3

## 7 SUMMARY AND CONCLUSIONS

We have developed a conceptual framework for modeling the endogenous emergence of trust relationships. We have applied the trust framework to modeling the dynamic relationships between producer (upstream) and consumer (downstream) agents in a supply chain network model. The results indicate that considerations of trust relationships as exemplified in the reciprocation of actions, in the form of order and shipment fulfillment, can build sustainable relationships within the supply chain that significantly alter the structure of the supply chain when compared with standard allocation heuristics used in the industry that do not consider social factors. Furthermore, these trust relationships may alter the dynamic behavior (performance) of the supply chain in ways that improve its stability. This paper has shown how social factors, such as trust, could be considered in modeling supply chains, in addition to the economic and structural factors that are commonly considered in such modeling. In future work, we will expand the limited number of test cases studied here to the full range of parameter values, agent heuristics, and possible network topologies to determine whether this conclusion can be generalized more broadly.



**FIGURE 8** Upstream trust relationships for Distributor Agent 3

### ACKNOWLEDGMENT

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**DISCUSSION:****SUPPLY NETWORKS****(Saturday, October 9, 2004, 3:45 to 5:45 p.m.)**Chair and Discussant: *Richard Cirillo, Argonne National Laboratory***Learning to Order in Supply Networks: An Agent Modeling Study**

**Richard Cirillo:** We have the somewhat dubious distinction of trying to return the group from the brink of war to a more peaceful environment, both internationally and locally. We have a number of papers now that are going to focus on the application of agent-based modeling to supply chains and some economic situations associated with them. Our first paper is by Yifeng Zhang from the University of Illinois at Chicago; he's going to be talking about learning to order in supply networks.

**Yifeng Zhang:** I'm a doctoral student at the University of Illinois at Chicago, and this is a joint work with my adviser, Sit Bhattacharyya. I'm working on determining the performance of machine learning algorithms when applied to modeled agent supply networks.

[Presentation]

**Cirillo:** We'll now open the floor for discussion.

**Unidentified Speaker:** I really like your paper, and I think it's very important because I think we desperately need to find a good learning algorithm that we can incorporate into models, one that works well enough that we can say that people must be using something like this in the real world. I have one question. I see that these Q learning algorithms and experiments require 50,000, 100,000, or 1 million repetitions to get the thing to converge. Would it be fair to say that it would take 1 million years to converge a supply chain system in the real-world analogy?

**Zhang:** I think that depends on the complexity of your supply chain or supply network. Also, it depends on the efficiency of your program. But, yes, for a very complex supply chain, the learning would take a lot of time. That's one of the challenges from a computer science perspective.

**Unidentified Speaker:** I have a follow-up question. Could it be that real systems out in the world have prelearned elements that operate close to an optimal learning situation, so that the challenge then would be to respond to deviations, which would not involve a learning process that was so onerous? Would that be a possibility?

**Zhang:** I guess, yes. In the real world, supply chains are run by human beings, who after many years of experience have learned how to operate them close to the optimal situation. But I think this model gives you a tool for examining some new situations. You can do experiments with this model.

**Cirillo:** We have time for one more question.

**Brian Pijanowski:** Brian Pijanowski, from Purdue. Very interesting work. I've worked with artificial neural networks that do similar things, and I've found that they learn fairly quickly. We're talking about, say, less than 10 to 20 training cycles. You presented it with rather complex data, and it exhibited some learning. Have you thought about using or comparing your technique against some other tools, such as neural networks?

**Zhang:** No, we did not make comparisons with neural networks. But I think this one's learning process is not as quick as you describe — I mean tens of cycles — because the system itself is very dynamic. That's why, for example, even if you keep the SSC value constant, the profit fluctuates a lot. That partly explains why the learning takes so long. It's not as if there's a corresponding profit for every SSC value. That's not case for this model.

**Cirillo:** We'll see if we have time for some more questions at the end of the session. Let's press on with our next presentation.

### **Agent-based Distributed Simulation Platform for Evaluating Production Planning Strategies in Forest Product Supply Chains**

**Cirillo:** Luis de Santa-Eulalia is going to talk about, "An Agent-based Simulation Platform for Production Planning Strategies Evaluation in Forest-Product Supply Chains." So we're moving into the woods now.

