Fostering Industrial Symbiosis With Agent-Based Simulation and Participatory Modeling

David F. Batten

Keywords:

coevolutionary learning
companion modeling
complex systems science
complexity
eco-efficiency
industrial ecology (IE)

Summary

The sciences of industrial ecology, complex systems, and adaptive management are intimately related, since they deal with flows and dynamic interdependencies between system elements of various kinds. As such, the tool kit of complex systems science could enrich our understanding of how industrial ecosystems might evolve over time. In this article, I illustrate how an important tool of complex systems science—*agent-based simulation*—can help to identify those potential elements of an industrial ecosystem that could work together to achieve more eco-efficient outcomes. For example, I show how agent-based simulation can generate cost-efficient energy futures in which groups of firms behave more eco-efficiently by introducing strategically located clusters of renewable, low-emissions, distributed generation. I then explain how role-playing games and participatory modeling can build trust and reduce conflict about the sharing of common-pool resources such as water and energy among small clusters of evolving agents. Collective learning can encourage potential industrial partners to gradually cooperate by exchanging by-products and/or sharing common infrastructure by dint of their close proximity. This kind of coevolutionary learning, aided by participatory modeling, could help to bring about industrial symbiosis.

Address correspondence to:
Dr. David F. Batten
CSIRO Marine and Atmospheric Research
Private Bag 1, Aspendale, Victoria 3195,
Australia
david.batten@csiro.au
www.complexsystems.net.au/index.php?page=profiles&profile=10

DOI: 10.1111/j.1530-9290.2009.00115.x

Volume 13, Number 2

Introduction

Traditionally, business, the community, and the environment have been viewed as separate systems, operating independently of—even in opposition to—one another. For example, industrial systems tend to emphasize the independence and competitiveness of firms, whereas ecological systems emphasize interaction and interdependence. Awareness of the real interdependencies between these systems is increasing, however, and this highlights the need for a systems-oriented framework that protects the natural environment while improving business performance. Industrial symbiosis is evolving to unite the needs of industrial and natural systems. By working together, a community of firms can enjoy a greater collective economic and environmental benefit than the sum of the benefits each would realize if it strove to optimize its own performance alone.

A close relationship exists among industrial symbiosis, complex systems science, and the adaptive management of natural resources. All of these involve interdependencies between system elements of various kinds. Our world's ecosystems are inherently difficult to manage successfully because of the complexity and uncertainty associated with their ongoing evolution. Much of this complexity and uncertainty stems from human sources. For example, economic agents in a market or social agents in a community are continually making decisions about whether and how to work together in a competitive or a cooperative manner. What they decide has important implications for the biosphere in which we all live. Thus, it is imperative that we expand our limited knowledge about how and why people choose to interact with each other in one way or another and how their collective decisions affect our biosphere and its ecosystems as time passes.

Fortunately, complex systems science can help to deepen our currently primitive understanding of how human ecosystems might grow and change over time. Complex systems science is sufficiently different from normative science that we may view it as a new kind of experimental science. Traditional observation and experimentation are still alive and well, of course, but they have been joined by a new, experimental breed of computational science known as *simulation*.

In this article, I illustrate how two tools of complex systems science—*agent-based simulation* and *participatory modeling*—can help researchers to identify how various participants in an industrial ecosystem could work together to achieve more eco-efficient outcomes. For example, I show how agent-based simulation can generate alternative energy futures in which groups of firms behave more eco-efficiently by introducing strategically located clusters of renewable, low-emissions, distributed generation. Also, I explain how role-playing games (RPGs) and participatory modeling could support some of the broader goals of industrial symbiosis—helping to identify, build trust among, and evolve small clusters of agents who gradually discover the mutual benefits of collective learning, exchanging by-products and sharing common infrastructure by dint of their close proximity.

Like Axtell and colleagues (2001), I argue that the general problem of *agency*—the behavior of intelligent individuals facing bounded rationality, imperfect incentives, and limited information—lies at the very core of industrial ecology (IE). The phenomena studied in IE originated from the recognition of some economic externalities and departures from socially optimal behavior by industry and consumers, due to inappropriate incentives, distorted markets, and imperfect regulations. Two important potential roles for agent-based simulation and participatory modeling in IE could be, therefore, (1) to explicitly explore alternative (e.g., eco-efficient) rules and incentives that behaviorally realistic clusters of agents could face in empirically credible environments, and (2) to instill trust and cooperation among agents who possess and exchange only limited information.

In the next section, I examine some methodological aspects of agent-based simulation as a forerunner to looking at ways industrial ecologists might exploit such tools to identify eco-efficient clusters of industrial symbionts. In later sections, I treat industrial symbiosis as emergent system behavior of a complex industrial system and then turn to a discussion of what kinds of electric power and water systems may suit clusters of potential industrial symbionts. Because electricity markets are complex adaptive systems, agent-based simulation can provide a flexible means of exploring the influence that the repetitive interaction of a cluster of market participants exerts on the evolution of the system as a whole. For such explorations, I make use of an agent-based electricity market model known as the National Electricity Market Simulator (NEMSIM). Although NEMSIM was designed for Australia only, my results suggest that greater use of distributed generation would be consistent with the ambitions of industrial ecology.

Recently, French and other European researchers attempted an iterative, participatory approach to multiagent problems, using both RPGs and participatory agent-based simulation. The aim was to build trust among a group of stakeholders and improve their understanding of the alternative evolutionary outcomes that are possible when they interact with each other and their environment. Sometimes known as *companion modeling*, this approach ensures that stakeholders participate fully in the construction of models to improve the models' relevance, establish trust, and increase model use for the collective assessment of scenarios. This facilitates shared learning and collective decision making through interdisciplinary and "implicated" research to strengthen the adaptive management capacity of local communities. An example is discussed later in the article, suggesting that the field of industrial ecology could be better equipped to deal with the increased complexity of integrated eco-industrial park management problems if it makes greater use of the companion modeling approach among prospective park tenants and stakeholders.

A Primer on Agent-Based Simulation

Since the release of Conway's Game of Life, cellular automata (CAs) have been used as models in many areas of the physical and environmental sciences, biology, mathematics, and computer science as well as in the social sciences. They are a useful modeling platform, because cells on a grid that switch on or off according to states of neighboring cells can represent a host of dynamic phenomena—individuals, attitudes, or actions, for example. A CA models any world in which space can be represented as a uniform grid, time advances by steps, and the "laws" of that world are represented by a uniform set of rules that compute each cell's state from its own previous state and those of its nearby neighbors.

Once one wishes to develop automata to represent human beings, who are far more complex in their internal processing and their behavior, one enters the world of agent-based simulation (sometimes called multiagent systems). Such automata are usually called *agents*, and there are several streams of thought on how the agents should be designed, built, and used. Although there is no generally agreed definition of what an agent is, the term usually implies an autonomous, intelligent entity that may interact or communicate with other autonomous, intelligent entities (Batten 2000). As with CAs, there are rules governing interactive behavior, and the agents "operate" on one or several environments of some sort.

