A Wholesale Power Trading Simulator With Learning Capabilities

Toshiyuki Sueyoshi and Gopalakrishna Reddy Tadiparthi

***Abstract*—The US wholesale power market comprises a large commodity market. The growth in power trading is due to the ongoing deregulation policy of the electric power industry. Most deregulation scenarios indicate a further separation of power production from transmission and retailing. The power production is opened to more competition. Unfortunately, the power trading mechanism is not clearly investigated in the level that we can predict a price change in the U.S. wholesale power market. Such a price change in the U.S. wholesale power market is explored from a simulation system with learning capabilities. Using the new intelligence system, we investigate the bidding strategies of traders in the wholesale power market and examine how the price change occurs under different economic and engineering environments.**

***Index Terms*—Electricity competition, machine learning, market model, strategic pricing, wholesale power trading.**

I. Introduction

DEREGULATION of the electric power industry is a general business trend occurring in many industrial nations. Regulated or state-owned monopoly markets have been deregulated and competition has been introduced into the electric power industry. The business trend first occurred in the United Kingdom [10] and was followed by other nations such as New Zealand, Sweden [2], Norway [1], and Australia [6]. Such deregulation could be also found in American jurisdictions such as New England, New York, California, and Pennsylvania-New Jersey-Maryland (PJM). Recently, Japan has been planning to deregulate her wholesale power market. Eighteen electric power firms will open a new wholesale exchange power market in April 2005 ****AUTHOR: PLEASE CONFIRM/UPDATE****.

Electricity has several unique features that are different from other commodities. First, it cannot be stored as found in other commodities. Second, a constant monitoring system is required to stabilize a balance between supply and demand; both are often expressed by a nonlinear relationship. Third, most residential consumers are, on a short time, unaware of or indifferent to a price change. In other words, price elasticity is considerably small, compared with other commodities. Finally, the demand is influenced by a change in temperature and a seasonal change. A large demand occurs on electricity in summer and winter, depending upon the place where the demand occurs.

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In addition to the above unique features regarding electricity, a price change in the wholesale power market occurs due to other socio-economic and engineering factors. Such factors include: 1) an imperfect market structure; 2) a possible existence of a market power; 3) an occurrence of congestion in transmission; 4) different speculation views among traders; 5) imperfect information on electricity transmission, (f) different bidding approaches among traders; 6) a system failure and a maintenance problem; and 7) a price change of fuel (e.g., coal, oil, and natural gas). Thus, the wholesale power market can be considered as a complex system.

Many individuals, who are involved in the power industry, are looking for a policy guidance regarding how to determine an appropriate pricing system of electricity. To investigate the business/policy issue, this study examines the wholesale power market by a simulation study, because the numerical approach is more effective in dealing with the complex system than the analytical (mathematical) approach. Many different types of traders participate in a dynamic pricing mechanism of the power market on simulation. Thus, the purpose of this research is to develop a trading simulator that predicts a price fluctuation of the wholesale power market.

The remaining structure of this article is organized as follows: The next section briefly reviews previous research efforts on power trading. Section III describes the industrial structure of the current U.S. wholesale power market. Section IV describes the computational structure of the proposed simulator. Section V documents simulation results. Section VI concludes this study, along with future research extensions.

II. Previous Research

This literature review indicates the position of the proposed approach by comparing itself with other previous research efforts on the power trade issue. The previous research is methodologically classified into the following three groups.

A. Behavioral Analysis

The first group discussed their bidding strategies of traders in the deregulated power market [15], [19], [7]. The behavioral aspect of trading was examined from a perspective of bilateral electricity contracts that need a risk hedge in the power market [9], [21]. Game theory was used to investigate their negotiation behaviors for bilateral and multilateral contacts [32], [11], [25], [30]. A contribution of this research group is that these research efforts provide the analytical features of electricity trading behaviors. For example, it provides analytical rationale and explanation regarding how a market power(s) makes an impact on a wholesale price. Meanwhile, the behavioral research excludes important uncontrollable factors such as different speculations and bidding preferences among traders. Consequently, this type of analytical approach is methodologically limited in price predictability of the power market.

B. Economic Analysis

The second group of research has developed mathematical models (e.g.,integer programming, stochastic programming and forecasting models) to find an optimal bidding strategy. The power allocation, derived from the optimal bidding strategy, needs to satisfy transmission requirements from a demand side of electricity [3], [8], [16], [18], [26]. An important feature of the second group is that the research efforts do not consider the behavioral aspect of traders, as identified in the first group. A main objective of these approaches is to achieve the economic efficiency of the power market.

C. Numerical Analysis

The last group of previous research efforts fully utilizes computer science methods (e.g., neural networks (NNs), a genetic algorithm, and a multiadaptive learning model) to predict a change of power price and a dynamic fluctuation of other factors (e.g., weather) that influence the amount of electricity demand. The NN technique, incorporating a learning process, was applied for one-hour ahead forecasting of a power demand based upon a given temperature [22], [29]. The volatility of power price was also measured by NNs [33]. The NN technique is a widely used numerical approach that heuristically approximates the dynamic trend of a power price by duplicating the learning process of a human brain. A methodological strength of NNs is that the approach is so flexible that the estimation reliability of NNs is considerably high. However, the NN estimation lacks a mathematical rationale. Moreover, the convergence rate of NNs is very slow in producing a final estimation result(s), because many weights are associated with the NN computation. In the same vain, a genetic algorithm was applied to understand bidding strategies in the power market [20]. The approach is useful when the power market is not volatile. In addition to the NN technique and the genetic algorithm, Jacobs [13], Bagnall [5], and Morikiyo and Goto [17] have considered the power market from a multiagent adaptive system [27] and applied a simulation-based approach to understand the dynamic bidding process of the power market. These research efforts comprise the third subgroup of the numerical analysis. A methodological benefit of the approach is that many traders are considered as agents with different bidding preferences. (See Axelrod [4] for a detailed discussion on historical and current issues on agent-based modeling.)

Admitting the previous contributions on power trading, this study explores the wholesale power market from a simulation study, because the market can be considered as a complex system, as mentioned previously. Furthermore, a machine learning process is incorporated into the proposed approach to understand both how traders accumulate their knowledge and how to use their experiences for power trading. Thus, this research belongs to the above third group. However, this type of research has been not sufficiently explored in the previous research efforts.

Finally, this research is concerned with numerical analysis on power trading. Therefore, we do not discuss its public policy issues. Readers who are interested in the policy perspectives on power trading can find many previous research efforts such as Joskow and Schmalensee [14], Stoft [28], Schweppe *et al.* [24], and Wilson [31]. See also [23] for a detailed description on electric power from a general engineering perspective.

III. Industrial Structure of U.S. Wholesale Market

The U.S. wholesale market is functionally separated into: 1) a transmission market and 2) a power exchange market. This study focuses upon only the power exchange market. (Research on bidding behaviors on transmission is an important future extension of this study.)

The U.S. wholesale power exchange market is further functionally broken down into: 1) a real-time market (transaction on a five-minute interval); 2) an hour-ahead market; 3) a day-ahead market; and 4) a long-term market (transaction from one week to five or more years). Each market has unique features in terms of an auction/exchange process and transmission agreement.

This research focuses upon trading strategies for both a Day-Ahead (DA) market and a Real Time (RT) market, because their bidding behaviors of traders in both DA and RT markets have a close bidding linkage between them. Moreover, the two markets are important in the investigation of a price fluctuation in the wholesale power market. In this study, the RT market 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. Many researchers (e.g., Stoft, [28, p. 204]) consider that the DA market is a "financial and forward" market because all the transactions in the DA market stop one day prior to RT and the bidding decisions in the DA market are determined by the speculation of traders. Meanwhile, the RT market can be considered as a "physical and spot" market, because the delivery of power in the RT market is not optional like that of the DA market. All traders enter the market to correspond to actual power flows. Hence, the aspect of financial speculation is very limited in the RT market. Thus, the RT can be considered as a physical market. In the RT market, traders need to make their decisions within a limited time (e.g., one hour or five minutes). So, it can be considered as a spot market.

