A Multi-Agent Simulation for the Electricity Spot Market

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Abstract

A multi-agent system designed to represent newly deregulated electricity markets in the USA is aimed at testing the capability of the multi-agent model to replicate the observed price behavior in the wholesale market and developing a smart business intelligence which quickly searches the optimum offer strategy responding to the change in market environments. Simulation results show that the optimum offer strategy is to withhold expensive generating units and submit relatively low offers when demand is low, regardless of firm size; the optimum offer strategy during a period of high demand is either to withhold capacity or speculate for a large firm, while it is to be a price taker for a small firm; all in all, the offer pattern observed in the market is close to the optimum strategy. From the firm's perspective, the demand-side participation as well as the intense competition dramatically reduces the chance of high excess profit.

Keywords: *Multi-Agent Simulation; Kalman Learning; Decision Theory; Optimal Strategy; Electricity Auction*

I. Introduction

Newly deregulated electricity markets have exhibited unsatisfactory results, most notably in California. Since electricity is a central component of modern economies, market operators and regulatory agencies continually introduce new types of market structures to obtain a more reliable electricity market. Recent introduction include new auction rules, a reserve market, demand-side participation, a customer's choice of retail services, financial hedging tools, and even new industries, such as power brokers, marketers, and load aggregators (North et al, 2002). Furthermore, deregulation and unbundling of the generation, transmission, and distribution functions provide many choices for a supplier, such as vertical integration, merging with other firms, entering into the new market, or divesting from the market. This variety of choices for generating firms, customers, and the market operators implies that electricity markets are not fixed, but continue to change.

This type of evolving market requires suitable modeling tools that can be used to test the new market structures and new market rules before they are applied to real markets. Agent-based modeling techniques make it possible to represent electricity markets with multiple agents, to test new market structures in advance, and to plan ahead for by correcting flaws in the design.

This paper employs a computer-generated multi-agent simulation method for modeling wholesale electricity markets in order to understand 1) dynamic interactions between offer behavior of supply firms and market price, and 2) how each firm adjusts its offer strategies to suit the production conditions and market conditions.

In section II, the multi-agent system is initiated by defining each of its elements. Section III illustrates the learning and decision algorithm. Then, section IV describes five market scenarios tested in this paper. In section V, simulation results are discussed. Lastly, section VI concludes this study.

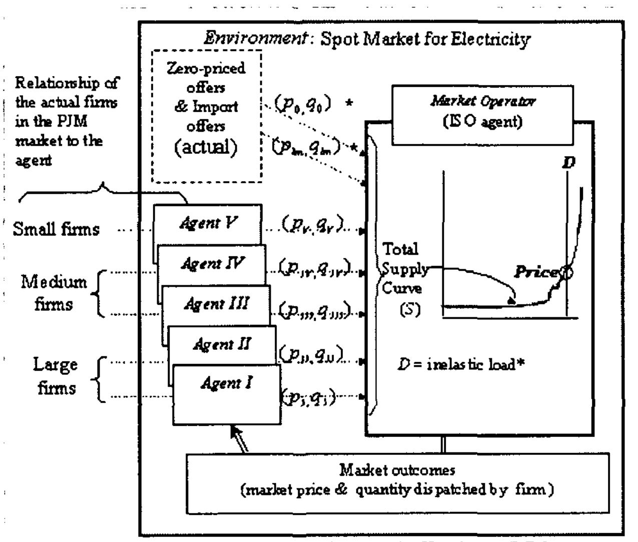
II. Defining a Multi-Agent System

A multi-agent system consists of three main elements: the environment, agent, and task. Figure 1 shows how these elements are incorporated into the multi-agent system for simulating a market for electricity. A description of each component follows:

The environment:

The environment represents the domain in which a decision-maker or an agent interacts. In our multi-agent system, the environment is a spot market for electricity. This multi-agent system is not specifically aimed at modeling the Pennsylvania-New Jersey-Maryland (PJM) market, but we use the industry structure and operating rules of the PJM market in 1999 for the following reasons: 1) the PJM market was restructured in 1999, and consequently, we can observe the initial offer behavior as well as evolutional changes of offer behavior in repeated auctions, 2) a number of price spikes, which are important issues for policies, are observed in the market, 3) offer data in PJM provides rich information about industry structure and the actual offer behavior of individual firms, which can be used to build the industry structure among firm agents and to evaluate the performance of the multi-agent model in replicating observed behavior, and 4) in 1999, PJM had one settlement market, which makes the initial test of a multi-agent system easier compared to a two settlement market.

Referencing the PJM market in 1999, we define the following characteristics of the environment: 1) any level of offer is allowed if it does not exceed the price cap, 2) the last accepted offer price (i.e. the highest offer) sets the market price, and all accepted offers are paid the same market price (i.e. a uniform price auction), 3) the market is a one-settlement system, 4) in cases of supply shortage, withheld generators are randomly recalled at the price cap to meet load, 5) import offers can set the market price, and 6) demand is inelastic in the auction (i.e. there is no price-responsive load) and the pattern of load used in the simulation is exogenous.



