An Electric Power Trading System: Network-based Framework and Simulator with Learning Capabilities

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Abstract—Software has been developed for studying and understanding a price change of the US wholesale power market (Sueyoshi and Tadiparthi, 2005). The software can be used as an effective decision making tool by traders for simulating and modeling of the power market. It can be also considered as a worthy effort towards creating a framework for assessing new trading strategies in a competitive electricity trading environment. This paper covers the broad areas of simulation, trading strategies and machine learning as well as the procedure to use the software. An effort has been made to find the best strategic technique for traders in supply and demand sides.

Keywords—Electricity markets, Agent-based models, Simulation software, Machine learning

1. INTRODUCTION

Power industry, mostly dominated by vertically integrated utilities, is undergoing significant changes in the structure of its market and regulations. The power industry is now becoming competitive, unlike in the past where it was controlled by monopoly utilities. The traditional centralized-operation approach is being replaced by a market environment. This is called "deregulation of the electricity market." The deregulation allows new players to compete for providing wholesale electric services by setting their own prices in an auction format, rather than negotiating with state regulators on a fixed rate. Numerous wholesale power markets are moving towards liberalization and competition. Along with the deregulation, many corporate leaders and policy makers face a difficulty in both predicting and understanding a price change of the wholesale electricity. The price change occurs due to many un-controllable factors such as a weather condition, a demographic change and different trading strategies among traders. Software tools are required for the power industry to predict the price change and understand such market activities.

Furthermore, we need both a new approach that studies evolution of the wholesale power market and a strategic reaction to changing economic and regulatory environment in which they operate using a simulation.

In this study, we have developed a new simulation system, referred to as "EPTS (Electric Power Trading System)", where software agents represent market entities such as generators and wholesalers. The software agents have their own trading objectives and strategies. They can also adjust their trading strategies in the simulation process on the basis of previous trading efforts' success or failure. (See Sueyoshi and Tadipathi (2005), for a detailed description on the computer algorithm.)

The simulator proposed in this study includes several types of negotiation mechanisms found in electricity markets to let the user test his/her trading strategies and learn the best way to negotiate in each mechanism. The user can define the model for simulation.

The structure of this article is organized as follows: The next section conducts a literature survey that indicates the position of the proposed power trading system by comparing itself with other studies concerning on-line trading auctions. Section 3 briefly describes the structure of the US wholesale power market. Section 4 describes a numerical representation of the wholesale market that is incorporated into the proposed power trading simulator. Section 5 presents a computational scheme for the power trading. Section 6 provides a description on the software. Section 7 documents the simulation functions of the proposed simulator. A concluding comment and future extensions are summarized in Section 8.

2. PREVIOUS WORKS

Online trading is a typical electronic commerce application. A seller places merchandise online, noting a bid price and a cut-off date. A buyer can tell suppliers what he or she is looking for, and then wait for the appropriate merchandise to come up for bid. Many commercial trading

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companies have recently established an Internet presence. One such company is Netmarket which is an example of a single company that sells a variety of products at discounted prices (compared to the original manufacturer's suggested price). Although the products sold at this site are bought from different vendors, this is not a true "multiple sellers-multiple buyers" center. Rather, Netmarket abstracts out the many sellers and thus shows each example as a single individual selling product. Netbill is another electronic commerce system (see Sirbu and Tygar (1995)). This system allows merchants to sell images and articles over the Internet in a safe and secure manner.

Unlike traditional auctions where bidders and auctioneers gather at a physical location, online sellers and buyers worldwide can interact 24 hours a day and seven days a week. Negotiation is probably among the least supported of the trading processes in electronic commerce (see Kumar and Feldman (1998)) Similarly, a number of agent-based auction systems such as AuctionBot, Kasbah and Tete-a-Tete have emerged (see Bunn and Oliveira (2001)). AuctionBot is a general purpose Internet auction server developed at the university of Michigan. It allows users to choose from a selection of auction types. Buyers and sellers can bid according to the multi-lateral distributive negotiation protocols of the created auction, although price is the only comparison allowed in the system. Kasbah is a web-based multi-agent classified advertising system. It provides users with several negotiation strategies based on linear, quadratic, and exponential functions without much consideration on dynamic changing market conditions. Tete-a-Tete presents a negotiation approach to retail sales by providing value comparisons and the ability to find the best matching buyers and sellers based on different distributed constraint satisfaction technique.

Artificial Intelligence technologies used in many of the other trading agent systems have been discussed in Greenwald (2003). Recent research has also focused on combinatorial auctions. They are auctions where agents may submit bids to multiple goods. A technique to deal with the complexity of combinatorial auctions has been explored in Tennenholtz (2002). They have employed the b-matching techniques in various ways to efficiently address the complexity of the combinatorial auction problems. Recent research has focused on using agents to support auction services because of their autonomous nature. A multi-access and multi-functional auction system which can be accessed through the web and Wireless Application Protocol (WAP) enabled devices has been developed by Chan et al. (2003). Ezhilchelvan and Morgan (2001) discussed distributed system architecture and an implementation framework for conducting dependable Internet based on-line auctions. In this model, there is a server for each local market which exercises policies best suited to local conditions and these servers are connected to each other by Internet or by a high bandwidth private network. An Internet auction method which uses decentralized servers reducing the superfluous information derived from bidders has been proposed in Funasaka et al.

(2002).

