

Agent-based Approach to Handle Business Complexity in US Wholesale Power Trading

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Abstract-- This study documents the practicality of an agent-based approach by examining how two groups of agents handle business complexity related to power trading. Three important findings are identified in this research. First, the proposed approach can estimate fluctuations of electricity prices as well as other well-known methods such as neural networks and genetic algorithms. Second, multiple learning capabilities incorporated in adaptive agents do not have an advantage over limited learning capabilities in predicting the market price of electricity. Finally, a theoretical extension of multiple learning capabilities may have potential for developing the agent-based approach for power trading.

Index Terms— Power Trading, Agent-based Approach, Numerical Analysis, Machine Learning

I. INTRODUCTION

AN agent-based approach has been applied to investigate various complex systems. See, for example, Tesfatsion [1]. The applicability of the approach is found in not only computer science but also decision science and operations research. For example, Samuelson [2] has discussed how to apply it to various social systems from the perspective of optimization. Similarly, Makowski *et al.* [3] have assembled seventeen articles, all of which discuss practical linkages between the approach and complex systems.

An agent-based application in the power industry is also found in [4]. The study incorporates several adaptive learning capabilities, based upon reinforcement learning (Erev and Roth [5, p.859]), in modeling various types of agents. In the application, [4] has developed a new simulator in which agents can develop various bidding strategies to deal with the complexity of power trading.

From a theoretical perspective concerning power trading, the study [4] still has two major drawbacks. First, [4] does not document the practicality of the simulator. Second, [4] does not describe how to incorporate “power law of practice” and “law of effect” in the simulator. The first law implies that adaptive agents need to include a learning curve that “tends to be steep initially and then flatter.” The second law indicates

that “good outcomes in past are more likely to be repeated in future.” See Roth and Erev [6, p.171]. The two laws are originated from a large experimental psychology literature on both human and animal learning. Both laws have been long served as a theoretical basis for developing adaptive agents.

In addition to the two laws, [5,6] have provided us with an important implication regarding adaptive behaviors: “high rationality does not appear to have an advantage over lower rationality in predicting an equilibrium point from mixed strategies within a framework of game theory”[5, p.857]. This implication is important for this study and is referred to as “Erev-Roth’s first assertion.” Moreover, in the conclusion of [5, p. 875], the two researchers have left a future research issue: “whether a theory of very high rationality behavior may provide a basis for a predictive theory of observed behaviors.” The issue is also important and is referred to as “Erev-Roth’s second assertion,” hereafter.

As an extension of [4], this study develops two groups of adaptive agents who investigate the dynamics of electric power trading. The first group consists of agents who are equipped with multiple learning capabilities. Their learning capabilities include a risk-averse utility function and a long-term view on how to obtain a reward from electric power trading. This group is referred to as “Type I” in this study. Meanwhile, the other group of agents looks for a short-term gain via limited learning capabilities. They do not incorporate any utility functions. Thus, the second group is less informed than Type I. This group of agents is referred to as “Type II” in this research.

This study has three research agendas. First, the practicality of an agent-based approach needs to be documented by a methodological comparison. Second, the two laws discussed by Erev and Roth [5,6] need to be incorporated into agents in Type I. Finally, the two assertions of Erev-Roth need to be re-examined by the two types of adaptive agents.

The remaining structure of this article is organized as follows: The next section describes three hypotheses to be examined in this study. This section also provides a literature review on power trading. Section III describes the industrial structure of US wholesale power market. Section IV describes how agents participate in power trading. Section V discusses the adaptive behaviors and algorithms of agents in Types I and II. Section VI numerically examines the three hypotheses. Section VII summarizes this study along with future research extensions.

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II. HYPOTHESES AND LITERATURE REVIEW

A. Three Hypotheses

Hypothesis 1 (Practicality): The agent-based approach performs as well as other well-known methods (i.e., neural networks and genetic algorithms) in predicting the market price of electricity.

Erev-Roth's first assertion (high rationality does not appear to have an advantage over lower rationality) is restated for this study as follows:

Hypothesis 2: Type II predicts a price change of electricity more accurately than Type I in a real auction market.

The better estimation capability of Type II does not immediately imply better trading decisions when the two groups exist together in a same power market. In addition to the estimation capability, agents need other learning capabilities to obtain a reward. This concern is discussed in Erev-Roth's second assertion (whether a theory of very high rationality behavior may provide a basis for a predictive theory of observed behavior). Their assertion is restated as follows:

Hypothesis 3: Type I outperforms Type II in a power market where the two groups compete with each other. The performance of the two groups is measured by a total reward.

The following three comments are important in understanding the above three hypotheses: First, a rationale to support the second hypothesis is that a real power trader usually makes a bidding decision within a limited time. Consequently, the bidding decision of the trader is characterized by "bounded rationality" [7]. Meanwhile, agents of Type I are equipped with multiple learning capabilities and a utility function. Hence, they may have a higher winning probability than Type II (limited learning capabilities). This expectation supports the third hypothesis.

Second, the second hypothesis compares between Types I and II in the estimation accuracy of electricity price fluctuations. The market price is a final result of the bidding strategies of real traders. Therefore, the second hypothesis depends upon how well the two groups of adaptive agents can duplicate human decision making in power trading. Meanwhile, the third hypothesis examines which group of adaptive agents outperforms the other in terms of a total reward; that is, it examines the competition between Types I and II as machine learning models. An influence of human decision making is considerably excluded from the investigation. Thus, the second and third hypotheses are mutually exclusive. The result of the third hypothesis suggests a future research direction regarding how agents incorporate adaptive behaviors.

Finally, Erev-Roth's reinforcement learning is related to only one parameter so that implications obtained from their adaptive models are very limited in the development of machine learning. For example, a very well-known toolkit for modeling agent-based simulations, referred to as "Recursive Porous Agent Simulation Toolkit (Repast)," incorporates a modified version of Erev-Roth reinforcement learning. Repast, developed at the Santa Fe Institute, is utilized for simulating the dynamics of a power market in Veit *et al* [8].

Unfortunately, the agent-based approach uses only generators as adaptive agents who bid only a quantity. The research [8] incorporates neither wholesalers nor price bidding in the simulation study. In contrast, the adaptive agents proposed in this study do not have any limit on the number of parameters.

B. Previous Research on Power Trading

Previous research is classified into the following groups:

Behavioral Analysis: This group discussed the bidding strategies and behaviors of traders in a power market [9-11]. The behavioral aspect was examined from long-term bilateral electricity contracts that needed a risk-hedge strategy [12-13]. Game theory often served as a basis for investigating a negotiation behavior for the bilateral contracts [14-16]. This research group contributed to analytical features of trading behaviors. For example, it provided an analytical rationale regarding how market power made an impact on the wholesale price of electricity. Meanwhile, the behavioral research excluded important uncontrollable factors such as different degrees of speculation and different bidding preferences among traders. Consequently, this type of analysis is methodologically limited on price predictability.

Numerical Analysis: This group fully utilized computer science techniques (e.g., NNs: Neural Networks and GAs: Genetic Algorithms) to predict a price change under the dynamic fluctuations of other factors (e.g., weather) that influenced the electricity demand. The NN technique, incorporating a learning process, was applied for one-hour-ahead forecasting of power demand based upon a given temperature [17-18]. The volatility of market price was also measured by an NN application [19]. A methodological strength of NNs exists in flexibility. The predictability of NNs is considerably high [20]. However, the estimation reliability of NNs lacks a theoretical rationale. In the same vein, the GA method was applied to understand bidding strategies for power trading [11]. The GA method is useful when an electric power market is not volatile.

Agent-based Analysis: This group developed multi-agent adaptive systems that investigated a dynamic bidding process for electric power trading [4, 21-25]. In this analysis, traders are adaptive agents with different bidding preferences and strategies. Their bidding decisions are influenced by many uncontrollable factors. This group opened up a new type of numerical analysis to deal with business complexity on power trading. However, the previous studies described only the development of agent-based models and simulations. Almost no research, except [4], described the incorporation of learning capabilities in the modeling process of agents. Furthermore, comparison with other methods (e.g., NNs) has never been explored. Consequently, it is difficult to assess whether the agent-based approach is practical or not. Moreover, the previous research [4] existed within the scope of simulation. No research applied the approach to predict price fluctuations of real electricity market. This research belongs to the last group.