The agents emanating from the literature on (distributed) artificial intelligence often correspond to self-contained software or hardware units (e.g., robots) that control their own actions on the basis of their perceptions of their operating environments. Multiple agents are designed to work together to achieve a desired goal. Typically, their goal is prespecified, and they are engineered to achieve it with a very low error tolerance. Although purposive, systems in which human agents interact with ecological systems, for example, often display open-ended outcomes. Here the collective behavior is unknown in advance but emerges during the simulation. Some of the emergent outcomes can be unexpected and undesirable (Perez and Batten 2006). The field of artificial life has been the source of inspiration for this open-ended kind of simulation (Langton 1995). Imbuing agents with beliefs, desires, and intentions (BDI agents) is one classical approach to human agent representation within a computer.

In agent-based simulation, rules governing agents' behaviors can range from simple "if—then" statements to quite sophisticated machine learning algorithms (e.g., genetic algorithms) that provide agents with a learning capability to modify and improve their behavior during the simulation. Parameters of the model are set to represent a real situation of interest, and the model is run for several hundreds of iterations, until a satisfactory solution is found. When possible, simulation models make use of historical data to ensure that they can replicate the qualitative behavior of the real system. Replication of historical outcomes does not mean that the model is a reliable one for exploring future scenarios, however. Data mining is also used to ensure that agents behave in ways that realistically depict how individual decisions are made in that type of system.

It is important to note that agent-based simulations can provide valuable information about the dynamics of the real worlds that they emulate. Complex systems scientists see them as more useful than equations-based methods in a world of multiple possible futures, partly because they are built synthetically "from the bottom up" (Epstein and Axtell 1996). As a variety of agents interact within a social simulation, for example, the results show how their collective behaviors govern the performance of the entire system—for instance, the emergence of a successful product, a congested area of traffic, or a polluted water system. This is of benefit to stakeholders, because they may see a role for themselves (as agents) in the simulation as well as an opportunity to learn from the simulated outcomes.

Agent-based simulations are also powerful tools for "what if" scenario analysis. As certain agents' characteristics (i.e., behavioral rules) change, the impact of the change can be seen in the simulation's collective results. These *adaptive learning* features give agent-based simulation an edge over more traditional mathematical modeling and optimization methods. The simulation sometimes generates outcomes or strategies that a scientist or stakeholder might never have imagined.

Participatory approaches that make use of agent-based simulation have developed rapidly in Europe during the last decade. Sometimes known as *companion modeling*, they use RPGs and participatory agent-based simulation to build trust among a group of stakeholders and improve the stakeholders' mutual understanding of the alternative evolutionary outcomes that are possible when humans interact with one another and with our natural environment (Bousquet et al. 1998; Barreteau 2003; Perez and Batten 2006).

In a later section of this article, I illustrate the use of participatory agent-based simulation and RPGs to facilitate water management negotiations in Bhutan. For more detailed explanations and discussion of different kinds of agent-based simulations and their growing contribution to the social, economic, and ecological sciences, see work by Epstein and Axtell (1996), Axelrod (1997), Batten (2000), Tesfatsion and Judd (2006), Janssen and Ostrom (2006), and Perez and Batten (2006). For a look at the programming side of agent-based models, see work by Gilbert and Troitzsch (1999).

Industrial Symbiosis as Emergent Behavior of a Complex Industrial System

How could agent-based simulation promote industrial symbiosis? In the latter, the overall goal is to maximize the reuse of by-products that are otherwise dumped as wastes, thereby having a positive effect on environmental, human, and social capital (Frosch and Gallopoulos 1989). As most readers of this journal know, the term *symbiosis* was borrowed from ecology and means "living together." Economic agents that can exchange resource streams profitably owing to their close proximity and output-to-input affinity are known as *symbionts*. In the Danish township of Kalundborg, for example, four symbiotic companies—a power station, an oil refinery, a pharmaceutical plant, and a gyproc plant—somehow managed to self-organize together over a period of 30 years to provide today's mutually profitable role model for industrial symbiosis.

Although the Kalundborg story has been widely discussed in the literature on eco-industrial parks, it is important to understand how the four symbiotic Kalundborg agents came together in the first place. There was no grand design, nor did cooperation emerge overnight. Industrial symbiosis coevolved gradually over 30 years or more (see Ehrenfeld and Gertler 1997). The manager of Asnaes Power Station has been quoted as saying that the existing economic incentives were generally enough to generate most of Kalundborg's symbiosis. According to Lowe and Evans (1995, 49), Jorgen Christensen, the vice president of Novo Nordisk in the 1990s, has been quoted as follows:

> I was asked to speak on how we designed Kalundborg. We didn't design the whole thing. It wasn't designed at all. It happened over time. It's not the kind of thing that you can engineer in a moment and drop in place. It takes more time. . . . At the time, we were just doing what was profitable and what made sense. . . . Until now, we have had no formal organization, no common board or budget. We do what pairs of us think is a good idea.

Doing what pairs or small clusters of agents think is a good idea is an excellent example of self-organization. An important point to note is that there is no central controller involved. Many social and technical systems elsewhere in the world *are* shaped by a centralized mind-set. Most people seem to think that instructions invariably come from an external source (e.g., an architect's building plans). As Mitch Resnick (1999, 4) put it,

> At some deep level, people seem to have strong attachments to centralized ways of thinking. When people see pattern in the world, like a flock of birds, they often assume that there is some type of centralized control. According to this way of thinking, a pattern can exist only if someone (or something) creates and orchestrates that pattern. Everything must have a single cause, an ultimate controlling factor.

By way of contrast, natural systems that achieve their remarkable structure and form by their own internal processes are called *self-organizing systems* (Haken 1983; Nicolis and Prigogine 1977). In these open systems, pattern and structure emerge by way of interactive processes within the system, without any overall control from an external instructor or guidance from a master plan. The exciting aspect of this discovery is that we are just beginning to realize that self-organization is responsible for a very broad range of pattern-formation processes in both living and nonliving systems, including geographical and industrial systems (Batten 1982).

Formally, self-organization is a dynamic process in which pattern at the global level of a system emerges solely from interactions among its lower level components (or agents). In turn, the global pattern may influence the future decisions of agents. The rules governing interactions among the system's components are executed via only local information, however, without any reference to the global pattern. In other words, pattern is an *emergent* property of the system, rather than a property imposed on the system from outside by an external agent or controller.

Emergent properties of a system cannot be deduced from one's knowledge of the system's lower level components and the interactions between them. They are higher level, global phenomena. In the terminology of dynamical systems, emergent properties are particular *attractors* of the system. A particular pattern is one emergent property out of many that self-organizing systems display, crafted collectively by a specific set of interactions among the agents involved.

Clustering, with eco-efficiencies derived from interenterprise cooperation, can be viewed as an emergent property of a self-organizing industrial system that is complex, adaptive, and selective (Batten 1982; Wallner 1999). Firms arranged in clusters are able to achieve synergies and leverage economic advantage from shared access to information and knowledge networks, supplier and distribution chains, markets and marketing intelligence, special competencies, resources, infrastructure, and support institutions available in a specific locality (Batten and Cook 2008).

