Paper

An Evolutionary Computation for Supplier Bidding Strategy in Electricity Auction Market

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The daily bidding strategy in a day-ahead electricity auction market is studied from a supplier's point of view. An improved evolution strategy is developed to evolve the bidding strategy and to maximize the supplier's profit in a long run. A competitive day-ahead electricity auction market, where no supplier possesses the market power and all suppliers winning the market are paid based on their own bid prices, is assumed here. The dynamics and the incomplete information of the market are emphasized. A market clearing system is also included in the implementation. An agent-based simulation method is presented in this paper. The simulation results show the feasibility of the proposed bidding strategy.

Keywords: Electricity auction market, Evolution strategy, Supplier bidding strategies

1. Introduction

In the past decade, the electric utility industry in many countries around the world has been undergoing fundamental structural changes to introduce competition and enhance efficiency. The traditional vertically integrated utility is deregulated to open up the system to the market, in response to the pressures of privatization and customer demands. Electricity and services can be sold and purchased as a commodity through different market structures. Under this deregulated and competitive environment, economics and profitability have become the major concern of every electric supplier, and each supplier will act in his/her own self-interest in this new environment.

Among the proposed market structures, the electric auction market has been widely experienced and implemented in different countries with different protocols. Market participants – electric suppliers, and distribution companies – are required to submit their sealed bids to the auction market to compete for power energy. All participants winning the auction will be paid based on the rules agreed upon by the participants. Thus the bidding strategy which is essential for a successful business in this auction market is becoming one of the most important issues in the electric industry. Market participants can improve their benefits dramatically by strategic bidding.

Developing bidding strategies for competitive suppliers have been studied by many researchers in recent years. Game theory [1] is naturally the first choice to deal with this issue, and much work has been done using this traditional theory. In [2], a Nash game approach is used to study the pricing strategy in the deregulated power marketplace, where each participant has incomplete information about his rivals. A method, which uses Cournot non-cooperative game theory to determine the optimal supply quantity for each power producer in an oligopoly electricity market, is presented in [3]. The results show that the estimation accuracy of production cost functions of rivals plays an important role in this market. Different electricity market rules and their effects on bidding behaviors in a non-congestion grid are analyzed in [4]. The authors conclude that generators can take advantage of congestion in their strategic bidding behavior.

But game theory is not the only solution to this problem. In fact, due to the complexity, dynamics and uncertainty of the restructured electricity market, evolutionary computation algorithms and reinforcement learning are receiving increasing attention recently and are becoming major tools in solving this problem. A genetic algorithm is developed in [5] to evolve the bidding strategies of participants in a double auction market. Markov Decision Process is used to optimize the bidding decisions to maximize the expected reward over a planning horizon in [6], The optimal bidding problem is modeled as a stochastic optimization problem in [7], and, a Monte Carlo approach based method and an optimization based method are developed to solve this problem. In [8], an agent-based simulation method is proposed, in which each agent uses a "naive reinforcement learning algorithm" to explore and exploit successful bidding strategy. However, this approach fails to use public information of the market and to combine each agent's business type (risk averse or opportunistic) in developing the bidding strategy for each agent.

In this paper, the bidding strategy is studied from the supplier's point of view in a day-ahead electricity auction market, and the bidding process is treated as a dynamic and continuous process. Each supplier is designed to have the ability to use the public information

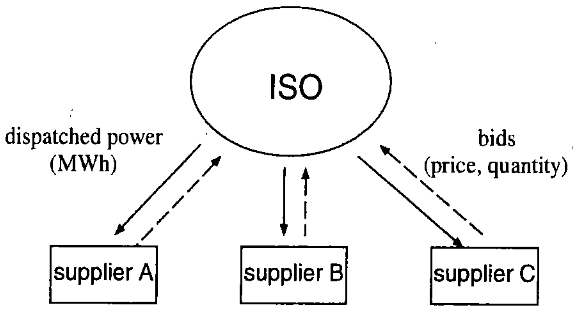

Fig. 1. The relationship of suppliers and the ISO.

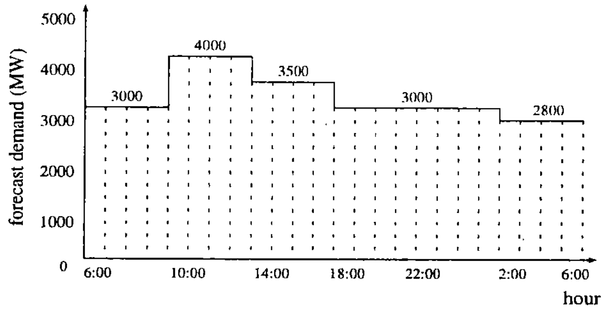

Fig. 2. An example of forecasted load profile by the ISO.

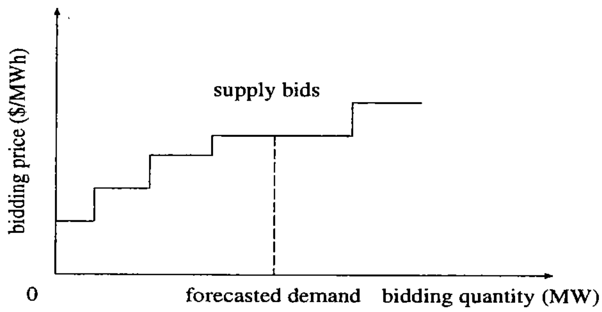

Fig. 3. An example of supply curve.

of the market and be able to explore and exploit his optimal (successful) bidding strategy over the bidding process. The business type of each supplier is considered here. It is assumed that no supplier possesses the market power, that can be used to manipulate the market price to satisfy his/her own benefit. Because the bidding information of each supplier is confidential, each supplier is also assumed to have only information on his/her own cost and the publicly available information of market, but lacks information on other rivals. The market suppliers are also assumed to be so many that it is very difficult for each supplier to estimate other suppliers' bidding behaviors.

