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AGENT-BASED MODELING OF ELECTRIC POWER MARKETS

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ABSTRACT

A novel agent-based model, the Electricity Market Complex Adaptive System (EMCAS) model, is designed to study market restructuring and the impact of new technologies on the power grid. The agent-based approach captures the complex interactions between the physical infrastructure and the economic behaviors of various agents operating in an electricity market. The electric power system model consists of power generating plants, transmission lines, and load centers. The electric power market is composed of generating company agents who bid capacity and prices into power pools administered by an Independent System Operator (ISO). The ISO agent balances supply and demand for day-ahead markets. EMCAS also simulates real-time market operation to account for the uncertainties in day-ahead forecasts and availability of generating units. This paper describes the model, its implementation, and its use to address questions of congestion management, price forecasting, market design, and market power.

1 INTRODUCTION

Electric power plays an important role in the economic vitality and everyday conveniences of our society. The physical electric power grid has been described as the most complex system ever built, consisting of millions of individual technical components that operate in complete synchronization to efficiently deliver electric power from generators to consumers through millions of miles of interconnected wires. The physics of the infrastructure (e.g., electric power generation, transmission, distribution) is well known; power flow modeling of the electricity grid consists largely of solving systems of nonlinear equations. Yet, 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. The decision-making behavior of firms in the power industry and the market structure with its associated rules of engagement are important factors in understanding how the electric power system operates. A typical power market consists of decision-making "agents" that control generating company resources (generating company agents), consume electric power and establish load requirements (demand agents), balance supply and demand (for example, an Independent System Operator (ISO) or Power Exchange), and aggregate consumer demand (load aggregator agents).

Essentially, modeling the electric power market consists of balancing supply and demand over time through a dynamic price discovery mechanism, all constrained by the physics of electricity.

Agent-based modeling (ABM) is a natural approach to modeling socio-technical systems, such as the electric power grid and market, in which the physical infrastructure is modeled along with its decision-makers and operators (Macal and North 2002; Macal et al. 2008; Macal and North 2010). Early agent-based simulations of electricity markets include: Bower and Bunn (2000, 2001), Bunn and Oliveira (2001, 2003), Petrov and Sheblé (2000), Nicolaisen, Petrov, and Tesfatsion (2001), and others. Critical surveys of agent-based electricity models are given by Zhou, Chan and Chow (2007) and Weidlich and Veit (2008). These early models tended to be of small scale and were often intended to illustrate the ability of ABM to represent the range of complex and heterogeneous decision making behaviors of agents observed in the real world. Including agent learning and adaptation are critical for developing realistic models of the electric power market. More recently, Babic (2014) has conceptualized an ABM for smart grid applications.

This paper describes a large-scale, high-fidelity, agent-based simulation model of the electric power grid called the Electricity Market Complex Adaptive System model (EMCAS). The model was originally developed as an electronic laboratory to help understand the implications of electricity market restructuring. More recently, EMCAS is being applied to understand the impacts of new technology developments on the availability, price, and reliability of electric power over large sections of the power grid. Although EMCAS has a long history and various aspects of the model and initial prototypes are documented in a variety of sources (e.g. North et al. 2002; Conzelmann et al. 2004; Koritarov 2004; Argonne National Laboratory 2006; Cirillo et al. 2006), it is continuing to be used and further developed for new applications. EMCAS is one of the few examples of large-scale agent-based models whose results have been used by policy makers in understanding the dynamics of a very complex socio-technical system.

This paper is organized as follows. Section 2 describes the electric power system and the EMCAS model. Section 3 illustrates experiments with the model to understand the emergence of market power. Section 4 concludes with lessons learned.

2 MODELING THE ELECTRIC POWER MARKET

The description of EMCAS here generally follows the main threads of the ODD (Overview, Design concepts, and Details) protocol for describing agent-based models (Grimm et al. 2010).

EMCAS is structured in two layers – the physical infrastructure layer, which models the electric power system and its physical components, and the business layer, which contains the decision-making agents that plan and operate the power grid. Agents make decisions at the business layer that then affect change at the physical infrastructure layer. Agents include generation companies, demand companies, transmission companies, distribution companies, independent system operators, consumers, and, potentially, regulators. The business layer, agents, and agent interactions constitute the electric power market in which electricity supply and demand is balanced through contractual arrangements through a day-ahead bidding process (Figure 1).