Although eco-clustering is a desirable property of an industrial system, it is merely one of many emergent properties that such a system can display as it coevolves over time. Several other emergent properties are less desirable from an environmental viewpoint. Agent-based simulation is a way of exploring the collective behavior that a self-organizing system might display by studying a range of emergent outcomes associated with the many alternative pathways that such a system might follow under different conditions—now and in the future. Then can we begin to identify conditions under which some of the more desirable outcomes might be more likely to emerge.

Tuning the *rules* is an important skill in agent-based simulation. For example, Jorgen Christensen identified several conditions for a new Kalundborg to develop (Lowe and Evans 1995):

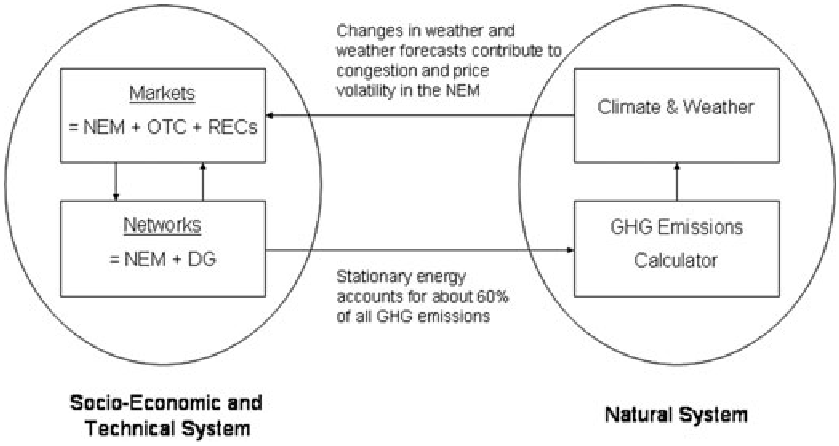

Figure 1 The national electricity market (NEM) as a complex adaptive system. OTC = over-the-counter markets; RECs = renewable energy credits; DG = distributed generation of electricity; GHG = greenhouse gas.

- Industries must be different and "fit" each other.
- Arrangements must be commercially sound and profitable.
- Development must be voluntary, in close collaboration with the authorities.
- A short physical distance between the partners is necessary for economy of transportation.
- Managers of the different plants must all know and trust each other.

The above conditions can be programmed into an agent-based simulation model as part of its set of internal rules. Sensitivity studies could show just how close partners might need to be in geographical space, how different yet complementary they need to be in terms of their inputs and output, and so on.

Electricity Systems as Potentially Symbiotic Complex Adaptive Systems

Nowadays, electricity markets are an evolving system of complex interactions among nature, physical structures, market rules, and participants. They exhibit a high degree of interdependency with other markets—such as those for fuels, carbon dioxide (CO_2), renewable energy credits (RECs), capital, and other financial markets (e.g., over-the-counter markets)—and with other sectors (e.g., industry, households). In brief, they possess the intrinsic features of a *complex adaptive system* (see figure 1). Participants face risk and volatility as they pursue their goals, making decisions based on limited information and their own mental models of how they believe the whole system operates. A diverse collection of agents participate in this market. They adopt different strategies, have different capacities, use different generation technologies, have different forms of ownership, are often located at different sites, face different grid constraints, and must operate increasingly in a carbon-constrained marketplace. In summary, their objectives, beliefs, and decision processes vary markedly. Such a diversity of inputs may be expected to lead to a rich variety of collective outcomes.

One intrinsic feature of an electricity market as a complex adaptive system is that it features a "largish" number of intelligent agents, reacting to changes in demand (due to weather and consumer needs) and supply potential and interacting on the basis of limited information. Because no one agent is in control, some agents perform better than others. Some of the common collective outcomes include price volatility, inadequate reserves, network congestion, power failures, demand uncertainty, and unacceptably high levels of greenhouse gas (GHG) emissions. All of the above are emergent properties that have been observed in electricity systems, and all can be generated as endogenous, emergent phenomena in agent-based simulators of electricity systems (see, e.g., Bower and Bunn 2000; Bunn and Oliveira 2001; Nicolaisen et al. 2001; Veselka et al. 2002; Batten and Grozev 2006, 2008).

The interactions within an electricity market constitute a repeated game, whereby a process of experimentation and learning changes the behavior of agents in the market (Roth and Erev 1995). Market outcomes depend on how each agent responds to market design—including rules, market observations, operating procedures, and information revelation. It is often the case that particular agents (e.g., generator firms) gain more from these markets than others (e.g., retailers, local communities, or households), partly because they have more opportunities to learn about how to exploit the system and adapt their behavior to changing market conditions in profit-maximizing ways. Unfortunately, some of this profit-driven behavior exacerbates GHG emissions.

Some forms of cooperative behavior by small groups of generator companies lead to the exercise of *market power*, causing dramatic price fluctuations from day to day (Nicolaisen et al. 2001; Bunn and Oliveira 2003; Hu et al. 2005). Temperature variations and network congestion can play a similar role. Like most industries in which a large number of agents interact, many of the evolving markets for electric power have become more complex.

Economic volatility is one aspect of the problem. The need to mitigate ecological impacts—especially GHG emissions—has also highlighted the need to develop methods capable of addressing economic and ecological uncertainties consistently within an integrated framework. We now believe that GHGs contribute significantly to global warming. In Australia, the stationary energy sector accounts for almost 50% of these emissions. Electricity generation dominates this sector, with 66% of the emissions, and is thus the major culprit in terms of total emissions. Yet if the key participants in this sector were to partner in more eco-efficient ways, the amount of GHG emissions could be cut significantly.

Agent-based simulation provides a flexible means of exploring the influence that the repetitive interaction of agents exerts on the evolution of the system as a whole. Static models neglect the fact that interacting agents have good memories, learn from past experiences (and mistakes) to improve their decision making, and adapt simultaneously to changes in several environments (natural, economic, technical, and institutional). Thus, agent-based simulation techniques can shed light on some of the complex, interactive features of electricity markets that static equilibrium models ignore.

NEMSIM: The National Electricity Market Simulator

NEMSIM is an agent-based simulation model representing Australia's national electricity market as an evolving system of complex interactions among human behavior, technical infrastructures, and the natural environment. Users of NEMSIM can explore different evolutionary pathways under various assumptions about trading and investment opportunities, institutional changes, ecological outcomes, and technological futures—including alternative learning patterns as participants grow and change. In the spirit of industrial ecology, the simulated outcomes can help to identify futures that are more eco-efficient (e.g., that maximize profits in a carbon-constrained future). Questions about sustainable development, market stability, infrastructure security, price volatility, and GHG emissions can be explored with the help of this simulation system (see Batten and Grozev 2006, 2008).