Finally, the risk hedge behavior of a trader(s) in the long-term market is different from their trading approaches in the other power markets. The power trading for the long-term contract is bilaterally determined between a generator and a wholesaler/retailer. Hence, the long-term market is excluded from the investigation of this study.

A. Auction Theory

According to [12], the auctions are classified into the following four types: 1) *English:* buyers start bidding at a low price—the highest bidder wins and pays the last price bid; 2) *Dutch:* the auctioneer starts very high and calls out progressively lower prices. The first buyer, who accepts the price, wins and pays the price; 3) *Vickrey (second-price):* buyers submit sealed bids. The winner pays the price of the highest losing bid; and 4) *Sealed-bid (first-price):* buyers submit sealed bids. The winner pays the price that is the highest among bids.

When examining the four types of auction from the perspective of wholesale power trading, it is important to note that all the auctions, listed above, belong to a single-settlement system where traders bid their prices once to determine a winning price. However, the wholesale power trading examined in this study belongs to a two-settlement system (TSS), where traders bid their prices in the DA market and then make their bids again in the RT market (Stoft [28, p. 210]). Furthermore, multiple biddings are accepted in the DA and RT markets.

B. Design of Power Market (Bilateral vs Central as Well as Exchange Versus Pool)

As mentioned previously, this study does not consider bilateral trading (e.g., a long-term market). The bilateral trading usually responds slowly because it lacks a transparent market price. Meanwhile, the power allocation for DA and RT is traded in a centralized market [often found in an Independent System Operator (ISO)] that provides traders with a transparent price. Consequently, traders in the central market find an efficient set of trades much faster and easier than those in the bilateral market.

The central market is functionally separated into an exchange market and a pool market. The power exchange market is defined as a centralized market that does not use side payments (Stoft [28, p. 223]). In the exchange market, wholesalers pay the same price to generators at any given time and location. A trader simply trades with exchange at the trader location. California's Power Exchange is an example of the standard power exchange in operation. In the market, traders use multiple rounds of bidding (24 hourly bids) to determine a market price and can implement full nodal pricing, where the nodal price implies a price at every node or bus of a power network. Meanwhile, the pool market is adopted by PJM and NYISO (New York ISO). In the market, generators report a detail of their costs and limitations to a market operator. The market operator then computes which generators need to be started ahead of time. It finds an optimal allocation under an assumption that all bids and demand forecasts are correct. The market operator may find a market price whose level is lower than the price that generators can start up. In this case, these generators can receive side payments.

IV. Simulation Structure for Power Trading

A. A Market Design for Wholesale Power Trading

In the proposed simulator, the wholesale power market is structured by the DA and RT markets. In each market, generators (suppliers) and wholesalers/retailers (buyers) consist of trade agents whose bidding strategies are examined in our simulation study. Each trader independently behaves for the enhancement of his/her own interest or benefit. Based upon the previous bidding results (success/ failure), each trader accumulates knowledge for his/her future decision-making.

We acknowledge that the proposed simulator cannot perfectly duplicate real trading behaviors in the power trade markets. Hence, this study needs to consider first how to structure DA and RT markets from their bidding strategies and economic rationales of traders. Then, different parameters regarding bidding strategies and different initial starting points are used to express their various trading behaviors in the two markets. Furthermore, it is widely accepted that a reward obtained from his/her previous trading often becomes a major economic incentive for many traders. The learning process incorporated in the simulator can be considered as a computational approach in which a trader tries to maximize a total amount of reward obtained from power trading.

The bidding processes of traders in both DA and RT markets can be visually summarized in Fig. 1. The assumption and bidding strategies incorporated in Fig. 1 are summarized as follows.

Assumption: n generators ($\mathrm{i} = 1, \ldots, \mathrm{n}$) and k wholesalers ($\mathrm{j} = 1, \ldots, \mathrm{k}$) participate in the DA and RT markets at the tth period ($\mathrm{t} = 1, \ldots, \mathrm{T}$).

Supply Side Strategy in DA Market: s_{it}^{m} is the maximum power generation capacity of the ith generator at the tth period. The generator bids s_{it}^{1} as the amount of power generation for the DA market ($s_{it}^{1} \leq s_{it}^{m}$). Here, the superscript "1" indicates the DA market and the subscript "t" indicates a power delivery time. The bidding amount s_{it}^{1} is expressed by $\alpha_{it}\, s_{it}^{m}$, where α_{it} ($0 \leq \alpha_{it} \leq 1$) is a parameter to express the ratio of the bidding amount to the maximum capacity.

Let MC_{it} be the marginal cost of the ith generator at the tth period. Each generator determines a bidding price (p_{it}^{1}) for the DA market by $p_{it}^{1} = \mathrm{MC}_{it}/(1-\beta_{it})$. Here, β_{it} ($0 \leq \beta_{it} < 1$) is a mark-up rate of the generator for the DA market. The mark-up rate expresses numerically how much the bidding price is inflated from the marginal cost. The mark-up rate reflects a price strategy toward the DA trading. Considering different magnitudes of β_{it}, the simulator examines various price strategies in the DA market.

After s_{it}^{1} and p_{it}^{1} are submitted by all generators into ISO, the organization determines the real allocation ($\hat{s}_{it}^{1}$) for each generator in the DA market. The real allocation ($\hat{s}_{it}^{1}$), determined by the DA market, is different from s_{it}^{1} (a bidding amount).

Supply Side Strategy in RT Market: In the wholesale market, each generator is expected to allocate the whole generation capacity to the DA and/or RT market. Hence, the ith generator bids $s_{it}^{0} = s_{it}^{m} - \hat{s}_{it}^{1}$ in the RT market, where the superscript "0" indicates the RT market. The pricing strategy of the generator is expressed by $p_{it}^{0} = \mathrm{MC}_{it}/(1 - \eta_{it})$, where η_{it} is a mark-up rate ($0 \leq \eta_{it} < 1$) and p_{it}^{0} is the bidding price of the generator. In the RT market, ISO obtains their bids on s_{it}^{0} and p_{it}^{0} from all generators to determine $\hat{s}_{it}^{0}$ (a real allocation for the generator) and $\hat{p}_{t}^{0}$ (a market price) through the RT market.

Demand Side Strategy in DA Market: A wholesaler predicts an expected amount of electricity demanded on a delivery day, using a forecasting method. (The forecasting technique will be discussed in the proceeding subsection.) Let e_{jt} be the demand estimated by the jth wholesaler or ISO. The wholesaler predicts a bidding price (w_{jt}^{1}) by using an inverse function (IF) of demand. That is, $w_{jt}^{1} = \mathrm{IF}(e_{jt})$. In the proposed simulator, the wholesaler makes a demand bid (d_{jt}^{1}) whose amount is less than or equal to e_{jt}. That is, $d_{jt}^{1} = \delta_{jt} e_{jt}$, where δ_{jt} ($0 \leq \delta_{jt} \leq 1$) is a parameter to express how each bid is strategically reduced from the demand estimate. Similarly, the bidding price for demand is determined by $\mathrm{p}_{\mathrm{jt}}^{1}=\lambda_{\mathrm{jt}}\mathrm{w}_{\mathrm{jt}}^{1}$. Here, λ_{jt} $(0\leq\lambda_{\mathrm{jt}}\leq 1)$ is a parameter for price adjustment from the estimated price. Both $\mathrm{d}_{\mathrm{jt}}^{1}$ and $\mathrm{p}_{\mathrm{jt}}^{1}$ are submitted to ISO and then the organization determines $\hat{\mathrm{d}}_{\mathrm{jt}}^{1}$ (a real power allocation to the wholesaler) and $\hat{\mathrm{p}}_{\mathrm{t}}^{1}$ (a market price) in the DA market.

