SIMULATING ENERGY MARKETS AND INFRASTRUCTURE INTERDEPENDENCIES WITH AGENT-BASED MODELS

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ABSTRACT

National infrastructure systems are becoming more complex and interdependent. Markets and industries for electric power, natural gas, petroleum, and telecommunications are examples of physical network infrastructures and markets that are undergoing rapid evolution. For example, electric power markets, which have pioneered the transition from a regulated monopolistic system to decentralized open markets, have faced many challenges. The continuing restructuring of the natural gas industry is another example. This paper explores the use of agent-based modeling methodologies to simulate interactions among the interdependent infrastructures, focusing on the electric power and natural gas systems. Aspects of modeling infrastructure agent behaviors include agents' selection of objectives, pricing and bidding strategies, learning and adaptation regarding market evolution, and capacity expansion decisions. Modeling the decision processes and actions of the individual agents (e.g., natural gas suppliers, transmission companies, and independent power producers) is informed by approaches to modeling agent behavior that are being taken in the computational social sciences.

1 INTRODUCTION

National infrastructure systems are becoming more complex and interdependent. Electric power, natural gas, petroleum, and telecommunications are examples of physical infrastructures and markets that are undergoing rapid evolution. For example, electric power markets that have attempted the transition from a regulated monopolistic system to decentralized open markets have faced many challenges. The restructuring of the natural gas industry is another example.

As the national infrastructures become more competitive and are squeezed to maximize efficiencies, as safety margins narrow, and as systems approach their design limitations, infrastructures are becoming more physically and economically interdependent. Recently, breakdowns in the infrastructure markets and systems have become the object of the public's attention. The California electricity crisis and the natural gas price spike of December 2000 are examples. These incidents have the potential to create ripple effects in other infrastructures and raise important questions concerning the extent of infrastructure interdependencies, such as:

- Is it possible to quantify the physical and economic interdependencies among the infrastructures?
- How long does it take for disruptions, whether physical or economic, in one infrastructure to propagate through another infrastructure?

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- Under what conditions or system states could amplification occur in which disruptions in one infrastructure propagate through other infrastructures, thereby leading to unstable behavior?

- How will the infrastructures adapt or adjust to shocks and disruptions, both physical and economic?

- More specifically, will the electric power and natural gas industries co-evolve in such a way as to increase interdependencies? What are the implications for the stability of both systems?

These questions are extremely difficult to address using traditional modeling and simulation approaches. However, agent-based simulation is a natural approach to simulating the dynamics and diversity of agents within interdependent infrastructures. In this regard, there is a natural connection to the social sciences through the representation of behaviors of individuals and organizational structures. As Thomas, et al. (2002) observe:

> The rules of business are at least as important as the rules of physics when it comes to the generation, sale, and delivery of electrical power, for example, as well as the other infrastructures. The decision-making behavior of firms in an industry and the financial vehicles that allow a utility to exist and conduct business are crucial to gaining an understanding of the system evolution.

Modeling the decision processes and actions of the individual agents (electric power generation companies, natural gas suppliers, transmission companies, independent power traders, and others) involved in the operation and use of the commodities provided by the infrastructures presents a formidable challenge. This paper explores the use of agent-based modeling methodologies to simulate interactions among the interdependent infrastructures, focusing on the electric power and natural gas systems. Section 2 describes the salient features of the electric power and natural gas systems for modeling these industries in an agent simulation framework. Applicable notions from agent simulation and computational social sciences are discussed in Section 3. Section 4 presents an agent-based simulation approach to the analysis of infrastructure interdependencies.

2 THE ELECTRIC POWER AND NATURAL GAS SYSTEMS

2.1 Electric Power

The physical infrastructure of the electric power system comprises several components that generate, transmit, distribute, and utilize electricity (Figure 1) (Sadaat, 1999). Electric power plants consist of one or more generating units of varying sizes that use various fuels. In Illinois, for example, generating units are fueled primarily by uranium (nuclear), coal, natural gas, or oil. Other portions of the United States, especially the Northwest, rely on hydroelectric generation