III. US WHOLESALE POWER MARKET

The electric power business is separated into the following four functions: (a) generation, (b) transmission, (c) distribution and (d) retailing. Generally speaking, two types of transaction exist in the wholesale market. The first one is a bilateral (usually long-term) exchange contract between a generator(s) and a wholesaler(s). The other transaction is a short-term, auction-based transaction. In the short-term transaction, a market operator (like PJM) accepts bids from both generators and wholesalers. The operator then determines the market price and quantity of electricity. Thus, this type of wholesale market is controlled and coordinated by an ISO (Independent System Operator) that operates not only a wholesale market but also a transmission market [26]. This study focuses upon the wholesale market because we are interested in a market mechanism of electric power trading.

The US wholesale market is functionally separated into (a) a power exchange market and (b) a transmission market. The power exchange market is further functionally separated into (a-1) a Real Time (RT) market, (a-2) an hour-ahead market, (a-3) a Day-Ahead (DA) market and (a-4) a long-term contract market. These markets need to integrate the supply capabilities so as to satisfy a constantly changing demand on electricity. Coordinated auctions are used for the first three exchange markets. Bilateral contracts are used for the fourth market.

In this study, RT implies not only the real time market but also the hour-ahead market, because the two are functionally similar and decided on the same day. DA is a “financial and forward” market, because all the transactions in the market stop one day prior to RT. Furthermore, bidding decisions in DA are determined by the speculation of traders. Meanwhile, RT is a “physical and spot” market, because the power delivery in RT is not optional like in DA. All traders enter RT to correspond to actual flows of electricity. Hence, the aspect of financial speculation is limited in the market. Thus, RT is a physical market. Furthermore, traders in RT need to make their decisions within a limited time. So, RT is a spot market, as well. See [27, p.204] for a description on differences between DA and RT.

IV. AGENT-BASED AUCTION MODEL

Let us consider a wholesale market with two settlements for DA and RT, where n generators ($i = 1, \dots, n$) and k wholesalers ($j = 1, \dots, k$) participate for T periods ($t = 1, \dots, T$). The traders are adaptive agents in this study. The “ t ” indicates a specific period for real delivery of electricity.

Supply Side in DA: The i -th generator at the t -th period bids s_{it}^1 ($s_{it}^1 \leq s_{it}^m$), where s_{it}^m is the maximum amount of power generation capacity. Here, the superscript “1” indicates DA. The bidding amount is expressed by $s_{it}^1 = \alpha_{it} s_{it}^m$, where α_{it} ($0 \leq \alpha_{it} \leq 1$) is a decision parameter to express the ratio of the bidding amount to the maximum generation capacity.

The bidding price of the generator is determined by $p_{it}^1 = MC_{it} / (1 - \beta_{it})$. Here, MC_{it} is the marginal cost of the generator and β_{it} ($0 \leq \beta_{it} < 1$) is a mark-up ratio that indicates

how much the bidding price of the generator is increased from the marginal cost. The mark-up ratio reflects the pricing strategy of the generator.

Demand Side in DA: A wholesaler predicts an electricity demand on a delivery day, using a forecasting method (e.g., moving average). Let e_{jt} be the demand estimate of the j -th wholesaler at the t -th period. Then, the wholesaler predicts a price estimate (w_{jt}^1) by using a function (F) of demand, $w_{jt}^1 = F(e_{jt})$. [See Figure 4 of [4] that depicts the demand function.] The wholesaler determines a bidding amount (d_{jt}^1) by $d_{jt}^1 = \delta_{jt} e_{jt}$. Here, δ_{jt} ($0 \leq \delta_{jt} \leq 1$) is a decision parameter to express the reduction of the bidding amount from the demand estimate.

The bidding price of the wholesaler is determined by $p_{jt}^1 = \lambda_{jt} w_{jt}^1$. Here, λ_{jt} ($0 \leq \lambda_{jt} \leq 1$) is a decision parameter to indicate the reduction of the bidding price from the price estimate.

After all traders submit their bids on amounts and prices to the ISO, the DA market determines \hat{p}_t^1 (market price for DA), \hat{s}_{it}^1 (power request to the i -th generator in DA) and \hat{d}_{jt}^1 (power allocation to the j -th wholesaler in DA) for the t -th period.

Supply Side in RT: The i -th generator at the t -th period bids the amount $s_{it}^0 = (s_{it}^m - \hat{s}_{it}^1)$ in the RT market, where the superscript “0” indicates RT. The bidding amount for RT is a difference between the maximum generation capacity and the real allocation from the DA market. Furthermore, the bidding price (p_{it}^0) of the generator is expressed by $p_{it}^0 = MC_{it} / (1 - \eta_{it})$, where η_{it} is the mark-up ratio of the generator ($0 \leq \eta_{it} < 1$).

Demand Side in RT: All the wholesalers must deliver the amount of electricity (r_{jt}) demanded by end-users. Therefore, they bid only their amounts, not prices, in the RT market. The j -th wholesaler at the t -th period bids an amount, d_{jt}^0 ($= r_{jt} - \hat{d}_{jt}^1$), in the market. The RT market within the ISO determines \hat{p}_t^0 (market price for RT), \hat{s}_{it}^0 (power request to the i -th generator in RT) and \hat{d}_{jt}^0 (power allocation for the j -th wholesaler in RT) for the t -th period.

Auction Process in DA and RT: The auction process of the two settlements in the ISO is visually summarized in Figure 1. The difference between DA and RT is depicted in Figures 2 and 3. Figure 2 visually describes the DA market coordination mechanism within the ISO. In the proposed simulator, the ISO reorders the bids of generators and wholesalers. The supply side combinations (s_{it}^1 and p_{it}^1) are reordered according to the ascending order of the bidding prices. The demand side combinations (d_{jt}^1 and p_{jt}^1) are reordered according to the descending order of the bidding prices.

In Figure 2, the ISO allocates the generation amount (s_{it}^1)

of the first generator to satisfy the demand (d_{1t}^1) of the first wholesaler. Such a power allocation is continued until an Equilibrium Point (EP) is found in the DA market. In Figure 2, EP is the equilibrium point, where the supply from the five generators are used to satisfy the demand required by the three wholesalers. Consequently, p_{5t}^1 (the bidding price of the fifth generator) becomes the market price (\hat{p}_t^1) for DA.

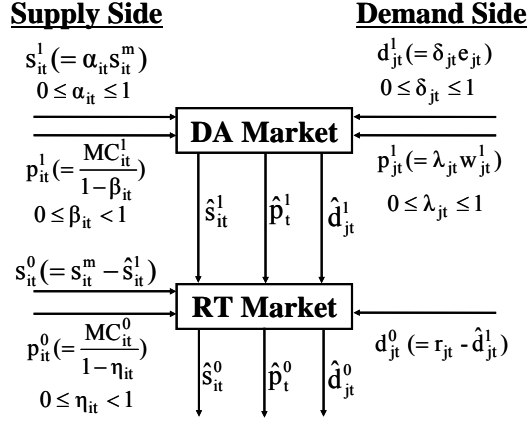


Fig 1: Settlement System (Numerical Expression)

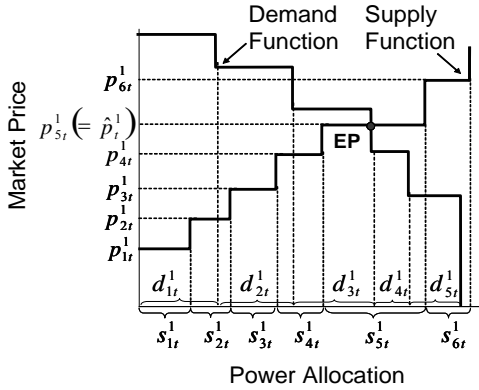


Fig 2: An Equilibrium Point in DA

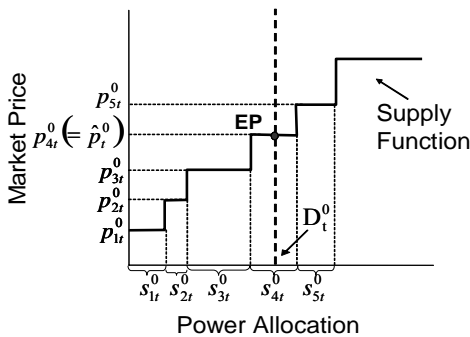


Fig 3: An Equilibrium Point in RT

Figure 3 depicts the market coordination mechanism of generators in RT where their bids are reordered according to the ascending order of the bidding prices, as found in the DA market. Meanwhile, wholesalers submit only their demands, but not bidding prices, because the demand of end users must be always satisfied. In Figure 3, the ISO accumulates the

generation amounts until the total demand is satisfied. In the figure, D_t^0 is such a point at which the total demand satisfies the following condition:

$$D_t^0 = \sum_{j=1}^k d_{jt}^0 = \sum_{j=1}^k (r_{jt} - \hat{d}_{jt}^1)$$

In Figure 3, EP is the equilibrium point where four generators are used to satisfy the total demand required by wholesalers. Consequently, p_{4t}^0 (the bidding price of the fourth generator) becomes the market price (\hat{p}_t^0) for RT.