There have been quite a few software applications developed based on agent-based simulation for competitive electricity markets (see Nicolaisen et al. (2001)). For example, PowerWeb (see Bakos (1997), Zimmerman (2001)) considers single uniform auction with fixed demand. The Auction Agents for Electric Power Industry project (see Acronymics (2004), Bakos (1998)) implements a Dutch auction, which is a specific type of auction mechanism. SEPIA (Simulator for Electric Power Industry Agents) studies just bilateral contracts (see Benassi (1999), Samad and Harp (1996)). A computational aspect of auction mechanism for the power industry can be found in his research (see Sheblae (1999)).

The research efforts of Bunn and Oliveira (2001), Monclar and Quatrain (2001), and Nicolaisen et al. (2001) are relevant to our research in agent-based simulation. Unfortunately, they discuss only the market in England and Wales. Villar and Rudnick (2003) present another important simulation application focusing particularly on hydroelectric power station parameters. Meanwhile, their study (see Contreras et al. (2002)) presents an interesting lab experience that shows the practical utility of electricity market simulators. The Electricity Market Complex Adaptive System (EMCAS) (see North et al. (2002)) provides an interesting e-laboratory for testing regulatory structures where agents have strategies based on learning and adaptation.

Comparing the previous research works on on-line trading and its related software development for the power industry, we can identify the following unique features of this research: (a) First, the wholesale power market incorporated in this study is functionally separated into two markets (day ahead market and real time market) A trader can make a bidding decision in the day ahead (DA) market and then make another decision in the real time (RT) market, depending upon the result in the DA market. Thus, two-settlement system (TSS) auctions are incorporated into the proposed simulator. Such a research effort cannot be found in the previous research works. (b) Second, each trader is designed to have his/her own learning capability. The learning capability is based upon a sigmoid function that provides a winning probability from previous bidding results. Such a learning capability cannot be found in the previous research. (c) Finally, traders can communicate with each other through a network capability incorporated into the proposed software. That is unique, as well.

3. MARKET STRUCTURE

The main objectives of an electricity market are to ensure the security of the system, efficient operation and further to decrease the cost of electricity through competition (see Shahidehpour et al. (2002)). The market environment typically consists of a pool as well as a floor for bilateral contracts. The pool market can be found in an Independent System Operator (ISO) such as PJM (Pennsylvania-New Jersey-Maryland). Meanwhile, the bilateral contract market can be found in California ISO.

The proposed software can be used for the PJM type of wholesale power market.

The electricity industry is functionally separated into the following four divisions: (a) generation, (b) transmission, (c) distribution and (d) retailing. An electric utility, maintaining all the four functions, is referred to as an "IOU (Investor-Owned Utility)". An IOU participates in the wholesale power market, along with other power generators. Many electricity retailers and wholesalers buy electricity through the wholesale power market and retailers distribute it to consumers (end-users).

As mentioned previously, the proposed software considers the pool market that is a marketplace where electricity-generating companies submit production bids and prices and wholesale companies submit consumption bids. A market operator, like ISO, regulates the pool using a market-clearing tool to set the market price. This results in a market-clearing price that is listed, along with a set of accepted production and consumption bids. In the pool market, an appropriate market-clearing tool is an auction mechanism (see Klemperer (1999) and Sheblae (1999)).

The US wholesale power market is functionally separated into transmission market and power exchange market. The software focuses upon only the power exchange market. The US wholesale power exchange market is further functionally broken down into a RT market (transaction on a five minute interval), an hour-ahead market, a DA market and 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.

The software mainly focuses upon trading strategies for both DA and RT markets, because the 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. 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 in this study. Meanwhile, the DA market can be considered as a financial market, because a decision for the market is for the next day power delivery, so that there is a time for making a profit based upon demand forecasting and speculation.

4. NUMERICAL REPRESENTATION OF POWER MARKET

The power market, virtually created on simulation, is structured by the TSS in DA and RT markets. In each market, each generator or wholesaler (including a retailer) is represented by an intelligent agent. Each trading intelligent (autonomous) agent has an objective to

maximize his/her profit. They gain their knowledge from previous data and from experience. Based on the agent's previous bidding result (success/failure), each agent accumulates knowledge for future bidding strategy.
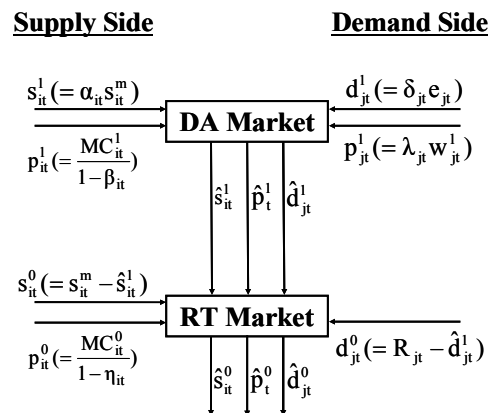

Figure 1. Bidding structure for wholesale market.

It is very difficult to perfectly duplicate the real trading behaviors in our artificial wholesale power market. Hence, this study needs to consider on how to represent the DA and RT markets. The combination of different parameters is used to express various bidding amounts and prices of the trading agents. The bidding processes of the traders in the two markets can be visualized in Figure 1. (The figure is originally discussed in Sueyoshi and Tadiparthi (2005).) The notation used in Figure 1 is explained as follows: The superscript '1' is used for representing DA and the other superscript '0' is used for representing RT.

It is assumed that "n" generators and "k" wholesalers participate in the competitive market. The simulator can be run for the total time "T". Each period represents a DA and RT market at time t ($t = 1$ to T). The subscript 'i' indicates ith generator ($i = 1$ to n) and subscript 'j' indicates jth wholesaler ($j = 1$ to k).