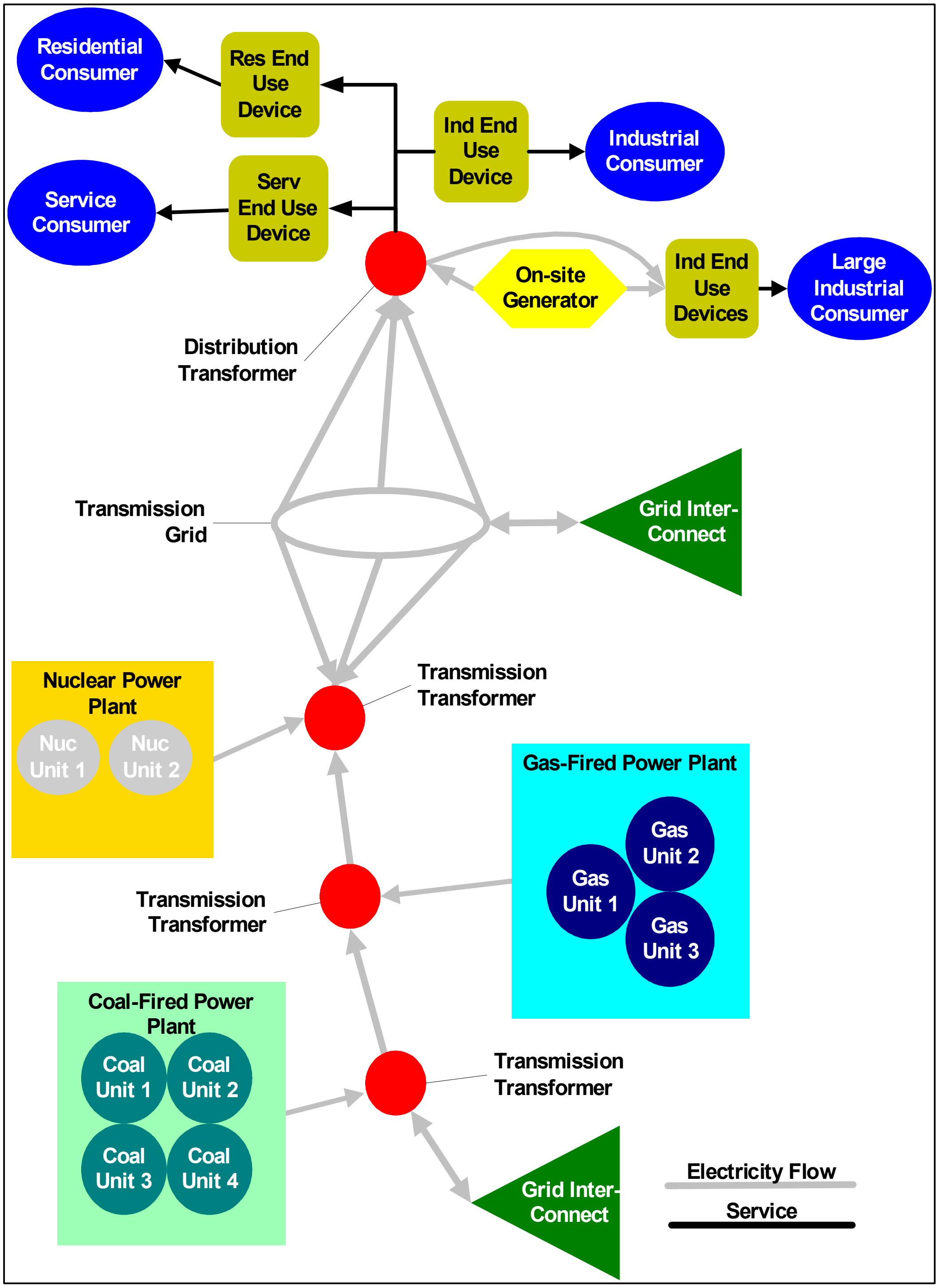

FIGURE 1 Electric Power System

where hydropower resources are abundant. Electricity is transmitted over an electric power network or grid. Generators and distribution subnetworks are connected to the grid at points called buses.

Generators create voltage potential, which is necessary for electric current to flow. Electricity is transmitted over long distances at high voltages to minimize losses. Transmission lines have capacity limits that are largely based on the physical properties of the lines. Transformers increase or decrease voltage levels at various points on the grid, which is necessary for efficient transmission and conversion to voltage levels for final use. The response of the electric grid is almost immediate. When a generator increases its power output, the effects are felt instantly throughout the network.

Electricity demand or load has a characteristic time-dependent profile that varies by sector (e.g., household, service industry, heavy industry). Load varies by hour of the day, day of the week, and season, due to societal and commercial consumption patterns and the weather. A typical electricity load pattern has load that is fairly low throughout the night, increasing from early morning and continuing throughout the day to a peak in the afternoon before declining toward the evening. It is typical for the system load to vary by a factor of 2 between base and peak hours during the course of a single day during the peak production season. Generating units, depending on fuel type, take more or less time to start up or shut down from full production capability, at which point the unit functions most efficiently. Start-up and shutdown costs may be sizable, so it may be desirable to continue to operate units at a loss during periods of reduced load to avoid the added costs of shutting down and restarting the unit. To generate enough electricity to meet the load, generating units can be cycled into production during base, peak, or intermediate demand periods based on the relative operating and fuel costs and response rates of the individual units.

The laws of physics endow the electric power system with some unique properties from an infrastructure point of view. Electricity cannot be stored, generally, but can be converted to other energy forms on a temporary basis; this is not currently done for electric power production on a large scale. Practically all electric power generation is in the form of alternating current. As a generator spins, it creates a voltage level and a corresponding current flow that fluctuates according to a sinusoidal wave. Such a wave is characterized by amplitude and frequency, and frequencies must be synchronized throughout the network to ensure the maximum flow of electricity and minimize energy losses. Increased electrical generation at a node (bus) has the effect of increasing the voltage at the node, which in turn affects the current flowing on *all* links (transmission lines) connected to the node. Electricity cannot be sent from point A to point B in the same way that most other discrete physical commodities are shipped from A to B, or the way that packets are routed over the Internet. The analogy often used for electricity transmission is increasing the flow of water through an interconnected set of pipes by increasing the pressure at any single point.

The physical aspects of the real electric power system are much more detailed and complex than described here. There exist very sophisticated physics-based models that consider all of the salient features of electric power generation and transmission, at least in enough physical detail to plan and operate the electric power grid successfully. At least one research program has been initiated on modeling the physical components of the electric power system in an agent modeling framework (Amin, 2000; Wildberger, 1997).

Figure 2 shows the typical decision-making agents in the electric power industry. Decision making operates in various time scales or decision levels that include everything from hourly unit dispatch to day-ahead, week-ahead, month-ahead, year-ahead, and multiyear time frames. At each decision level, supply agents make decisions regarding the operation of the generating resources they manage and formulate marketing strategies. Different types of markets are available to players at each time scale. For example, these could include markets for bilateral contracts, spot market pool, and ancillary services. Decision-making behavior includes decisions regarding bid pricing for day-ahead power generation and ancillary services markets, bilateral contracts, generating unit scheduling, and long-term capacity expansion. The decision process may be segmented. For example, one type of strategic decision made every day in the electric power industry is on what hourly generation prices to bid into the day-ahead market and each generation unit's schedule for the following day (Wen and David, 2001); another decision is to coordinate these generation bids for the ancillary services (such as reserve) markets (Wen and David, 2002).

2.2 Natural Gas

The physical infrastructure of the natural gas system comprises several components that produce, process, transport, distribute, and use natural gas (Figure 3). Natural gas is extracted from fields by wells, processed to separate gas constituents and remove moisture and impurities, and transported through the interstate pipeline system. Natural gas imports in the form of liquefied natural gas (LNG) are sizable in some parts of the United States, and the processing of LNG is part of the natural gas infrastructure. Natural gas is transported long distances through transmission pipelines. Compressor stations are distributed along pipelines at regular intervals to boost pressure and regulate the flow of gas. Gas is transported cross-country at high pressures and moves at high velocities. Pipelines have capacity limits based on the diameter of the pipe segments. Natural gas is a compressible fluid and, within limits, more gas can be moved through or stored in a pipeline with corresponding pressure increases in a process called line packing. It may take days for gas that is injected into the interstate pipeline system to reach its cross-country destination.