Demand-Side Strategy in RT Market: In the RT market, all the wholesalers specify their required quantities on electricity. It is assumed that they must purchase all the necessary electricity from DA and/or RT markets. Let R_{jt} be a real demand for the jth wholesaler on the delivery day. The wholesaler specifies the purchasing amount, $\mathrm{d}_{\mathrm{jt}}^{0}(=\mathrm{R}_{\mathrm{jt}}-\hat{\mathrm{d}}_{\mathrm{jt}}^{1})$, in the RT market. ISO adjusts all the requests from market participants to determine $\hat{\mathrm{d}}_{\mathrm{jt}}^{0}$ (a real allocation) and $\hat{\mathrm{p}}_{\mathrm{t}}^{0}$ (a market price) through the RT market.

Finally, the following three additional comments are important for understanding Fig. 1.

1) The design of the DA and RT markets has a computational benefit that the bidding prices and power allocations are numerically expressed by the parameters on the range between 0 and 1. As a result of such numeration, the trading structure for the wholesale power market can be artificially duplicated by the simulator.
2) Information on $\mathrm{s}_{\mathrm{it}}^{\mathrm{m}}$, $\mathrm{MC}_{\mathrm{it}}$, e_{jt}, $\mathrm{w}_{\mathrm{jt}}^{1}$ and R_{jt} needs to be given to the simulator. The remaining other variables are determined by each trader.
3) The simulation needs to satisfy the following condition:

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

B. Function of ISO in DA and RT Markets

In the DA market, n generators bid their $\mathrm{s}_{\mathrm{it}}^{1}$ and $\mathrm{p}_{\mathrm{it}}^{1}$. Similarly, k wholesalers bid their $\mathrm{d}_{\mathrm{jt}}^{1}$ and $\mathrm{p}_{\mathrm{jt}}^{1}$ in the DA market. How can we coordinate these bidding prices and amounts to obtain a market price? Such a required market coordination mechanism can be found in ISO.

Fig. 2 visually describes the market coordination mechanism of ISO in the DA market. In the proposed simulator, ISO reorders their biddings of generators and wholesalers. That is, the supply side combinations ($\mathrm{s}_{\mathrm{it}}^{1}$ and $\mathrm{p}_{\mathrm{it}}^{1}$) are reordered according to the ascending order of these bidding prices ($\mathrm{p}_{\mathrm{it}}^{1}$). Thus, the bidding process can be considered as a sealed English auction with acceptance of multiple bids. Meanwhile, the demand side combinations ($\mathrm{d}_{\mathrm{jt}}^{1}$ and $\mathrm{p}_{\mathrm{jt}}^{1}$) are reordered according to the descending order of these bidding prices ($\mathrm{p}_{\mathrm{jt}}^{1}$). The bidding process can be considered as a sealed Dutch auction with acceptance of multiple bids. In Fig. 2, ISO allocates the generation amount ($\mathrm{s}_{1\mathrm{t}}^{1}$) of the first generator to satisfy the demand ($\mathrm{d}_{1\mathrm{t}}^{1}$) of the first wholesaler. Such a power allocation is continued until an equilibrium point is found in the DA market. In Fig. 2, the equilibrium point is identified as EP, where the four generators are used to satisfy the demand required by the three wholesalers. Consequently, $\mathrm{p}_{4\mathrm{t}}^{1}$ (the bidding price of the fourth generator) becomes the market price ($\hat{\mathrm{p}}_{\mathrm{t}}^{1}$) for all participating traders in the DA market.

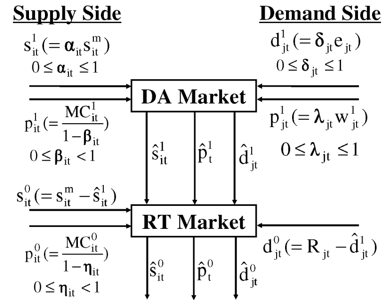

Fig. 1. Bidding structure for wholesale market.

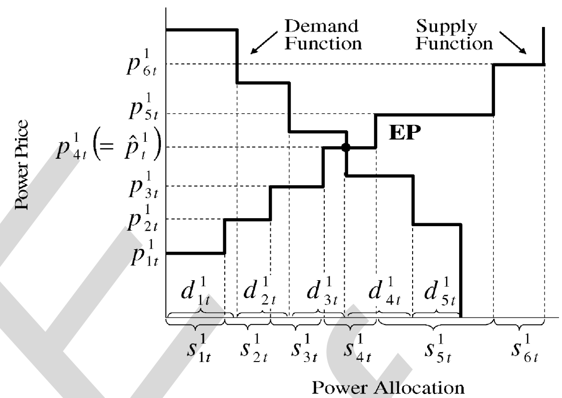

Fig. 2. Equilibrium point in DA market.

Fig. 3 depicts the market coordination mechanism for the RT market, where generators bid both $\mathrm{s}_{\mathrm{it}}^{0}$ and $\mathrm{p}_{\mathrm{it}}^{0}$. The combination of quantities and bidding prices are reordered according to the ascending order of these bidding prices ($\mathrm{p}_{\mathrm{it}}^{0}$). Meanwhile, wholesalers submit their demands ($\mathrm{d}_{\mathrm{jt}}^{0}$), but not the bidding prices, because the RT market is a physical market where the demand of end users must be always satisfied. In Fig. 3, ISO accumulates the generation amounts until the total demand is satisfied. In the figure, $\mathrm{D}_{\mathrm{t}}^{0}$ is such a point, where

$$\mathrm{D}_{\mathrm{t}}^{0}=\sum_{\mathrm{j}}\mathrm{d}_{\mathrm{jt}}^{0}=\sum_{\mathrm{j}}\left(\mathrm{R}_{\mathrm{jt}}-\hat{\mathrm{d}}_{\mathrm{jt}}^{1}\right).$$

In Fig. 3, an equilibrium point is identified as EP, where five generators are used to satisfy the total demand required by wholesalers. Consequently, $\mathrm{p}_{5\mathrm{t}}^{0}$ (the bidding price of the fifth generator) becomes the market price ($\hat{\mathrm{p}}_{\mathrm{t}}^{0}$) for all participating traders in the RT market.

C. Demand Forecasting

Each wholesaler (or ISO) needs to forecast the demand of electricity. In this study, average, moving-average, exponential smoothing, and random forecasting methods are used to estimate the amount of demand. A choice from the four forecasting techniques depends upon each wholesaler. Since a description on the average and random forecasting are trivial to us, this study omits the description on those methods except noting the following.

a) *Moving Average*: This method averages a data set for only the last z periods as the forecast for the next period. That

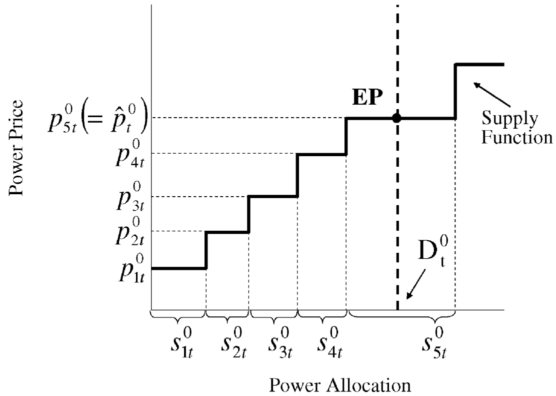

Fig. 3. Equilibrium point in RT market.

is, $e_{jt} = \sum_{r=t-z}^{t-1}(R_{jr}/z)$, where R_{jr} is the observed real demand of the jth wholesaler at the rth period.

b) *Exponential Smoothing*: This method uses the following formula: $e_{jt} = \mu R_{jt} + (1-\mu)e_{jt-1}$, where μ $(0 < \mu < 1)$ is referred to as a smoothing constant.