2.1 Modeling the Electric Power System

The electric power system consists of electric power plants; individual generating units at plants; node injection and withdrawal points (i.e., buses); load centers in which consumer power demand on the system is aggregated; and transmission lines of various voltages and capacities along which power flows. These components of the power system are represented in individual detail and are connected through a network. Solving the power network gives the voltages and current flows along each branch and for each node according to Kirchoff's Laws. Complex formulations of the power grid are highly non-linear alternating current (AC) models. Solving the AC model requires extensive computational resources that make solving a combined grid and agent market model infeasible. In EMCAS, a simpler direct current (DC) optimal power flow model (DC-OPM) balances generation and load (i.e., equilibrates supply and demand) across the network subject to transmission link capacities (Frank, Steponavice, and Rebennack 2012; Argonne National Laboratory 2006). The DC formulation is a linearized model of the power grid in which the phase angles between current and voltages throughout the network are assumed to be constant, whereas in the AC formulation these are variables. Studies have shown that the DC model can be a good approximation to the corresponding AC model and so this has been adopted in EMCAS (Overbye, Cheng, and Sun 2004). The DC formulation is used for scheduling and market clearing purposes in real-world electricity markets as well.

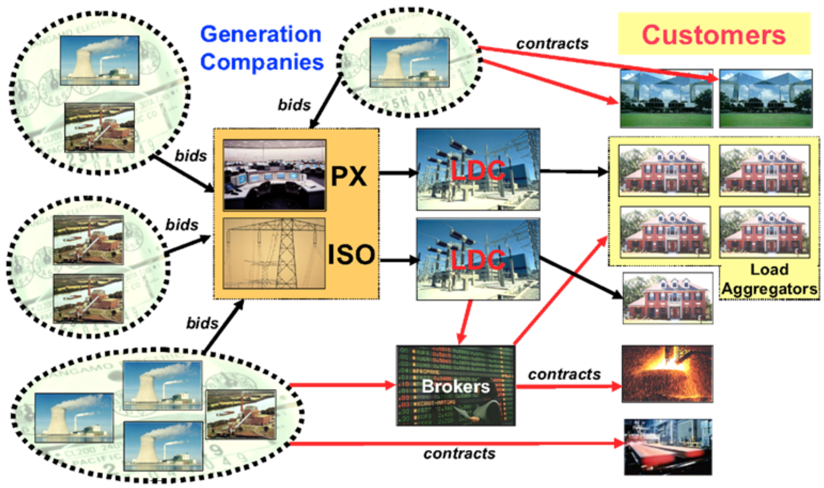

Figure 1: Electric power market.

2.2 Modeling Power Markets with Agents

There are several types or classes of agents in EMCAS (Table 1). Each agent class has its own set of heuristics by which it makes decisions. In object-oriented terminology, these are implemented as methods operating on the agents at the class level. Agent classes can be readily expanded if needed due to the extensibility of the underlying object-oriented implementation.

GenCo agents own power plants of various fuel types and operational characteristics located across the grid. A GenCo's objective is to make profits by selling electric power at prices that are at or above its marginal production costs. A GenCo does this by bidding its portfolio of available plant generation capacity at prices of its choosing according to its bidding strategy. A bid is a time profile of hourly prices and quantities for the next 24-hour period. The ISO agent (described below) accepts or rejects a GenCos bids after all bids are entered. A GenCo may adjust its bidding strategy over time as it learns which strategies are more successful at being accepted by the ISO and attaining profits. A GenCo also may learn how much market power it has. Market power occurs when an agent has the ability to influence prices while at the same time increasing its own profits. GenCo bidding strategies have been the subject of much empirical research and have been the basis for a number of participatory simulation games.

The ISO agent administers the market by balancing power supply and demand in day-ahead and real-time markets. An electric power market can operate under various market rules depending on how it is set up. The two most common alternatives are: pay as bid, in which the price received by a producer is equal to their bid price, or uniform pricing, in which everyone in the market receives the same market clearing price for the power they generate. In this way, the simulation can be used for market design to evaluate alternative market rules in advance of their implementation. In the following discussion, we assume a

Table 1: Electric power market agents.