At regional gas markets called hubs, gas is traded and physically routed or wheeled to final regional destinations. When gas reaches a service area, it can be stored in large quantities, typically in underground storage fields (aquifers or abandoned gas fields) for future use. Gas from a transmission pipeline or withdrawn from storage field enters the distribution system through a city gate station that regulates pressure and flow. The gas is then sent through a distribution network that includes a series of regulators that reduce pressure to standard levels appropriate for final consumption. Unlike electricity, natural gas can be readily stored. Gas demand or load has a characteristic time profile or shape that varies by sector (e.g., residential, commercial, and industrial) and mix of loads. Although load varies by hour of the day, and day of the week as in the case of electricity, these fluctuations can be buffered by storage capability and line pack. The main problem facing natural gas supply is that load varies by season and highly depends on weather, which makes forecasting natural gas consumption difficult.

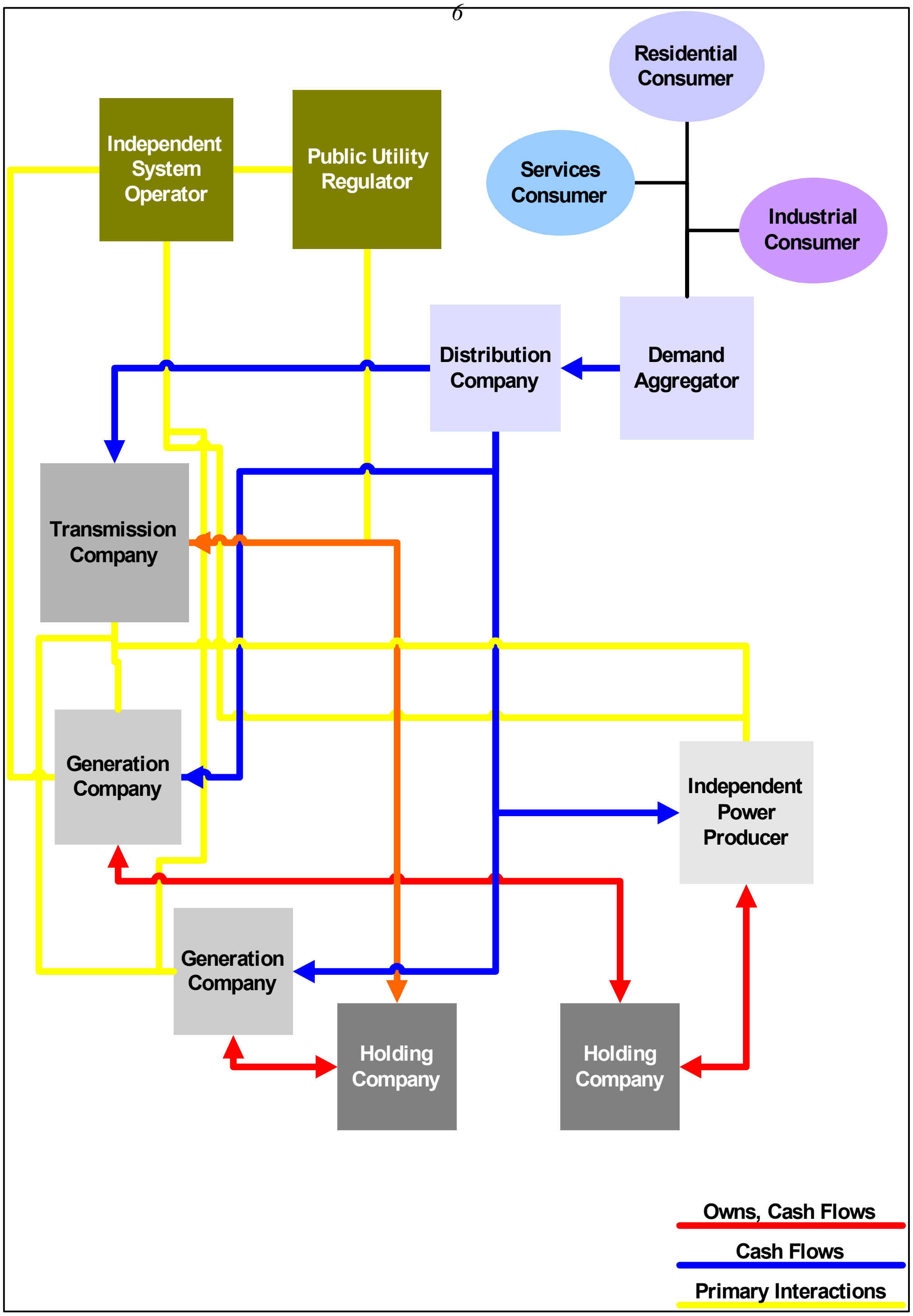

FIGURE 2 Electric Power Industry Decision-making Entities

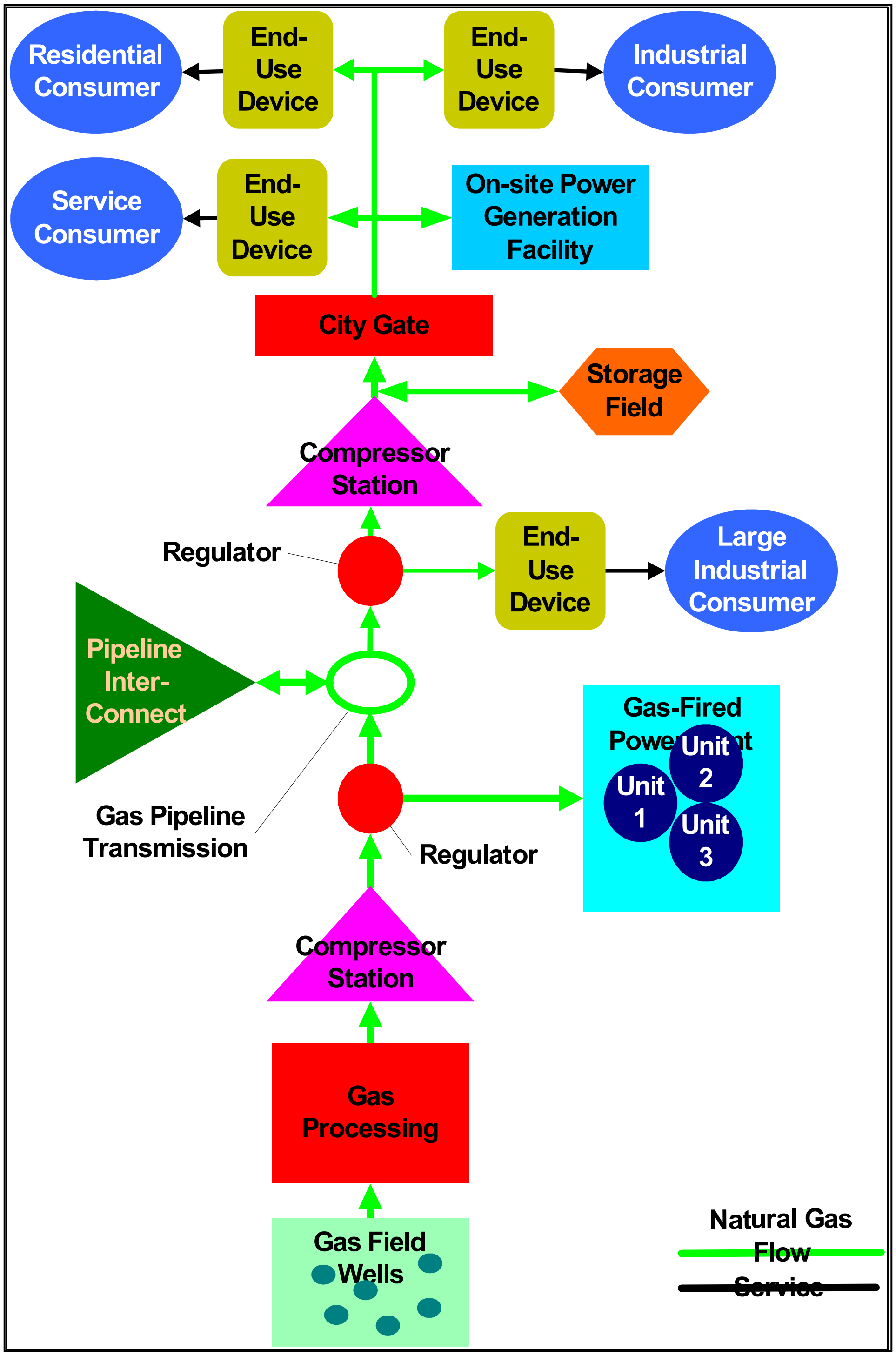

FIGURE 3 Natural Gas System

The physical aspects of the real gas network are much more detailed and complex than described here. Very sophisticated physics-based models consider all of the salient features of gas transport and distribution, at least in sufficient physical detail to plan and operate the system successfully.

Figure 4 shows the typical decision-making agents that make up the natural gas industry. Strategic decisions in the natural gas industry depend on such factors as portfolio of gas supply, storage contracts, and weather effects, primarily seasonal effects (Knowles and Wirick, 1998; Rosenkranz, 1989). The typical decision problem faced by the natural gas supplier consists of maximizing earnings per share, maximizing rate of return on investment, and finding co-rerelated business opportunities that generate a high rate of return. The local distribution company's (LDC's) decision problem centers on gas storage in regions where a large portion of gas supply in the winter months may come from storage. The typical LDC decision problem consists of deciding on the quantity of gas to