Comments: The following comments are important in understanding the market mechanism of DA and RT:

(a) In Figure 1, we need to specify information regarding ($s_{it}^m, MC_{it}, e_{jt}, w_{jt}^1, r_{jt}$). Decision parameters and mark-up ratios ($\alpha_{it}, \beta_{it}, \eta_{it}, \delta_{jt}, \lambda_{jt}$) are unknown and need to be initialized as random numbers on $[0,1]$ in the simulator. The simulator creates various bidding strategies for generators and wholesalers by changing these magnitudes. The final power allocation between supply and demand needs to satisfy the following condition:

$$\sum_{i=1}^n s_{it}^m \geq \sum_{i=1}^n (\hat{s}_{it}^1 + \hat{s}_{it}^0) = \sum_{j=1}^k (\hat{d}_{jt}^1 + \hat{d}_{jt}^0)$$

(b) It is possible for agents to make an over-contract in such a manner that they sell (or buy) more than an available capacity (or expected demand). However, the over-contract may provide a wholesaler with an excess amount of electricity. Furthermore, a generator is required to prepare an over-capacity generation plan. Thus, the power market becomes cost-ineffective. In reality, the wholesaler can sell the excess amount of electricity to another wholesaler, and the generator can obtain electricity from another generator and supply it to a power market if necessary. The simulator used for this study does not consider such a trade because the trading process is complicated and the computation is time-consuming. Thus, for our computational convenience, this study does not consider the over-contract.

(c) In the simulator, we avoid specifying the mark-up ratios because agents gradually adjust themselves toward a better combination of these ratios even if they are initialized to different values. It is true that the mark-up ratios for the DA market are independently determined in the machine-learning process for agents, but selection of the mark-up ratios for the RT market often depends upon bidding results of agents in the DA market. For example, when a generator loses in the DA market, he may select a small mark-up ratio so that the bidding price of the generator is close to the marginal cost. Consequently, the generator expects to win in the RT market. An opposite result is observed when the generator wins in the DA market.

(d) This study is interested in comparing the observed market prices of electricity with its estimates obtained from the proposed two groups of adaptive agents (Types I and II). Hence, this study does not consider a bidding strategy for the DA and RT markets in future.

(e) Finally, it is assumed that each generator tries to fully utilize a maximum capacity in this study. The assumption is slightly inconsistent with reality because a generator has a security margin of capacity in order to avoid operating at full capacity. The security margin is not considered in this study.

The assumption is primarily for our research convenience because the influence of the security margin is very limited. If necessary, we can incorporate the security margin into the proposed modeling process by subtracting the margin from the maximum capacity of each generator.

Rewards to Traders: Rewards to generators and wholesalers are listed in [4, p. 1334].

V. AGENT-BASED ALGORITHMS (TYPE I AND TYPE II)

A. Adaptive Behavior

In the simulator, agents accumulate knowledge from both their bidding results and observed market prices in order to adjust their proceeding bidding strategies. The adaptive process is separated into a Knowledge Accumulation (KA) process ($t \leq Z$) and an Own-Bidding (OB) process ($t \geq Z+1$). The selection of Z depends upon each agent. So, different agents have different KA periods.

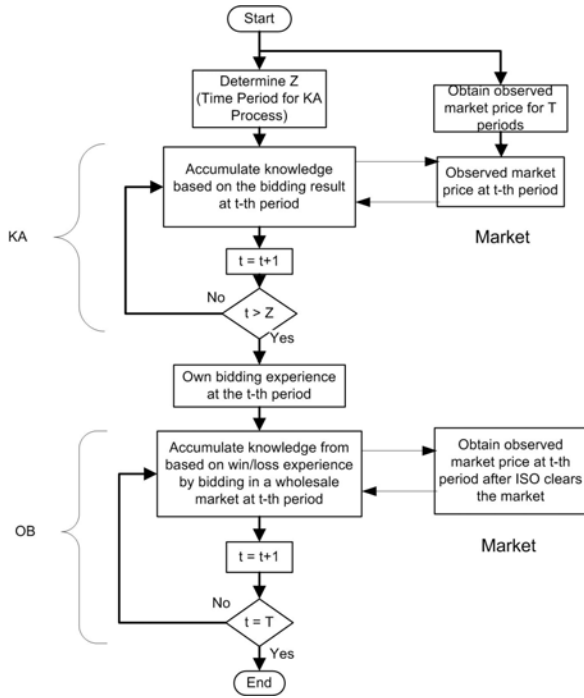


Fig. 4: Adaptive Process for KA and OB

The KA process is a practice period in which agents access the market price and quantity of electricity. Then, they have win-lose experience as a result of their bids. Agents constantly update and accumulate their knowledge based on the win-lose experience at each trade.

After the KA process is over, agents enter the OB process in which they compete with each other in a power market. They can access the observed market prices and their knowledgebases established in the KA process. Based upon learning algorithms, agents bid in the power market. The bidding results in the OB process update each agent's knowledgebase. Figure 4 depicts such a whole adaptive process of KA and OB.

B. Traders in Type I

“Law of Effect”: Each agent in Type I constantly looks for an increase in estimated winning probability. In other words, the agent looks for a combination of decision parameters that increase a winning probability. The adaptive behavior is due to the law of effect discussed by Erev and Roth [5,6]. In this study, the law of effect is expressed by a sigmoid decision rule.

Sigmoid Decision Rule: The win or lose of each trade is a binary response. To express an occurrence of the binary response, we use a sigmoid model that can predict a winning probability. Mathematically, the probability cumulative function of the sigmoid model is expressed by $F(\sigma) = \int_{-\infty}^{\sigma} e^u / (1 + e^u)^2 du = 1 / (1 + e^{-\sigma})$. The win or lose status of the i -th generator is predicted by the following linear probability model:

$$R_{it} = c_{i0} + c_{i1}\alpha_{it} + c_{i2}\beta_{it} + c_{i3}\eta_{it} + \varepsilon_t. \quad (1)$$

Here, R_{it} is a reward given to the i -th generator at the t -th period. Parameters are denoted by c_{i0} , c_{i1} , c_{i2} and c_{i3} . An observational error is listed as ε_t . These parameters are all unknown and need to be estimated by OLS (Ordinary Least Squares) regression. The winning probability (Prob) is estimated as follows:

$$\begin{aligned} \text{Prob}(\text{WIN}_t) &= \text{Prob}(R_{it} \geq 0) \\ &= \text{Prob}\{\varepsilon_t \geq -(\hat{c}_{i0} + \hat{c}_{i1}\alpha_{it} + \hat{c}_{i2}\beta_{it} + \hat{c}_{i3}\eta_{it})\} \\ &= 1 - \frac{1}{1 + \text{EXP}(\hat{c}_{i0} + \hat{c}_{i1}\alpha_{it} + \hat{c}_{i2}\beta_{it} + \hat{c}_{i3}\eta_{it})} \\ &= \frac{\text{EXP}(\hat{c}_{i0} + \hat{c}_{i1}\alpha_{it} + \hat{c}_{i2}\beta_{it} + \hat{c}_{i3}\eta_{it})}{1 + \text{EXP}(\hat{c}_{i0} + \hat{c}_{i1}\alpha_{it} + \hat{c}_{i2}\beta_{it} + \hat{c}_{i3}\eta_{it})}. \quad (2) \end{aligned}$$

The symbol (^) indicates a parameter estimate obtained by OLS. The above equations suggest that the winning probability can be predicted immediately from the parameter estimates of the sigmoid model.