* actual zero-priced offers and imported offers in the PJM

Figure 1. Multi-Agents in the Electricity Spot Market

The agents:

An *agent* is a computer program that is placed in the environment, and is capable of autonomous action in order to meet its objectives (Weiss, 1999). Figure 1 shows two categories, a group of firm agents (Agent I - Agent V) and a market operator agent (ISO). The former represents power-generating firms, while the latter represents an ISO. From perspective of classifying agents, firm agents are CI agents, which learn from previous experiences to perform the desired task efficiently, but the ISO agent is not a CI agent since it does not learn, but simply applies a fixed set of rules to determine the market price and forecast load.

There is no difference among firm agents except the amount of installed capacity. To minimize simulation time, we reduce the number of firms in the market (i.e. eleven) to five agents (see Figure 1). A firm agent can represent multiple firms of which the installed capacity is similar to each other. Besides offers submitted by individual firms, the sum of zero price offers and offers from outside the PJM area are incorporated into the total supply curve. The sum of all zero price offers represents the aggregate of generating capacity from hydro generators. These offers are not determined by individual firms, because all hydro capacity is submitted with a zero offer price under the market rules. Consequently, hydro capacity is treated as given data in our system. Imported offers are submitted by firms located out of the PJM area, and therefore, offers from imports are treated as given data.

Note that end-user customers or distributors are not designated as separate agents in our system for the following reasons: 1) load is absolutely inelastic, and end-user agents do not affect market outcomes because the actual load is treated as given data, and 2) distributor agents are not necessary, because bilateral trading with generators is not allowed in our system. The role of distributors, who tell the ISO how much power they want to buy from the spot market, is implicitly included in the ISO agent, who buys electricity to meet the entire load. Even if a price-responsive load schedule exists, the function of a distributor in adjusting the load by a pre-determined schedule of interruptible loads can also be built into the ISO agent instead of introducing a separate distributor agent.

The task:

In a multi-agent system, a group of CI agents execute the given task. As shown in Figure 1, five firm agents (Agent I - Agent V) and a market operator agent (ISO) interact in a multi-agent system. The task of the five firm agents is to submit offers, (p_I, q_I) - (p_V, q_V), into the spot market. By submitting offers, they try to earn as much expected profit as possible.

The task of the ISO agent is to operate the electricity market using the rules of a uniform price auction. Market operations include the following tasks : 1) aggregate offers submitted by individual firm agents, zero price offers and imported offers, 2) calculate the total supply curve (S), 3) find the optimum dispatch schedule to minimize the cost of purchasing the amount of electricity needed to meet the load, 4) set the market price, 5) recall generators originally withheld from the market in case of supply shortage, 6) inform each agent of how much it sells and the corresponding earnings, 7) post the market price paid to agents, and 8) post a new load forecast for the next trading period. Using this load forecast, a firm agent derives the residual demand curve for the next trading period. Note that the task of the ISO agent does not include intervention in the market in order to stabilize the market price or change the market rules. This exclusion implies that a firm agent will not be worried about policy intervention, but will exercise whatever market power it possesses.

In contrast to machine learning, where multi-agent systems are commonly applied, our system has no overall task and no supervising agent to control the overall process. Within our system, each firm agent competes with other firm agents to maximize its own profit. All firm agents determine their offers synchronously and independently, and the ISO agent operates the spot market independently. This reflects the market rules that prevent one firm from communicating with another on offer strategies. Assuming that the electricity market is continuously operated in this way, the task horizon is infinite. This excludes the possibility of atypical offers that a firm agent may make at the end of the simulation period. Due to the sequential process, in which the ISO agent waits for firm agents to submit offers and each firm agent waits until the ISO agent determines the price and the dispatch schedule and opens a new round, the interaction mode between the firm agent and the ISO agent is asynchronous.

III. Learning Algorithm and Decision Rules

Model-based Kalman-adaptive learning:

A firm agent in our multi-agent system anticipates forthcoming market conditions using the residual demand curve, and the residual demand curve is updated whenever new information is available. New information is embodied in the price prediction error. Using the price prediction error, a firm agent modifies two parameters of the residual demand curve using Kalman filtering techniques.

Specifying the learning model:

The analytical approach here is to specify a model of the residual demand faced by an individual firm and to estimate it using an econometric model. As Mount (2000) noted, the results are conditional on the empirical model specifications adopted. In an early study, I showed that the total supply curve was sharply kinked for the last few units of the capacity offered and an inverse function (1) fitted this shape of the supply curve reasonably well. Hence we specify the residual demand function of individual firms based upon the following total supply curve.