go into storage in advance of winter, deciding on an acceptable level of risk regarding the severity of next winter's weather, deciding on a storage fill schedule, and deciding on capital investments to improve the situation. For example, capital investments could consider improving the deliverability system, adding compressors or more storage capacity, and possibly extending the pipeline system.

2.3 Market Mechanisms

Electricity markets are undergoing major restructuring in response to deregulation. Electricity market trading is becoming much less tied to the traditional operations-based goals of reliability maximization and cost minimization. Buying and selling of electric power are beginning to resemble the trading of many commodities in both the spot and future markets (Stephenson and Paun, 2001). The natural gas industry also continues to undergo a major restructuring (Leitzinger and Collette, 2002; Economides, et al., 2001). Both markets are expected to be in transition for some time to come.

The selection of particular market rules that will be applied in the deregulation process is a key concern of companies, organizations charged with industry oversight, and industry analysts. Even competitive markets can be set up with significantly different market rules that lead to quite different outcomes. The types of markets that are available and the specific rules under which each market operates influence the decisions made by the market players and the evolution of the industry. For example, Bower and Bunn (2000) compared markets in which all suppliers bid into a common pool to markets in which bilateral mechanisms predominated. Different market rules can create different degrees of market power. A general issue of concern is how to appropriately mix regulation and competition for the restructured energy industry (David, 2001) in a manner that minimizes the potential market power of market participants and minimizes costs to the consumer.

2.4 Interdependencies

The electric power and natural gas markets are undergoing fundamental transformations in the sources of fuel for electric power generators. Large electric generators that use natural gas as a fuel source are rapidly gaining market share, due to their relatively capital construction costs and relatively short construction lead times (1 to 2 years). Many types of gas-fired electric