Learning Agents in NEMSIM

The NEMSIM project is part of the Australian Commonwealth Scientific and Research Organization's (CSIRO's) Energy Transformed Flagship research program, which aims to develop low-emissions, eco-efficient energy systems. An overview of the simulation system is shown in figure 2. In NEMSIM, silicon agents represent natural resource companies, generator firms, network service providers, retail companies, the market operator, and others. In NEMSIM, most agents simply buy and sell electricity in a simulated environment. A few agents may engage in resource exchanges and recycling of by-products.

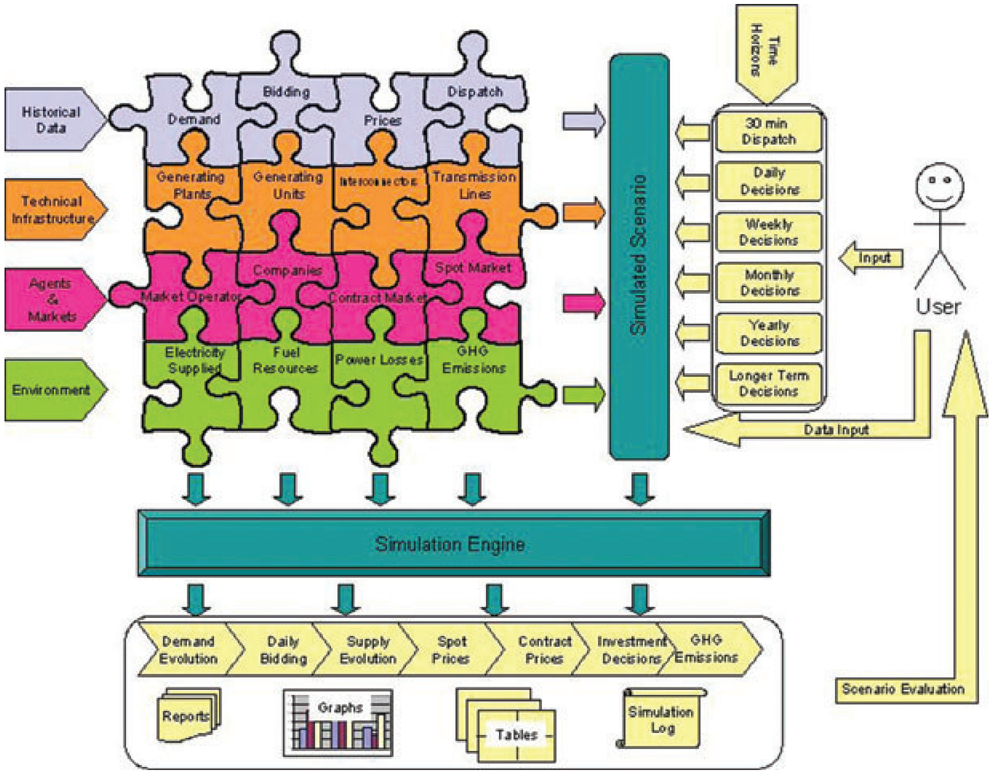

Figure 2 An overview of the National Electricity Market Simulator (NEMSIM). GHG = greenhouse gas.

It is important to note that agents can (and usually do) have different goals. Instead of just maximizing their own profits, some pairs of agents may recognize the benefits of trying to maximize joint profits and minimize CO_2 emissions by working together. Other agents may be willing to share common infrastructure (e.g., distributed energy or recycled water) that is eco-efficient or use other nearby firms' by-products as feedstock for their energy generation. It is among these more innovative agents that the potential for symbiosis lies.

NEMSIM treats agents as being uniquely intelligent, making operational and strategic decisions using the individual information available to them. It is important to note that they are adaptive, learning to modify their behavior to realize their goals more efficiently. Learning algorithms can allow agents to *look back* (learn from historical performances), *look sideways* (learn to anticipate or cooperate with other participants), and *look ahead* (take future plans and forecasts into account).

In an adaptive market, no single agent has control over what all the other agents are doing. Because of the way the market is structured, some may exert more influence on market outcomes. The overall outcome is not always obvious, because it depends on many factors. NEMSIM provides a platform on which simulated agents interact, constrained only by realistic rules and the physical grid system. Agents' individual and collective behaviors coevolve from the bottom up, sometimes producing unexpected emergent outcomes at the system level.

NEMSIM as a GHG Emissions Calculator

Simulated agent life in NEMSIM unfolds in three "environments": first, a *trading environment* in which transactions can occur in interlinked markets; second, a *physical grid* of sites, generation units, lines, and interconnectors across which electricity flows; and third, a *natural environment*, which provides resources and accumulates GHG

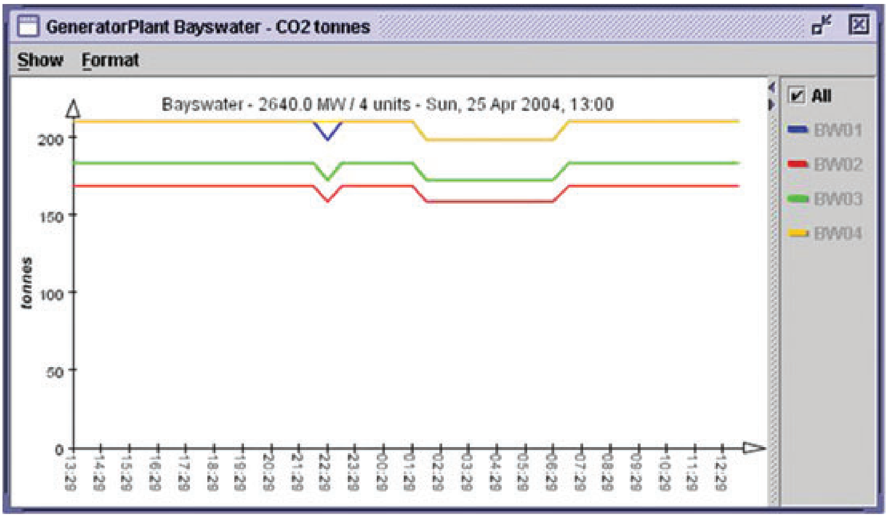

Figure 3 National Electricity Market Simulator (NEMSIM) greenhouse gas (GHG) emissions calculator: graphical plot for a generator plant.

emissions. Each environment is separate from the agents, which operate on and interact with it. The links and feedback effects between these environments have an important influence on the eco-efficiency of any simulated scenario of the future.

NEMSIM estimates the GHG emissions associated with electricity generation of a given simulation scenario by way of bottom-up aggregation. This approach allows quite precise modeling of the emissions up to the level of each generating unit, accommodating a variety of changes in the operational, technological, company, market, and regulatory values and parameters. The advantage is that such an agent-based framework allows slow changes to accumulate over long periods as well as sudden changes due to the emerging events based on the decision making and interactions of the participating agents.

NEMSIM calculates the GHG emissions due to electricity generation on a fossil fuel consumption basis using fuel-specific (generation technology) emission factors. A set of generation technologies are modeled: conventional black coal-pulverized fuel, conventional brown coal-pulverized fuel, natural gas simple cycle, and so forth. The set of generation technologies is specified in an XML input file that allows changes to generation technologies and their parameters to be introduced easily.