Total supply function:

$$P_t = -\frac{1}{A_t + B_t \cdot \left(\overline{IC} - Q_t\right)^2 / \overline{IC}^2} \qquad (1)$$

where

P_t = Market price at time t (\$/MWh)

Q_t = sum of offered capacity (MW/h) from all firms at time t

$\overline{IC}$ = total installed capacity in the market

Residual demand function:

The residual demand function for a firm i, which controls $\bar{r}_i$ percent of the total installed capacity, is derived from the total supply function (1) as follows:

$$P_t = \frac{1}{A_{i,t} + B_{i,t} \cdot (\overline{C}_i - (D_t - Q_{i,t}))^2 / \overline{C}_i^2} \qquad (2)$$

where

P_t = market price (\$/MWh) at time t

$Q_{i,t}$ = quantity (MW/h) dispatched by firm i at time t

$\overline{C}_i = (1 - \bar{r}_i) \cdot \overline{IC}$, total installed capacity of all firms except firm i

D_t = load (MW/h) at time t

$A_{i,t}, B_{i,t}$ = parameters of the residual demand curve faced by firm i at time t

All variables of the residual demand function which relate total quantity dispatched by firm i, $Q_{i,t}$, to the market price P_t are known or approximated at the beginning of time t except two parameters ($A_{i,t}$ and $B_{i,t}$). This is because 1) total installed capacity in the market ($\overline{IC}$) is fixed in the short run, and every firm knows this value, 2) the market share of firm i, $\bar{r}_i$, is fixed in the short run, and 3) the load forecast approximates the actual load with a known distribution, $N(D_{t|t-1}, \hat{\sigma}_t^2)$. This is the typical situation underlying a time-varying parameter model.

A time varying parameter model[1] is used to estimate the residual demand curve, because the parameter estimates of the residual demand function are only indirectly observable and vary over time. A time-varying parameter model consists of a measurement and a transition equation, represented by equations 3 and 4, respectively.

Measurement equation:

$$\frac{1}{P_{t|t-1}} = \underbrace{\left[1 \quad (\overline{C} - D_{t|t-1} + Q_t)^2 / \overline{C}^2\right]}_{H_{t|t-1}} \cdot \begin{bmatrix} A_{t|t-1} \\ B_{t|t-1} \end{bmatrix} + e_t \qquad (3)$$

$$\left(\frac{1}{P_{t|t-1}} = H_{t|t-1} \cdot \beta_{t|t-1} + e_t\right)$$

where

$P_{t|t-1}$ = market price for time t expected at time t-1

Q_t = quantity dispatched (MW/h)

$\overline{C} = (1 - \bar{r}_i) \cdot \overline{IC}$, total installed capacity of all firms except firm i

$D_{t|t-1}$ = load forecast (MW/h) for time t used at time t-1

$A_{t|t-1}, B_{t|t-1}$ = parameters for time t estimated at time t-1, $\beta_{t|t-1} = [A_{t|t-1} \quad B_{t|t-1}]'$

e_t = stochastic disturbance, *iid. N(0,R)*

The measurement equation 3 is the inverse of the residual demand function (equation 2). In general, a time-varying parameter model specifies a pre-determined dynamic structure for the transition equation.

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[1] The residual demand curves are estimated for a firm, firm i. For the simplicity in the expression, the subscript i is ignored from the next step. In other words, the estimated parameters, the predicted market price, the quantity dispatched, the market share, and the installed capacity implicitly indicate those of firm i, unless additional explanations or a subscript are not specifically designated.

Transition equation:

$$\begin{bmatrix} A_{t|t-1} \\ B_{t|t-1} \end{bmatrix} = \underbrace{\begin{bmatrix} f_{11} & 0 & f_{12} & 0 \\ 0 & f_{21} & 0 & f_{22} \end{bmatrix}}_{F} \cdot \begin{bmatrix} \hat{A}_{t-1} \\ \hat{B}_{t-1} \\ \hat{A}_{t-2} \\ \hat{B}_{t-2} \end{bmatrix} + \begin{bmatrix} v_{1t} \\ v_{2t} \end{bmatrix} \qquad (4)$$

$(\beta_{t|t-1} = F_1 \cdot \hat{\beta}_{t-1} + F_2 \cdot \hat{\beta}_{t-2} + v_t)$

where

F = transition matrix

$\beta_{t|t-1}$ = parameter estimate for time t estimated at time t-1,

$\beta_{t|t-1} = [A_{t|t-1} \quad B_{t|t-1}]'$

$\hat{\beta}_{t-1}$ = unbiased parameter estimator for time t-1 adjusted at time t-1, $\hat{\beta}_{t-1} = [\hat{A}_{t-1} \quad \hat{B}_{t-1}]'$

v_t = stochastic disturbance, *iid. N(0,Q)*

The transition equation 4 shows that the parameter estimates of the residual demand function, A_t and B_t, follow a second order Markov process. This implies that only the market conditions at *t-1* and *t-2* are informative for *predicting the market conditions at time t. Note that the* 'hat' of $\hat{\beta}_t$ refers to an unbiased estimator of $\beta_t : E[\hat{\beta}_t - \beta_t]$=0, while $\beta_{t|t-1}$ is a step ahead estimate of β_t.

Kalman updating process:

Figure 2 shows how the residual demand function combined with a Kalman filter receives market information and predicts the market price.