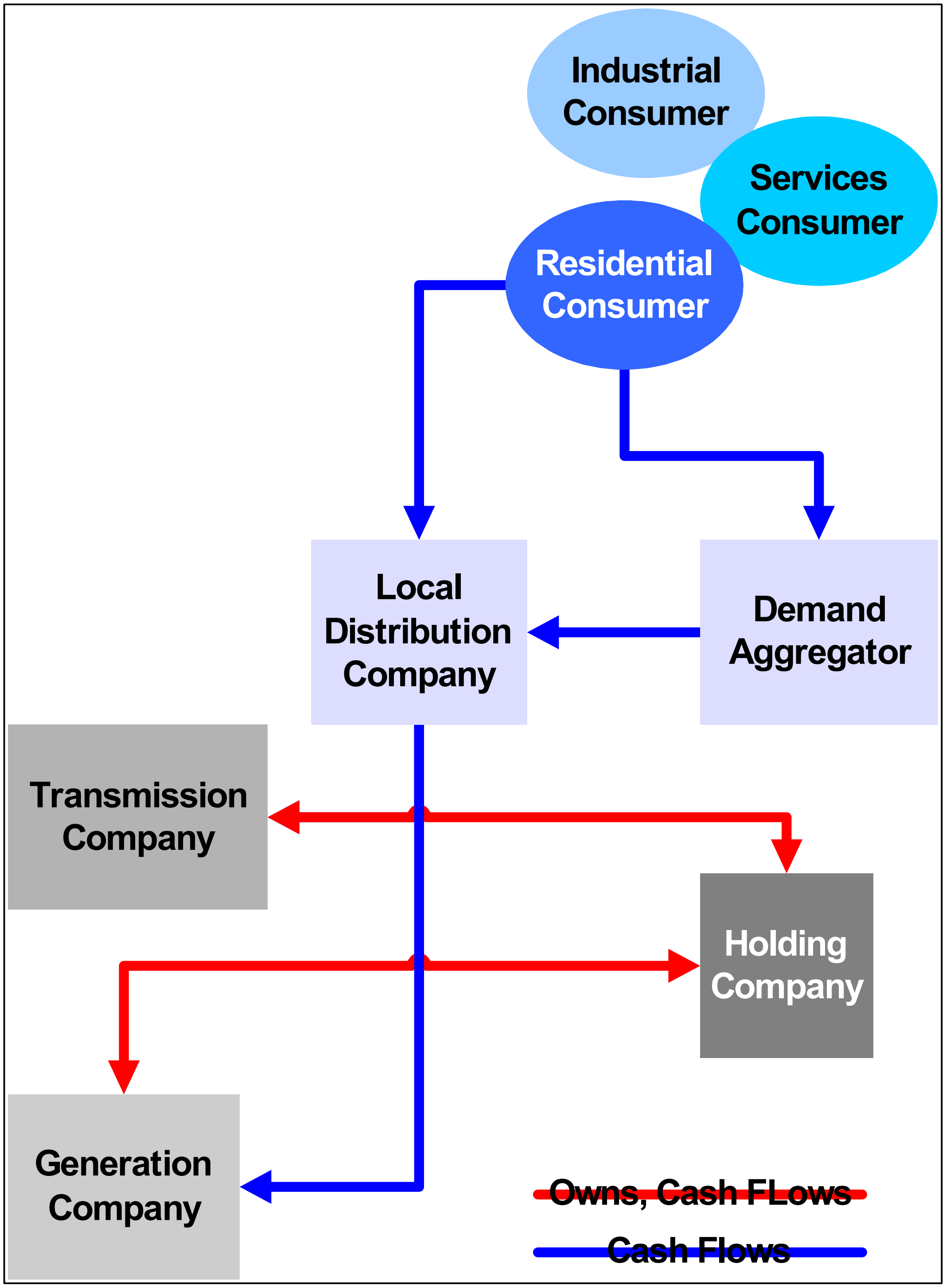

FIGURE 4 Natural Gas Industry Decision-making Entities

generating units can be started up or shut down in a very short time with minimal cost. Small gas-fired units are commonly used to respond to short-term fluctuations in peak electricity load. The recent expansion in the construction and use of gas turbine peaking units for electric power generation, due to technology improvements, favorable economics, and readily available gas supply, has introduced an interdependency between the electric power and natural gas infrastructures of potentially sizable proportions (Anderson, 2000). In addition, the increased use of natural gas for electric power production has led to the observed correlation of electricity and natural gas futures prices over diverse markets (Emery and Liu, 2002).

3 SIMULATION OF THE INFRASTRUCTURE

3.1 Agent Simulation

Several models have been developed for the electric power industry. These systemwide models include economic factors and physical constraints unique to the electric power industry. Fewer system-wide models have been developed for the natural gas industry (Avery, et al., 1992; Bopp and Kanan, 1996; Guldmann and Wang, 1999; MacAvoy and Moshkin, 2000). In both the electric power and natural gas cases, these models are formulated and solved using traditional techniques, such as optimization, in which an organizational objective function is specified and maximized, or discrete event simulation, in which the steps in a dynamic process are modeled. Market outcomes for electric power markets have been modeled using traditional game theoretic equilibrium frameworks (Moitre, 2002; Nguyen and Wong, 2002). Models using traditional simulation and optimization techniques have limitations in addressing questions about the stability, robustness, and interdependent evolution of infrastructure industries, as they lack the capability to model agent adaptation in response to changing economic and physical factors.

The sheer complexity of the types of decisions that need to be made in the electric power and natural gas industries, uncertainty regarding the data upon which the decisions are based, and the short time frames for decisions are all factors that preclude the practicality of formulating or solving in real-time "optimal" decision problems for these industries as a whole. To a large extent, these systems have always been too complex to model adequately. For example, modeling economic markets has often relied on the notions of perfect markets, homogeneous agents, and long-run equilibrium. The need to capture transitory behaviors of the infrastructure in response to disruptions is a key issue in infrastructure interdependency analysis, as evolutionary paths may affect the long-run configuration of the infrastructure.

Agent-based simulation (ABS) offers a promising modeling alternative to capturing and discovering realistic infrastructure behavior as compared to traditional simulation approaches. An ABS consists of a set of agents and a framework for simulating their decisions and interactions. An agent is a self-directed software representation of a decision-making unit. The complexity of an ABS arises from the interaction patterns among the agents. Emergent system behavior is a common result from agent simulations and occurs when the behavior of a system is more complicated than the simple sum of the behavior of its components (Bonabeau, et al., 1999). ABS is related to a variety of other simulation techniques, including discrete event simulation (Law and Kelton, 2000) and distributed artificial intelligence or multiagent systems. Although many traits are shared, ABS is differentiated from these approaches by its focus on achieving "clarity through simplicity" as opposed to maximizing representation detail (Sallach and Macal, 2001). Agents typically are modeled as having bounded rationality, meaning that they make decisions using limited internal decision rules that depend only on imperfect local information. Agent simulation is more amenable to modeling the segmented decision processes as they exist in real infrastructure industries.

Infrastructures lend themselves to structuring agent interaction patterns as networks, which can be readily defined and represented. Modelers are beginning to realize that the topology of networks of interacting agents influences the dynamic behaviors of the network as a whole and therefore the emergent properties of the system. For example, Watts (1999) characterized the topology of electric power system networks for the State of New York and found that it exhibited a scale-free distribution of link-node connectivity, which has considerable implications for reliability and economic features of the infrastructure in general.

3.2 Computational Social Science

New developments in computational environments and modeling toolkits have opened up the possibility of and even created the demand for integrating diverse fields of knowledge and investigation into practical frameworks for modeling real-world problems. Tesfatsion (2002) notes:

> Advances in modeling tools have been enlarging the possibility set for economists…. Researchers can now quantitatively model a wide variety of complex phenomena associated with decentralized market economies, such as inductive learning, imperfect competition, endogenous trade networks formation, and open-ended co-evolution of individual behaviors and economic institutions.

The complex interactions and interdependencies among electricity market participants are much like those studied in game theory (Picker, 1997). Unfortunately, the strategies used by many electric power and natural gas market participants are often too complex to be modeled using standard game theoretic techniques. In particular, the ability of market participants to repeatedly probe markets and adapt their strategies adds complexity.