4.1 DA market

In the DA market, traders submit their respective bids for auction. A bid can be considered as a 2-tuple (price and quantity).

Supply Side: The ith generator bids (s_{it}^1, p_{it}^1). s_{it}^1 is the amount of power generation in Kilowatt Hours (KWH) that the generator makes available in the DA market. p_{it}^1 is the price that the generator is charging per unit electricity ($/KWH). s_{it}^m is the maximum power generation capacity of the ith generator ($i = 1, 2, \ldots, n$) at the tth period. The available power generation is expressed in terms of the maximum power $s_{it}^1 = \alpha_{it} \times s_{it}^m$, where α_{it} ($0 \le \alpha_{it} \le 1$) is a parameter to express the ratio of bidding amount of electricity to the maximum generating capacity of the i-th generator at the t-th period of the power delivery day. The price, p_{it}^1, is expressed in terms of the marginal cost (MC_{it}^1). Marginal Cost (*MC*) of generation is defined as the operations and maintenance (O&M) cost of the

generating plant needed to supply the immediate demand for electricity. Usually, the marginal cost is listed on the website of ISO. Since the decisional making of each trader is myopic, the MC serves as a basis of cost computation in a short run. (Of course, we know that a long-run cost is different from the *MC*-based cost calculation. It is hardly acceptable that a trader bids on a basis of the long-term cost.) It is given by $p_{it}^1 = MC_{it}^1/(1-\beta_{it})$. Here, β_{it} $(0 \le \beta_{it} < 1)$ is a mark-up rate. The mark-up rate is used to express the numerical increase of the bidding price from the marginal cost. The mark-up rate reflects the trader's pricing strategy toward the DA trading.

Demand Side: The *j*th wholesaler bids (d_{jt}^1, p_{jt}^1). d_{jt}^1 is the amount of power (KWH) that the wholesaler predicts for the next day consumption. p_{jt}^1 is the price that the wholesaler is ready to pay per unit of electricity ($/KWH). The wholesaler uses its own demand- forecasting algorithm to predict the demand on a particular day. Let e_{jt} be the demand estimated by the *j*th wholesaler or ISO. The wholesaler predicts a bidding price by using an inverse function (*IF*) of demand, i.e. $w_{jt}^1 = IF(e_{jt})$. d_{jt}^1 is expressed in terms of e_{jt} given by: $d_{jt}^1 = \delta_{jt}e_{jt}$, where δ_{jt} $(0 \le \delta_{jt} \le 1)$ is a parameter to express the strategic reduction of each bid from the demand estimate. Similarly, a bidding price for demand is determined by $p_{jt}^1 = \lambda_{jt}w_{jt}^1$. Here, λ_{jt} $(0 \le \lambda_{jt} \le 1)$ is a parameter for price adjustment from the estimated price.

After all the generators and wholesalers submit their respective bids to the market, a market clearing algorithm is employed to find out the power allocation. Such an algorithm gives out results, at every period, such as $\hat{d}_{jt}^1$ (a real power allocation to the *j*th wholesaler), $\hat{s}_{it}^1$ (a real power generation amount for *i*th generator) and $\hat{p}_t^1$ (a market clearing price in the DA market).

4.2 RT market

In the RT market, generators submit their bids in the form of a 2-tuple (price and quantity). But, wholesalers have to specify only their real demand on electricity. Therefore, it is assumed that they must purchase all the necessary electricity in the RT market in order to satisfy an actual power demand (so, it is a physical market, not a financial market like DA).

Supply Side: The *i*th generator bids (s_{it}^0, p_{it}^0). s_{it}^0 is the amount of power generation (KWH) that the generator makes available in the RT market. p_{it}^0 is the price that the generator is charging per unit electricity ($/KWH). s_{it}^0 is expressed as the remaining amount of power that the generator can produce after the allocation in the DA market (so, $s_{it}^0 = s_{it}^m - \hat{s}_{it}^1$). The price, p_{it}^0, is expressed in terms of the marginal cost (MC_{it}^0). It is given by

$p_{it}^0 = MC_{it}^0/(1-\eta_{it})$. Here, η_{it} $(0 \le \eta_{it} < 1)$ is a mark-up rate. The mark-up rate reflects the trader's price strategy toward the RT trading.

Demand Side: Let R_{jt} be the real demand for the wholesaler on the delivery day. Then, the wholesaler needs to specify the demand procured from the RT market, in order to satisfy the real demand that is computed by $d_{jt}^0 = R_{jt} - \hat{d}_{jt}^1$. In the RT market, ISO adjusts all the requests from market participants to obtain $\hat{d}_{jt}^0$ (a real amount of power allocation) and determines $\hat{p}_t^0$ (a market price in the RT market) through a competitive market clearing function.

5. MARKET CLEARING ALGORITHMS

A few market clearing algorithms for the power market can be found in the literature. All of them are structured by a single settlement system, not TSS which is incorporated into the proposed software. The TSS auction is widely used in ISO like PJM. The algorithm of the software can be specified in the following manner.

5.1 Market clearing algorithm for DA market

Let the pair (s_{it}^1, p_{it}^1) represent the bid submitted by the *i*th generator in the DA market. Let the pair (d_{jt}^1, p_{jt}^1) represent the bid submitted by the *j*th wholesaler. The power allocation algorithm for the *t*th period can be specified as below:

1. Sort the pairs (s_{it}^1, p_{it}^1) in the ascending order with respect to p_{it}^1.

2. Calculate the cumulative supply for each generator ($i = 1, \ldots, n$). The cumulative supply of *i*th generator is the sum of supply quantities (including its own supply) whose bidding price is less than the bidding price of *i*th generator. The cumulative supply of *i*th generator is represented by $S_{it}^1 \left(= \sum_{a=1}^{i} s_{at}^1 \right)$.