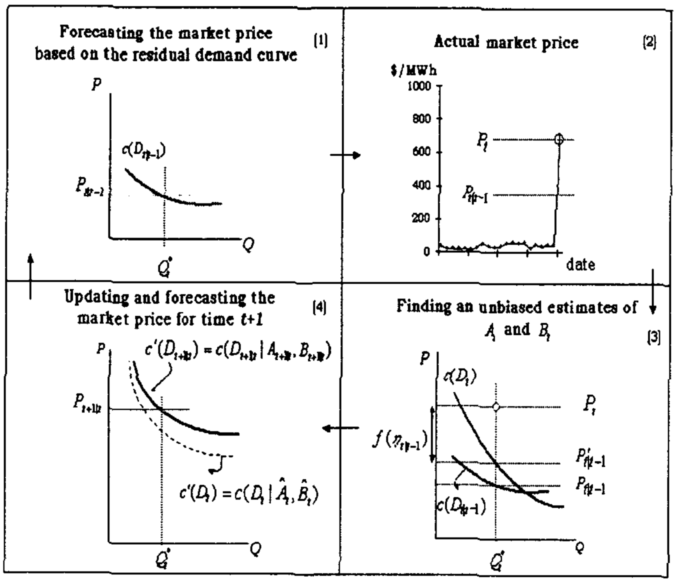

Figure 2. Predicting Market Price Using the Residual Demand Curve

Suppose that a firm has the residual demand curve as shown in box (1) of Figure 2. On this residual demand curve, the market price at time t is expected to be $P_{t|t-1}$ if the quantity dispatched by this firm is Q_t^*. On the following day, at time t, the actual market price for dispatching Q_t^* is realized at P_t, which is much higher than the expected market price of $P_{t|t-1}$ (see box (2) in Figure 2). If the residual demand curve is correct, the actual market price should be the same as the price prediction, $P_{t|t-1}$, within a statistically allowed disturbance range. In other words, the prediction error implies that the residual demand curve of this firm was incorrect. Moreover, the forecasting error contains new information, previously unknown to the firm.

Note that the residual demand curve is defined by two *parameter estimates, and the load forecast approximates the* actual load. Hence, there are two sources of price prediction error: 1) the load forecasting error, $(D_t - D_{t|t-1})$ and 2) mis-specified parameter estimates, $(\hat{A}_t - A_{t|t-1})$ and $(\hat{B}_t - B_{t|t-1})$. In order to determine unbiased estimates of the two parameters, we need to extract the proportion of the price prediction error caused by load forecasting error. Box (3) in Figure 2 shows this process. The residual demand curve at time t is re-defined using the actual load (D_t) instead of the load forecast ($D_{t|t-1}$). The adjusted price prediction, $P'_{t|t-1}$, corresponds to the same dispatched quantity Q_t^*. The distance between the actual market price (P_t) and the adjusted price prediction ($P'_{t|t-1}$) measures the price prediction error caused by the estimation errors for $A_{t|t-1}$ and $B_{t|t-1}$. This price prediction error is used to determine unbiased parameter estimates at time t, $\hat{A}_t$ and $\hat{B}_t$, to make the observed market outcome of (P_t, Q_t^*) closer to the adjusted residual demand curve.

Box (4) in Figure 2 is the new residual demand curve for time $t+1$, which is determined by a new load forecast for time $t+1$ ($D_{t+1|t}$) and new parameter estimates. The new parameters estimates, $A_{t+1|t}$ and $B_{t+1|t}$, are determined by the second order Markov process using the previous unbiased estimates of the two parameters. Note that these parameters determine the shape of the residual demand curve. The new residual demand in Box (4) is more curved and the predicted market price for time $t+1$ is higher than before at the same dispatched quantity, Q_t^*, reflecting the influence of the price spike. The new residual demand curve for time $t+1$ is also affected by the new forecast of load, $D_{t+1|t}$, represented by the change of $c'(D_t) = c(D_t \mid \hat{A}_t, \hat{B}_t)$ to $c'(D_{t+1|t}) = c(D_{t+1|t} \mid A_{t+1|t}, B_{t+1|t})$ in box (4).

Imperfect perception and dynamic learning:

Kalman-adaptive learning allows for imperfect perception and dynamic knowledge, because 1) a firm agent perceives the market state with stochastic disturbances (i.e. imperfect perception), and 2) an agent with fixed knowledge is unable to modify its understanding of the environment, but each firm agent in our multi-agent system updates its understanding of the spot market whenever new information is available (i.e. dynamic knowledge).

Decision Rules

While a learning algorithm explains how a firm agent recognizes market conditions, the decision rules explain how the firm agent selects the optimum offer under given market conditions. Since given market conditions are estimated by the residual demand curve, the optimum offers are based upon the updated residual demand curve. We assume that each firm only pursues the profit maximization; the cost and capacity structure are identical among firms; the highest marginal cost is \$55/MWh, which intends to exclude the speculation driven by the marginal cost.

Stochastic Optimization Under Uncertainty:

Suppose that the block capacity is $Q_H^* - Q_L^*$, the marginal cost of this block is mc and a firm considers whether to submit the offer price of $offer_p$. For any offer in the auction, there are three possible outcomes determined by the market price P:

1) $P > offer_p$	Fully dispatched
2) $P = offer_p$	Partially dispatched
3) $P < offer_p$	Not dispatched

Expected net profit of an offer:

The expected profit is calculated as the excess profit above the operating cost (i.e. marginal cost + stand-by cost). In place of calculating the expected profit, we calculate the expected net profit as the difference between the expected profit of the target block and the total expected profit of the pre-selected blocks, because 1) the optimum offer maximizes both the expected profit and the expected net profit, and 2) the block is withheld if it does not increase the expected profit of the firm.