The main attributes of each generation technology are the *emission* GHG *factor* and the *net energy efficiency*—how much of the embodied energy of the fossil fuel is transformed into electricity. One can also define the net energy efficiency for a selected generating unit to allow flexibility over the longer term, when the efficiency may change. This approach allows easier comparison between different plants, companies, and regions. Its accuracy is inferior, however, as it does not include indirect emissions that usually show moderate variability by region, company, and technology.

A typical example of a NEMSIM output window for GHG emissions is depicted in figure 3. This graphical plot displays company data, and (for commercial reasons) the values are illustrative only. A regional summary graph of GHG emissions is shown in figure 4. Although the numbers are only illustrative, other options for output windows and reports pertaining to GHG emissions are available within NEMSIM. For additional details regarding NEMSIM's capabilities, see work by Batten and Grozev (2006, 2008).

Region Summary - CO2 Emissions tonnes

Show

Time	New South Wales	Queensland	Snowy	South Australia	Tasmania	Victoria
Sun 25 Apr. 1730	5365.13	4546.14	0.0	902.17	0.0	4054.66
Sun 25 Apr. 1800	5365.13	4534.05	0.0	893.62	0.0	4385.35
Sun 25 Apr. 1830	6075.4	5303.93	0.0	867.84	0.0	4716.05
Sun 25 Apr. 1900	6075.4	5098.78	0.0	915.1	0.0	4716.05
Sun 25 Apr. 1930	6075.4	5009.61	0.0	959.85	0.0	4716.05
Sun 25 Apr. 2000	5838.64	4407.6	0.0	964.35	0.0	4716.05
Sun 25 Apr. 2030	5838.64	4569.81	0.0	949.56	0.0	4716.05
Sun 25 Apr. 2100	5838.64	4350.17	0.0	977.92	0.0	4716.05
Sun 25 Apr. 2130	6075.4	5455.05	0.0	949.2	0.0	4716.05
Sun 25 Apr. 2200	7700.98	3707.74	0.0	1210.59	0.0	4054.66
Sun 25 Apr. 2230	6803.78	3707.74	0.0	1330.8	0.0	3721.03
Sun 25 Apr. 2300	7117.16	3707.74	0.0	1328.76	0.0	3625.42
Sun 25 Apr. 2330	6797.49	3707.74	0.0	1328.01	0.0	3553.27
Mon 26 Apr. 0000	7557.34	4197.5	0.0	1330.91	0.0	3481.11
Mon 26 Apr. 0030	6490.4	3707.74	0.0	1317.54	0.0	3517.19
Mon 26 Apr. 0100	7269.58	3707.74	0.0	1200.74	0.0	3711.25
Mon 26 Apr. 0130	7355.75	3707.74	0.0	1331.51	0.0	3481.11
Mon 26 Apr. 0200	6785.4	3707.74	0.0	1200.21	0.0	3707.83

Figure 4 National Electricity Market Simulator (NEMSIM) regional summary table for greenhouse gas (GHG) emissions.

The Eco-efficiency of Distributed Generation

Does the deregulation of electricity markets promote eco-efficiency and the wider use of distributed generation (DG)? Clinton Andrews (2001) posed such a question recently with respect to the so-called introduction of competition into the U.S. electric power industry. Andrews' analysis of broad sectoral trends revealed little evidence of eco-efficiency gains, and his status report on "soft-path" DG technologies suggests that there are technical and institutional barriers that add inertia to the system, thereby hindering such eco-efficient innovations.

DG is loosely defined as a set of small-scale power generation technologies located close to customers, where the power is used. It is not an entirely new idea, given that Thomas Edison's very first power station followed the concept of DG—produce power near the user. Also, small generators have been used as backup generators and on-site power systems for a long time. Today the most common means of achieving economical provision of electricity to an entire country is through the model of large power stations coupled with extensive transmission and distribution networks so that power production and use can be separated by hundreds of kilometers—economically.

Recently, considerable technological progress has seen the development of much more competitive DG technologies (e.g., microturbines, fuel cells, photovoltaics, and wind systems). Potential benefits from these newer DG technologies are reduced cost, higher service reliability, higher power quality, and increased energy efficiency (see Pepermans et al. 2005). DG is a promising solution for the security of electricity supply, providing distributed and diverse energy source infrastructure. Some types of renewable, distributed generation can also provide a significant environmental benefit in terms of reducing GHG emissions. Not all DG is environmentally beneficial, however, given that smaller generating plants are usually less efficient in terms of thermal efficiency and fuel utilization.

Fortuitously, DG can be of help to electricity consumers and energy utilities. In combination with demand-side management, it can offer electric utilities alternatives to system capacity investment in large central generation, transmission, and distribution (Hoff et al. 1996). Because it can help to manage peak load demands, it could reduce price volatility and companies' market power. Deregulation is an additional reason for the growing level of interest in DG.

Network integration of DG is a very complex issue, significantly different from the conventional networking of generating units and transmission lines (Ackermann et al. 2001). For example, the traditional distribution network infrastructure allows power to flow only in one direction. In the case of DG, the power should be able to flow in both directions—to and from the customer. This is clearly more eco-efficient. One has to take into account the additional cost of the network protection system, which has to be designed and implemented, when assessing economic impacts and conducting reliability analysis of DG.

Potentially, small clusters of low-emissions DG can serve local communities and eco-industrial developments more reliably than large, centralized power stations, while also reducing GHG emissions and earning income by reexporting some power to the main electricity grid. Serious uptake of DG, however, will require new clusters of small generating units with recyclable feedstocks, new grid systems, new markets, new participants (e.g., aggregators), and new rules that are not as inhibiting as those that Andrews (2001) identified.

One way to explore conditions under which new industrial clusters of DG could work ahead of their introduction is to use agent-based simulation to create "would-be worlds" of new agents, environments, and rules inside a computer and see what happens as they evolve over time. If agents and their actions are allowed to evolve endogenously inside an agent-based, computational simulation model, new industrial clusters of agents that could make more eco-efficient use and reuse of our solid, liquid, and gaseous resources could be discovered.

Agent-based models such as NEMSIM can help us to identify the advantages and disadvantages of DG (e.g., as an anchor tenant for an eco-industrial park [EIP], by providing a reliable local and renewable energy source that may be shared by all of the park's tenants). NEMSIM aggregates a number of homogeneous DG units into clusters of DG. Each cluster may aggregate units that use the same generation technology and possess similar operational characteristics, but they are not necessarily identical in terms of capacity or manufacturer. Aggregation is based not only on similarity of generation parameters but also on location (e.g., for a load center). In summary, simulators such as NEMSIM could play an import role in exploring potentially symbiotic outcomes that involve the shared use of locally generated electric power.