**Luis de Santa-Eulalia:** I'm a Ph.D. student at Laval University, in Quebec, and these are my co-authors, my adviser and co-adviser. Actually, I am not a social scientist. I'm a computer scientist. My background is in industrial engineering. First, I will briefly introduce my work, and after that I will present our problem, a supply chain problem. Next, I will briefly discuss our experimental planning platform and a future challenge that we have called the simulation hub. Finally, I'll end with some concluding remarks.

[Presentation]

**Cirillo:** We can take a few questions while our next speaker is getting set up.

**William Lawless:** Bill Lawless. Have you gotten any results on what are you doing in the last slide that you showed — on the simulation? Are you looking at predicting and forecasting? How does that match up with the sensory data that you have?

**de Santa-Eulalia:** This is a very important question. It's very important to compare the simulated data against real data, but we haven't done that yet. We will start the simulation at a later time.

**Lawless:** When do you think you might have that?

**de Santa-Eulalia:** I think in two years. Yes, in two years.



**Elenna Dugundji:** Elenna Dugundji, University of Amsterdam. I was wondering how far along you were on the second-to-last slide where you talked about the simulation hub. I realize that you said this is one of your future challenges, but I was wondering if you could add a few more words about how far along you are and what are the main challenges that you expect to face to be able to do this.

**de Santa-Eulalia:** To answer your question, the layer that has a set of agents that incorporate a lot of algorithms for operations research to produce production plans using mathematical methods is ready now. Our next challenge is to implement and validate the simulation layer. After that, we will consider how to integrate a lot of systems together and show how to integrate the different simulations in this system by using the ideas discussed in the last presentation of the high-level architecture, for example.

**Steve Upton:** Steve Upton, Referentia. Have you thought about simulating the whole thing with the simulation embedded in the system before you start building all of the other stuff? You've got the legacy systems; those actually can be simulations in your simulation.

**de Santa-Eulalia:** That's a very interesting idea. I haven't thought about that, perhaps because I think it's hard to simulate a real supply chain using the traditional approach. We're talking about a lot of information, and a company often doesn't want to share its model.

## Growth of a Hydrogen Transportation Infrastructure

**Cirillo:** Next we move out of the forest and off into the wild blue yonder of the future. Craig Stephan is going to talk to us about, "Growth of a Hydrogen Transportation Infrastructure."

**Craig Stephan:** I'm sure you're all aware of the work that's been stimulated recently by federal government funding on developing hydrogen-powered vehicles. These are either vehicles that use fuel cells or simply internal combustion engines that operate on hydrogen. There are benefits and drawbacks to going to hydrogen-powered vehicles. One benefit is that they don't emit CO<sub>2</sub>, which is an important greenhouse gas, and, as a result, will not contribute to global warming. They also reduce our nation's dependence on petroleum.

[Presentation]

**Unidentified Speaker:** It was a very nice presentation about focusing on and modeling a policy issue. I just wondered if you were contemplating building models in which hydrogen-powered vehicles were given away free to a small set of teenagers, who would automatically drive enough miles to create the fueling stations in vast supply.

**Stephan:** Well, that's an interesting idea. I would suggest that you go try to sell it to our upper management and see how far you get.

**Unidentified Speaker:** Definitely a social dynamics question.

**William Lawless:** Bill Lawless. I enjoyed the presentation, too. I do a lot of work with the Department of Energy's Savannah River Site, and people there are experts in tritium. They

also have been working on the hydrogen economy for some time, and they've got some cars running. One of the things that I was struck by in a presentation recently was the great caution with which they approach these vehicles when refueling. I think that there's an unexplored component of this meaning the hazards associated with hydrogen, in addition to the storage problem.

I think would be interesting to look at these hazards because if there are explosions, or what have you, and loss of life early on, that might change the outcome substantially, particularly because we don't have the history that we have with petroleum and gasoline. Also, I think it would be interesting to look at a trade-off study with hybrids, which I think are much safer and have a much more immediate payoff.

**Stephan:** I completely agree with all of the remarks you made. We've been working internally on a study comparing hybrid, diesel, hydrogen, and fuel cell vehicles with respect to the amount of savings there would be in CO<sub>2</sub> generation and the like. My personal feeling is that auto companies and fuel cell manufacturers should continue working on hydrogen because it ultimately might be the fuel of the future. But I don't think we should do that at the expense of looking at more conventional approaches like diesels and conventional hybrid vehicles.