Suppose a firm determined the optimum offer of the second block at *O2*, and then searches for the optimum offer of the third block. The optimum offer for this block is found numerically to maximize the following expression (5):

$$\begin{aligned} \Delta E[\pi \mid offer_p]_{t|t-1} \quad (5) \\ = \int_{D_H}^{\infty} Q_H \cdot (P[D,Q_H] - mc) \cdot f(D)dD \\ + \int_{D_L}^{D_H} Q[D, offer_p] \cdot (offer_p - mc) \cdot f(D)dD \\ + \int_{D_{O2}}^{D_L} Q_L \cdot P[D,Q_L] \cdot f(D)dD \\ - sb \cdot (Q_H - Q_L) \\ - \int_{D_{O2}}^{\infty} Q_L \cdot P[D,Q_L] \cdot f(D)dD \end{aligned}$$

where

$\Delta E[\pi \mid offer_p]_{t|t-1}$ = expected net profit for time t conditional on the offer price (\$/h)
$offer_p$ = offer price (\$/MWh)
$P[D,Q]$ = market price (\$/MWh) when load is D and the capacity dispatched by this firm is Q
Q_L = maximum total capacity dispatched when the block is not dispatched (MW/h)
Q_H = minumum total capacity dispatched when the block is fully dispatched (MW/h)
$Q[D, offer_p]$ = capacity dispatched by the firm when the offer sets the market price
$\overline{IC}$ = total installed capacity in the market
$\bar{r}$ = the proportion of the firm's installed capacity to $\overline{IC}$
$(Q_H - Q_L)$= size of the block
mc = marginal cost (\$/MWh)
sb = stand-by cost (5\$/MWh)
f(D) = probability density function of the load (D)
D_H = minimum load for full dispatch (MW/h)
D_L = maximum load for not being dispatched (MW/h)
D_{O2} = maximum load that the offer for the previous block, O2, is not dispatched (MW/h)

The first, second and third components of the objective function correspond to the first (fully dispatched), second (partially dispatched, offer sets the market price) and third (not dispatched) outcomes, respectively. The fourth component is the total stand-by cost. The expected profit of this offer is, therefore, the sum of these four components. On the other hand, the fifth component represents the expected revenue for the pre-selected blocks (the first two blocks in this case). Hence, the expected net profit of $offer_p$ is the difference between the sum of the first four components and the fifth component. The optimum offer of the third block is determined to maximize this difference, the expected net profit.

Withholding decision:

After finding the optimum offer for a block, the next step is to determine whether to withhold the block. If a block is operating and the expected net profit of the optimum offer is positive, the block is submitted into the auction. If the expected net profit is negative but the withholding penalty is larger than the magnitude of the negative expected net profit, the block is submitted into the market in order to save the withholding penalty. If the expected net profit is negative and the magnitude is larger than the withholding penalty, the block is withheld.

Action Dimensions:

Dimensions of the agent action (Santamaria, 1997) are defined as: 1) a discrete action space, because the block offer price can be selected between $0 to $1000 MW per hour with a discrete interval of $1, and the offer quantity is either 0 or the entire capacity of the block, 2) a discrete decision time space, because each agent in our system executes a decision at a fixed time interval, and 3) a stochastic outcome, because market prices and the earnings of a firm agent for exactly the same set of offers are affected by the actual load, contingencies, and the actual offers of other agents.

IV. Market Simulation Scenarios

The multi-agent model is applied to five different market scenarios. Considering the three components of a multi-agent system, the task and environment are almost identical for the five market scenarios, while the characteristics of the firm agents vary. For each scenario, the number of simulation rounds is fifty. The daily load in the PJM market from June 15, 1999 to August 3, 1999 is used in all five scenarios as an exogenous input. The rationale for defining each scenario follows:

Scenario 1- purely competitive agent:

The distinction in scenario 1 is that each firm agent submits its total installed capacity at true cost into the market. This scenario therefore defines the ideal market price and purely competitive offer behavior. The results are used as benchmarks to measure the degree of price distortion and the level of monopolistic offer behavior in the other scenarios. In the other four scenarios, each firm agent determines the offer curve to maximize the expected profit.

Scenario 2- base:

Eleven generators in the PJM market are represented by five different firm agents, and these agents submit optimum offer curves into the market. This scenario is termed *'base'* since the firm agents represent the actual size and cost structure in the PJM market. The objective of the *base* scenario is to test the capability of the multi-agent model to replicate the price volatility and the heterogeneous offer behavior of individual firms observed in electricity markets. The simulation results of the scenario 2 are used to evaluate the impacts of market policies and industry structures in the remaining three scenarios.

In order to optimize the offer curve, each firm agent perceives the market conditions using a Kalman adaptive learning algorithm and selects the optimum offer curve.

Scenario 3- price responsive load:

The distinction of the *price responsive load* scenario is the inclusion of demand-side participation. Everything else is the same as in scenario 2, but the ISO agent adjusts the load according to a pre-determined load reduction schedule. This schedule represents interruptible contracts between distributors and end-users to cut the demand gradually if the market price is above a certain level. The initial load is the same as the load in scenario 2, but it is reduced by steps of two percent when the market price exceeds $300/MWh, $500/MWh, $700/MWh and $900/MWh.