The reward of the j -th wholesaler at the t -th period is determined by the following linear probability model:

$$R_{jt} = c_{j0} + c_{j1}\delta_{jt} + c_{j2}\lambda_{jt} + \varepsilon_t \quad (3)$$

Hence, the winning probability is estimated as

$$\begin{aligned} \text{Prob}(\text{WIN}_t) &= \text{Prob}(R_{jt} \geq 0) \\ &= \frac{\text{EXP}(\hat{c}_{j0} + \hat{c}_{j1}\delta_{jt} + \hat{c}_{j2}\lambda_{jt})}{1 + \text{EXP}(\hat{c}_{j0} + \hat{c}_{j1}\delta_{jt} + \hat{c}_{j2}\lambda_{jt})}. \quad (4) \end{aligned}$$

The KA and OB processes of the j -th wholesaler provide three parameter estimates of the sigmoid model. Two (\hat{c}_{j1} and \hat{c}_{j2}) of the three parameter estimates are important in determining the bidding strategies of the wholesaler. Both are associated with the two decision parameters (δ_{jt} and λ_{jt}), respectively. If a parameter estimate is positive, the wholesaler should increase his corresponding decision parameter in order to enhance a winning probability. Conversely, an opposite strategy is needed if the estimate is negative. Thus, the sign of each parameter estimate provides information regarding which decision parameter needs to be increased or decreased. However, the winning probability, obtained from the sigmoid model, does not immediately imply that a trader can always win

in a wholesale market with the estimated probability. The probability estimate is a theoretical guess. The win or lose is determined through the market mechanism of DA and RT.

“Power Law of Practice”- Exponential Utility Function:

From the “power law of practice,” this study assumes that all agents in Type I have an exponential utility function. The exponential utility function represents a risk aversion preference on a smooth concave function. [See Chapter 9 of [28] for various utility models.] We select it from many utility functions because its utility value exists between 0 and 1.

Mathematically, the exponential utility function is expressed by $U(R_{jt}) = 1 - \text{EXP}(-\zeta R_{jt})$ on $R_{jt} \geq 0$, where ζ indicates a parameter to express the level of risk aversion.

Returning to (3), the utility value (ϕ_{jt}) on the reward (R_{jt}) of the j -th wholesaler at the t -th period is measured by $\phi_{jt} = 1 - \text{EXP}(-\zeta R_{jt})$. Hence, given ϕ_{jt} , the reward is expressed by

$$R_{jt} = -\ln(1 - \phi_{jt})/\zeta = \hat{c}_{j0} + \hat{c}_{j1}\delta_{jt} + \hat{c}_{j2}\lambda_{jt}. \quad (5)$$

Here, “ln” stands for a natural logarithm. After obtaining the parameter estimates of the sigmoid model along with a given utility value or its range, the wholesaler prepares his bidding strategy for the next ($t+1$) period. In the simulator, the bidding strategy for the next period is specified as follows:

$\lambda_{jt+1} \rightarrow \lambda_{jt} + \tau\Delta_{jt}^{\lambda}$ and $\delta_{jt+1} \rightarrow \delta_{jt} + \tau\Delta_{jt}^{\delta}$, where $\Delta_{jt}^{\lambda} = \lambda_{jt}^U - \lambda_{jt}^L$ and $\Delta_{jt}^{\delta} = \delta_{jt}^U - \delta_{jt}^L$. The prescribed quantities (λ_{jt}^U and λ_{jt}^L) indicate the upper and lower bounds on λ_{jt} , respectively.

Similarly, the other prescribed quantities (δ_{jt}^U and δ_{jt}^L) also indicate the upper and lower bounds on δ_{jt} , respectively. The unknown parameter (τ) indicates the magnitude of the bidding change.

Along with the changes and given ϕ_{jt+1} , (5) becomes

$$-\ln(1 - \phi_{jt+1})/\zeta = \hat{c}_{j0} + \hat{c}_{j1}(\delta_{jt} + \tau\Delta_{jt}^{\delta}) + \hat{c}_{j2}(\lambda_{jt} + \tau\Delta_{jt}^{\lambda}) \quad (6)$$

From (6), the magnitude is determined by

$$\tau = -\left(\ln(1 - \phi_{jt+1})/\zeta + \hat{c}_{j0} + \hat{c}_{j1}\delta_{jt} + \hat{c}_{j2}\lambda_{jt}\right) / \left(\hat{c}_{j1}\Delta_{jt}^{\delta} + \hat{c}_{j2}\Delta_{jt}^{\lambda}\right) \quad (7)$$

Comment: The description of a wholesaler’s utility function can be extended to that of a generator.

Algorithm for Bidding Strategies: Based upon the sign of parameter estimates of the sigmoid model, the j -th wholesaler has nine (3x3) different bidding strategies (with $t = 1$ as the start):

Step 1: Set initial bids from knowledgebase in KA or OB. A forecasting method (e.g., moving average or exponential smoothing) with different time periods is used to compute the initial bids. Also, set the upper (δ_{jt}^U and λ_{jt}^U) and lower (δ_{jt}^L and λ_{jt}^L) limits.

Step 2: Use the OLS regression to obtain parameter estimates of the sigmoid model from the knowledgebase. Obtain the magnitude (τ) from (7).

Step 3: Based upon the signs of parameter estimates, change the decision parameters according to the following conditions:

- (a) If $\hat{c}_{j1} > 0$ & $\hat{c}_{j2} > 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt} + \tau\Delta_{jt}^{\delta}, \lambda_{jt} + \tau\Delta_{jt}^{\lambda} \right\}$
- (b) If $\hat{c}_{j1} > 0$ & $\hat{c}_{j2} = 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt} + \tau\Delta_{jt}^{\delta}, \lambda_{jt} \right\}$
- (c) If $\hat{c}_{j1} > 0$ & $\hat{c}_{j2} < 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt} + \tau\Delta_{jt}^{\delta}, \lambda_{jt} - \tau\Delta_{jt}^{\lambda} \right\}$
- (d) If $\hat{c}_{j1} = 0$ & $\hat{c}_{j2} > 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt}, \lambda_{jt} + \tau\Delta_{jt}^{\lambda} \right\}$
- (e) If $\hat{c}_{j1} = 0$ & $\hat{c}_{j2} = 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt}, \lambda_{jt} \right\}$
- (f) If $\hat{c}_{j1} = 0$ & $\hat{c}_{j2} < 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt}, \lambda_{jt} - \tau\Delta_{jt}^{\lambda} \right\}$
- (g) If $\hat{c}_{j1} < 0$ & $\hat{c}_{j2} > 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt} - \tau\Delta_{jt}^{\delta}, \lambda_{jt} + \tau\Delta_{jt}^{\lambda} \right\}$
- (h) If $\hat{c}_{j1} < 0$ & $\hat{c}_{j2} = 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt} - \tau\Delta_{jt}^{\delta}, \lambda_{jt} \right\}$
- (i) If $\hat{c}_{j1} < 0$ & $\hat{c}_{j2} < 0$, then $(\delta_{jt+1}, \lambda_{jt+1}) = \left\{ \delta_{jt} - \tau\Delta_{jt}^{\delta}, \lambda_{jt} - \tau\Delta_{jt}^{\lambda} \right\}$

Step 4: Compute d_{jt}^1 and p_{jt}^1 based upon $(\delta_{jt}, \lambda_{jt})$. Then, the

wholesaler submits the two bids to DA. If $t = T$, then stop. Otherwise, go to Step 5.

Step 5: If the wholesaler loses, then drop information regarding the bids from the current knowledgebase and go to Step 1. If the wholesaler wins, then go to Step 6.

Step 6: Add information regarding the bids into the current knowledgebase and go to Step 1.

Comments: (a) Even if each trader keeps the same strategy, his bidding result may be different from that of the previous bid because the wholesale market determines the price and amount of power allocation. (b) The algorithm for a generator is the same as that of a wholesaler, as discussed above. An exception can be found in Step 3 where the algorithm for the generator needs to consider 27 (=3x3x3) bidding strategies. The algorithm for the generator needs to consider three decision parameters. We do not discuss the algorithm here to avoid a descriptive duplication.