3. Sort the pairs (d_{jt}^1, p_{jt}^1) in the descending order with respect to p_{jt}^1.

4. Calculate the cumulative demand for each wholesaler ($j = 1, \ldots, k$). The cumulative demand of *j*th wholesaler is the sum of demand quantities (including its own demand) whose bidding price is greater than the bidding price of *j*th wholesaler. The cumulative demand of *j*th wholesaler is represented by $D_{jt}^1 \left(= \sum_{b=1}^{j} d_{bt}^1 \right)$.

5. Find an equilibrium point in this market by comparing the cumulative amount of supply with that of the demand. If there is the equilibrium point, go to *Step* 6. If there is no equilibrium point, the market clearing price is set to 0 and no trading was possible in the DA market. Go to *Step* 8.

6. A projection of the equilibrium point on the Y-axis gives

the market clearing price $\hat{p}_t^1$ of the DA market.

7. Allocate electricity for the *t*th period. All generators with $p_{it}^1 \le \hat{p}_t^1$ can supply power (s_{it}^1) for price $\hat{p}_t^1$ to the DA market and all wholesalers with $p_{jt}^1 \ge \hat{p}_t^1$ can receive power (d_{jt}^1) for the same price $\hat{p}_t^1$ from the DA market. All the other traders, who did not obtain any power allocation in DA, still have a bidding chance in the RT market for selling and buying.

8. Stop.

5.2 Market clearing algorithm for RT market

In RT market, only the generators bid and the wholesalers have to accept the price decided by the market clearing algorithm. Let (s_{it}^0, p_{it}^0) be the bid posted by *i*th generator in the RT market. This can also be considered as a supply function where $p_{it}^0 = f(s_{it}^0)$. Let d_{jt}^0 be the quantity required for *j*th wholesaler in the RT market. The market clearing algorithm can be described as below:

1. Sort the pairs (s_{it}^0, p_{it}^0) in ascending order with respect to p_{it}^0.

2. Calculate the cumulative supply for each generator ($i = 1$ to n). The cumulative supply of *i*th generator is represented by $S_{it}^0 \left(= \sum_{a=1}^{i} s_{at}^0 \right)$.

3. Calculate the aggregate demand of the wholesalers at the *t*-th period $D_t^0 \left(= \sum_{j=1}^{m} d_{jt}^0 \right)$.

4. If $D_t^0 \le \sum_{i=1}^{n} s_{it}^0$, then go to *Step* 5. Otherwise, go to *Step* 7.

5. The equilibrium point is determined via comparing the cumulative amount of supply by the total demand.

6. Allocate the electricity. Let $\hat{p}_t^0$ be the market clearing price that is obtained from the equilibrium point. Then, all generators with $p_{it}^0 < \hat{p}_t^0$ can supply power (s_{it}^0) for price $\hat{p}_t^0$ to the RT market and all wholesalers receive power (d_{jt}^0) for the same price $\hat{p}_t^0$ from the RT market.

7. Stop.

5.3 A reward for generators and wholesalers

A reward for the *i*-th 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 $\hat{p}_t^1 \ge p_{it}^1$, 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 $\hat{p}_t^0 \ge p_{it}^0$, the generator can provide electricity so that it produces a profit $(\hat{p}_t^0 - MC_{it})\hat{s}_{it}^0$.

Consequently, the reward for the *i*-th generator can be summarized as follows:

If $\hat{p}_t^1 \ge p_{it}^1$ and $\hat{p}_t^0 \ge p_{it}^0$,
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 $\hat{p}_t^0 \ge p_{it}^0$, then $(\hat{p}_t^0 - MC_{it})\hat{s}_{it}^0$,

If $\hat{p}_t^1 \ge p_{it}^1$ 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 *j*-th wholesaler. If $\hat{p}_t^1 > p_{jt}^1$ then the wholesaler cannot access a power supply through the DA market. Meanwhile, if $\hat{p}_t^1 \le p_{jt}^1$, 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. Hence, let p^R be the retail price. Then, the reward for the *j*-th wholesaler can be specified as follows:

If $\hat{p}_t^1 \le p_{jt}^1$ and $\hat{d}_{jt}^0 > 0$,
then $p^R(\hat{d}_{jt}^1 + \hat{d}_{jt}^0) - \hat{p}_t^1 \hat{d}_{jt}^1 - \hat{p}_t^0 \hat{d}_{jt}^0$,

If $\hat{p}_t^1 > p_{jt}^1$ and $\hat{d}_{jt}^0 > 0$, then $p^R(\hat{d}_{jt}^0) - \hat{p}_t^0 \hat{d}_{jt}^0$,

If $\hat{p}_t^1 \le p_{jt}^1$ and $\hat{d}_{jt}^0 = 0$, then $p^R(\hat{d}_{jt}^1) - \hat{p}_t^1 \hat{d}_{jt}^1$, and

If $\hat{p}_t^1 > p_{jt}^1$ and $\hat{d}_{jt}^0 = 0$, then the reward becomes zero.