It is true that different agents have different preferences on their forecasting methods. However, it is also true that we cannot perfectly duplicate their minds related to future demand prediction. Hence, this study provides a choice in which all the traders can select one of the four methods for their forecasting.

The inverse function (IF) of demand used in this study may be depicted in Fig. 4. As visually described in Fig. 4, the demand is structurally separated into a residential use (the left hand side from the vertex) and an industry/business use (the right hand side from the vertex). The former has low price elasticity, while the latter has relatively high price elasticity. Hence, the slope (a_r) of the residential use is higher than the slope (a_b) of the industrial/commercial use. The intercept of the two lines are expressed by c_r (for the residential use) and c_b (the industrial/business use). The four coefficients need to be specified by each wholesaler (or ISO). In Fig. 4, e_j^m indicates the maximum amount of power estimation of the jth wholesaler. In the DA market, each wholesaler forecasts the demand estimate (e_{jt}) and its related price (w_{jt}^1) on the IF of demand. As mentioned previously; since the market is DA, the wholesaler determines his/her bidding amount (d_{jt}^1) in a manner that the quantity is less than or equal to e_{jt}. Moreover, the bidding price (p_{jt}^1) is set to be smaller than the price estimate (w_{jt}^1).

D. A Reward to Traders

In the proposed simulator, traders are looking for the best combination of bidding prices and amounts in order to maximize their individual rewards.

A reward for the ith generator may be specified in the following manner. If $\hat{p}_t^1 < p_{it}^1$, then the generator cannot have any chance to produce power, so resulting in no profit in the DA market. Meanwhile, if $\hat{p}_t^1 \geq p_{it}^1$, then the generator receives a total profit $(\hat{p}_t^1 - MC_{it})\hat{s}_{it}^1$. Similarly, if $\hat{p}_t^0 < p_{it}^0$, the generator loses a chance to generate electricity, so resulting in no profit in the RT market. Meanwhile, if $\hat{p}_t^0 \geq p_{it}^0$, the generator can provide electricity so that it produces a profit $(\hat{p}_t^0 - MC_{it})\hat{s}_{it}^0$.

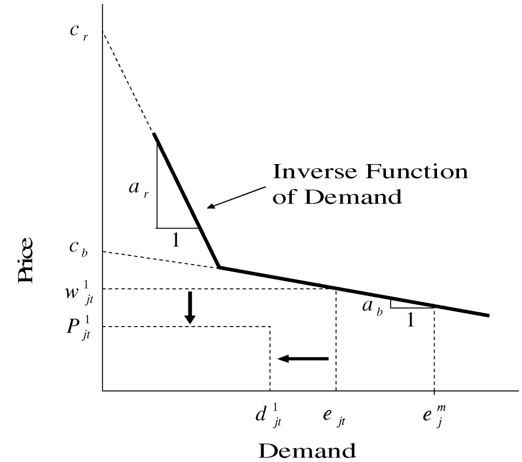

Fig. 4. Inverse function of demand.

Consequently, the reward for the ith generator can be summarized as follows:

if $\hat{p}_t^1 \geq p_{it}^1$ and $\hat{p}_t^0 \geq p_{it}^0$, then $(\hat{p}_t^1 - MC_{it})\hat{s}_{it}^1 + (\hat{p}_t^0 - MC_{it})\hat{s}_{it}^0$
if $\hat{p}_t^1 < p_{it}^1$ and $\hat{p}_t^0 \geq p_{it}^0$, then $(\hat{p}_t^0 - MC_{it})\hat{s}_{it}^0$,
if $\hat{p}_t^1 \geq p_{it}^1$ and $\hat{p}_t^0 < p_{it}^0$, then $(\hat{p}_t^1 - MC_{it})\hat{s}_{it}^1$, and
if $\hat{p}_t^1 < p_{it}^1$ and $\hat{p}_t^0 < p_{it}^0$, then the reward becomes zero.

Next, we return to the reward to the jth wholesaler. If $\hat{p}_t^1 > p_{it}^1$, then the wholesaler cannot access a power supply through the DA market. Meanwhile, if $\hat{p}_t^1 \leq p_{jt}^1$, then the wholesaler can obtain the power from the DA market. Similarly, if $\hat{d}_{jt}^0 > 0$, then the wholesaler can access the power supply in the RT market. An opposite case can be found if $\hat{d}_{jt}^0 = 0$. The wholesaler usually provides electricity whose price is ruled by a regulatory agency(s). Hence, let p^R be the retail price. Then, the reward for the jth wholesaler can be specified as follows:

(a) if $\hat{p}_t^1 \leq p_{jt}^1$ and $\hat{d}_{jt}^0 > 0$, then $p^R(\hat{d}_{jt}^1 + \hat{d}_{jt}^0) - \hat{p}_t^1\hat{d}_{jt}^1 - \hat{p}_t^0\hat{d}_{jt}^0$
(b) if $\hat{p}_t^1 > p_{jt}^1$ and $\hat{d}_{jt}^0 > 0$, then $p^R(\hat{d}_{jt}^0) - \hat{p}_t^0\hat{d}_{jt}^0$
(c) if $\hat{p}_t^1 \leq p_{jt}^1$ and $\hat{d}_{jt}^0 = 0$, then $p^R(\hat{d}_{jt}^1) - \hat{p}^1\hat{d}_{jt}^1$, and
(d) if $\hat{p}_t^1 > p_{jt}^1$ and $\hat{d}_{jt}^0 = 0$, then the reward becomes zero.

E. Machine Learning

In the proposed simulator, traders accumulate knowledge from their bidding results to adjust their bidding strategies. The learning process incorporated in the simulator is separated into: 1) a knowledge accumulation (KA) process ($t < Z$) and 2) an own-bidding (OB) process ($t \geq Z + 1$). Fig. 5 depicts such a learning process.

The KA process provides each trader with a win-loss experience as a result of their biddings. In the process, all parameters are obtained from a random number generation. After the learning process is over, traders start their own bidding decisions based upon their previous trading experiences. Of course, they

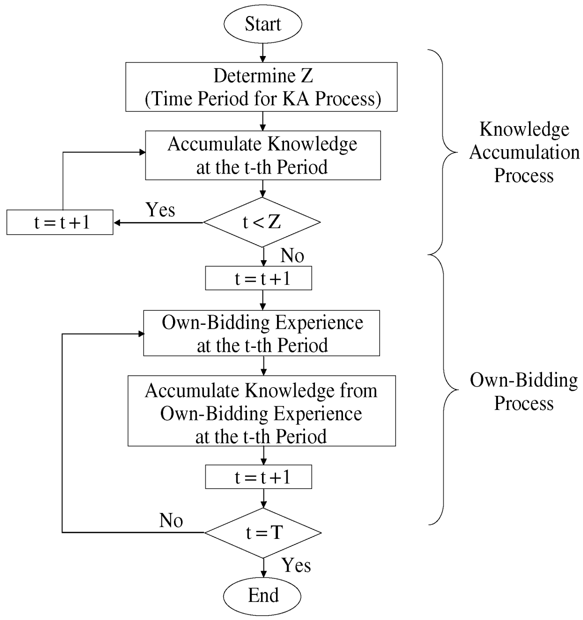

Fig. 5. Adaptive learning process.

update and accumulate their knowledge at each trading. The bidding/learning process is considered as the OB process in this study. The proposed simulator incorporates an adaptive sigmoid decision rule. The decision rule can be analytically specified as follows.