C. Traders in Type II

In addition to Type I, this study develops agents in Type II who prepare the proceeding bidding strategies only from the current bidding results. So, the bidding strategies are myopic. They are equipped with neither the exponential utility function nor the sigmoid decision rule, both of which are incorporated in Type I.

Figures 5 and 6 visually describe the bidding strategies of agents in Type II. In the two figures, equilibrium points for DA and RT are depicted on $EP(\hat{q}^1, \hat{p}^1)$ and $EP(\hat{q}^0, \hat{p}^0)$ respectively, along with supply and demand curves. Centering on each equilibrium point, each figure is separated into four regions. The north-east region indicates that a generator (GEN) loses in the DA market. Let us consider that a current bid for the DA market exists on A along a supply curve in Figure 5. The generator loses in the DA market because the bidding price is higher than the market price on equilibrium. So, the generator loses an opportunity to supply electricity and reduces both the bidding price and quantity for the proceeding DA market. An opposite strategy is observed on C in the south-west region where the generator wins in the DA market. The north-west region indicates that a wholesaler (WS) on B wins in the current DA market, because the bidding price is higher than the

market price on equilibrium. So, the wholesaler obtains electricity through the DA market and decreases the bidding price and increases the bidding quantity to obtain more profit in the proceeding DA market. An opposite strategy is found on D in the south-east region where the wholesaler loses in the DA market.

The bidding strategy in the DA market illustrated in Figure 5 is shifted to the RT market of Figure 6. As mentioned previously, the RT is a physical and spot market, so a generator's bidding strategy in the RT market is different from that for the DA market. The pricing strategy for the RT market is identified by the two arrows in Figure 6. A wholesaler enters the RT market with his strategy on quantity. The wholesaler does not have any strategy concerning price, because he must satisfy demand of end-users without any choice about price. As listed at the bottom of Figure 6, the total amount of demand submitted by all wholesalers is listed as $\sum d_j^0$, and it determines the quantity of EP.

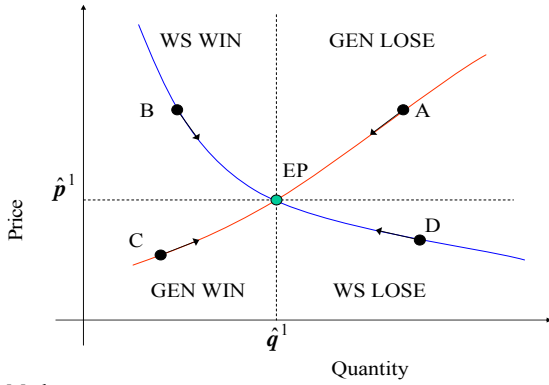


Fig. 5: DA Market

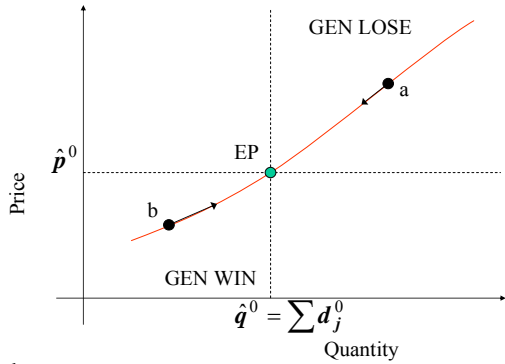


Fig. 6: RT Market

The bidding strategy of agents in Type II is separated into the following four strategies for the DA market:

- (a) If the j -th wholesaler wins in the current DA market, then he increases the bidding amount and decreases the bidding price for the proceeding DA market as follows:

$$d_{jt+1}^1 = d_{jt}^1 + |q_{jt+1} - d_{jt}^1| \delta_{jt+1} \quad \text{and} \quad p_{jt+1}^1 = p_{jt}^1 - |p_{jt}^1 - \tilde{p}_{jt+1}| \lambda_{jt+1} \quad (8)$$

The above strategy indicates that the next bidding amount (d_{jt+1}^1) is increased from the current bidding amount (d_{jt}^1)

by $|q_{jt+1} - d_{jt}^1| \delta_{jt+1}$, where $q_{jt+1} - d_{jt}^1$ is a difference

between a forecasted amount (for the proceeding DA market) and the current bidding amount. The difference in an absolute value is adjusted by δ_{jt+1} . Similarly, the next bidding price (p_{jt+1}^1) is reduced from the current bidding

price (p_{jt}^1) by $|p_{jt}^1 - \tilde{p}_{jt+1}| \lambda_{jt+1}$. Here, the wholesaler compares the current bidding price with the forecasted price estimate (\tilde{p}_{jt+1}), obtained from the knowledgebase.

The difference between them in an absolute value is adjusted by λ_{jt+1} .

- (b) If the j -th wholesaler loses in the current DA market, then he decreases the bidding amount and increases the bidding price for the proceeding DA market as follows:

$$d_{jt+1}^1 = d_{jt}^1 - |q_{jt+1} - d_{jt}^1| \delta_{jt+1} \quad \text{and} \quad p_{jt+1}^1 = p_{jt}^1 + |\tilde{p}_{jt+1} - p_{jt}^1| \lambda_{jt+1} \quad (9)$$

The difference between (8) and (9) is identified by the quantity reduction and price increase in (9).

- (c) If the i -th generator wins in the current DA market, he increases both the bidding amount and price for the proceeding DA market as follows:

$$s_{it+1}^1 = s_{it}^1 + |s_{it+1}^m - s_{it}^1| \alpha_{it+1} \quad \text{and} \quad p_{it+1}^1 = p_{it}^1 + |\tilde{p}_{it+1} - p_{it}^1| \beta_{it+1} \quad (10)$$

The above strategy indicates that the next bidding amount (s_{it+1}^1) is increased from the current bidding amount (s_{it}^1)

by $|s_{it+1}^m - s_{it}^1| \alpha_{it+1}$ where $s_{it+1}^m - s_{it}^1$ is a difference between

a maximum generation capacity (for the proceeding DA market) and the current bidding amount. The difference in an absolute value is adjusted by α_{it+1} . Similarly, the next bidding price (p_{it+1}^1) is increased from the current bidding

price (p_{it}^1) by $|\tilde{p}_{it+1} - p_{it}^1| \beta_{it+1}$. Here, the generator compares the current bidding price with the price estimate (\tilde{p}_{it+1}) that is obtained from the current knowledgebase.

The difference between them in an absolute value is adjusted by β_{it+1} .

- (d) If the i -th generator loses in the current DA market, he decreases both the bidding price and amount for the proceeding DA market as follows:

$$s_{it+1}^1 = s_{it}^1 - |s_{it+1}^m - s_{it}^1| \alpha_{it+1} \quad \text{and} \quad p_{it+1}^1 = p_{it}^1 - |p_{it}^1 - \tilde{p}_{it+1}| \beta_{it+1} \quad (11)$$

The difference between (10) and (11) can be found in the quantity and price reduction in (11).

Comment: The RT pricing strategies of a generator is depicted in Figure 6. The RT strategies correspond to (c) and (d) for the DA market. A wholesaler bids only an amount of electricity in RT.

D. Functions Improved from Previous Simulator [4]

The learning algorithm of Type I originates from [4]. Three major differences between [4] and this study are summarized as follows:

- (a) Accessibility to Market Price: Agents in [4] make their bidding decisions without knowing market prices of electricity. In contrast, agents in this study make their bidding decisions

by utilizing not only the win-lose experience but also the observed market prices.

(b) **Exponential Utility Function:** This study assumes that all agents are “risk-averse” and their decisions are mathematically structured by an exponential utility function. The incorporation of the utility function satisfies the “power law of practice” required for adaptive learning. The study [4] does not have any utility function.

(c) **Type II:** The study [4] does not consider agents belonging to Type II. This agent group corresponds to traders whose adaptive behaviors are characterized by limited learning capabilities.

VI. PRICE ESTIMATION AND SIMULATION STUDY

A. Examination of First and Second Hypotheses

1) Data Sets and Market Composition

Two data sets on the PJM are obtained from the website: <http://www.theice.com>. The wholesale price is measured in \$/MWH (\$/Mega Watt Hour) and the quantity to be traded is measured in MWH.

TABLE I
SUMMARY STATISTICS FOR MARKET PRICE (\$/MWH)

Market	Mean	Median	Standard Deviation	Skewness	Kurtosis	Sample Size
PJM-DA	49.62	49.29	9.03	0.38	1.20	289
PJM-RT	49.62	49.09	9.07	0.44	1.42	289

The obtained data set consists of Trade Date, Average Price and Volume. Table I documents a statistical summary on the PJM markets used in this study.