Scenario 4- 6 big:

Scenario 4 is termed '*6 big*', since total installed capacity in the market is the same as it was in the previous three scenarios, but there are only 6 identical firms instead of 11 different firms. Each firm is represented by the cost structure of the largest firm agent (*Agent I*), scaled to the appropriate size. The other characteristics are the same as the *base* scenario. This scenario tests the effects of a more concentrated industry structure on the market price and the offer behavior.

Scenario 5- 30 small:

This scenario is the opposite of the previous scenario. The total installed capacity in the market is the same as it was in the previous four scenarios, but the number of firms is increased to 30. Each firm is represented by cost structure of the smallest agent, *Agent V*, scaled to the appropriate size. Other characteristics are the same in the *base* scenario. This scenario investigates the effect of a decentralized industry structure on the market price and the offer behavior.

V. Simulation Results

Simulation results of each scenario are summarized by the simulated market price and the simulated offer curves of two of the firm agents. The selected offer curves correspond to the largest (Agent I) and the smallest (Agent V) firm agent, and show how the offer behavior changes with firm size.

Market price:

Figures 3 and 4 plot the actual daily maximum price and the simulated market prices for the five scenarios. The actual market price plotted at the top of Figure 3 is relatively low during the non-peak load period, while it is relatively high and volatile during the peak load period. The average market price is $207/MWh and there are 10 price-spike days in the sample of 50 days.

Price behavior simulated in the *purely competitive agent* scenario is the second plot of Figure 3. This shows that competitive market prices are relatively low in both the non-peak load period and the peak load period. The average market price in this scenario is only $45/MWh, less than a quarter of the actual average price.

When each firm agent acts strategically to set the offer curve, the market price is much higher than the competitive level. The average market price of the *base* scenario (scenario 2) shown in Table 1 is \$318/MWh, which is 7 times the competitive level of \$45/MWh in scenario 1. The third plot of Figure 3 shows the *base* scenario. The price volatility during the peak load period observed in the PJM market is replicated by the *base* scenario, but it is even higher. There are 15 price spikes in scenario 2 compared to 10 observed price spikes. The bottom plot of Figure 3 shows that price volatility is substantially reduced when load is price-responsive in scenario 3. The market price in the *price-responsive load* scenario barely exceeds the threshold point of \$300/MWh needed to activate the interruptible load schedule. The average market price is reduced by 53 percent compared to the *base* scenario and the number of price spikes is reduced from 15 in scenario 2 to 2 in scenario 3.

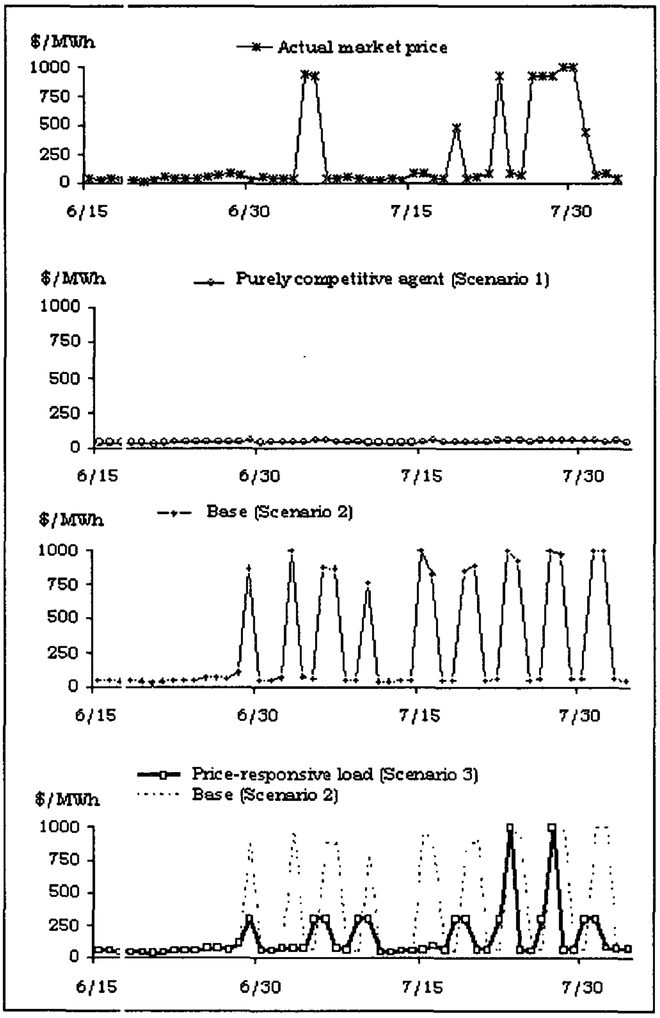

Figure 3. Actual and Simulated Prices for Scenarios 1, 2 and 3

Figure 4 shows how the market price is influenced by changing the industry structure. The price behavior of the *6 big* scenario is plotted at the top of Figure 4. This result shows that price spikes persist in the market on either peak load days or non-peak load days when the number of firms is small. The average price of the *6 big* scenario increases to \$655/MWh, and there are 33 price spikes, over twice as many as the *base* case. Hence, the common belief that six competitors should be sufficient to make a competitive market workably is not upheld in our multi-agent system.