Just a quick remark on safety. I also agree with you there. Ford had an unfortunate experience with the batteries for electric vehicles, and we had some fires with the batteries. As you know, some solvable problems could kill the whole affair if they occurred early. Again, my personal feeling is that hydrogen is not more dangerous than gasoline; its dangers are simply different than those of gasoline.

**Cirillo:** We have time for one more question.

**Unidentified Speaker:** I have a minor technical question. I didn't understand the distinction between worry and inconvenience in general and worry and inconvenience specifically for hydrogen vehicle drivers.

**Stephan:** Let's talk about worry. For every driver agent, I looked at what his worry was at each time step. Remember, worry was the accumulated worry that he generated in making his various random trips. I simply took the average of all the drivers, whether they drove conventional vehicles or hydrogen vehicles. I'm sorry, I probably didn't make one thing clear. When we calculate worry, it's not just the hydrogen drivers that are contributing to that value; it's everybody. I'm driving a conventional vehicle, and I want to know whether I should buy a hydrogen vehicle, so I'm going to watch out for hydrogen stations. So worry is both actual worry for hydrogen-fueled drivers and the potential worry for those who would consider switching to hydrogen.

**Cirillo:** Very good. Thank you very much, Craig.

## **Emergent Structures from Trust Relationships in Supply Networks**

**Cirillo:** Our last speaker is Chick Macal, who is going to talk about emergent structures from trust relationships in supply chains.

**Chick Macal:** Well, Dick, since you recited the title, I will point out a couple of things. First, this is a conference on emergence. We are in a supply chain session, and I ask for your trust on this.

[Presentation]

**Dugundji:** Elenna Dugundji, University of Amsterdam. I thought this was a wonderful presentation. I had a question about your last demonstration. I wonder if you had developed any intuition about why you get such a pattern under the conditions of your model.

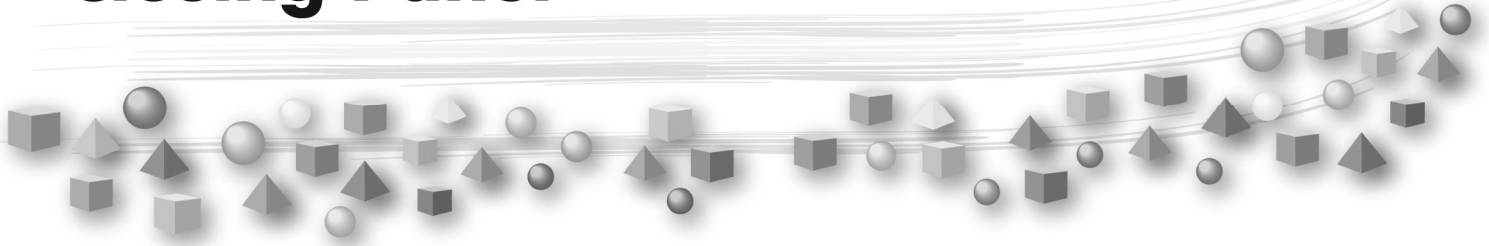
**Macal:** The short answer has to do with the fact that slight differences in inventory create situations in which agents run out of inventory to meet the orders that are coming upstream. Then there's the fact that the running out occurs at slightly different times and places because of the initial variation. That causes the trust relationships along the immediate links to be degraded, and that, in turn, causes the trust relationships to have a cascading effect that permeates through the network.

There is also the effect of certain effects cascading down the network and then cascading back up the network again. By the time the process stabilizes, there's no real intuition that I've yet been able to find as to calling out the winners in advance. You'll notice it's not necessarily the ones who had that extra unit of resource because of the dynamics of the situation. But I would say this, the really exciting part is the trust relationship. You have essentially positive feedbacks such that when trust starts to decay, it really collapses at the individual-link or relationship level. Many of these links that are just getting a boost for trust are just as likely to be destroyed. The other links, by comparison, have trust building themselves up. As a result, you've got these positive feedback loops destroying trust and building it up. They are occurring at different places in the network, staged through different time space. At this point, that's about the best answer I can give.