Agent: Generating Company (GenCo) Attributes: • GenCo identifier • Power plants owned Objectives: Maximize net revenues Behaviors: *Dispatch Strategy*: Decide how and when to operate generation equipment. *Bidding Strategy:* Decide on what prices to charge and how much generation capacity to submit into market. Submit bid to day-ahead market.
Agent: Independent System Operator (ISO) Attributes: • ISO identifier • GenCos bidding power into day-ahead energy and ancillary services markets • Load zones supplied with power Objectives: Balance power supply and demand. Maximize net social welfare. Behaviors: *Planning function:* Forecast next day weather, system demand and available system generation capacity. Make information available to all agents. *Pool market function:* Operate the pool market for energy and ancillary services. Administer price setting market rules (e.g., Locational Marginal Pricing). *Scheduling function:* Accept or reject GenCo bids and bilateral contracts based on load flow balancing. *Dispatching function:* Dispatch generators in real time to match demand. Maintain necessary security requirements *Settlement function:* Apply settlement rules to calculate payments to and receipts from GenCos, DemCos, and TransCos
Agent: Demand Company Agent (DemCo) Attributes: • DemCo identifier • Associated customer agents • Nominal aggregate load consumption profile (annual by hour) computed from consumer load profiles • Associated load center connection points in transmission network Objectives: Maximize net revenues Behaviors: Create aggregate load from customer demand. Submit nominal load forecast and bids to ISO.
Agent: Customer Agent (Cust) Attributes: • Cust identifier • Nominal load consumption profile (annual by hour) Objectives: Satisfy end-use service needs for power. Minimize costs. Behaviors: Establish electricity load in response to customer service needs and electric power prices
Agent: Transmission Company Agent (TransCo) Attributes: • TransCo identifier • Transmission assets owned Objectives: Supply power over transmission grid to meet load center (distribution) requirements. Minimize cost. Behaviors: Transmit electric power from generation points to distribution networks

version of EMCAS that models uniform pricing, the most common market clearing rule in current electricity markets.

The simulation operates in two modes, day-ahead and real-time, which corresponds to how the market works in the real world. In the day-ahead mode of the simulation, the ISO decides which bids will be accepted and which GenCos will produce power for the following day in power and ancillary services markets. In real-time mode of the simulation, generating company agents whose bids have been accepted then provide power into the simulated market for the following day.

The ISO equilibrates supply and demand by solving the DC-OPF (Direct Current-Optimal Power Flow) network optimization problem for market clearing quantitates and prices at each link and node of the network. The DC-OPF is solved twice each simulated day, once in day-ahead planning mode, given the expected system load and the hourly bid (price/generation capacity) offers by the GenCos, and again in real-time operations mode, given the actual (simulated) system load and the actual GenCo unit availability. The DC-OPF gives spatially distributed, locational marginal prices (LMPs) for electricity, dispatch schedules for generators, and power flows throughout the transmission network. Demand company agents (DemCos) aggregate customer demand for electric power. Customer agents (Cust) have nominal load consumption profiles in planning mode that are adjusted by stochastic variations of weather (temperature) in the real-time mode of the simulation. Transmission company agents (TransCos) transport power across the grid from power plant injection points to distribution networks.

In addition to agents, the physical components of the power system are modeled, as shown in the UML (Unified Modeling Language) class diagram in Figure 2. Agents are “connected” to (interact with) the power grid in terms of the power system assets that they own and control.