The first data set on PJM-DA represents the daily average market price obtained from PJM-West Peak for DA from November 7th, 2003 to January 4th, 2005. A high volatility of the wholesale price is observed when it suddenly spikes up from a low of \$25.95 (MWH) on December 24th, 2003 to a high of \$82.58 (MWH) on January 14th, 2004. The correlation between PJM-DA demand and price is low (0.1893).

The second data set on PJM-RT represents the daily average market price for PJM-W RT peak price from November 7th, 2003 to January 4th, 2005. The correlation coefficient between PJM-RT demand and price is very small (0.0624), as well. A major price change occurs from a low of \$26.75 (MWH) on December 24th, 2003 to a high of \$84.13 (MWH) on January 15th, 2004. The correlation between DA and RT market prices is high (0.9982).

Comment: The correlation between price and demand is low in the PJM because most residential consumers are unaware of or indifferent to a price change. This implies that standard competitive market equilibrium may not explain price fluctuations of electricity. To handle this unique feature of electricity, two computational capabilities are incorporated in the simulator. The first capability is that agents in Type I utilize forecasting methods (e.g., exponential smoothing) in their computation processes. The other is that commercial and residential consumers are treated separately in estimating price from demand. Such a separation is depicted in Figure 4 of [4]. Combining such computational capabilities, the simulator

enhances the predictability of agents in estimating fluctuations of market prices.

In addition to the computational aspect, this study needs to mention that in using the data set on the PJM, we are not dealing with the identification problem of estimating real supply and demand curves. Rather, the simulator makes artificial supply and demand curves based upon the PJM market composition and trader configuration. Hence, there is a gap between real power trading and artificial trading. Of course, such a gap can be reduced by accessing more information on real supply and demand curves.

Market Composition and Trader Configuration: An approximate market composition and the market share of PJM are obtained from the Western Hub definition file available from the PJM website (<http://www.pjm.com/markets/energy-market/downloads/20050101-hub-definitions.xls>). In total, 24 generators and 69 wholesalers are listed in the Western Hub. The generator market share is listed as follows: 15 generators’ share at 2% each, 7 generators’ share at 4.2% each, 1 generator’s share at 18%, and 1 generator’s share at 22.6%. The wholesaler market share is separated as follows: 16 wholesalers’ share at 0.61% each, 44 wholesalers’ share at 1.45% each, 8 wholesalers’ share at 2.85% each, and 1 wholesaler’s share at 3.64%. The simulator uses this market composition. The KA period for agents is varied from 5 to 40. The maximum price is set at 85.00 (\$/MWH) and the minimum price at 25.00 (\$/MWH).

Comment: The length of the KA period and the upper and lower limits of price may influence the result of the simulation study. This study does not examine these influences. Hence, as a future research task, we need to extend the simulation study by changing the length of the KA period and the price limits.

2) Alternate Approaches

Evaluation Criterion: An evaluation criterion is estimation accuracy (%) which is defined as:

$$1 - \frac{1}{N} \sum_{t=1}^N \left| \frac{\text{Real Market Price}(t) - \text{Estimated Market Price}(t)}{\text{Average Real Market Price}} \right|$$

Here, N stands for the number of evaluation periods. This criterion is suggested by Shahidepour *et al.* [20, p. 79].

Direct Formula (DF): As the first alternative, we employ a direct formula in which price is considered to be proportional to load. The following formula is used for predicting the price:

$$\text{Price}(t) = [\text{Load}(t)/\text{Load}(t-1)] \times \text{Price}(t-1)$$

See [20, p.77]. A spreadsheet application, like Microsoft Excel, is used to compute the DF.

Neural Network (NN): The second alternative is NN whose use for price estimation has been recommended by many researchers (e.g., [20, Ch.2]). We use a Radial Basis Function Neural Network (RBFNN) to forecast the market price of electricity. [See, for example, MATLAB Neural Network Toolbox, Version 6.1.0.450 Release12.1, that is listed in a web site: <http://www.mathworks.com/products/neuralnet/>.] The RBFNN is widely used for finding an approximation of a non-linear function as well as for finding interpolation values of a function defined only on a finite subset of real numbers. As found in many NN methods, the structure of the proposed use of NN is separated into an input layer, an output layer and a

hidden layer(s). The hidden layer consists of neurons with a Gaussian activation function. There is a non-linear mapping from the input layer to the hidden layer, and there is a linear mapping from the hidden layer to the output layer.

The NN method consists of the following two steps: training and testing. For PJM-DA and PJM-RT, the first 72 data points are used for training, and the next 217 data points are used for testing. The most commonly used NN is a feed-forward NN because it uses fewer neurons. In the case of a radial basis network, the number of neurons used in the input layer and hidden layer is equal to the number of input vectors. In this experiment, we use a radial basis network because of its superior prediction accuracy. We create the radial basis network with the function 'newrbe'. We initialize the bias to be 0.8326 ($\sqrt{-\ln(0.5)}$); i.e., the spread is set to 1.

The inputs of NN for predicting PJM-DA price are day-of-the-week, temperature, and DA demand. When predicting a PJM-RT price, inputs of NN are day-of-the-week, temperature, RT demand, and corresponding DA market price. For each of these predictions, 144 neurons (72 neurons in input layer + 72 neurons in hidden layer) are used. Even though a standard feed-forward NN would use fewer neurons, we chose RBFNN because of its better prediction capability and shorter training time.

Genetic Algorithm (GA): We use the Genetic Algorithm Toolbox for MATLAB, developed at the Department of Automatic Control and Systems Engineering of The University of Sheffield, UK, for running our experiments [source:<http://www.shef.ac.uk/acse/research/ecrg/gat.html>].

The parameters used in the GA are specified as follows: population size = 120, crossover probability = 0.8, mutation probability = 0.001, maximum generation = 12000. The objective of each agent is to maximize a total reward obtained after n iterations. Therefore, the objective function of the GA is to maximize the total reward obtained by agents. The individual calculation for rewards is given by equations in [4, p. 1334].

Each individual in the population is encoded by a 9-bit binary number. This encoding represents the day-of-the-week (three bits), temperature (two bits), and demand (four bits). The day-of-the-week may be any value in the range: Monday through Friday. The temperature is divided into three categories, Low, Mild, and High. The demand (x) is categorized into eight divisions: (a) $x < \text{mean} - 3\text{SD}$, (b) $\text{mean} - 3\text{SD} < x < \text{mean} - 2\text{SD}$, (c) $\text{mean} - 2\text{SD} < x < \text{mean} - \text{SD}$, (d) $\text{mean} - \text{SD} < x < \text{mean}$, (e) $\text{mean} < x < \text{mean} + \text{SD}$, (f) $\text{mean} + \text{SD} < x < \text{mean} + 2\text{SD}$, (g) $\text{mean} + 2\text{SD} < x < \text{mean} + 3\text{SD}$, and (h) $\text{mean} + 3\text{SD} < x$. Here, SD stands for a standard deviation of demand. The GA method is initialized with a random population size of 120 (5 days-of-the-week \times 3 temperature categories \times 8 demand categories) individuals. The maximum generation parameter in the GA method is set to 12,000. This termination condition produces the best result for the above specified encoding. The crossover probability and mutation probability are set to arbitrary values of 0.8 and 0.001.

3) Methodological Comparison

Table 2 compares the performance of Types I and II with those of DF, NN and GA methods. The values in Table 2 show average estimation accuracies (%) over 289000 simulations (=289 transaction days \times 1000 replications). Here, the number of transaction days (=289) is selected because we observe daily-based average market prices in 289 days (from November 7th, 2003 to January 4th, 2005). In each simulation, we apply the five methods to estimate the daily-based average market prices. We repeat the simulation 1000 times by changing different values on parameters. At the end of the whole simulation process, we obtain 1000 price estimates that are compared with the observed average market prices of electricity.

To describe how the proposed approach estimates accurately the price fluctuations of electricity, Figure 7 visually compares observed price fluctuations of PJM-DA with its estimates obtained from Type II. A close approximation is easily identified between the two groups of fluctuations in Figure 7. Similar results are found for Type I.