Market prices in the *30 small* scenario, shown at the bottom of Figure 4, are relatively low but not as low as the competitive scenario. The average market price is \$67/MWh in scenario 5, which is 50 percent higher than the competitive level of \$45/MWh. However, \$20/MWh of this high average price is caused by the single price spike. Without this price spike, the *30 small* scenario would be close to competitive as expected. The overall conclusion is that the stochastic characteristics of an electricity market make it inappropriate to use the standard rules for defining a competitive market. More firms are needed to make this type of auction competitive than a typical auction in which the quantity sold is deterministic.

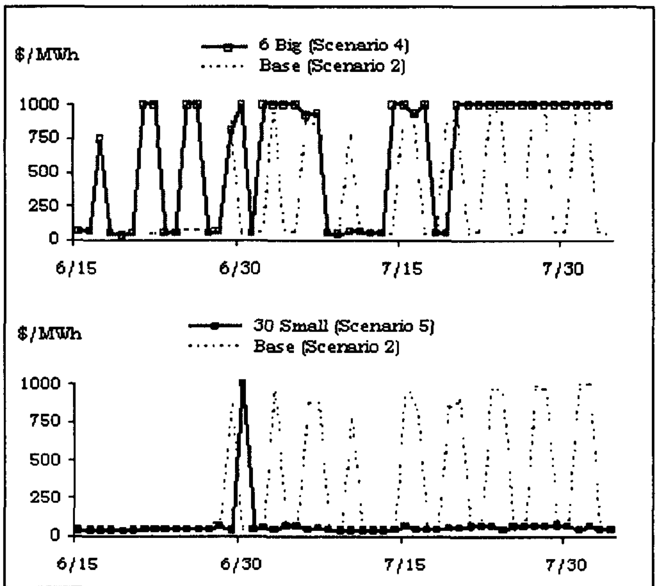

Figure 4. Simulated Market Prices for Scenarios 2, 4 and 5

Table 1 Actual and Simulated Market Prices

		Mean	StD	Freq. (>\$300)
Actual market price		\$207.4	338	10
Simulated (mixed-sizes)	Purely competitive agent	\$45.2	8	0
	Base	\$317.5	409	15
	Price-responsive load	\$148.9	205	2
Simulated (the same size)	6 Big	\$655.4	451	33
	30 Small	\$66.7	136	1

Offer curves of two different firm sizes:

The price spikes in the simulations imply that at least one firm agent exercises market power. Figures 5 and 6 show the offer curves of a large firm (*Agent I*) and a small firm (*Agent V*) on a typical non-peak load day (June 15, 1999) and a typical peak load day (July 27, 1999), respectively.

Figure 5 compares the offer curves of the two agents for the first three scenarios (scenarios 1, 2 and 3). The dotted line generated by the *purely competitive agent* scenario shows all capacity offered into the auction at the true cost. In scenarios 2 and 3, the offer curves for the non-peak load show that some capacity is withheld (Cournot behavior) regardless of firm size. However, the proportion of the capacity withheld is larger for the large firm than the small firm. The impact of the price-responsive load schedule on the offer behavior is minor for both firms during the non-peak load period.