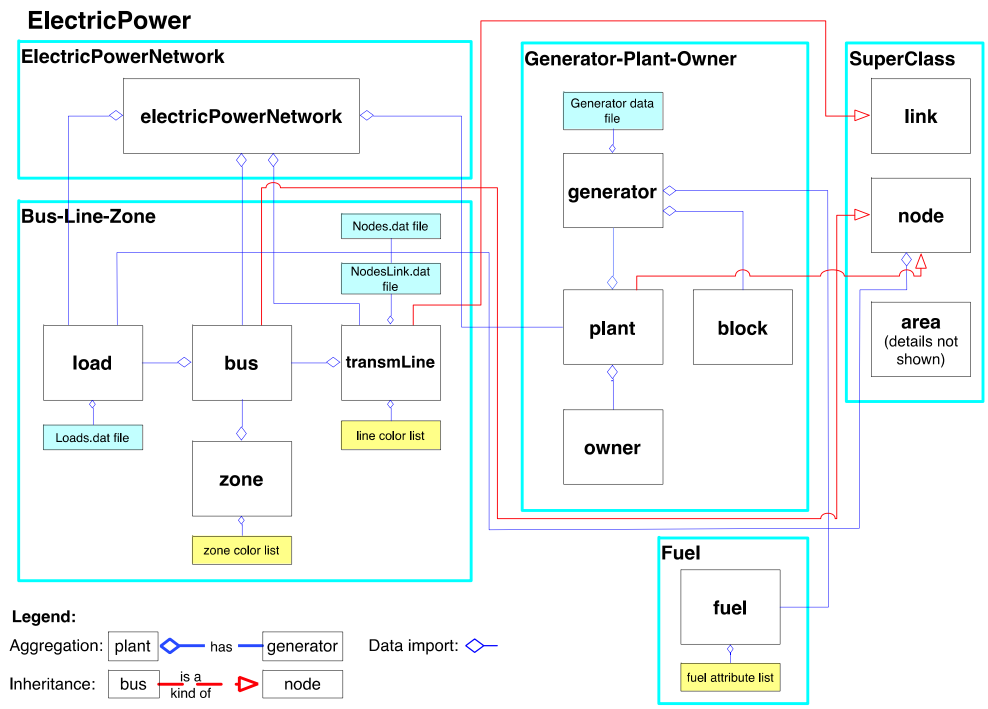

Figure 2: UML class diagram for electric power grid.

2.3 Process Overview and Scheduling

The process flow of the day-ahead component of the simulation is shown in Figure 3. The simulation is time-stepped with a step size of one hour, and is run over an entire year. This time span captures the hourly fluctuations in daily electricity demand and seasonal effects due to the weather as well as the maintenance cycles of generating units as they go offline and reenter service.

2.4 Stochasticity

In the simulation of real-time operations, unforeseen events, such as unplanned plant outages and weather events can result in higher load requirements by customers. These events are represented stochastically based on empirical weather data and plant outage data. They cause the power supply and demand levels that were in balance in day-ahead mode to be out of balance in the real-time mode. When this happens, the ISO uses any available resources to balance demand and supply including bringing on additional capacity in real-time mode that had been contracted for in day-ahead mode, reflecting real-world ISO behaviors and outcomes.

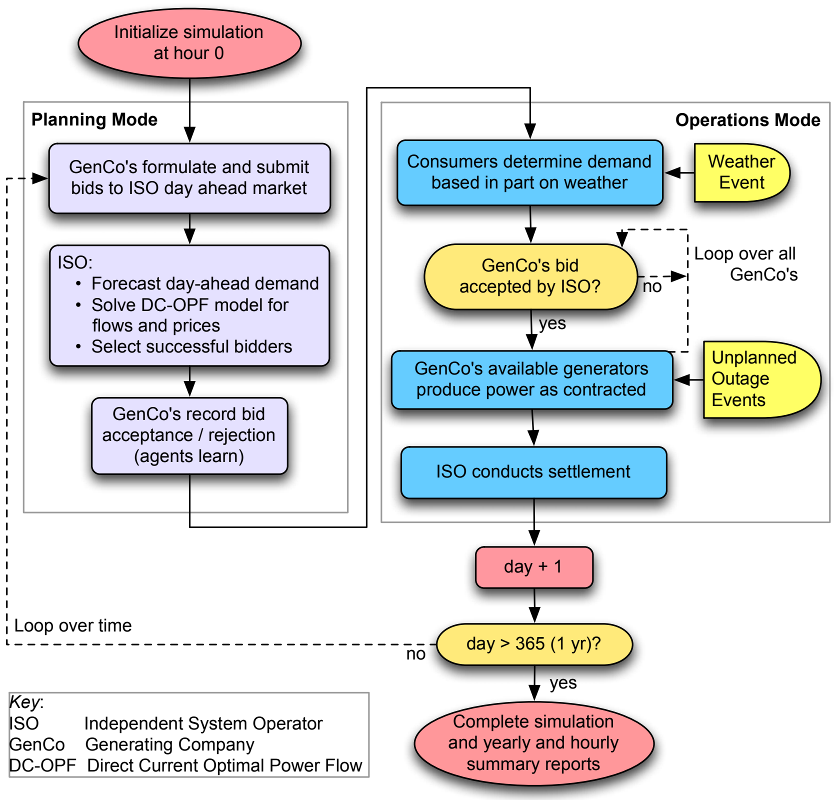

Figure 3: Simulation process for the day-ahead electric power market.