TABLE II
ESTIMATION COMPARISON AMONG FIVE APPROACHES

Market	Estimation Accuracy (%)				
	Direct Formula (DF)	Genetic Algorithms (GA)	Neural Network (NN)	Agent-based Approach (Type I)	Agent-based Approach (Type II)
PJM-DA	52.39	77.33	69.53	75.46	90.29
PJM-RT	6.63	80.56	82.97	81.24	91.51
Mean	29.51	78.95	76.25	78.35	90.90

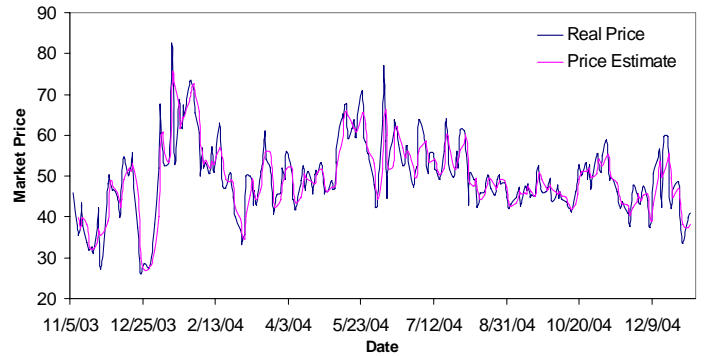


Fig. 7. Real Price and Price Estimate (PJM-DA/Type II)

Comments: (a) Types I and II incorporate both KA and OB processes. A testing set is used for KA while a learning set is used for OB. The proposed agent-based approach, including the two adaptive models, uses an online learning algorithm, whereas the NN and GA methods use an offline algorithm. Figure 7 has two curves. The curve represented by blue shows an original market price curve. The red curve shows its estimated curve obtained from both KA (10 days) and OB (279 days). (b) The selection of a particular KA/OB period influences the estimation accuracy, so this study repeats the estimation process 1000 times. The OB period should be considerably longer than the KA period because the KA is a

practice period and the OB is a real bidding period. (c) If we use crossover and mutation probabilities which are different from the current settings, the computation results of the GA method differ from the ones summarized in Table 2. For example, a GA with a crossover probability of 0.8 produces a result that differs from the result after the probability is set as 0.1. A similar concern applies to the mutation probability. We have conducted sensitivity analysis to confirm whether there is any major change in the results obtained from both the NN and GA methods. The sensitivity analysis identifies that there is a difference in the performances of the NN and GA methods. The best results of the two methods are listed in Table 2.

Findings from Table 2 and Figure 7 can be summarized as follows:

Finding 1: The DF is the most error-prone method and hence inefficient. All the estimation accuracies of DF are less than those of the other methods. The agent-based approach (Type II) outperforms the other approaches. The estimation accuracies confirm the first hypothesis that the agent-based approach (Types I and II) performs as well as the other well-known methods (DF, NN and GA) in price estimation.

Finding 2: The average estimation accuracy (90.90%) of Type II outperforms the accuracy (78.35%) of Type I. The result confirms the second hypothesis.

Since the above two findings are obtained from a data set on the PJM, these implications are limited in scope. Therefore, we need to extend the simulation study using data sets related to other US power markets (e.g., California ISO). That is an important future research extension of this study.

B. Examination of Third Hypothesis

To examine the third hypothesis, we conduct a simulation study in which agents of Types I and II coexist and bid against each other in an artificial market. The market is not supplied with any real market price data. The market price is determined only as a result of bidding by agents. The parameters of each agent are varied according to the well-known Ito's Lemma. A detailed description of the lemma can be found in [29]. Ito's lemma is widely used to generate random walks of market price. In the model, the market price in the next period is calculated by using the formula: $p(t+1) = e^{\nu\Delta t + \sigma\varepsilon(t)\sqrt{\Delta t}} p(t)$. The initial price, $P(0)$, is initialized as \$50, $\nu = 0.15$, and $\sigma = 0.40$. Δt is a basic period length. Both ν and σ are yearly rates and t represents time. We simulated daily prices of electricity. So, $\Delta t = 1/365$ is used in the model. A random number (ε) is generated from a normal distribution of mean 0 and standard deviation 1.

The simulation experiments have five different compositions between Types I and II. Each simulation experiment is structured by $T = 365$ ($t = 1, 2, \dots, T$) in each run. The experiment is duplicated 1000 times with different parameters. Table 3 compares the average winning ratio of Type I with that of Type II under these different compositions. The first column of Table 3 indicates the percentage composition of Types I and II. For example, the first row

illustrates an experiment in which agents belonging to Types I and II consist of 20% and 80% of the total number of agents, respectively. The second and third columns of Table 3 indicate the average quantity traded in each simulation and the range of the marginal cost of generators used on all runs, respectively.

In this simulation study, generators are divided into three groups based on marginal costs. The experimental setup consists of 50 generators which include 10 nuclear generators with a maximum capacity of 100000 MWH, 20 coal-mining generators with a maximum capacity of 35000 MWH, and 20 hydro-electric generators with a maximum capacity of 35000 MWH. The marginal costs for the nuclear, coal, and hydro are assumed to be \$50, \$35 and \$20, respectively. A sample of the 50 generators is randomly selected for each experiment.

Meanwhile, there are a total of 14500 wholesalers who are classified into the following eight groups: (# of Wholesalers, Demand Estimate) = (1000, 10000KWH), (2000, 50000KWH), (5000, 100000KWH), (2500, 200000KWH), (2500, 250000KWH), (500, 300000KWH), (500, 400000KWH) and (500, 500000KWH). A sample of the 14500 wholesalers is randomly selected for each experiment.

TABLE III
AVERAGE WINNING RATIOS OF TYPE I AND TYPE II

Composition of Type (I, II)	Avg. total quantity traded in each simulation (1000 MWH)	Range of Marginal Cost in each simulation	Avg. Winning Ratio			
			Type I		Type II	
			Gen	WS	Gen	WS
(20%,80%)	203	25-50	0.35	0.32	0.13	0.20
(40%,60%)	205	25-50	0.35	0.39	0.12	0.14
(50%,50%)	210	25-50	0.37	0.37	0.15	0.11
(60%,40%)	202	20-50	0.39	0.38	0.13	0.10
(80%,20%)	212	35-50	0.40	0.41	0.08	0.11

For our comparison, 50 generators and 14500 wholesalers (e.g., 24 generators and 69 wholesalers) are randomly re-sampled from the above combination between Types I and II. The average winning ratios are listed in the last column. Here, the average winning ratio of each agent group in Table 3 is calculated by the total reward obtained by each group divided by the total sum of all the groups. The average implies a mean of 365000 simulations (= 365 periods x 1000 times). One finding from Table 3 is summarized as follows:

Finding 3: Agents belonging to Type I outperform those of Type II in an artificial power market. For example, as listed in the first row (Type I: 20% and Type II: 80%), the average winning ratio of Type I (generators) is 35%, which is considerably higher than the corresponding 13% of Type II (generators). Similarly, wholesalers of Type I have 32% as an average winning ratio while those of Type II exhibit 20%. Similar average winning ratios are identified in other combinations of Types I and II. Thus, the third hypothesis is confirmed by the result.

Comments: (a) The wholesale price of electricity is cyclical over time with a stochastic jump in the cycle. Thus, price fluctuations of electricity are not perfectly random-walked as investigated in this study. This result indicates a shortcoming

of the current study. As an initial step, this study assumes that the market price is initialized randomly in the artificial market. We need to investigate further how to generate price in the artificial power market. For such a research purpose, a mean-reverting model with seasonality is useful for generating artificial data sets regarding power trading. See Bhanot [30] for a detailed description on the mean-reverting model. There are several mean-reverting models, each of which is associated with different assumptions. Hence, we need to examine which model is the best fit within the simulation study. That is an important future extension of this research.

(b) The real data set related to the PJM in Table 1 contains 24 generators and 69 wholesalers. Meanwhile, the simulation study of Table 3 samples randomly various combinations of data sets from a total population of 50 generators and 14500 wholesalers. Thus, the data sets used for this simulation study are part of the whole artificial data sets. For example, a data set that contains 25 generators and 70 wholesalers is selected randomly from the three groups of 50 generators and the eight groups of 14500 wholesalers. Since the selection is implemented by random sampling, we obtain 1000 different combinations between generators and wholesalers. In the simulation for Table 3, the number of generators is varied from 20 to 30 while the number of wholesalers is varied from 56 to 84. The random re-sampling process is repeated 1000 times in such a way that each trader combination is close to the real PJM composition. Of course, we admit that the result of Table 3 may not perfectly represent the reality of PJM. However, there is considerable closeness to reality in terms of the number of traders.