**Cirillo:** Very good. Thank you very much.



# Closing Panel





## CLOSING PANEL

BRIAN PIJANOWSKI, Purdue University  
FABIO ROJAS, Indiana University, Bloomington  
NOSHIR CONTRACTOR, University of Illinois at Urbana-Champaign

**Charles Macal:** We're going to have the closing panel now. We have Brian Pijanowski, Fabio Rojas, and Nosh Contractor on the panel. Brian Pijanowski, who is from Purdue University, has been here for the whole conference. Nosh Contractor, from the University of Illinois, specializes in communication. Fabio Rojas is from Indiana University, and his specialty is sociology. With that, I'm turning things over to Brian.

**Brian Pijanowski:** Thanks. I put together some general observations. I took a lot of notes, and I thought that the presentations throughout the three days were outstanding. Every presentation was of high quality, had lots of information, and I learned a lot. I'm an ecologist; I think about spatial systems, so some of the perspectives I'm going to bring to this conference relate to that background.

The first observation, of course, is that I've always thought that this has been a first-rate conference. And the price was right. So thanks to the sponsors for doing a fabulous job of organizing this and doing it at no cost to us, other than a hotel bill. I wish more conferences were like this.

I was really excited on the first day when I started seeing and hearing about Repast and GIS. Talk about that integration really excited me when we were here last year. Seeing how far this group has come is truly, truly amazing, and to have these tools tightly coupled excites me as a spatial ecologist.

The discovery of space is one of the final frontiers with many sciences. When you look at some of the ecological literature, in particular, you realize that looking at biophysical systems across space is one of the more complex dimensions of the science. I'm hopeful that the integration of these tools will start to enrich our thinking about agent-based systems and how they actually behave in space.

The third observation I have is that we can begin to potentially integrate what I would call the social theory and the theories of the spatial sciences with these tools. You really don't have to go too far to look at some of the major components of the spatial sciences because they are encapsulated, for the most part, within GIS, within the structure of the systems, to the point that many people are speaking not in terms of graphic information systems, but in terms of geographic information science — that captures both the tools and the idea of space.

I also think that location could be one of the integrating themes tying together the social and natural systems because you can now bring in the dynamics of those systems, with space acting as an integrating force. I'm excited about that potential. However, I think we need more dialogue between social scientists and the ecologists who are thinking about agent-based spatial systems.

Another caveat is that we're opening up the potential for spatial tools to bring more data into our models. There is a massive amount of spatial data out there. It's overwhelming, but what's exciting is that we can now think through some models that have some reality, at least in a spatial context. There are going to be some challenges along the way, technical ones that all of us have gone through, as with the learning curves of GIS, such as getting the databases together in the same projection. That's kind of like GIS 101. You get students to sit down behind GIS, give them two shaped files, and, lo and behold, they don't overlay, which is because they're in different projections. So there are going to be some challenges along the way, and some learning curves.

We got Repast a couple of hours ago, and Kostas fired up one of the GIS layers that we work with here. This involves land use; we have a national database. The whole thing is about three-quarters of a terabyte in size, so it's a significant database, and this is showing Chicago, southern Lake Michigan — very, very complicated, very, very detailed land use down to about 300 different categories of land use. We can now start thinking about dispersing our agents across this spatial simulation environment.

The fourth observation I had is that when I compare this conference against some others, I find it is well balanced in the way in which we talk about tools, theory, and applications. I don't see that in other conferences, and it's really exciting to see people communicate about tools, theory, and applications all at the same time. I think that means that we're going to see rapid advancements in the science, because we're all thinking about these ideas simultaneously.

The fifth observation involves this notion that we talked about earlier today and yesterday — the idea of simplicity and complexity — which seems to me to not be cut and dried. It may be an eye-of-the-beholder perception, but I wonder whether we can refer to our models as both simple and complex at the same time. They *are*, I think, in many cases. There are some complex dimensions to many of our models. However, at the same time, they *are* simple.

And then, observation six, I can't wait for next year.

**Fabio Rojas:** My name is Fabio Rojas. I teach in the Sociology Department at Indiana University, and it's a great pleasure for me to be here again. I participated as a commentator or as a chair of a panel about two or three years ago and had the pleasure of seeing multiple versions of the same projects and seeing them grow in richness and in their appeal to a wide range of audiences.

I personally find this an interesting conference for the same reasons that our previous speaker mentioned. There are many people from many different fields — from engineering, management, forestry, urban studies, sociology, and psychology. It's a pleasure to see that kind of interdisciplinary work in one place.