6. DESCRIPTION ON THE SOFTWARE

Figure 2 depicts the virtual wholesale market where three generators (green) and three wholesalers (red) participate to trade electricity between them. Each trader can connect to the wholesale market via Internet that is linked to a system operator who controls the market. A server, along with a data base system, opens the wholesale power market under the control of the system operator.
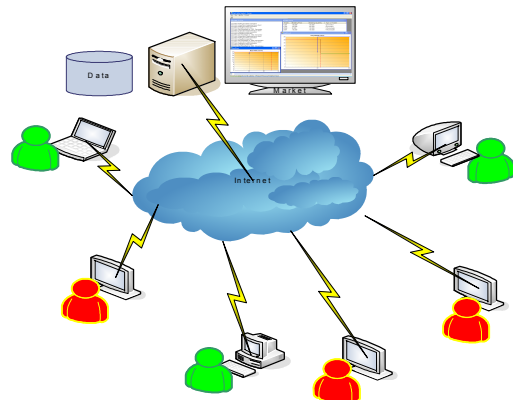

Figure 2. Network-based auction.

To operate the proposed network-based power auction, it needs to include a scientific programming language that

must provide tools to measure performance and must allow developers to express the problem domain easily and effectively. It should also be able to produce efficient high-performance code, which can be carefully fine-tuned. C# is one of the languages which can be used for such a purpose (see Gilani (2004)). Like all other .NET-targeted languages, C# compiles to Microsoft intermediate language (MSIL), which runs on the common language runtime (CLR).

6.1 Main window

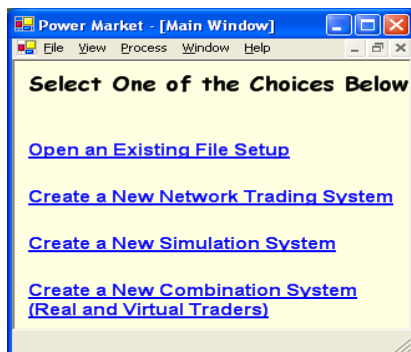Figure 3 depicts the welcome screen on main window where all the menu options of our software are listed.

Figure 3. Main window.

There are four trading functions on main window:
(a) Existing: It opens up the previously saved power trading setup that can be modified for a new trading.
(b) Real trading: It provides a wholesale power trading where we participate in a virtual market as traders. The virtual market functions like a real power market. It is possible for us to use it as a real power trading system at ISO.
(c) Simulation: It creates a new wholesale power trading where all traders are artificially generated with their learning capabilities.
(d) Real/Virtual co-existence: It provides a power trading where we (as real traders) participate in the trading with artificially generated traders equipped with their learning capabilities. The market provides real traders with an opportunity to learn their trading strategies by competing with the virtual traders with artificial smartness.

Hereafter, our description focuses upon the operation of simulation, because the other three functions are very similar to the simulation function. Figure 4 documents a sequence of steps that has to be performed to conduct the simulation. First, the user is prompted to enter the number of iterations (i.e. total number of cycles or days he would like to simulate) to be simulated. After entering the number of iterations, the user has to create generator and wholesaler entities and then start the simulation. All the above choices are provided as hyperlinks. The "review settings" and "save settings" options are provided as buttons.

6.2 Design of generators

By clicking the "create generators" option, the user can model the generator entity. A user-interface is presented to create "generators". The interface is conceptually divided into 4 divisions. This is illustrated in Figure 5. The user can input the maximum supply and marginal cost either in the form of a text file or a constant value. The data, if supplied in a text file, should be in the form of a "tab limited text file" with the first column representing the price and the second column representing the quantity. The bidding strategy that the user would like to use can be specified by choosing one of the radio buttons next to the strategy names.
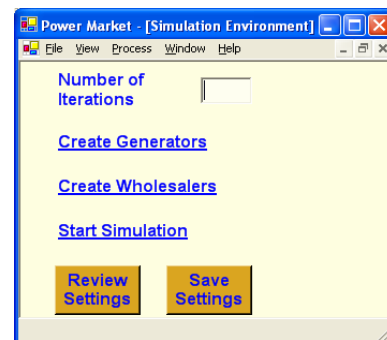

Figure 4. New simulation system setting.

In Figure 5, eight (= 2 × 4) different combinations of parameters are examined to investigate their market strategies of generators (GN). Table 1 summarizes the parameter settings from the perspective of trading strategies. A data set for each generator is obtained randomly on the range of the three parameters.
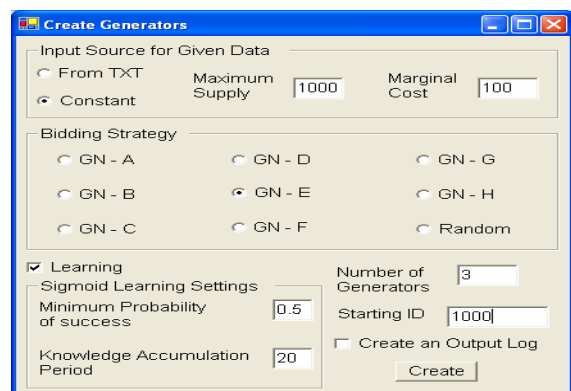

Figure 5. Generator creation wizard.

The user can either decide to include learning or not, depending upon a simulation model he/she is trying to build. If the user chooses a learning generator, he can specify the knowledge accumulation period (< total number of iterations) and the minimum probability of success (between 0 and 1). This pertains to the sigmoid learning settings and is explained in appendix of this article. Each generator is given a trader identification number. The user can specify the number of generators of this kind of settings and create them by pressing the "create" button.