Companion Modeling for Industrial Symbiosis

Recently, several researchers have advocated an iterative, participatory approach to multi-agent problems, using role-playing games (RPGs) and participatory agent-based simulation. The aim is to build trust among a group of stakeholders and improve their understanding of the alternative evolutionary outcomes that are possible when humans interact with our natural environment (Bousquet et al. 1998; Barreteau 2003; Bousquet et al. 2005; Perez and Batten 2006, chapters 3 and 12). Participatory approaches have grown rapidly in parts of Europe and are now commonly known as companion modeling. Typically, researchers join with stakeholders in a repeated, multistage process involving game playing and modeling. Specific stages in the process may include

- field study and data analysis,
- RPGs,
- agent-based simulation development and implementation, and
- other computational experiments.

Researchers at French Agricultural Research Centre for International Development (CIRAD) in Montpellier have developed a companion modeling platform known as Common-Pool Resource Multi-Agent Systems (CORMAS), dedicated to the study of common-pool resource problems with the aid of agent-based simulation (see Bousquet et al. 1998; http://cormas.cirad.fr/indexeng.htm). They have undertaken many applications in Africa and Asia, working together with the local stakeholders to develop RPGs and agent-based simulations for practical natural resource management problems (Bousquet et al. 2005). Participatory approaches recognize that management does not only consist of understanding the state of the ecosystem and its dynamics but also addresses the social process leading to this ecological state and those that may lead to more preferred states. In other words, what are

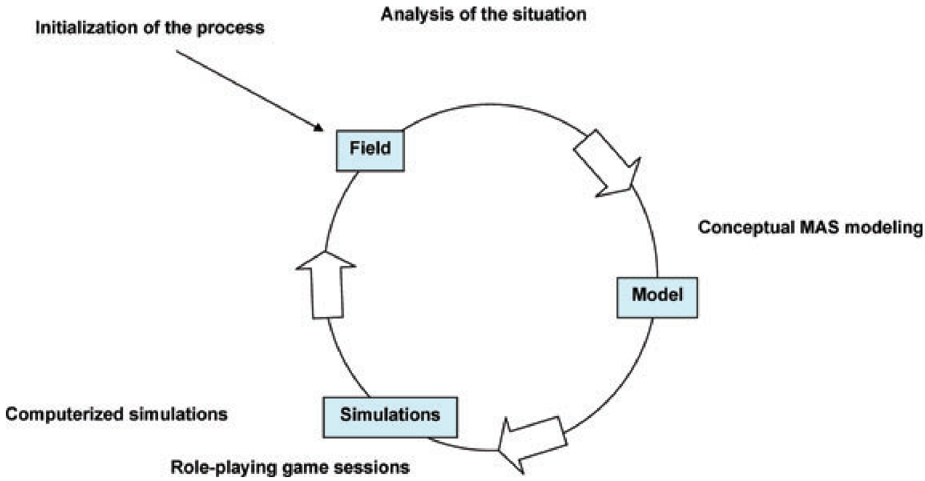

Figure 5 The companion modeling process. MAS = multi-agent system.

important are the solutions emerging from the interactions among the different stakeholders.

Could a companion modeling approach help to achieve industrial symbiosis among potential stakeholders in an EIP? Critics of the EIP concept often suggest that a primary obstacle to EIPs' formation is the reluctance of tenants to become interdependent. They may not trust one another, may be unwilling to share common infrastructure (e.g., energy or water), or may disagree with EIP regulations. To be effective, an EIP management system must display fundamental respect for the autonomy of each participating company. This suggests that, if possible, constraints on tenants' autonomy should be developed via participatory approaches, in which each tenant can understand his or her role, express concerns, and see that his or her views are taken into account. In this way, trust can be built up gradually and future conflicts avoided.

A fundamental assumption of EIP operation is that companies can self-organize and self-regulate their behavior more effectively than any outsiders, provided information flows and feedback loops are in place. Principles of self-organization and self-regulation are central to establishing trust and dissolving the fear that participation in a community of companies could undercut the autonomy of members. A well-designed environmental management system for the eco-park and its members will provide the structures for feedback that support this self-regulation. An iterative, companion modeling approach may help to build trust and achieve the required degree of self-organized regulation.

Building Trust in a New Institution

Gurung and colleagues (2006) used RPGs and agent-based simulation, following the companion modeling method, to facilitate water management negotiations in Bhutan. Their methodology is interesting for industrial ecologists because it demonstrates a way of resolving conflicts such as the sharing of common-pool resources by establishing a concrete, self-regulated agreement and also creating an institution for collective management. Their conceptual model begins with an RPG. Stakeholders play the game, thus validating the proposed environment, the behavioral rules, and the emergent properties of the game. It is then relatively easy to translate the RPG into a computerized simulation model that allows different scenarios to be explored. Later, the stakeholders themselves can create a managerial institution.

The steps in the companion modeling process are depicted in figure 5 and consist of three stages that can be repeated as many times as needed:

1. Field investigations and a literature search on the observed world supply information are performed to help generate explicit hypotheses for modeling.

2. Modeling converts existing knowledge into a formal tool, to be encapsulated as a simulator.
3. Simulations are conducted according to an experimental protocol either on a computer or through an RPG, to challenge the former understanding of the system and to identify new key questions for new focused investigations in the field.

This process is called companion modeling because it is often used in the mediation process (the social dimension of the companion) and it coevolves with the social process (temporal and adaptive dimensions). A crucial question was how to use these models in an interactive way with stakeholders. Given that an RPG or simulation is a specific kind of representation among other possible ones, albeit a simplified one, Gurung and colleagues (2006) decided to present it in an explicit and transparent way, so as to avoid, as much as possible, the "black box effect," which can annoy stakeholders.

Comparison of the lessons learned from the two gaming sessions held for the Bhutan project indicated that, over the period between the two RPGs, community members informally discussed and even assessed the impact of their decisions about resource sharing. One player reported taking part in discussions on water sharing before attending the second RPG session. In both cases, the importance of sharing water was the most important lesson for all players. Compared with the lessons learned in the first RPG, 90% of the players in the second game learned of the need for and benefit of water management and sharing (70% water sharing, 10% canal management, and 10% on-farm water management). This shared learning is an important output from an RPG and should have a dramatic influence on the way the players involved will behave in the future.

The farmers of two conflicting villages willingly accepted the RPG as a means of expressing their concern about water sharing. Results from the game sessions confirmed that the RPG had been effective for collective learning, learning about the problem, and building trust about the process. The game outputs fostered better understanding of the water-sharing problem and its impact, and the use of three particular scenarios created a friendly environment for the active participation of the players.

The information generated by the diagnostic study and the RPGs was then used to implement the agent-based simulation model, the objective being to simulate alternative scenarios of how the future could unfold. Suitable entities were identified, and an initial class diagram was constructed to show all model entities, attributes, methods, and their structural relationships. Full details of this class diagram and the model can be found in the article by Gurung and colleagues (2006).

Some critical findings were that the RPG facilitated self-motivating and nonconfrontational interactions among the players, that the stakeholders' (here farmers') knowledge and understanding of water sharing increased significantly between the two games, and that the collective mode of communication facilitated better and more frequent exchange of water. The role of the computerized simulation model was to explore scenarios that were collectively identified during the RPG sessions by the stakeholders. Gurung and colleagues (2006) concluded that the RPG may be looked upon as an open simulation model, in the sense that the environment is defined together with the agents, their roles, some of their actions and interactions, and the overall schedule of the agents' interventions. A degree of freedom was left to the players, as it would be in real-life situations of interest (e.g., potential industrial tenants for an EIP).