Adaptive Sigmoid Decision Rule: The win or lose of a trader is considered as a binary response. To express an occurrence of the binary response, a sigmoid model is widely used to predict its probability. Mathematically, the probability cumulative function of the sigmoid model is expressed by $\mathrm{F}(\sigma) = \int_{-\infty}^{\sigma} \mathrm{e^u}/(1+\mathrm{e^u})^2 \mathrm{du} = 1/(1+\mathrm{e}^{-\sigma})$. The win/loss status of the ith generation is predicted by the following linear probability model:

$$\mathrm{r_{it}} = \mathrm{c_{i0}} + \mathrm{c_{i1}}\alpha_{\mathrm{it}} + \mathrm{c_{i2}}\beta_{\mathrm{it}} + \mathrm{c_{i3}}\eta_{\mathrm{it}} + \varepsilon_{\mathrm{t}}. \tag{1}$$

Here, $\mathrm{r_{it}}$ is a reward given to the ith generator at the tth period. Parameters are denoted by $\mathrm{c_{i0}}, \mathrm{c_{i1}}, \mathrm{c_{i2}}$, and $\mathrm{c_{i3}}$. An observational error is listed as ε_{t}. Those parameters are unknown and hence, need to be estimated by ordinary least squares (OLS) regression. The winning probability (Prob) of the jth generator at the tth period can be specified as follows:

$$\begin{aligned}\mathrm{Prob}(\mathrm{W_t}) &= \mathrm{Prob}(\mathrm{r_{it}} \geq 0)\\ &= \mathrm{Prob}\{\varepsilon_{\mathrm{t}} \geq -(\hat{\mathrm{c}}_{\mathrm{i0}} + \hat{\mathrm{c}}_{\mathrm{i1}}\alpha_{\mathrm{it}} + \hat{\mathrm{c}}_{\mathrm{i2}}\beta_{\mathrm{it}} + \hat{\mathrm{c}}_{\mathrm{i3}}\eta_{\mathrm{it}})\}\\ &= 1 - \frac{1}{1+\mathrm{e}^{(\hat{\mathrm{c}}_{\mathrm{i0}} + \hat{\mathrm{c}}_{\mathrm{i1}}\alpha_{\mathrm{it}} + \hat{\mathrm{c}}_{\mathrm{i2}}\beta_{\mathrm{it}} + \hat{\mathrm{c}}_{\mathrm{i3}}\eta_{\mathrm{it}})}}\\ &= \frac{\mathrm{e}^{(\hat{\mathrm{c}}_{\mathrm{i0}} + \hat{\mathrm{c}}_{\mathrm{i1}}\alpha_{\mathrm{it}} + \hat{\mathrm{c}}_{\mathrm{i2}}\beta_{\mathrm{it}} + \hat{\mathrm{c}}_{\mathrm{i3}}\eta_{\mathrm{it}})}}{1+\mathrm{e}^{(\hat{\mathrm{c}}_{\mathrm{i0}} + \hat{\mathrm{c}}_{\mathrm{i1}}\alpha_{\mathrm{it}} + \hat{\mathrm{c}}_{\mathrm{i2}}\beta_{\mathrm{it}} + \hat{\mathrm{c}}_{\mathrm{i3}}\eta_{\mathrm{it}})}}.\end{aligned}$$

The symbol (^) indicates a parameter estimate obtained by OLS. The above equations suggest that the winning probability can be determined immediately from parameter estimates of the sigmoid model. (The sigmoid model is often incorporated into a neural network computation. The proposed learning process can be, therefore, considered as a simple application of the neural network. The sigmoid model is often called "a logit model" by economists.)

The winning probability of the jth wholesaler at the tth period can be obtained, via replacing (1), by the following linear probability model:

$$\mathrm{r_{jt}} = \mathrm{c_{j0}} + \mathrm{c_{j1}}\delta_{\mathrm{jt}} + \mathrm{c_{j2}}\lambda_{\mathrm{jt}} + \varepsilon_{\mathrm{t}}. \tag{2}$$

The winning probability can be specified as

$$\mathrm{Prob}(\mathrm{W_t}) = \mathrm{Prob}(\mathrm{r_{jt}} \geq 0) = \frac{\mathrm{e}^{(\hat{\mathrm{c}}_{\mathrm{j0}} + \hat{\mathrm{c}}_{\mathrm{j1}}\delta_{\mathrm{jt}} + \hat{\mathrm{c}}_{\mathrm{j2}}\lambda_{\mathrm{jt}})}}{1+\mathrm{e}^{(\hat{\mathrm{c}}_{\mathrm{j0}} + \hat{\mathrm{c}}_{\mathrm{j1}}\delta_{\mathrm{jt}} + \hat{\mathrm{c}}_{\mathrm{j2}}\lambda_{\mathrm{jt}})}}.$$

Learning Algorithm: In the proposed learning process, each trader constantly looks for an increase in the estimated winning probability. In other words, the trader looks for a combination of parameters that produces a high winning probability. To describe the learning process more clearly, we consider the own bidding process of the jth wholesaler at the tth period. For a visual description, this study considers the learning algorithm from the perspective of the wholesaler, because the bidding process can be expressed as a two-dimensional figure. The algorithm discussed here can be easily extended to that of a generator. Such a description on the generator needs a three-dimensional figure.

The knowledge accumulation process of the wholesaler provides three parameter estimates of the sigmoid function. Two parameter estimates ($\hat{\mathrm{c}}_{\mathrm{j1}}$ and $\hat{\mathrm{c}}_{\mathrm{j2}}$) are important in determining the bidding strategies of wholesalers and both are associated with two decision variables (δ_{jt} and λ_{jt}), respectively. If a parameter estimate is positive, the wholesaler should increase its corresponding decision variable to enhance his/her winning probability in the wholesale market. (Note that the winning probability, obtained from the sigmoid function, does not immediately imply that the trader can win in the wholesale market with the estimated probability. That is a theoretical guess. The win or lose is determined through the DA and RT market mechanism.)

Based upon the signs of parameter estimates obtained from the knowledge accumulation process, the wholesaler has nine different bidding strategies (with $\mathrm{t} = 1$ as the start).

Step 1: Set the initial bidding variables as ($\delta^{\mathrm{c}}_{\mathrm{jt}}$, $\lambda^{\mathrm{c}}_{\mathrm{jt}}$). Also, set the upper ($\delta^{\mathrm{U}}_{\mathrm{jt}}$ and $\lambda^{\mathrm{U}}_{\mathrm{jt}}$) and lower ($\delta^{\mathrm{L}}_{\mathrm{jt}}$ and $\lambda^{\mathrm{L}}_{\mathrm{jt}}$) bounds on the bidding variables based upon the bidding strategy of the jth wholesaler. Both $\delta^{\mathrm{L}}_{\mathrm{jt}} \leq \delta^{\mathrm{c}}_{\mathrm{jt}} \leq \delta^{\mathrm{U}}_{\mathrm{jt}}$ and $\lambda^{\mathrm{L}}_{\mathrm{jt}} \leq \lambda^{\mathrm{c}}_{\mathrm{jt}} \leq \lambda^{\mathrm{U}}_{\mathrm{jt}}$ are required conditions on the two parameters. In the case where no information is available, ($\delta^{\mathrm{c}}_{\mathrm{jt}}$, $\lambda^{\mathrm{c}}_{\mathrm{jt}}$) are determined by the moving average or exponential smoothing score of the previous biddings in the KA process. Furthermore, $\delta^{\mathrm{U}}_{\mathrm{jt}} = \lambda^{\mathrm{U}}_{\mathrm{jt}} = 1$ and $\delta^{\mathrm{L}}_{\mathrm{jt}} = \lambda^{\mathrm{L}}_{\mathrm{jt}} = 0$ are used as these decision variables.