I'm just going to mention a few thoughts that I've had regarding the place of computational sociology. I'm a sociologist. I know very little about engineering. I know very little about these other fields. So let me talk about something that I do know about and how some of the research today might fit into that larger perspective.

One piece of good news is that there's been a great growth in computational sociology since the last time I offered comments at the concluding panel. It would be a lot easier for the



presenters today to communicate their ideas and findings to sociologists than it would have been two or three years ago. Even four or five years ago, most people in sociology didn't even understand what a simulation was, but that's really changed.

For example, the *Annual Review of Sociology* has published a review article on computational methods and another review article on mathematical sociology that often touches on computational methods. One of the flagship journals, the *American Journal of Sociology*, will dedicate an entire issue to computational issues. Other top publications in sociology have also published simulations or papers that include simulations in them at least once or twice a year.

One of our speakers this afternoon talked about computational experimentation. There are many more articles today that present an empirical result and then ask how typical the result is by considering a different specific model. Many more papers are appearing with that kind of reasoning in them than, say, only two or three years ago. Of course, there are a number of specialty journals, which I think are great places for people to find out about different kinds of computational work from all perspectives.

My big interdisciplinary ax to grind, which I'll subject my captive audience to for the next minute or so, is that I find a lot of computational work is not systematic. I don't mean that in the sense of going through a parameter space or estimating the effects of one parameter on another, but essentially in terms of what mathematicians might call axiomitization.

For example, in social psychology and sociology, and there were some papers at this conference concerning social psychology, there are 8 million diffusion models, even more influence models, and they're all over the place. One question I have is, what do they have in common? Why do we rebuild the same model over and over again? I don't know. That's the first question that I wish we'd think about at a more abstract level. You could you come up with a set of axioms that characterize or influence your diffusion processes. Then you could say, "Well, perhaps the influence that people have on other people in adopting certain forms of transportation is an example of a such-and-such style system." We have no idea how to do that. It would be great if we did.

The second big concern is similar, a basic question about social psychology and social structure, where once again we have many different models of how, for example, the very last paper in the last panel (Chick's paper on supply chain dynamics); there's a bit of trust in there, and some social structure emerges from that. I'd like to encourage all of the political scientists and anthropologists and other social scientists in this room to think about different kinds of social structure, not just stable networks, but organizations and states and family structures and kinship structures. I invite you to try to come up with common themes. You could do that in terms of certain psychological mechanisms leading to certain other kinds of social structures. That kind of reasoning is, once again, not present in contemporary sociology or in many of the other social sciences.

Another topic that I think deserves a lot more attention in sociology is a big topic with one of our organizers, David Sallach. It involves the construction of meaning. If you look at a lot of agents in many of the papers, they have very straightforward rules for doing things. Maybe there are many parameters that go into the rules, but basically the kinds of things that these agents think about are essentially high school algebra problem-solvers. Maybe we need something a little bit bigger.

For example, during the question-and-answer session, somebody talked about neural networks. In sociology and the social sciences, we don't see very complicated actors who learn things and process lots of information. They may have a lot of parameters, but the parameters often have some sort of linear rule or some sort of threshold rule. We have very, very simple agents.

My fourth ax to grind involves my colleagues. I hope I can inspire them to think more carefully about rationality. One paper addressed rationality this weekend, but we don't have a systematic inventory of when people are rational. They're bound to be rational; they're following rules; they're following heuristics. How do the social structures, the outcomes, and the aggregate outcomes really change? Of course, we have this great technology in which we can build models in which you can provide answers for a specific case, but we don't have a systematic approach.

Once again, thanks very much to our organizers, Chick, Dave, and Mike. Thank you to The University of Chicago and Argonne National Laboratory for putting this on for many years, and thanks to all for presenting your great papers. I hope that these kinds of axes to grind, this pushing people to think more systematically about the underlying logic of all these different models, so they come up with comprehensive ways of looking at them — I hope that'll inspire some good thinking and an interesting dialogue. Please e-mail me if you have cool ideas to share.

Thank you very much.