Computational social science (Epstein and Axtell, 1996), which involves the use of agent simulations to study complex social systems, offers appealing extensions to traditional game theory. Social agents have a behavioral “repertoire” — behaviors they are capable of acting upon. For example, such a behavioral repertoire may consist of reproduction (the ability to form new firms and create larger organization structures, for example, through mergers), resource gathering (revenue generation), vision and perception of the behaviors of other agents (visibility), credit, trade, and cognitive complexity (decision-making sophistication). Behavioral experiments (Erev and Roth, 1998) can motivate candidate heuristics (Sterman, 1987) for modeling complex but generally applicable decision-making behaviors; these heursitics can be tested in agent simulations.

4 AN APPROACH TO AGENT-BASED SIMULATION OF THE INFRASTRUCTURE

Agent-based simulation applications to modeling infrastructure industries are very recent. Special-purpose agent-based simulation tools such as Swarm (Burkhart, et al., 2000), the Recursive Agent Simulation Toolkit (Repast) (Collier and Sallach, 2001), StarLogo, and Ascape are among the most widely used options for implementation of ABS models. A few electricity market ABSs have been constructed, including those created by Bunn and Oliveira (2000), Petrov and Sheblé (2000), and Veselka et al. (2002). ABS has been applied to analyzing the new electricity trading arrangements for England and Wales (Bunn and Oliveira, 2001). North (2001a) applied ABS to identify infrastructure factors in electric power generation and transmission leading to local price spikes. North (2001b) demonstrated the feasibility of applying agent simulation to quantify the extent of interdependencies between the electric power and natural gas infrastructures. Thomas, et al. (2002) present a conceptual modeling framework for examining infrastructure interdependencies. These models have demonstrated the potential of agent simulations to act as electronic laboratories, or "e-laboratories," suitable for repeated experimentation under controlled conditions.

The ABS approach to infrastructure interdependency analysis consists of representing the physical and behavioral aspects of the infrastructures as a system of highly connected, interacting agents (Figure 5). Agents interact in terms of physical and financial flows and by exchanging information on system performance; key economic parameters are essential to model realistic system operation and adaptation. As an agent is a representation of a decision-making unit, the emphasis on modeling the behavioral components within the infrastructure translates into identifying the primary decision-making processes that are carried out. Each agent has rules of behavior and a decision-making capability that broadly considers salient aspects of the immediate environment and other agents' behaviors. Ideally, organizations could be modeled explicitly as collections of agents that form spontaneously in response to the physical and economic variables in the simulation. The goal of developing the simulation is to monitor and understand the behavior of various system properties (such as reliability and stability), and market issues (e.g., pricing, market share patterns, company profitability, cost recovery).

The physical properties of the electric power and natural gas systems have several implications as to how to structure an agent simulation that includes behavior agents in conjunction with its physical representation. In effect, these physical properties define a topology and create a "landscape" of constraints within which an agent simulation must operate.

4.1 Modeling Issues

Several modeling issues are relevant to the practical application of agent simulation to infrastructure analysis.

4.1.1 Aggregation

Aggregation of the physical and behavioral components of the infrastructure for representation in an agent simulation is necessary to some degree and is especially so in representing multiple infrastructures and their interactions. Aggregation represents a trade-off

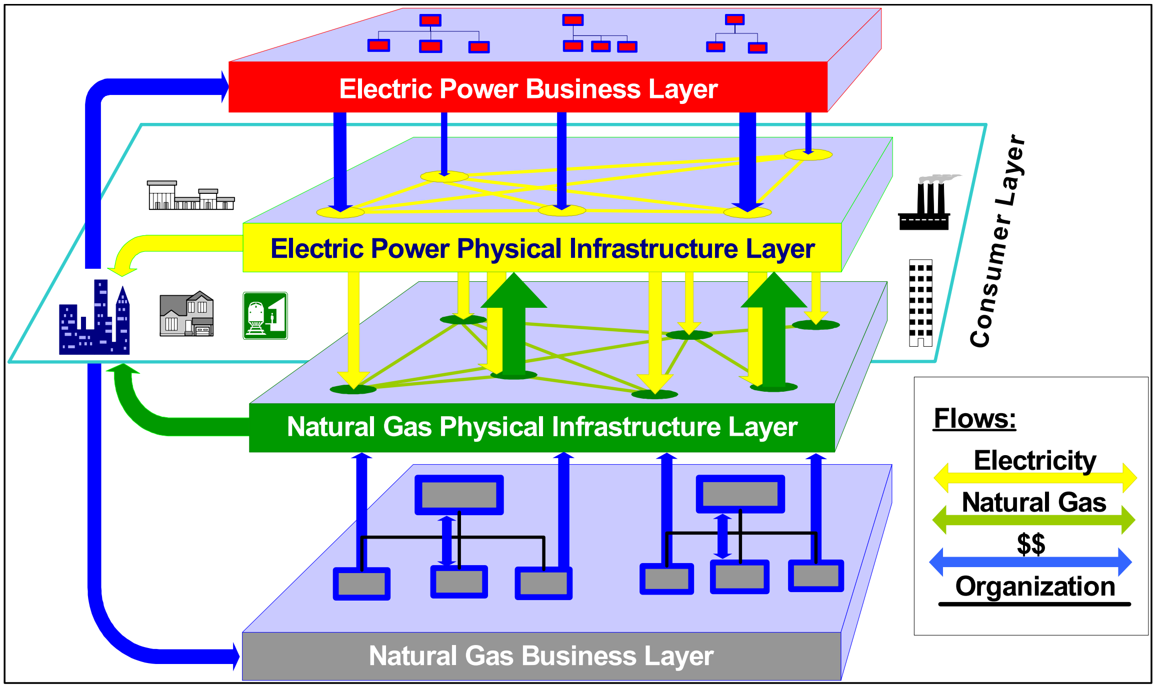

FIGURE 5 Interdependencies between Electric Power and Natural Gas Systems

among various factors such as computational performance and data availability on the one hand and "correspondence credibility" and accuracy on the other hand. Modeling agents at more detail establishes credibility through more direct, one-to-one correspondence between the real system and their representation in the modeled system. Accuracy improves to a point as more detail is included and then levels off. For example, an aggregate model of consumer behavior may be nearly as accurate as the results obtained from a model in which each consumer's behavior is simulated individually. As agents are modeled at greater levels of detail, computational performance degrades, and data requirements become infeasible to satisfy with available and accurate data. The level of aggregation needed for modeling the infrastructure while reasonably satisfying these trade-offs appears to be consistent with the representations shown in Figures 1–4.