Step 2: Use OLS to obtain parameter estimates of the sigmoid function from the KA process.

Step 3: Based upon the signs of the parameter estimates, the decision variables on bidding are changed as follows:

(a) If $\hat{\mathrm{c}}_{\mathrm{j1}} > 0$ & $\hat{\mathrm{c}}_{\mathrm{j2}} > 0$, then $(\delta_{\mathrm{jt}}, \lambda_{\mathrm{jt}}) = \{\delta^{\mathrm{c}}_{\mathrm{jt}} + (1/2)\zeta, \lambda^{\mathrm{c}}_{\mathrm{jt}} + (1/2)\zeta\}$. (b) If $\hat{\mathrm{c}}_{\mathrm{j1}} > 0$ &

$\hat{c}_{j2} = 0$, then $(\delta_{jt}, \lambda_{jt}) = \{\delta^c_{jt} + (1/2)\zeta, \lambda^c_{jt}\}$. (c) If $\hat{c}_{j1} > 0$ & $\hat{c}_{j2} < 0$, then $(\delta_{jt}, \lambda_{jt}) = \{\delta^c_{jt} + (1/2)\zeta, \lambda^c_{jt} - (1/2)\zeta\}$. (d) If $\hat{c}_{j1} = 0$ & $\hat{c}_{j2} > 0$, then $(\delta_{jt}, \lambda_{jt}) = \{\delta^c_{jt}, \lambda^c_{jt} + (1/2)\zeta\}$. (e) If $\hat{c}_{j1} = 0$ & $\hat{c}_{j2} = 0$, then $(\delta_{jt}, \lambda_{jt}) = \{\delta^c_{jt}, \lambda^c_{jt}\}$.

(f) If $\hat{c}_{j1} = 0$ & $\hat{c}_{j2} < 0$, then $(\delta_{jt}, \lambda_{jt}) = \{\delta^c_{jt}, \lambda^c_{jt} - (1/2)\zeta\}$. (g) If $\hat{c}_{j1} < 0$ & $\hat{c}_{j2} > 0$, then $(\delta_{jt}, \lambda_{jt}) = \{\delta^c_{jt} - (1/2)\zeta, \lambda^c_{jt} + (1/2)\zeta\}$.

(h) If $\hat{c}_{j1} < 0$ & $\hat{c}_{j2} = 0$, then $(\delta_{jt}, \lambda_{jt}) = \{\delta^c_{jt} - (1/2)\zeta, \lambda^c_{jt}\}$. (i) If $\hat{c}_{j1} < 0$ & $\hat{c}_{j2} < 0$, then $(\delta_{jt}, \lambda_{jt}) = \{\delta^c_{jt} - (1/2)\zeta, \lambda^c_{jt} - (1/2)\zeta\}$.

Note that $\zeta = \min\{\delta^U_{jt} - \delta^c_{jt}, \delta^L_{jt} - \delta^c_{jt}, \lambda^U_{jt} - \lambda^c_{jt}, \lambda^L_{jt} - \lambda^c_{jt}\}$.

Step 4: Compute d^I_{jt} and p^I_{jt} using $(\delta_{jt}, \lambda_{jt})$ and submit the bids to the DA market. If $t = T$, then stop. Otherwise, go to Step 5.

Step 5: Set $t = t + 1$. If the trader loses (his/her reward is zero), then go to Step 1. If the trader wins (his/her reward is positive), then go to Step 6.

Step 6: Reset the bidding variables as the current ones. Reset the upper and lower bounds according to Table I below and go to Step 1.

Note that the above table implies, for example, that if $\hat{c}_{j1} > 0$ and $\hat{c}_{j2} > 0$, then the upper and lower bounds of the next $(t+1)$ step is set by $\delta^U_{jt+1} = \delta^U_{jt}$, $\lambda^U_{jt+1} = \lambda^U_{jt}$, $\delta^L_{jt+1} = \delta^c_{jt}$ and $\lambda^L_{jt+1} = \lambda^c_{jt}$. See the cell at the second column and the second row of the table. The remaining eight cases can be explained by a similar manner.

Fig. 6 visually describes the above learning process for strategic bidding. In the figure, the initial bidding variables of a trader (for wholesale) are expressed on C. There are four different directions toward NE (North-East), SE (South-East), NW (North-West) and SW (South-West). As specified in Step 3, the new bidding amounts can be identified on A, E, B, D, respectively. If a parameter estimate contains zero, these bidding amounts are found on i, f, g, h and C. (Note that if both parameter estimates are zero, the trader keeps the current strategy at the next bidding, so being on C in Fig. 6. Even if the trader keeps the same strategy, the market result may be different from the previous one, because the market determines the price and amount of power allocation.)

Step 3 uses a value of 1/2 in the nice bidding strategies to find these locations (i.e., A, E, .. ,g and h). There is no theoretical rationale on the selection of 1/2. However, the value selection indicates the center of each moving area that is shaped by the upper and lower bounds, as depicted in Fig. 6. Comparing it with other numbers (e.g., 1/4 and 3/4), the convergence speed under 1/2 is slight better than the others in this study. Furthermore, we cannot find any difficulty on convergence (e.g, no convergence) in this study. However, there is no theoretical justification on the convergence issue. That is an important future research task.

Thus, the parameter estimates of the sigmoid function obtained in the KA/OB process provide each trader with information regarding which is the best bidding choice among these nine alternatives. As long as the trader can win, the search area is reduced to a smaller bidding range.

TABLE I
UPDATES OF BIDDING VARIABLES

$\begin{pmatrix}\delta^U_{jt+1}\\ \lambda^U_{jt+1}\\ \delta^L_{jt+1}\\ \lambda^L_{jt+1}\end{pmatrix}$	$\hat{c}_{j2} > 0$	$\hat{c}_{j2} = 0$	$\hat{c}_{j2} < 0$
$\hat{c}_{j1} > 0$	$\begin{pmatrix}\delta^U_{jt}\\ \lambda^U_{jt}\\ \delta^c_{jt}\\ \lambda^c_{jt}\end{pmatrix}$	$\begin{pmatrix}\delta^U_{jt}\\ \lambda^c_{jt}+\frac{1}{2}\zeta\\ \delta^c_{jt}\\ \lambda^c_{jt}-\frac{1}{2}\zeta\end{pmatrix}$	$\begin{pmatrix}\delta^U_{jt}\\ \lambda^c_{jt}\\ \delta^c_{jt}\\ \lambda^L_{jt}\end{pmatrix}$
$\hat{c}_{j1} = 0$	$\begin{pmatrix}\delta^c_{jt}+\frac{1}{2}\zeta\\ \lambda^U_{jt}\\ \delta^c_{jt}-\frac{1}{2}\zeta\\ \lambda^c_{jt}\end{pmatrix}$	$\begin{pmatrix}\delta^U_{jt}\\ \lambda^U_{jt}\\ \delta^L_{jt}\\ \lambda^L_{jt}\end{pmatrix}$	$\begin{pmatrix}\delta^c_{jt}+\frac{1}{2}\zeta\\ \lambda^c_{jt}\\ \delta^c_{jt}-\frac{1}{2}\zeta\\ \lambda^L_{jt}\end{pmatrix}$
$\hat{c}_{j1} < 0$	$\begin{pmatrix}\delta^c_{jt}\\ \lambda^U_{jt}\\ \delta^L_{jt}\\ \lambda^c_{jt}\end{pmatrix}$	$\begin{pmatrix}\delta^c_{jt}\\ \lambda^c_{jt}+\frac{1}{2}\zeta\\ \delta^L_{jt}\\ \lambda^c_{jt}-\frac{1}{2}\zeta\end{pmatrix}$	$\begin{pmatrix}\delta^c_{jt}\\ \lambda^c_{jt}\\ \delta^L_{jt}\\ \lambda^L_{jt}\end{pmatrix}$