**Noshir Contractor:** And now it's just me between you and the end of this conference and hopefully a relaxed evening. I'll try to keep this as brief as possible. My name is Nosh Contractor. I'm from the University of Illinois in Urbana-Champaign. Like Fabio, I've had an association with this meeting for several years. I also want to thank Michael and Chick and David for drawing me in and welcoming me into this particular community over the last several years as a discussant and a respondent, and mostly as just a very active student, learning a great deal about a certain diversity and selection, based on the same points that you mentioned. It's not just diversity, but it's also high quality across these different sectors that makes this a very, very interesting event, and one that I look forward to every year. I think it's one of those events that runs the risk of becoming the victim of its own success. If the quality and the size are not managed, then it could go the way of many other events that get too large for their own good. So I would urge the organizers to continue to maintain the size of this event and not invite too many people other than those who are already here and a few other bright young scholars who want to be part of this, to keep that critical mass, but not make it too large.

In terms of the presentations, as I said, I think there has been an incredible evolution of ideas over the last few years — I would say a co-evolution of ideas, in keeping with some of the terminology that we use here. I didn't think of it as an ax to grind because that seemed a little too violent, but I do have a point that I have been pondering because of my own biases, as I've heard the presentations over the years, including right up to the very last one that Chick made. I may use that particular presentation to illustrate some of the issues just because of the recency effect for those of us here.

The issue that I want to talk about can be reduced to one word — *network*. In the interest of full disclosure, I should say that this is my own area of work. I just finished a book last year entitled, *Theories of Communication Networks*; it was published by Oxford. In that book, I looked at a lot of different theories of why we create, maintain, dissolve, and reconstitute

network links as individuals, agents, and aggregates. I have a whole chapter on why agent-based modeling is an important part of theory construction and theory testing within the context of networks.

With that as disclosure, not all agent-based models are modeling networks. However, I would suggest that almost any network model ought to be an agent-based model. I'd like to see even more agent-based models that specifically focus on the relationships among agents — what links come about; how they are created; how they are maintained; how they are dissolved; and how they may influence the creation, maintenance, and dissolution of new network links. I'd like to see more time spent on the implications of that. I think that lends itself very well to the sort of bottom-up approach that has been at the forefront of the defining features of a lot of agent-based models and has helped in understanding some of these emergent properties. As I said, I've seen a lot more this year than I did last year and in preceding years, but I still see incredible room for growth. I would suggest that we go beyond looking at the network properties of some of these situations, like the scale-free networks that we saw today.

A huge amount of literature in the social sciences — sociology, political science, communication, and other areas — focuses on the theoretical mechanisms that determine how these links get created, maintained, and dissolved. Chick, to go back to an example, used reciprocity as an important mechanism for how trust may be engendered or in some cases undermined. There are other examples. We've talked about friends of friends having an impact on trust. Balance theories are well-established, well-tested theories of how you look at different social science mechanisms that explain why that trust may be enforced.

There are also more macro-level issues, such as why trust may be greater between two agents if they are embedded within a highly connected network, as opposed to trust between two agents that may not be so high or trust that may not be preserved if those two networks are not embedded within a dense social network.

So there are sets of theories that focus on self-interest, on social exchange, on collective action, on proximity, on homophile, and on co-evolutionary mechanisms. I think that agent-based modeling researchers would do well to look at the catalogue of different mechanisms and see the extent to which they may be multiple theories that are simultaneously imposing on how these networks emerge and evolve within an agent-based system. I think there's a tremendous potential for growth here, and understanding new insights would be a good way of doing what we already do, combining social sciences with computational sciences, and so on. I think that ecology is one important area — looking at multiple theoretical mechanisms very systematically, while drawing upon what has already been done in the social sciences.

Now, this is not easy work, and I don't want to send mixed messages about it. One of the reasons it's hard work is an issue that I don't think has been well addressed by the agent-based community, but it's very germane to people who do social network analysis, and that is the special statistical challenges that arise when handling network data. Network data are not independent data, so many of the statistical techniques that we use in handling other kinds of data are not appropriate when you're looking at network data.

We saw today, and know from our past experience, that some of the best calibration and empirical validation rely on going out and collecting some data, getting some coefficients, and then using those estimates as a way of running different kinds of models. You do a regression,

get coefficients from there, get estimates from there, and do something in a dynamic context. As we saw this morning with Hedstrom's presentation, we looked at panel data, were able to get the coefficients, and then put them into a model to see what happens. I think that's exactly the right thing to do. But we have to be mindful that when we're looking at dynamic network data, traditional statistical techniques that we would use for non-network data do not always apply.