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This action will create the specified number of generators and then go back to the main window.

6.3 Design of wholesalers

By clicking "create wholesaler" option, the user can model the wholesaler entity. A user-interface for creating wholesalers pops up. This interface is conceptually divided into 7 categories. This is shown in Figure 6. The real demand to be used for simulation purposes can be either given in the form of a text file or using a formula. The user can select the appropriate option. The user can choose a historical file which contains previous consumptions for the wholesaler. Historical demand data is plotted as a graph to facilitate the visualization of the usage in the past. The user can create his/her own price estimation graph. The yellow colored line segment represents the price function for residential customers and the red colored line segment the price function for commercial customers. The slope of these lines and the functions can be modified by changing the parameters below the graph and by clicking "re-draw" on the graph. An option to include learning is included. This means that the wholesaler is an entity with learning capabilities. The parameters are the same as explained in the previous section. There are four options for choosing a forecasting method. They are "moving average", "exponential smoothing", "random" and "average". Choosing the respective option will prompt for the corresponding required parameters. The user also needs to enter the retail price (expressed in dollars) of the wholesaler throughout this simulation. The bidding strategy for this set of wholesalers can be chosen by using the radio buttons provided.

Table 2 documents trading strategies of wholesalers and the range of two parameters. After this the user can create as many such replications as required using the last text box by specifying the number of such wholesalers. The trader IDs of these wholesalers can be specified.
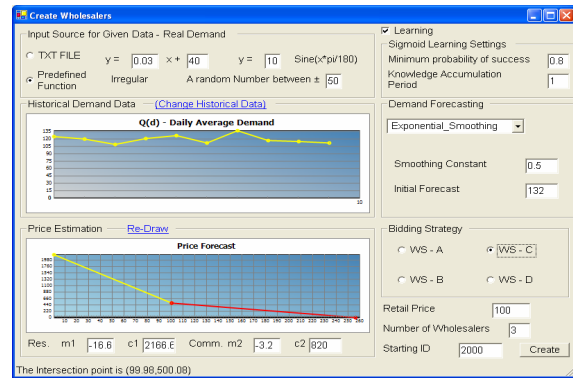

Figure 6. Wholesaler creation wizard.

7. SIMULATION

7.1 Description on computer monitor

After creating the simulation model, the user clicks "simulation" in the main window. This creates a new display window to show the simulations status. The simulation window, depicted in Figure 7, is showing four different graphs. The first graph shows the demand-supply curve in the DA market. The second graph shows the graph in the RT market. The third graph shows the price fluctuation, during every run, in the DA and RT market. The fourth graph shows the volume fluctuation and volume share of DA and RT market. This gives a simulation outline on how much the price and volume fluctuates during the whole simulation.
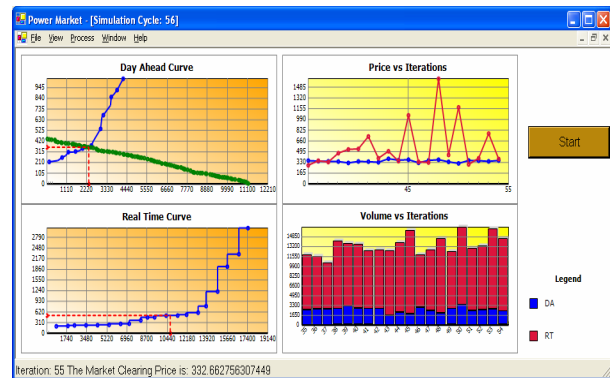

Figure 7. Computer monitor.

Table 1. Market and pricing strategies of generators

Generator	Preferred Market Focus (Quantity)	Risk Preference (Price)		Parameter Range		
		DT	RT	a_{it}	β_{it}	η_{it}
GN-A	DA	Risk-taker		(0.50, 1.00)	(0.50, 0.99)	(0.50, 0.99)
GN-B		Rick-taker	Rick-avoider	(0.50, 1.00)	(0.50, 0.99)	(0.01, 0.49)
GN-C		Rick-avoider	Rick-taker	(0.50, 1.00)	(0.01, 0.49)	(0.50, 0.99)
GN-D		Rick-avoider		(0.50, 1.00)	(0.01, 0.49)	(0.01, 0.49)
GN-E	RT	Rick-taker		(0.01, 0.49)	(0.50, 0.99)	(0.50, 0.99)
GN-F		Rick-taker	Rick-avoider	(0.01, 0.49)	(0.50, 0.99)	(0.01, 0.49)
GN-G		Rick-avoider	Rick-taker	(0.01, 0.49)	(0.01, 0.49)	(0.50, 0.99)
GN-H		Rick-avoider		(0.01, 0.49)	(0.01, 0.49)	(0.01, 0.49)

Table 2. Market and pricing strategies of wholesaler

Wholesaler	Preferred Market Focus (Quantity)	Rick Preference (Price)	Parameter Range	
		DA	δ_{it}	λ_{it}
WS-A	DA	Risk-taker	(0.50, 1.00)	(0.01, 0.49)
WS-B		Rick-avoider	(0.50, 1.00)	(0.50, 1.00)
WS-C	RT	Risk-taker	(0.01, 0.49)	(0.01, 0.49)
WS-D		Rick-avoider	(0.01, 0.49)	(0.50, 1.00)

Table 3. Summary statistics for power prices ($/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
PV	50.03	48.99	8.50	0.74	0.16	411
4C	49.60	47.35	9.29	1.05	0.98	411

7.2 Simulation Results

Data description: To document the practicality of the proposed simulator, we apply it to estimate the market price of US wholesale electricity. The estimation accuracy is compared with other well-known methods that are widely used in the power industry. Each data set is obtained from the website: http://www.theice.com. The wholesale price is measured in $/MWH (US dollars per mega watt hour) and the quantity to be traded is measured in MWH. The obtained data set consists of information on Trade Date, Average Price and Volume. Since we are interested in predicting the wholesale price, Table 3 documents a statistical summary on the four markets.