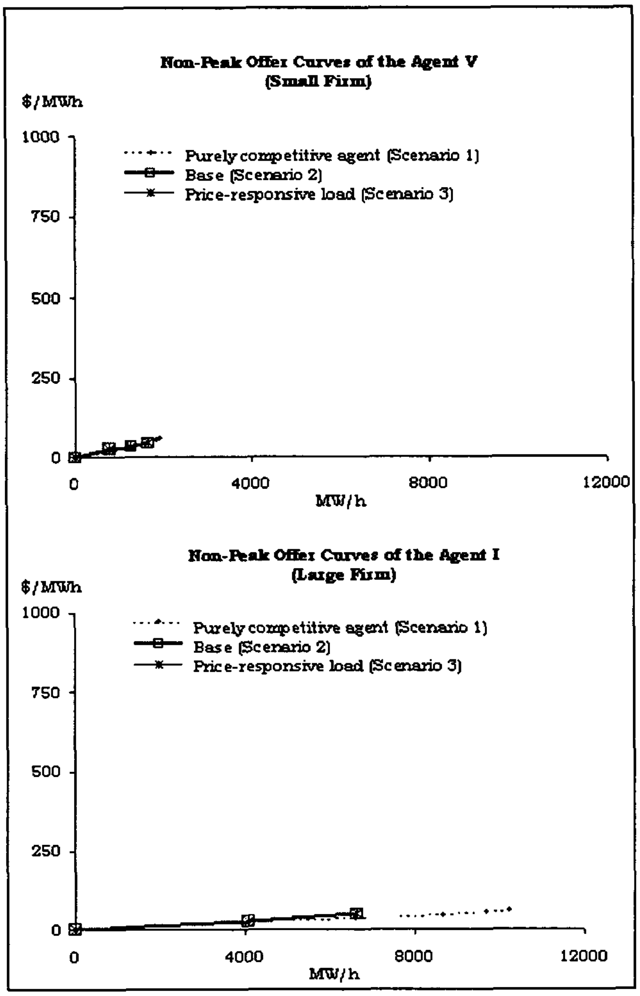

Figure 5. Non-Peak Offer Curves for Scenarios 1,2 and 3

Figure 6 illustrates the optimum offer curves submitted on the peak load day. Figure 6 shows that the small firm is a price taker in all three scenarios. No capacity is withheld when the load is high. In contrast, the large firm behaves as a heavy lifter in scenarios 2 and 3, and speculates and withholds capacity. With price-responsive load, the large firm speculates less but withholds more capacity.

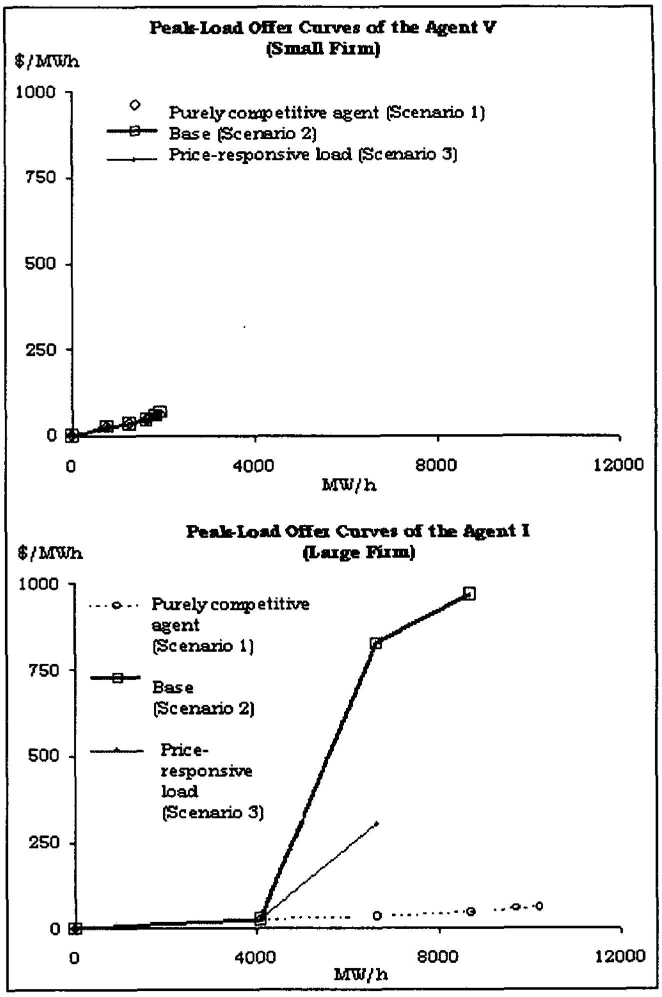

Figure 6. On-Peak Offer Curves for Scenarios 1,2 and 3

I do not picture the optimum offer curve for the 30 small firms (scenario 4) and the 6 big firms (scenario 5), but the optimum offer strategy is the same as that of the small firm for scenario 4 (top plot in Figure 6) whereas it is the same as that of the large firm (bottom plot in Figure 7). This implies that the best strategy is to be a price taker when the competition is intense although it does not provide high excess profit. In contrast, it is the optimum to exercise the market power when the market is oligopolic.

V. Conclusion

In this paper, we simulated the dynamic interaction between the offer behavior of individual firms and the market price. The market price is determined by offers simulated by several firm agents, each agent also reacts to the market price in the following period. In the base scenario, 1) evolutionally changes in offer behavior, 2) heterogeneous offer behavior by firm size, and 3) volatile market price behavior were demonstrated. These characteristics are similar to the behavior observed in the PJM market.

Three scenarios testing market policies showed the importance of price-responsive load and a less concentrated market structure in order to achieve efficiency in an electricity market. Price-responsive load and more competing firms mitigated price volatility and the monopolistic offer behavior of individual firms.

In spite of the capability explaining the observed offer behavior and price volatility, our multi-agent system is restricted. In terms of the learning algorithm, Kalman adaptive learning depends on a model, the residual demand curve. As a consequence, this learning algorithm cannot generate purely evolutionary changes in offer behavior. In addition, the risk-neutral attitude assumed for each firm agent does not reflect the various risk attitudes of the actual firms. A firm may be risk-prone until the expected profit reaches a minimum target level, then risk neutral for some range of profit, followed by risk averse after expected profit exceeds a target level. Specifying a pure-generating firm with no financial contracts also cause simulation bias since offer behavior may vary if a firm is vertically integrated or has financial contracts.

In terms of decision rules, our system is also restrictive since only the immediate reward is considered. In other words, an offer delivering less profit in the short run but more profits in the long run is not considered as the optimum offer strategy in our system. In addition, our firm agents select only one offer for a block as well as determining either to withhold or submit the entire block. Multiple offers are allowed for each block in the real market. Addressing these restrictions must be left to future study.

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