2.5 Model Validation

Electric power provision is a highly visible public policy issue scrutinized by the public and government. Validation of the model presents special challenges because controlled experiments cannot be performed on the power market to compare with model output. We developed a practical validation framework to establish credibility for EMCAS, as described in Macal and North (2005) and is summarized below. Few agent-based models in the electric power literature appear to have undergone validation testing, and Weidlich and Veit (2008) report that EMCAS appears to be the only model validated using different techniques. EMCAS results have been presented in public hearings before the Illinois Commerce Commission, and the model has withstood scrutiny by interested stakeholders.

The EMCAS database was assembled from several different structured databases. Not unexpectedly, data gaps and inconsistencies were immediately apparent when the databases were inspected. The need to map and cross-reference data field definitions and convert to common units to ensure consistency across data sources created additional complexities. A period of several months was required to iteratively refine and update the EMCAS database, consuming a large portion of the time allotted for the validation effort. SMEs consisting of power systems engineers, modelers, and economists, provided technical information and conducted face validity on the EMCAS model and its outputs. In day-long workshops, independent SMEs (i.e., independent of the model developers) from the electric utility industry, including former utility operators, industry consultants, and electric power market traders evaluated the scope and detail of the model at key points during the model design phase and provided critiques of agent behaviors, validating (or invalidating) agent strategies.

To inform the modeling effort, we conducted a "participatory simulation" with real people playing the roles of the agents in an electric power market. The participatory simulation validated key assumptions on agent behaviors, such as how quickly agents formulate and learn profit-maximizing strategies and the likely strategies the agents would use in various situations. Finally, two critical test cases were identified: (1) emergence of so-called "hockey stick" bidding strategies by generating company agents that have been observed in the real world as agents learn to respond to market incentives, and (2) replication of historical cases for system-wide outcomes. The emergence of hockey stick strategies in the EMCAS model was observed. The California experience in electric power deregulation of a few years earlier provided key indicators against which the results of EMCAS could be compared, such as runaway agent bid pricing under conditions of low system reserve margins.

Comprehensive testing of all plausible electric power agent bidding strategies in the price-quantity space was conducted. GenCo agents construct rational strategies to explore the price-quantity space in terms of the generating capacity they offer into the market and the price at which the capacity is offered. The strategies are designed to incrementally increase profits compared to a reference state, such as the profits obtained from the previous round of bidding. Extensive model runs over the space of agent behavior parameters were conducted (not reported here).

2.6 Modeling Platform

EMCAS is implemented in Repast (North, Collier, and Vos 2006), a general purpose free and open source agent-based modeling toolkit. At least one other electricity market model has been implemented in Repast (Zhang and Ma 2009). EMCAS's Repast 3 Java-based implementation runs on a range of computing platforms.

3 EXPERIMENTS WITH AGENT STRATEGIES

One of the primary questions and public policy issues concerning the future of electric power markets is the possibility for the emergence of market power among generating companies under new market restructuring rules and deregulation. Even under deregulation, markets have to be designed and structured to ensure economic competitiveness and economic efficiency, and there are many design choices. We conducted experiments to explore possible future electric power markets under various assumptions of agent behaviors, focusing on GenCo bidding strategies. Agent strategies are among areas of greatest uncertainty in the model. There are many strategies that GenCos may adopt, many of which have been observed in real-world electric power markets or for which the market clearly presents incentives for particular behaviors. GenCo agents can formulate a range of strategies in the price-quantity space, i.e., the prices and quantities of generation capacity offered into the day-ahead market.

In the set of experiments reported here, agents proposed strategies in the price-quantity-time space and adapted those strategies over time based on whether their bids were successfully selected for the day-ahead market and their profit levels experienced. Each agent offered to supply power to the day-ahead market at a price in varying percentages (0% to 650%) over its production cost, by 4-hour time blocks, over a 24-hour period. In response to the GenCo bids, the ISO selected those bids that were most cost-effective to supply power to the system. GenCos then supplied power to the real-time market if their bids were successful, computed their profits, and reformulated their bidding strategies in light of the new information in an effort to possibly increase profits in the next round of bidding. The bidding process was then simulated for the day-ahead and real-time markets over an entire year to capture seasonal load effects and variability. (Many other complex agent adaptive strategies were also tested with the model, which are not reported here.) We conducted these experiments on a model of the Illinois power grid. The model consists of 2,522 transmission lines, 1,908 buses, 66 power plants including 237 generating units comprised of 638 total generator blocks, 20 GenCos, 852 buses with loads, for 8,760 hours, collected into 18 load zones, and 113 geospatial objects.