The first data set on PJM-DA represents the daily average market price obtained from PJM-West Peak for the DA market during the period from November 7th, 2003 to January 4th, 2005. Here, PJM stands for a power market covering Pennsylvania, New Jersey and Mainland A high volatility of the wholesale price is observed when the price has suddenly spiked up from a low of $25.95 (MWH) on December 24th, 2003 to a high of $82.58 (MWH) on January 14th, 2004.

The second data set on PJM-RT represents the daily average market price for PJM-RT peak price during the period from November 7th, 2003 to January 4th, 2005. The correlation coefficient between PJM-RT demand and price is 0.0624, exhibiting that there is almost no correlation. It is interesting to know that the spike is similar to that of the DA market, occurring from a low of $26.75 (MWH) on December 24th, 2003 to a high of $84.13 (MWH) on January 15th, 2004.

The third data set on PV consists of Palo Verde peak prices from December 13th, 2002 to January 25th, 2005. The lowest price occurs on October 16th, 2003 with a price of $35.74 (MWH) and the highest price occurs on July 13th, 2004 with a price of $77.32 (MWH).

The fourth data set on 4C consists of Four Corners peak prices from December 13th, 2002 to January 25th, 2005. The highest price occurs on July 14th, 2004 with a price of $84.06 (MWH). The lowest price occurs on May 1st, 2003 with $34.00 (MWH). The correlation coefficient between demand and price in 4C is -0.0100.

An approximate market composition and market share of the PJM market is prepared from western hub-definition file, available from PJM website (http://www.pjm.com/markets/energy-market/downloads/20050101-hub-definitions.xls), in which 24 generators and 69 wholesalers are listed in the western hub. The generator market share is listed as follows: 15 generators' share is 2% each, 7 generators' share is 4.2% each, 1 generator's share is 18%, and 1 generator's share is 22.6%. The wholesaler market share is separated as follows: 16 wholesalers' share is 0.61% each, 44 wholesalers' share is 1.45% each, 8 wholesalers' share is 2.85% each, and 1 wholesaler's share is 3.64%. Our simulator uses this market composition. Unfortunately, this kind of market and trader information is not available for PV and 4C. Therefore, we use the same composition and market information of PJM to investigate PV and 4C. The regulatory maximum price is set to be (85.00 $/MWH) and the regulatory minimum price as 25.00 ($/MWH).

Evaluation criterion: The performance of the proposed approach is compared with those of the other three approaches. An evaluation criterion for such a methodological comparison is the total deviation of predicted values from real observations. This provides estimation accuracy (%) which is defined as

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

where N stands for the number of periods (transactions) used for our performance evaluation. This criterion is suggested by Shahidehpour et al. (2002, p. 79).

Methodology alternatives: As the first alternative, we employ a direct formula (DF) in which a wholesale 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 Shahidehpour et al. (2002), p. 77). A spreadsheet

application, like Microsoft Excel, is used to compute the DF.

The second alternative is neural network (NN) whose use for price estimation has been recommended by many researchers (e.g., Shahidehpour et al. (2002, Ch. 2)). We use radial basis function neural networks (RBFNN) to forecast the price of wholesale electricity. (see, for example, MATLAB neural network toolbox, version 6.1.0.450 release 12.1, that is listed in a website: (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 interpolating 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 operation consists of the following two steps: training and testing. For PJM-DA and PJM-RT, the first 72 data points were used for training and the next 217 data points were used for testing. For PV and 4C, the first 102 data points were used for training and the remaining 309 data points were used for testing. The most commonly used neural network is a feed forward NN because it uses very less number of 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 our experiments, we use a radial basis network because of its prediction accuracy. We created 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.

As the third alternative, we use the genetic algorithm toolbox for MATLAB, developed at the department of automatic control and systems engineering of university of Sheffield, UK, for running our experiments (source: http://www.shef.ac.uk/acse/research/ecrg/gat.html). The parameters used in the genetic algorithm were specified as follows: population size = 120, crossover probability = 0.8, mutation probability = 0.001, maximum generation = 12000. The objective of each artificial trader is to maximize the total profit obtained after n number of iterations. Therefore, the objective function of the genetic algorithm is to maximize the total profit obtained by traders.

Table 4 compares the performance of the agent-based approach with those of Direct Formulation (DF), Neural Network (NN) and Genetic Algorithm (GA). The values in Table 4 show average estimation accuracies over 289,000 simulations (= 289 transactions × 1000 duplications) for PJM market and 411,000 simulations (= 411 transactions × 1000 duplications) for PV-4C market. The estimation accuracy is listed by a percentage expression. To examine how the agent-based approach estimates properly a price fluctuation of electricity, Figure 8 visually compares an observed real price fluctuation of PJM-DA with its estimate obtained from the agent-based approach. A close approximation can be identified between the two
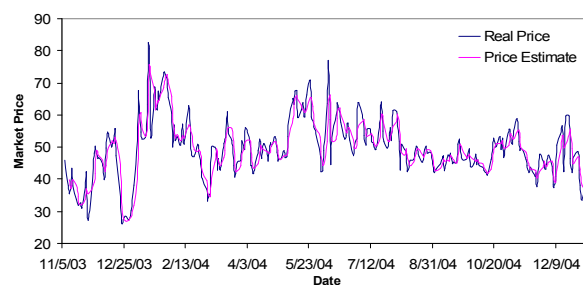
fluctuations in Figure 8.