That's the bad news. The good news is that there has been a lot of very exciting work within social networks recently that looks at new statistical techniques that are based in some ways on MCMC techniques that try to develop robust statistical parameters for an understanding of the dynamics of networks. For example, there is a whole line of work that my former colleague and Fabio's new colleague, Stanley Wasserman, has developed over the years — the  $p^*$  techniques for looking at random graph models. Philippa Pattison and Gary Robins at the University of Melbourne have done some very important work in this area. There are software tools that have been developed by Thomas Snijders and his group at the University of Groningen. They have a program called SIENA, which, given some of what I've heard in this room, may be of interest to you. It's S-I-E-N-A, Simulated Investigation of Empirical Network Analysis. SIENA allows you to estimate parameters for how different mechanisms and networks may change from one time period to the next.

I think that using those kinds of parameters — those kinds of techniques — and then dovetailing that back into the type of computational models we're talking about here provide a very promising new area, and I would strongly encourage some of you to either get your students or colleagues to see if there are presentations and research that you could do that would build on those kinds of models, so perhaps at Agent 2005 we may even have some papers that are able to combine those kinds of approaches.

Those are the theoretical and statistical moves in the network context that I think would be good ways of advancing agent-based research. Frankly, if I was talking to social network friends, I'd also say it advances social networks research in ways that would really benefit them.

In closing, there are a couple of comments we've heard today about complexity and simplicity. At the risk of repeating myself, as it turns out from a couple of years ago when we had a similar discussion — you know that we are in the Windy City. We can argue that there's been hot air in this room for some of the last two or three days, but there is another model, and this discussion about simplicity and generalizability and complexity goes back to empirical construction. For several decades there has been the GAS model that some of you may be familiar with, hence the allusion to hot air and Windy City. Familiar with the GAS model? Think of a clock. On the 12:00 is generalizability, at 4:00 is accuracy, and at 8:00 is simplicity. The argument here is that you can never have a model that does all of those things. If you try to put something at 2:00, between generalizability and accuracy, that model is not going to be simple. If you put something at 6:00, between accuracy and simplicity, it's not going to be generalizable. So, I think that debate that we've heard today goes on, but it's not germane just to computational or agent-based modeling; it's been there for all of theory construction, well before the term "agent-based modeling" was even coined.

Finally, I'd say for those of you who were here yesterday that I did not expect to learn some things. I didn't expect to spend as much time reflecting on whether two socks would make an entity or not. I'm also glad that I had the opportunity to share that discussion with many of you in this room. So thanks again for staying on this late. I appreciate it.

**Chick Macal:** Well, there's room for a question or two, just in case anyone wants to get something off their chest, so to speak. But, if not — and while you're considering that — I just want to say a few thank you's. I would like to thank very much my co-organizers. David Sallach — you ought to get a special hand — and Michael North, but also Michael North for doing the Repast training course. I'd especially I'd like to thank our closing panel: Brian Pijanowski, Fabio Rojas, and, again, Noshir Contractor. Thank you very much.

I'd like to thank our invited speakers, especially Roger Burkhart and Michael Macy and Peter Hedstrom. I'd like to thank the persons who prepared our conference materials, designed and implemented the Agent Web site, and eventually will prepare the proceedings: Margaret Clemmons and Michele Nelson.

I'd especially like to thank Kathy Ruffato for the enormous amount of administrative work. There are no limits to how much energy she puts into making this conference successful. I usually try to make myself scarce the week before because by then I can't handle it anymore. So she makes all of the decisions because she can't find me and David and Mike.

I'm sorry if I forgot anyone to thank. Also, the proceedings will be on a CD. It turns out that people seem to prefer that, and if you'd really like to, you could always print it out on a nice color printer because we do make it really nice. The document itself makes a nice hard copy, if that's what you'd like to have.

For those of you who have turned in your papers and done that paperwork, thank you very much. If there's anyone out there that hasn't, we will be coming after you, and we're going to get this put together as soon as we receive all the papers. There is an extreme amount of interest among the participants to read the papers that were presented, probably more interest than I've ever seen before. So I think it'll be unfortunate if somehow we weren't able to get the proceedings out very quickly. So turn in your papers. We know where you live.

In any case, again thank you very much, and let's declare Agent 2004 a success. We'll see you at Agent 2005. Thank you very much.

**Unidentified Speaker:** Well, we should definitely thank Chick for all that he's done in organizing, chairing, and so forth.



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