4 RESULTS AND DISCUSSION

Figure 4 shows the impact on one generation company, GenCo1, if it were to price all of its units in its portfolio increasingly above production cost. Results are shown for the peak-day of the year. When all GenCos price at their production costs, generation by GenCo1 was constant over the 24 hours. Portfolio generation drops, though, as bid prices increase above production cost. The reduction in output initially leads to a decrease in company operating profits for bid prices up to 150% above cost, as less expensive generation and adequate transmission capacity are available to meet the load, both from study-area and out-of-area sources. However, as bid prices continue to increase (200% above production cost), operating profits grow rapidly as a portion of the company's capacity is needed to meet the load, and transmission constraints limit the use of cheaper capacity from elsewhere. As the GenCo1's price increases, substitution by other producers limits GenCo1's profits. But only up to a point is this substitution possible because of grid restrictions that limit power transfer, and increased profits for GenCo1 eventually result.

Figure 5 compares generation and operating profits for GenCo1 over a range of bid prices for the above strategy (bid prices increased for all 24 hours) with a strategy where units are priced higher only during the afternoon from 2:00 pm to 6:00 pm, when the load is the greatest. While daily generation falls substantially if GenCo1 were to apply its pricing strategy for the entire day, generation remains fairly unchanged should the company try to exert its market power only in the afternoon. This appears to be a more attractive strategy for GenCo1 over most of the pricing range, particularly if the company is concerned with excessive cycling of its units, as generation under this strategy shows little variation throughout the day even as prices are increased significantly (results not shown).

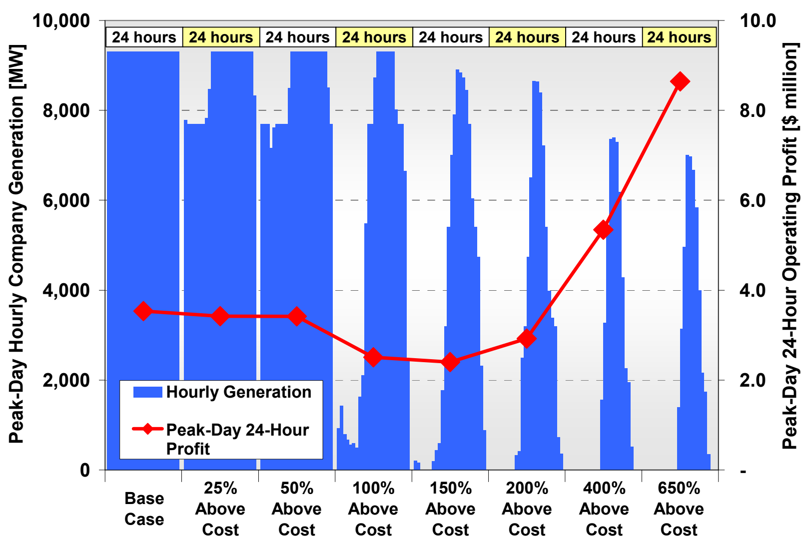

Figure 4: GenCo1 24-hour strategic bidding.

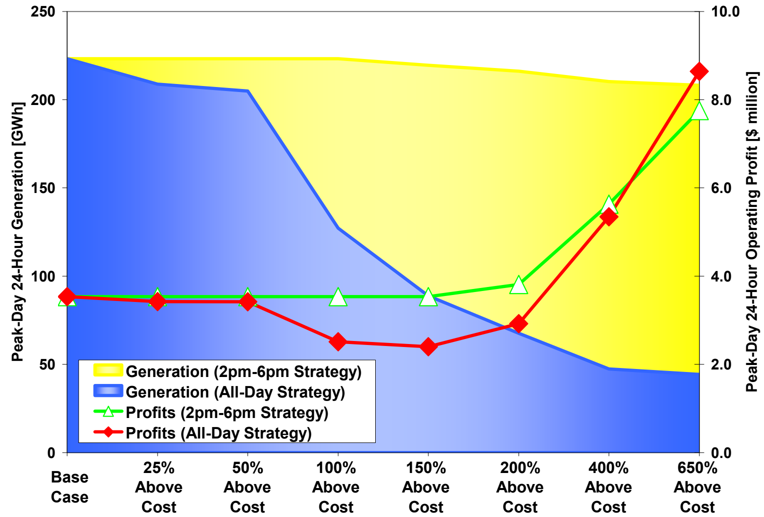

Figure 5: GenCo1 profits for different bidding strategies.