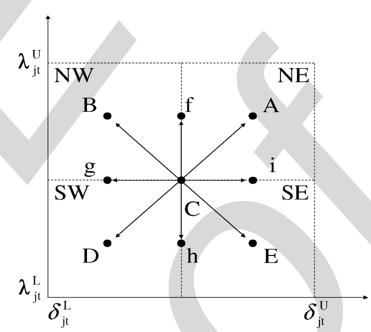

Fig. 6. Adaptive learning process.

F. A Visual Description on Computer Software

Fig. 7 depicts a monitor of our software that shows the DA and RT markets. The programming language of software is C# (Microsoft.NETFramework1.1).[1] We can observe the dynamics of equilibrium points in the DA and RT markets, as found in the top of the computer monitor. Those changes correspond to Figs. 2 and 3. The graph in the middle of Fig. 7 depicts the trend of market prices (in DA and RT markets). The last one at the bottom of Fig. 7 indicates the trend of power amounts traded in the two markets.

V. A SIMULATION STUDY

The following assertions are examined by our simulation study: 1) there are two wholesale power markets (DA and RT). Which market is important for generators? 2) What type of risk taking is important for generators? Table II sets parameter ranges to examine the two assertions. The table is structured by 2×2 factors, where the first 2 is related to DA or RT and the other 2 is related to pricing or quantity strategy. This simulation study excludes the strategies of wholesalers, because their

[1]Source: http://msdn.microsoft.com/netframework.

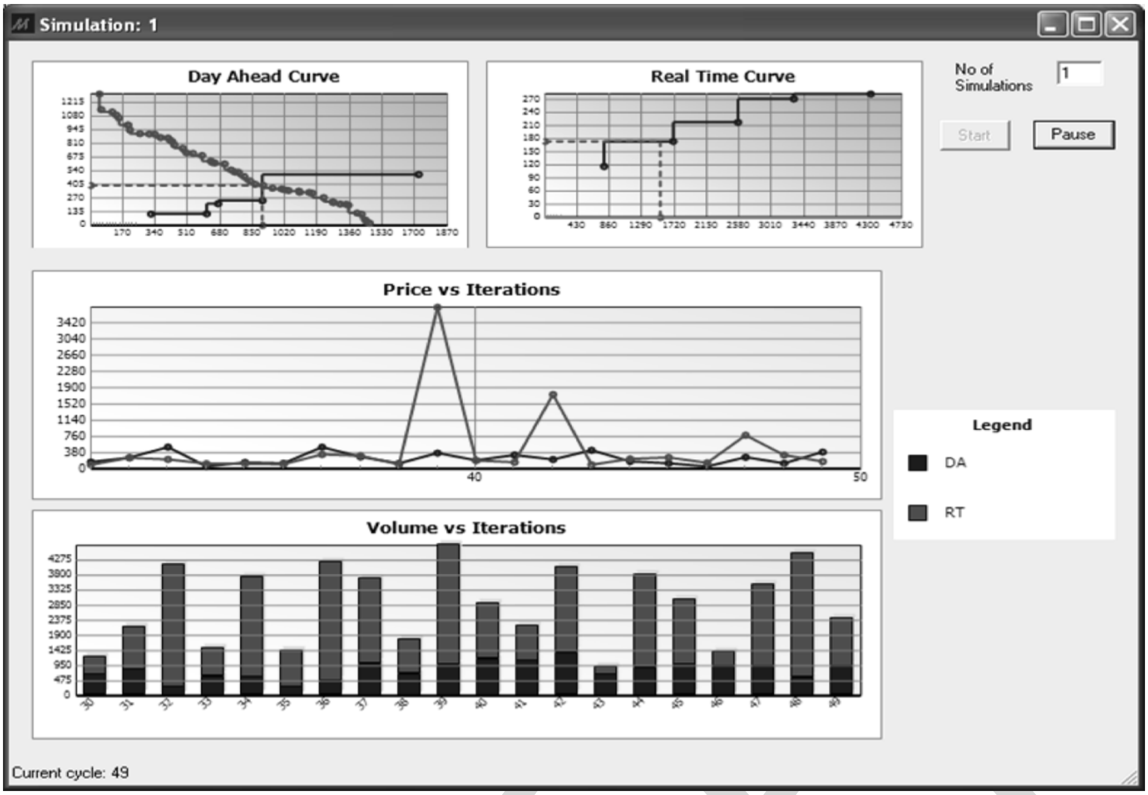

Fig. 7. Computer monitor of software.

TABLE II
MARKET AND PRICING STRATEGIES OF GENERATORS

Market / Strategy	DA	RT
Quantity	$0.5 \leq \alpha_{it} \leq 1$	$0.01 \leq \alpha_{it} < 0.5$
Price	Risk Taker : $0.5 \leq \beta_{it} \leq 0.99$ Risk Avoider : $0.01 \leq \beta_{it} \leq 0.49$	Risk Taker : $0.5 \leq \eta_{it} \leq 0.99$ Risk Avoider : $0.01 \leq \eta_{it} \leq 0.49$

decisions are often influenced by external factors such as a temperature change and a seasonal effect.

As depicted in Fig. 1, electricity is procured from either the DA or RT market. Hence, if a generator prefers to sell electricity mainly in the DA market, α_{it} is set to be between 0.5 and 1. Meanwhile, if the generator prefers to sell electricity mainly in the RT market, the parameter is set to be between 0 and 0.5. The pricing strategy of the generator is further separated into two cases (risk taker or risk avoider). Here, the risk taker looks for a high reward by offering a high bidding price. This type of bidding strategy leads to a high risk, because a probability, that the bidding price is larger than an equilibrium market price, becomes larger and consequently, a chance to sell his/her electricity becomes lower than before. Conversely, an opposite case (low risk and low reward) can be found in the risk avoider.

Parameters listed in Table II are used to express the bidding strategy of the generators. As structured in Table II, eight [$= 2\,(\mathrm{DA/RT}) \times 2\,(\mathrm{Risk-Taker}) \times 2\,(\mathrm{Risk-Avoider})$] different combinations of parameters are examined to investigate the market and pricing strategies.

Under each strategy, these parameters are randomly generated on the specified data ranges. Those ranges are selected arbitrarily in a way that the selection reflects the required types of market preference and pricing strategy.

In this study, ten generators belong to each group and their traders bid on the parameter ranges, as specified in Table II. The remaining parameters are randomly generated between 0 and 1. The total number of generators is 80 ($= 10$ generators $\times$ 8 groups). Meanwhile, 900 wholesalers are incorporated into the simulation study. In this situation, three different types of group mix are considered in terms of learning (L) and nonlearning (NL). In each case, the average reward of the generators equipped with the proposed learning process is compared with the average rewards of the remaining others without the learning process. Consequently, we can investigate strategic effectiveness related to the eight alternatives on market and pricing strategies.