4.1.2 Model Collaboration and Consistency

Even if one is able to model the physical infrastructure to the level of detail of individual components in an agent simulation, it is only an approximation to the dynamics of the actual infrastructure for a limited range of operational parameters. Very detailed physical models of regional electric power grids are used to operate the grid, plan transmission, and consider generation expansion. To include these complex physical models within an agent framework along with the decision-making agents is not feasible. Alternatively, the detailed physical models can be used to derive approximations to transmission network transfer capabilities for local neighborhoods in which the agent simulation operates. This entails establishing a close and

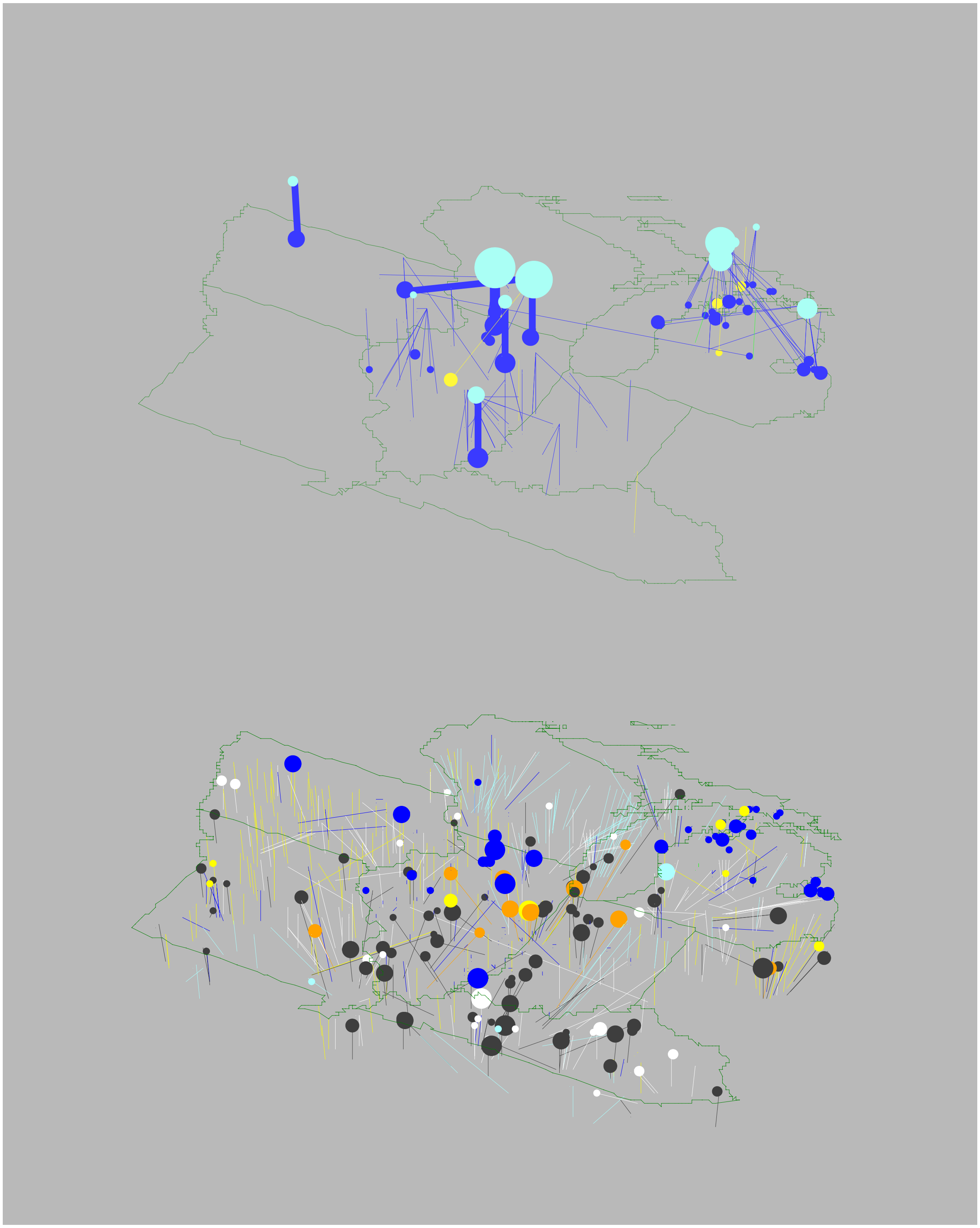

FIGURE 6 Regional Natural Gas (top) and Electric Power Plants and Facilities (bottom) and Ownership Relationships

ongoing “collaboration” between the agent simulation and the physical system model to ensure consistency between physical variables in each of the models. A similar situation exists for the natural gas industry. Detailed physical models for natural gas are based on mass balance relations and pressure and temperature variables.

4.1.3 Data

Of paramount importance is the issue of whether data are available to support the development of an agent simulation infrastructure model at the level of detailed complexity needed for credibility. Much of the data on the physical infrastructure are available from public sources, but compilation and integration of the data are a formidable task. The economic data and financial data on infrastructure markets also appear to be available. Data on the decision-making processes used by individual company agents included in a simulation may, however, be very difficult to acquire. The data problem is largely one of verifying the accuracy of the data and maintaining its currency. Figure 6 shows a preliminary network representation of regional infrastructure data for the natural gas and electric power systems and ownership relations.

4.1.4 Agent Decision Making

Aspects of decision-making behavior included within the scope of modeling infrastructure agent behaviors include agents’ objectives and risk preferences, future price expectations, and learning and adaptation in response to simulated market conditions. Each agent has a set of objectives such as maximizing profits, maximizing market share, maximizing capacity utilization, minimizing unserved energy, etc. Objectives may conflict with each other in that improvement in one objective may negate improvement in other objectives. For example, if a generation company agent tries to maximize the capacity factor of a unit at times of low market clearing prices, maximum profits may not be achieved. Each objective of an agent is represented by a minimum expected value, a maximum expected value, and a risk preference. An agent’s risk preference is broadly classified as risk-averse, risk-neutral, and risk-seeking and could be modeled using, for example, a von Neumann-Morgenstern expected multiobjective utility function. The overall utility is then computed as the weighted summation of all single-objective utilities. On the demand side, an objective of a demand agent could be minimizing the unserved energy to its customers.