Figure 6 shows results for a generation company, GenCo2, that is unable to exert market power. As GenCo2 increases its bid price during the entire day (24 hours) for its portfolio of units, company generation rapidly declines and finally reaches zero, as all of its generators will eventually be replaced by cheaper units. Operating profits turn negative, that is, GenCo2 starts losing money under this strategy, as it will continue to incur fixed operating expenses. Even if the company applies this portfolio strategy only during the afternoon peak hours, it still will face reduced profitability as some of its units drop out of the dispatch and the price increase does not compensate for its lower production.

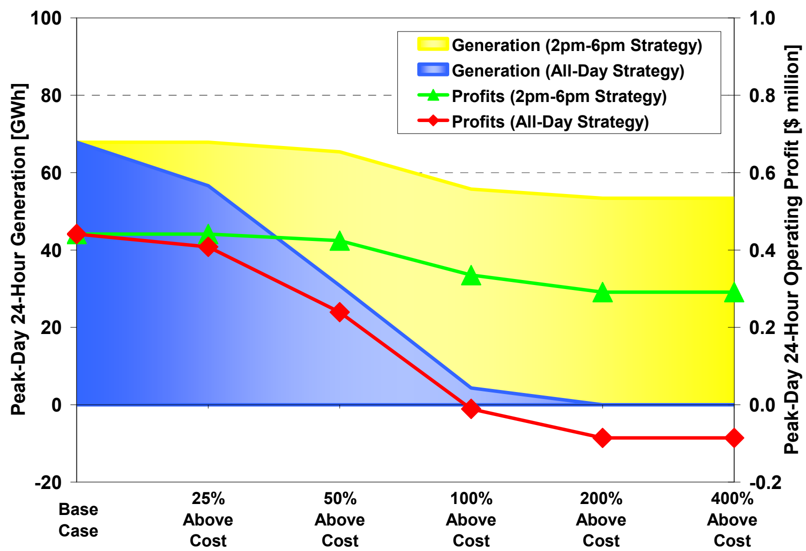

Figure 6: GenCo2 profits for different bidding strategies.

This analysis has shown that there is the potential for some companies to exercise market power (i.e., raise prices by unilateral action) and raise consumer costs under specific conditions, particularly when there is transmission congestion. These kinds of results and others from the EMCAS model have been entered into the public record of the Illinois Commerce Commission (ICC), June 6th, 2006. The full report (Cirillo et al. 2006) is available from the ICC web site http://www.icc.illinois.gov/.

5 CONCLUSIONS

We have developed a novel agent-based model of the electric power grid and market, EMCAS. We have used the model over the course of eight years to study several problems in electric power planning and analysis, including the restructuring of the Illinois power market, assessing the system-wide impacts of integrating wind energy technologies into the power grid, and evaluating the role and impact of smart-grid distribution technologies on the transmission network. The agent-based approach to modeling such socio-technical systems has proven its ability to model agent behaviors and strategies at a fine-grained level and understand their role in system-wide outcomes. Smart grid and demand management applications present interesting avenues of new research on adaptive customer behavior, for example, consumer response to real-time prices and smart metering.

We have learned some lessons from applying EMCAS and agent-based modeling more generally: (1) it is relatively easy to convince decision makers that an agent-based model could be relevant and useful because it considers adaptive agent behaviors that clearly embody how agents behave in the real world; it is much more difficult to credibly characterize the agent behavior, explain it, and validate it, (2) agent models, because they are highly disaggregated and built from the bottom-up, contain more assumptions and data than traditional models; there is a lot of explaining to do to decision makers about agent behaviors and their effects, and this adds to the burden of validation and making a case that one has a credible model, and (3) when explaining agent strategies to decision makers, certain questions seem to repeatedly arise: Are all the relevant agent strategies considered? Why is the model attributing certain strategies to some agents and not to others? Why do all the agents adopt the same strategy (which is clearly not a realistic situation)?

In the final analysis, all model results must be explainable and the reasons for why seemingly counter-intuitive results are obtained need to be easily explainable, or the results will not be credible or useful to decision makers. On this point "model explanation facilities," i.e., the ability of a model to explain its results, becomes critical for model credibility and is a promising area of further research.

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