Such strategies of generators and simulation results are documented in Table III (unit: \$1000). In the table, 100 replications are generated for each combination. Consequently, the total average listed at the last column of Table III indicates the average reward of 3000 [$=3\,(\frac{\mathrm{L}}{\mathrm{NL}}\ \mathrm{combinations})\times 10\,(\mathrm{generators})\times 100\,(\mathrm{replications})$] bids of each generator under eight different bidding strategies [i.e., Agent Types from a to h at the left hand side of Table III]. Findings from Table III can be summarized as follows.

TABLE III
EIGHT DIFFERENT STRATEGIES AND AVERAGE REWARDS

Agent Type	Preferred Market Focus (Quantity)	Risk Preference (Price)		70% NL and 30% L		50% NL and 50% L		30% NL and 70% L		Total Average
		DA	RT	Non-Learning (NL)	Learning (L)	Non-Learning (NL)	Learning (L)	Non-Learning (NL)	Learning (L)	
a	DA	Risk-taker		244.23	442.55	105.81	288.53	0.58	35.54	175.32
b		Risk-taker	Risk-avoider	2133.88	2311.79	1600.86	1840.73	1298.74	1509.51	1784.78
c		Risk-avoider	Risk-taker	224.20	84.26	122.85	141.50	72.43	45.70	122.70
d		Risk-avoider		2196.48	2379.38	1700.59	1890.85	1423.58	1562.05	1855.86
e	RT	Risk-taker		122.97	213.66	231.04	220.00	56.77	59.32	144.75
f		Risk-taker	Risk-avoider	2166.81	2328.41	1612.95	1817.89	1295.44	1505.84	1791.14
g		Risk-avoider	Risk-taker	240.52	16.99	152.26	81.76	102.57	20.86	111.95
h		Risk-avoider		2171.76	2349.68	1616.15	1832.93	1365.71	1529.44	1810.00

A. Finding 1

The combination between DA (in quantity allocation) and a risk-avoider (bidding price) produces the best reward ($1855.86) among the eight different strategies. The next ($1810.00) is the combination between RT and a risk-avoider. The worst performer ($111.95) is found on the combination between RT and risk-taker. All the traders, who use the strategies (a), (c), (e), and (g), result in low rewards ($175.32, $122.70, $144.75, and $111.95), because their bidding strategies in RT include a risk-taking decision on bidding prices. These results indicate that generators need to set their bidding prices in the manner that each price is not far above its marginal price. If they become greedy, they will not obtain their expected rewards.

B. Finding 2

The comparison between the first four strategy combinations and the remaining four indicates that the DA market is slightly more important than the RT market in terms of reward enhancement, because the former has more bidding freedom than the latter.

C. Finding 3

In the two wholesale markets, traders equipped with the learning capability outperform the other traders without the learning capability.

Here, it is important to note the following comments.

a) We have slightly changed the upper and lower bounds of these parameters (e.g., $0.55 \leq \beta_{\mathrm{it}} \leq 0.95$) to confirm the robustness of the above findings. The sensitivity analysis has produced an almost similar result documented in Table III.

b) This simulation study does not consider a special bidding case, like a "must-run" operation, in which a generator, like a nuclear power plant, provides a wholesale power market with free electricity in order to avoid a temporal cease of its generation facility.

VI. A CONCLUSION AND FUTURE EXTENSIONS

To predict a price change of the U.S. wholesale power market, a computer simulator with learning capabilities has been developed in this study. Using the software, we can investigate both how traders determine the market price in the DA and RT markets and how the price change occurs under different trading environments.

The proposed simulator has two important features. One of the two is that the two settlement system (DA and RT) is incorporated into the artificial wholesale power market of the simulator. The other important feature may be found in the learning capability of traders who accumulate their bidding experience and make a new bidding strategy to increase their winning probabilities. A simulation study is conducted and simulation results are summarized as the three findings in this study.

Using the proposed simulator, we can predict various nodal (local) wholesale power prices, each of which depends upon a grid system through which electricity is provided. Such a difference among nodal prices is generated in our simulator by using different marginal costs, different electricity loads and other economic and engineering concerns. Furthermore, the simulator can change the number of participating traders, depending upon the size of each grid system. Thus, the proposed simulator can be used for not only a single market price for an entire grid system, but also location-specific nodal prices for many different grid subsystems.

Since this study is an initial step, the proposed approach may be not perfect from a practical perspective. The following future research tasks are envisioned to enhance the practicality of the proposed simulator:

a) *Demand Side*: The wholesale power market is considered as a complex dynamic system whose many components are complicatedly connected to each other with imperfect information [24], [31]. As a result of the complexity, we cannot mathematically prove the methodological validity of our simulation results. Thus, a bidding strategy suggested by the proposed simulator does not always guarantee that it produces a positive reward. Such may be indeed a shortcoming of this type of simulation-based approach. To overcome the methodological problem, we need to obtain real data on wholesale prices from PJM and other power markets. Using the real data, we examine how the proposed simulator can accurately predict a real price fluctuation. Furthermore, a major source of the price fluctuation (and complexity) is often due to a temperature (weather) change and its related demand change. Hence, we need to incorporate data mining techniques into the proposed simulator to enhance our forecasting capability of the demand change.

b) *Market Function*: After the demand forecasting capability is added to our simulator, we need to incorporate a computer networking capability into the simulator. The computer network artificially opens a wholesale market where traders communicate with each other. In this research extension, game theory will serve as a conceptual basis for exploring how traders make a coalition to win their trades. Furthermore, we can investigate various types of negotiation and cooperation among traders. The behavioral study based upon the game theory will enhance the learning capabilities of traders to the level that the proposed simulator becomes a multiagent adaptive system.

c) *Supply Side*: After the network function is added to the simulator; each computer monitor, linked to the power trading network, is designed to show different types of cost on a computer monitor. Each trader can select which type of cost is used for his/her trading decisions. In this study, the marginal cost is used as a basis for determining a bidding price and a reward in the current simulator. The validity can be confirmed on the Web site of PJM where the marginal cost is listed for real power trading markets. This indicates that the marginal cost is used for the decisions of traders. However, it is true that other information on cost is also useful for traders if that is available for them on a computer monitor. For example, as discussed in [23, Ch. 4], the generators (or ISO) are expected to optimize their generation resources to satisfy a demand load at a minimized operation cost. The type of operation cost is referred to as "cost-based unit commitment (UC)." The cost concept is further extended by considering a transmission function that needs a careful monitoring process between supply and demand. The extended cost concept is referred to as "security-constrained unit commitment (SCUC)." The SCUC implies a total operation cost for generation scheduling, supplying load, maximizing power security, and managing other transmission constraints. Thus, the cost measures such as UC and SCUS need to be incorporated into the proposed simulator in addition to the marginal cost. The two cost concepts are closely related to a power transmission period. Therefore, both UC and SCUS need to be examined in a generation scheme with a specific time horizon.

d) *Transmission*: The simulator does not incorporate any aspect on the power transmission. As a result, for example, a price increase due to congestion has not been considered in this study, because the incorporation of transmission into the proposed simulator needs a large mathematical modeling capability on maximum network flow and its related algorithmic development. Furthermore, such congestion depends upon each grid system. Simply, different grid systems have different network structures. The system development, including the transmission constraints on an entire power system, needs to consider various regional and geographical concerns. Thus, the simulator excludes the transmission issue in our price setting mechanism. Of course, we will develop a simulation capability on transmission line constraints and add it to the proposed power exchange simulator in our future work.

The completion of the above research plan will enhance the practicality of the proposed simulator. It is believed that the network-based multiagent simulator can replace the software that is currently used for market operation in many wholesale power markets like PJM and California ISO.

Finally, it is hoped that this study makes a small contribution for research on the electric power industry. We look forward to seeing future research extensions, as indicated in this study.

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