Figure 8. Real price and price estimate.

Finding from Simulation: Table 4 and Figure 8 indicate that DF is the most error-prone method and hence inefficient. All the estimation accuracies of DF are much less than those of the other three approaches in the four markets. The agent-based approach outperforms the other approaches in the four markets.

8. CONCLUSIONS

As an extension of the previous study (see Sueyoshi and Tadiparthi (2005)), this research has discussed the software to analyze the competitive wholesale electricity market that can be separated into DA and RT markets. Using the software, we can predict the market clearing price in the two markets. Furthermore, we can investigate the bidding strategies of traders, controlling parameters incorporated into the software.

There are some shortcomings in this software which need to be addressed as future research tasks. First, the learning algorithm incorporated into the software needs to be further extended in a way that it can reflect different bidding strategies of traders. For example, the Bayes' theory can be added to the proposed sigmoid learning so that the combined use can enhance a winning probability. Moreover, a game theoretic approach adds another perspective on the learning capabilities addressed in this study. The basic communication framework needed for such a study has already been implemented. Second, the proposed approach should be extended to network capabilities so that a market operator exists in one place and traders exist physically in other places. They are linked on Internet, as designed in the software. An important task to be explored in the extension is to study how many traders obtain some consensus on the market clearing prices, under the price monitoring processes of public authority. This is an important extension of this software.

Finally, it is hoped that the software makes a small contribution for power trading. We are looking forward to observing future research extensions, as indicated in this study.

ACKNOWLEDGEMENT

Table 4. Comparison among four 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
PV	52.07	81.34	83.10	79.77	88.66
4C	18.79	80.66	80.92	80.98	79.34
Mean	32.47	79.97	79.13	79.36	87.45

Note: PV and 4C stand for palo verde RT market and four corners RT market.

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APPENDIX: CHOICE OF SIGMOID FUNCTION

In this Appendix, we discuss about the different strategies by which a trader benefits in a competitive power market. Since the space of this article is limited, we discuss the trader's strategy from the generator's point of view. Of course, our description here can be easily extended to the strategy of a wholesaler. Figure A-1 represents the conceptual diagram of a generator. The generator is an intelligent agent with a sensor, to sense the environment, and an actuator which takes the appropriate action after decision making. The controller is the module which takes

decisions. The Knowledge Base is a collection of previous data and future data stored in the form of a table. The learning algorithm module is the one which implements the different learning algorithms of the generator.

The sequence of learning inside the generator can be elaborated as follows:

1. The generator receives data at its sensor input periodically.
2. The sensor deposits the data into the knowledge base and lets the controller know that an input has arrived.
3. The controller, based on a decision making rule, chooses the appropriate learning algorithm and makes a decision on what the output should be.
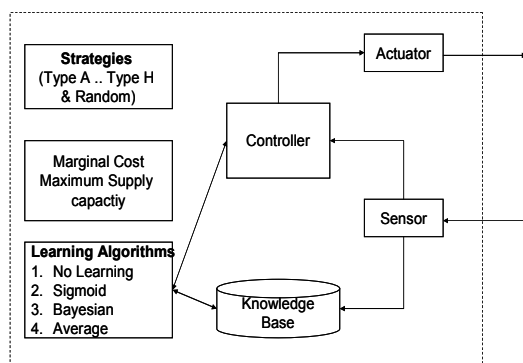4. Finally the controller outputs via the actuator in to the system environment.

Figure A-1. Generator as a learning agent.

A win or loss at an auction is considered as a binary response. A sigmoid model, as one of the four learning algorithms, can be used to predict the winning probability. The reward of any generator is predicted by a $reward = c_0 + c_1\alpha + c_2\beta + c_3\eta + \varepsilon$. Here, ε is the observational error. c_0, c_1, c_2 and c_3 are parameters of the sigmoid model which can be estimated by OLS (ordinary least squares) regression. The winning probability of a generator can be specified by $Prob(Win) = \dfrac{1}{1+e^{-\sigma \times reward}}$.

Here, a prescribed value (σ) is the slope of the sigmoid function. Let $\hat{c}_0, \hat{c}_1, \hat{c}_2 \ and \ \hat{c}_3$ be the estimates for c_0, c_1, c_2 and c_3 which satisfy the following condition:

$$\frac{1}{1+e^{-\sigma \times reward}} > \theta ,\qquad\qquad\qquad\text{(A-1)}$$

where θ is the threshold value of the winning probability. The probability implies a likelihood that a generator wins the power trading auction. This does not necessarily imply the generator's win. That is a theoretical guess. The trading market determines the real winning probability. However, it is not a bad idea for each generator to develop his/her bidding strategy based upon the estimate of the winning probability.

1. Initialize the upper and lower bounds of bidding strategy parameters (α, β and η).
2. Using OLS obtain the parameter estimates of the sigmoid function from the knowledge base.
3. The upper limits and lower limits of the parameters are reset by the parameter estimates of the sigmoid function.
4. Change the values of α, β and η according to those upper and lower bounds in a manner that such a change increases the winning probability. If $t = T$, stop. Otherwise, repeat *Steps* 2 to 3 for all t.