Some Ramifications for Industrial Symbiosis

What could companion modeling bring to industrial symbiosis? In participatory RPGs and computer simulations, an artificial environment is conceived from observation of real-life situations, several types of players are identified, and a schedule of activities or events is planned. In the context of an EIP, for example, the artificial environment might include a chessboard or grid representing the park site (without any buildings or tenants), key infrastructure networks (water and energy), and the atmospheric system. Players could include potential tenants (with simple facility profiles of inputs, outputs, and by-products), a government agent or regulator, and a park supervisor. The game or model itself could focus on some basic exchange processes (e.g., material inputs, by-product exchanges, or energy and water sharing) that could be measured in terms of a simple joint index of profitability and CO_2 emissions.

For the resulting model to be "playable," it cannot consider numerous time steps or dozens of players. Starting with the model implies that it will be simple and will not include many detailed processes. Conversely, starting with the RPG provides an immediate test of the realism of the model of each individual's behavior and of the emergent process. When the players play the game, they can comment on the actions planned for them. They validate the behavioral rules, but, more generally, they validate the model. They observe and comment on properties of the exchange system emerging from the interactions among the players (e.g., number of supply, by-product, or utility synergies), and they can comment on the links between various organizational levels.

The rules for decision making in the game should be the same as those in reality. For example, by-product exchanges should result primarily from pairs of players thinking that an exchange is a good idea. The park supervisor player can evaluate these ideas in terms of the joint index of profitability and CO_2 emissions. Refinements to the basic game could include a system for auctioning by-products run by an auctioneer.

Transcription of the model from the RPG implementation to computer simulation is often very easy. The challenge is to implement the decision-making process of pairs of players. The KISS ("keep it simple, stupid") principle applies for implementation of the decision-making process. The objective is not to implement a detailed decision-making process involving a lot of data and complex calculation but rather to see how simple behaviors lead to complex phenomena an a wide range of different outcomes. The example discussed in this article, along with others reported by the CORMAS group, show how simple decisions, if combined with different interaction protocols and different networks, often lead to complex outcomes that are still meaningful for the stakeholders. A tentative conclusion is that very simple models with a low degree of realism can be very useful and effective among a collection of motivated stakeholders.

RPGs or simulation models can be particularly useful in situations where researchers have attempted to promote discussions among key stakeholders without success, because such models can serve as mediator tools. For example, issues such as water or energy sharing between prospective tenants in an EIP can cause problems. In this situation, the computerized model can be designed (or redesigned) in a way that explores scenarios with and without water or energy sharing, with the output table comparing the environmental and economic costs and benefits of these.

In the work by Gurung and colleagues (2006), three model scenarios led to the conclusion that a managed watershed would increase benefits for all the stakeholders. Later, stakeholders (farmers, governmental organizations) participated in detailed discussions to reach an agreement on the establishment of a watershed committee. In other words, the first steps taken by stakeholders resulted not in the sharing of water among villages (which was the topic of the game) but in the creation of a watershed body. This shows how the game and the model are taken for what they are: mediation tools. Stakeholders are in control of the negotiation process and are able to see the difference between the model and reality. Thus, the actual risk of manipulation, which is a potential danger of this open-ended method, is low.

According to the stakeholders themselves, some of the benefits they realized by participating in RPGs were as follows:

- The game setting promotes *dynamic* discussions among players.
- Only after the game session ends are the real implications of the game fully realized; thus, the spontaneous actions and reactions generate new ideas that would not emerge otherwise.
- Players can use the RPG as means of communicating with their counterparts.
- The RPG seems, at first, like child's play, but it soon becomes a very strong tool to study complex interactions and collective dynamics.

- Alternating game sessions with plenary sessions allows people to relate the game to their real-life situation.
- Some local experience and knowledge are necessary for facilitating the process.
- The RPG can be used as a platform for conflict resolution.
- The RPG effectively provides equal opportunities for all strata of players to participate in the game.

In summary, the main aim of the companion modeling approach is to develop RPGs and simulation models integrating various stakeholders' viewpoints and to use them within the context of the stakeholders' platform for collective learning. This modeling approach ensures that stakeholders participate fully in the construction of models to improve the models' relevance, establish trust, and increase model use for the collective assessment of scenarios. The general objective is to facilitate dialogue, shared learning, and collective decision making through interdisciplinary and "implicated" research to strengthen the adaptive management capacity of local communities. By adopting such an approach, the field of industrial ecology could be better equipped to deal with the increased complexity of integrated EIP management problems, their evolving and continuous characteristics, and the possible impacts of technological progress and changes in the number of park tenants.

Conclusions

As stated earlier, the sciences of industrial ecology, complex systems, and adaptive management are intimately related, as they deal with flows and dynamic interdependencies between system elements of various kinds. As such, the tool kit of complex systems science could enrich our understanding of how industrial ecosystems might evolve over time. In this article, I have shown how an important tool of complex systems science—agent-based simulation—can help to identify potential elements of an industrial ecosystem that could work together to achieve more eco-efficient outcomes. For example, I showed how agent-based simulation can generate cost-efficient energy futures in which groups of firms behave more eco-efficiently by introducing strategically located clusters of renewable, low-emissions, distributed generation. Then I explained how RPGs and participatory modeling can build trust and reduce conflicts about the sharing of common-pool resources such as water and energy among small clusters of evolving agents.

Eco-industrial development projects based on industrial symbiosis are learning systems in which agents (if motivated) strive to gain economic and ecological benefits by clustering some of their activities together in geographical space and arranging mutually beneficial exchanges. Such learning processes are not evolutionary but *coevolutionary* and self-organizing (Batten 2000). They can encourage potential industrial partners to gradually cooperate by exchanging by-products or sharing common infrastructure by dint of their close proximity. This coevolutionary learning process, aided by participatory modeling, could help to bring about industrial symbiosis.

The purpose of agent-based simulation models and RPGs (like those discussed in this article) is not to predict the future but to generate and explore alternative futures that might develop under different conditions, thus affecting key stakeholders in different ways. Such models can explore various "what-if" scenarios under different eco-efficiency goals. Also, they can show the possible evolutionary trajectories of a given scenario under given conditions.

For example, the introduction of more DG of electricity into the marketplace involves a transition from the current paradigm of the centrally dispatched electricity grid to new, more decentralized ones. This may require new markets, new brokers, new technology, and new grid structures. Some of these distributed strategies can reduce the level of GHG emissions considerably. NEMSIM and similar simulators are *generative* tools that can identify the transition states needed to reach specific final states, including more eco-efficient ones. In an eco-industrial setting, two important challenges for agent-based simulation tools are (1) to achieve realistic representation of the adaptive behaviors of pairs of company agents with the help of a suitable learning algorithm and (2) to "validate" the model, mainly by collective stakeholder approval in a qualitative world where quantitative validation is mostly inappropriate.