Agents develop price expectations for the markets in which they participate. These expectations are based on a combination of public information available to all market participants, and private information available only to the specific agent. The differing private information available to the agents results in a diversity of price expectations. Initially, the agents have prior price expectations based only on public information (i.e., information on pool prices, system load, reserve margin). Agents may also have differing skills in forecasting the future markets and differ in the historical information available to them on the acceptance and rejection of their own bids. On the basis of results from the simulation, agents update their price expectations using private information on bids that are accepted and rejected and public information that is available to all participants.

An agent learns about market behavior and the actions of other agents based on an exploration process. Agents explore various marketing and bidding strategies and observe the results of their actions. Once a strategy is found that performs well, it is exercised and fine-tuned as subtle changes occur in the marketplace. When more dramatic market changes take place and a strategy begins to fail, an agent more frequently explores new strategies in an attempt to adapt to the dynamic and evolving supply and demand forces in the marketplace. Even when a strategy continues to perform well, an agent periodically explores and evaluates other strategies in its search for one that performs better. Through this process, agents engage in a price discovery process and learn how they may potentially influence the market through their own actions to incrementally increase their utility.

4.2 Prototype Agent Simulation

A preliminary prototype model SMART II+ has been developed to explore infrastructure interdependencies (North, 2001a). The model includes an integrated set of agents and interconnections representing (1) the electric power marketing and transmission infrastructure, (2) the natural gas marketing and transmission infrastructure, and (3) the interconnections between the two infrastructures in the form of natural-gas–fired electric generators. SMART II+ includes two different kinds of market agents — producers and consumers. Agents are connected by a complex physical network of links representing electric power transmission and natural gas transmission systems and nodes representing their transformation and interconnection. Each transmission link and pipeline link has a capacity which limits flow over the network.

Agents are also connected with the physical infrastructure network through ownership and financial relationships. Economic variables in the model consist of investment capital and generation capacity expansion for profitable producers, bankruptcy for noncompetitive organizations, and demand growth for successful consumers. Link capacity constraints and transmission losses have the effect of creating spatially separated regional markets for electricity and natural gas. The electric power infrastructure includes the gas-fired electric generators that buy fuel from the natural gas market. The resulting electricity is then sold in the electric power market.

Key market indicators derived from SMART II+ are market prices, unserved energy (UE) and gas-fired electrical generator market share (MS), as shown in Figure 7. Unserved energy is the energy demand that was not met by the market and represents a form of market failure. (UE is given as a percentage of total energy demand.) Natural-gas–fired electric generator market share is a measure of the electric generation capacity that is supplied by natural gas units and is a key indicator of infrastructure interdependency. Investigation of the interdependencies between the electric power and natural gas markets indicates that natural-gas–fired electrical generators are highly competitive, which causes their market share to rise rapidly. In turn, rising natural-gas–fired electrical generator market share radically increasing market interdependence. Finally, increasing market interdependence pits the electric power and natural gas markets against each other during simultaneous disruptions, since both markets are fighting for the same underlying resource — natural gas — driving up prices for both commodities.

5 SUMMARY AND CONCLUSIONS

Agent-based simulation offers promise for modeling the complexities of interdependent infrastructures, their co-evolution, and response to changing market conditions and physical disruptions. Detailed physical models can be used in collaboration with ABSs that include behavioral components and less-detailed representations of the physical systems. This approach provides more information about infrastructure interdependencies than can be produced by traditional simulations.

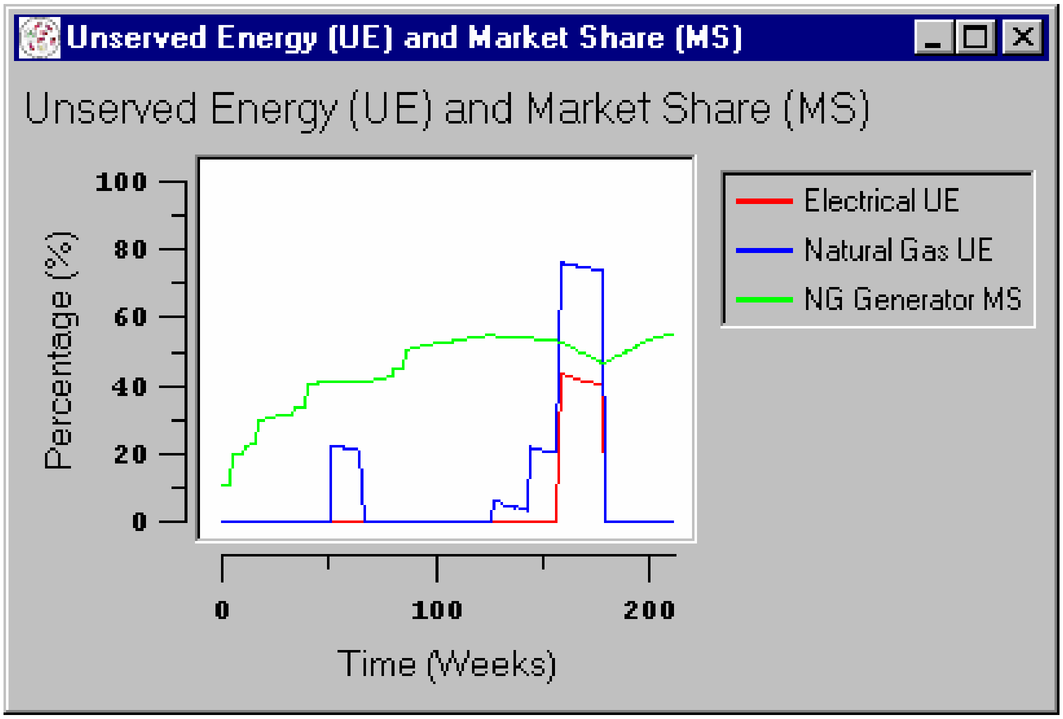

FIGURE 7 Unserved Energy and Natural Gas Generator Market Share in Response to Price Spike

6 ACKNOWLEDGMENT

The authors thank Vladimir Koritarov, Richard Cirillo, and Michael McLamore for helpful discussions on various aspects of the infrastructure systems. This work is sponsored by the U.S. Department of Energy under contract W-31-109-ENG-38.

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