VII. CONCLUSION AND FUTURE EXTENSIONS

An agent-based approach is a promising technique to deal with business complexity in US wholesale power trading. In this study, we have examined three hypotheses. The first hypothesis examined the methodological validity of the approach. For such an examination, the performance of the proposed simulator was compared with other well-known methods such as NNs and GAs. The comparison confirmed that the proposed approach performed as well as the other well-known methods in price estimation.

Two adaptive models were prepared for the remaining two hypotheses in this study. One group consisted of adaptive agents (Type I) who were equipped with multiple learning capabilities and an exponential utility function. Those agents had a long-term view on win-lose experience. The other group (Type II) consisted of adaptive agents who were equipped with limited learning capabilities. They were myopic and less informed in their bidding decisions. The result on the second hypothesis confirmed that Type II outperformed Type I in the estimation of price fluctuations in electricity. The result was consistent with the empirical result of Erev-Roth's first assertion [5,6].

The result on the second hypothesis does not immediately imply that adaptive agents with a high estimation capability serve as a theoretical basis for developing the agent-based approach. As suggested by Erev-Roth's second assertion [5,6], we need to explore further the theoretical aspect of multiple learning capabilities for adaptive behaviors from the

perspective of power trading. The simulation result on the third hypothesis confirmed that Type I outperformed Type II in an artificial market in terms of a total reward. The result indicates that a theoretical investigation of multiple learning capabilities is important for developing power trading agents.

This study discussed several research issues to be explored. In addition to the issues, the following four research agendas are important in future. First, the proposed simulator designs as many agents as an investigator requires. The bidding strategy of each agent is characterized by many decision parameters. Such a numerical representation does not perfectly express a real power trading environment. For example, electric power markets are often oligopolistic. This study does not consider such a market situation in the simulation. Hence, we need to investigate further the real power trading in an oligopolistic market. In this case, the proposed simulator needs to reduce the number of agents.

Second, Types I and II do not exhaust all possibilities regarding the behavioral models of traders. There are many types of adaptive behaviors which are different from Types I and II. This study does not examine robustness for every possible alternative set of behavioral assumptions. It can be imagined that the results obtained from this study are sensitive to model selection for agents. Therefore, we need to investigate further other behavioral models for power trading agents.

Third, this study does not sufficiently explore all possible bidding strategies of agents. We need to explore the strategic issue under current deregulation policies.

Finally, this study does not perfectly justify the use of a binary sigmoid rule (incorporated in Type I) in order to guess a winning probability. It is true that human intelligence may not have the speculation capability. However, machine intelligence can easily incorporate the capability. Hence, it is worth investigating how the rule works as a learning capability for Type I. The use of the sigmoid decision rule is justified by the previous research [4, p.1335]. In future, the speculation capability needs to be re-examined from the practical perspective of real power trading.

REFERENCES

- [1] Tesfatsion, L. 2001. Agent-based modeling of evolutionary economic systems, *IEEE Transactions on Evolutionary Computation*, **5**, 437-441.
- [2] Samuelson, D. 2005. Agents of change. *OR/MS Today*, **32**, 1, 26-31.
- [3] Makowski, M., Y. Nakamori, H.J. Sebastain. 2005. Advances in complex system modeling. *European Journal of Operational Research*, **166**, 593-858.
- [4] Sueyoshi, T., G.R. Tadiparthi. 2005. A wholesale power trading simulator with learning capabilities. *IEEE Transactions on Power Systems*, **20**, 1330-1340.
- [5] Erev, I., A.E. Roth. 1998. Predicting how people play games: Reinforcement learning in experimental games with unique, mixed strategy equilibria. *American Economic Review*, **88**, 848-881.
- [6] Roth, A.E., I. Erev. 1995. Learning in extensive-form games: Experimental data and simple dynamic models in the intermediate term. *Games and Economic Behavior*, **8**, 164-212.
- [7] Simon, H.A. 1985. *The Science of Artificial*. Boston, MIT Press.
- [8] Veit, D.J., A. Weidlich, J. Yao, S.S. Oren. Simulating the dynamics in two-settlement electricity markets via an agent-based approach. Available from <http://www.ieor.berkeley.edu/~jyao/pubs/yao-MS06.pdf>.

- [9] Cheng, J.W.M., F.D. Galiana, D.T. McGillis. 1998. Studies of bilateral contracts with respect to steady-state security in a deregulated environment. *IEEE Transactions on Power Systems*. **13**, 1020-1025.
- [10] Lamont, J.W., S. Rajan. 1997. Strategic bidding in an energy brokerage. *IEEE Transactions on Power Systems*. **12**, 1729-1733.
- [11] Richter, C.W., G.B. Sheble, D. Ashlok. 1999. Comprehensive bidding strategies with genetic programming/finite state automata. *IEEE Transactions on Power Systems*. **14**, 1207-1212.
- [12] Gedra, T.W. 1994. Optional forward contracts for electric power markets. *IEEE Transactions on Power Systems*. **9**, 1766-1773.
- [13] Rosenwald, G., C.C. Liu. 1996. Consistency evaluation in an operational environment involving many transactions. *IEEE Transactions on Power Systems*. **11**, 1757-1762.
- [14] Guan, X., Y.C. Ho, D.L. Pepyne. 2001. Gaming and price spikes in electric power markets. *IEEE Transactions on Power Systems*. **16**, 402-408.
- [15] Song, H., C.C. Liu and J. Lawarree. 2002. Nash equilibrium bidding strategies in a bilateral electricity market. *IEEE Transactions on Power Systems*. **17**, 73-79.
- [16] Villar, J., H. Rudnick. 2003. Hydrothermal market simulation using game theory: Assessment of market power. *IEEE Transactions on Power Systems*. **18**, 91-98.
- [17] Senjyu, T., H. Takara, K. Uezato, T. Funabashi. 2002. One-hour-ahead load forecasting using neural network. *IEEE Transactions on Power Systems*. **17**, 113-118.
- [18] Taylor, J.W., R. Buizza. 2002. Neural network load forecasting with weather ensemble predictions. *IEEE Transactions on Power Systems*. **17**, 626-632.
- [19] Zhang, L., P.B. Luh, K. Kasiviswanathan. 2003. Energy clearing price prediction and confidence interval estimation with cascaded neural networks. *IEEE Transactions on Power Systems*. **18**, 99-105.
- [20] Shahidehpour, M., H. Yamin, Z. Li. 2002. *Market Operations in Electric Power System*. John Wiley & Sons, NY, NY.
- [21] Jacobs, J.M. 1997. Artificial power markets and unintended consequences. *IEEE Transactions on Power Systems*. **12**, 968-972.
- [22] Bagnall, A.J. 2000. A multi-adaptive agent model of generator bidding in the UK market in electricity. *Proceeding of Genetic and Evolutionary Computation Conference*. Las Vegas, Nevada, 605-612.
- [23] Bunn, D.W., F.S. Oliveira. 2001. Agent-based simulation: An application to the new electricity trading arrangements of England and Wales. *IEEE Transaction on Evolutionary Computation*. **5**, 493-503.
- [24] Morikiyo, T, M. Goto, 2004. Artificial Trading for US Wholesale Electric Power Market. *Asia Pacific Management Review*. **9**, 751-782.
- [25] Axelrod, R. 1997. *The Complexity of Cooperation*, Princeton University Press, Princeton, NJ.
- [26] Wilson, R. 2002. Architecture of power markets. *Econometrica*. **70**, 1299-1340.
- [27] Stoft, S. 2002. *Power System Economics*, IEEE Press, Piscataway, NJ.
- [28] Luenberger, D.G. 1998. *Investment Science*. Oxford University Press, NY.
- [29] Ito, K. 1951. On a formula concerning stochastic differentials. *Nagoya Mathematics Journal*. **3**, 55-65.
- [30] Bhanot, K. 2000. Behavior of power prices: Implications for the valuation and hedging of financial contracts. *Journal of Risk*. **2**, 43-62.

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