References

Ackermann, T., G. Andersson, and L. Söder. 2001. Distributed generation: A definition. *Electric Power Systems Research* 57(3): 195–204.

Andrews, C. J. 2001. *Does electricity deregulation promote eco-efficiency: The case of distributed generation*. Paper presented at the American Collegiate Schools of Planning Annual Conference, 8–11 November, Cleveland, Ohio.

Axelrod, R. 1997. *The complexity of cooperation: Agent-based models of competition and cooperation*. Princeton, NJ: Princeton University Press.

Axtell, R., C. Andrews, and M.J. Small. 2001. Agent-based modeling and industrial ecology. *Journal of Industrial Ecology* 5(4): 10–13.

Barreteau, O. 2003. The joint use of role-playing games and models regarding negotiation processes: Characterization of associations. *Journal of Artificial Societies and Social Simulation* 6(2). http://jasss.soc.surrey.ac.uk/6/2/3.html. Accessed February 2009.

Batten, D. F. 1982. On the dynamics of industrial evolution. *Regional Science and Urban Economics* 12(3): 449–462.

Batten, D. F. 2000. *Discovering artificial economics: How agents learn and economies evolve*. New York: Westview Press.

Batten, D. F. and S. Cook. 2008. *Industrial symbiosis for Dandenong LOGIS: Final report, prepared for VicUrban Melbourne: Temaplan—CSIRO—VicUrban*.

Batten, D. F. and G. Grozev. 2006. NEMSIM: Finding ways to reduce greenhouse gases using multi-agent electricity modeling. In *Complex science for a complex world: Human ecosystems modeling with agents*, edited by P. Pascal and D. Batten. Canberra, Australia: ANU ePress.

Batten, D. F. and G. Grozev. 2008. Managing energy futures and greenhouse gas emissions with the help of agent-based simulation. In *Changing stocks, flows and behaviors in industrial ecosystems*, edited by M. Ruth and B. Davidsdottir. Cheltenham, Edward Elgar.

Bousquet, F., I. Bakam, H. Proton, and C. Le Page. 1998. CORMAS: Common-pool resources and multi-agent systems. *Lecture Notes in Artificial Intelligence* 1416: 826–838.

Bousquet, F., G. Trébuil and B. Hardy, eds. 2005. *Companion modeling and multi-agent systems for integrated natural resource management in Asia*. Los Banos, Philippines: IRRI Press.

Bower, J. and D. W. Bunn. 2000. A model-based comparison of pool and bilateral market mechanisms for electricity trading. *Energy Journal* 21(3): 1–29.

Bunn, D. W. and F. S. Oliveira. 2001. Agent-based simulation: An application to new electricity trading arrangements of England and Wales. *IEEE Transactions on Evolutionary Computation* 5(5): 493–503.

Bunn, D. W. and F. S. Oliveira. 2003. Evaluating individual market power in electricity markets via agent-based simulation. *Annals of Operations Research* 121: 57–77.

Ehrenfeld, J. and N. Gertler. 1997. Industrial ecology in practice: The evolution of interdependence at Kalundborg. *Journal of Industrial Ecology* 1(1): 67–79.

Epstein, J. M. and R. Axtell. 1996. *Growing artificial societies: Social science from the bottom-up*. Washington, DC: Brookings Institution Press.

Frosch, R. A. and N. E. Gallopoulos.1989. Strategies for manufacturing. *Scientific American* 266: 144–152.

Gardner, M. 1970. The fantastic combinations of John Conway's new solitaire game "life." *Scientific American* 223: 120–123.

Gilbert, N. and K. G. Troitzsch. 1999. *Simulation for the social scientist*. Buckingham, UK: Open University Press.

Gurung, T., F. Bousquet, and G. Trébuil. 2006. Companion modeling, conflict resolution and institution building: Sharing irrigation water in the Lingmuteychu watershed, Bhutan. *Ecology and Society* 11(2): 36–58.

Haken, H. 1983. *Advanced synergetics*. Berlin: Springer-Verlag.

Hoff, T., H. Wenger, and B. Farmer. 1996. Distributed generation: An alternative to electric utility investment in system capacity. *Energy Policy* 24(2): 137–147.

Hu, X., G. Grozev, and D. Batten. 2005. Empirical observations of bidding patterns in Australia's national electricity market. *Energy Policy* 33(16): 2075–2086.

Janssen, M. and E. Ostrom. 2006. Governing social-ecological systems. In *Handbook of computational economics: Volume 2. Agent-based computational economics*, edited by L. Tesfatsion and K. L. Judd. Amsterdam: North-Holland.

Langton, C. 1995. *Artificial life: An overview*. Cambridge, MA: MIT Press.

Lowe, E. A. and L. K. Evans. 1995. Industrial ecology and industrial ecosystems. *Journal of Cleaner Production* 3(1–2): 47–53.

Nicolaisen, J., V. Petrov, and L. Tesfatsion. 2001. *Market power and efficiency in a computational electricity market with discriminatory double auction pricing*. Economic Report No. 52. Ames: Iowa State University.

Nicolis, G. and I. Prigogine.1977. *Self-organization in non-equilibrium systems*. New York: Wiley-Interscience.

Pepermans, G., J. Driesen, D. Haeseldonckx, R. Belmans, and W. D'Haeseleer. 2005. Distributed generation: Definition, benefits and issues. *Energy Policy* 33(6): 787–798.

Perez, P. and D. Batten, eds. 2006. *Complex science for a complex world: Exploring human ecosystems with agents*. Canberra, Australia: ANU ePress.

Resnick, M. 1999. *Turtles, termites and traffic jams: Explorations in massively parallel microworlds*. Cambridge, MA: MIT Press.

Roth, A. E. and I. Erev. 1995. Learning in extensive form games: Experimental data and simple dynamic models in the intermediate term. *Games and Economic Behavior* 8: 164–212.

Tesfatsion, L. and K. L. Judd, eds. 2006. *Handbook of computational economics: Volume 2. Agent-based computational economics*. Amsterdam: North-Holland.

Veselka, T., G. Boyd, G. Conzelmann, V. Koritarov, C. Macal, M. North, B. Schoepfle, and P. Thimmapuram. 2002. *Simulating the behavior of electricity markets with an agent-based methodology: The EMCAS model*. Paper presented at the International Association for Energy Economists North American Conference, 6–8 October, Vancouver, British Columbia, Canada.

Wallner, H. P. 1999. Towards sustainable development of industry: Networking, complexity and eco-clusters. *Journal of Cleaner Production* 7: 49–58.

About the Author

David F. Batten coordinates CSIRO's Agent-Based Modelling Working Group (www.csiro.au/science/CABM.html) and Theme 5 (Cellular Automata, Agent-Based Modelling and Simulation) of the Australian Research Council's Complex Open Systems Research Network (COSNet; www.complexsystems.net.au/). Also, he manages Temaplan Australia, part of an international group of small, scientific consultancy firms specializing in industrial ecology and infrastructure analysis for industry and government.