This paper is organized as follows: Section 2 describes the model of electricity auction market. Section 3 presents the evolution strategy used to evolve the bidding strategy of a supplier. Section 4 shows the simulation results which are based on a multi-agent simulation method. Section 5 gives the conclusion and presents the future work.

2. A day-ahead electricity auction market

A day-ahead electricity auction market with no demand-side bidding is assumed here. In this day-ahead auction market, all suppliers wishing to sell power tomorrow must submit their bids today to an Independent System Operator (ISO), who will clear the market, determine which supplier should be used to meet the forecasted load, and check if the security and reliability constraints of the power system is satisfied. The relationship of the ISO and suppliers is shown in Fig.1.

Everyday suppliers submit their sealed bids with price ($/MWh) and quantity (MW) at which they are willing to sell during the next day to compete for the power load forecasted by the ISO. An example of forecasted power load by the ISO is shown in Fig.2. For simplicity, a daily bids is used here, that is, each supplier submits one bid everyday to compete for power load over all 24-hour of the next day.

The bids from suppliers are ranked by the ISO from the cheapest to the most expensive to construct a supply curve, see Fig.3. The ISO will then select the cheapest supplier until the load of each hour of the next day is met. It should be pointed out that we regulate in this clearing algorithm, when the bidding prices are equal, the supplier with smaller bidding quantity is given the first priority to be accepted to protect the medium-and-small size enterprises.

At the end of each trading day, each supplier is notified of his dispatched power (MWh), which is the quantity called into operation during the 24-hour of the next day, and the daily market price ($/MWh), which is assumed to be the only publicly available information to each supplier in this paper. The market price is defined to be the average bidding price P_{avg} of dispatched suppliers as follows:

$$P_{avg} = \frac{\sum_{i=0}^{n-1} Disp(i) * P(i)}{\sum_{i=0}^{n-1} Disp(i)} \quad \cdots\cdots\cdots\cdots\cdots \quad (1)$$

where n is the number of suppliers in the electricity auction market, $P(i)$ denotes the bidding price ($/MWh) of supplier i, and $Disp(i)$ represents the dispatched power (MWh) of supplier i.

Each supplier winning the market is paid based on the first-price rule [9], that is, a discriminatory pricing rule. Although the discriminatory pricing rule is not so much popular, it is used in UK balancing market [10]. According to this pricing rule, winners are paid at their own bid prices. The reward π_i from the bid of each supplier i is calculated based on the bidding price $P(i)$, the dispatched power $Disp(i)$ and the unit production cost C_i:

$$\pi_i = (P(i) - C_i) * Disp(i) \quad \cdots\cdots\cdots\cdots\cdots\cdots \quad (2)$$

It should be noted that, in this simplified model, each supplier's production cost is represented as a linear function of his dispatched power. In practice, the unit cost of each supplier's power supply varies with the total output of power supply.

3. Evolution strategy for supplier bidding

Evolution Strategies (ESs) [11] are algorithms which imitate the principles of natural evolution as a method to find solutions to optimization problems. In this section, we propose an algorithm which is similar to the (1+1)-ES algorithm to develop the bidding strategy for electricity suppliers.

3.1 (1+1)-ES algorithm: The (1+1)-ES algorithm is based on a two-member population and use a mutation operator to realize the evolution process. Each member of the population is termed as an individual, and is implemented by a data structure. Each individual represents a potential solution x to the problem to be solved, or, a point x in the search space. Each individual is evaluated and assigned a fitness value. During the evolution process, one individual (parent) x^t is used to reproduce the other individual (offspring) x^{t+1} using the mutation operation as shown in the following equation.

$$x^{t+1} = x^t + N(0, \sigma^2) \quad \cdots\cdots (3)$$

where x and σ are vectors, t is an integer and $N(0, \sigma^2)$ is vector of independent normal distributions with mean 0 and standard deviations σ. The offspring replaces the parent if his fitness is better than that of the parent. Otherwise, the offspring will be removed, and the parent survives.

The algorithm can be summarized as follows:

1 Generate a random individual (parent) and calculate its fitness,

2 Use mutation to create an offspring and calculate its fitness,

3 Replace the parent with the offspring if the fitness of the offspring is higher than that of the parent,

4 Go to *2*, until the stopping conditions are satisfied.

3.2 Evolution strategy for supplier bidding: In the daily repeated electricity auction market, each supplier will attempt to maximize his/her profit in a long run and to reduce risks. The need to maximize profit and manage risks at the same time is becoming a dominant industry problem [12]. Based on the (1+1)-ES algorithm, we develop a novel supplier bidding strategy, which takes into account the supplier's types and tries to balance the tradeoff between supplier's expected profits and risks. As we assumed in the above section that the production cost of each supplier is a linear function of his dispatched power, so each supplier will bid his maximum generation capacity (MW) everyday as his bidding quantity to attempt to maximize his profit in this auction market. Therefore, the bidding strategy is resulted in a bidding price decision-making problem.

As described earlier, we assume that the supplier has only information on his/her own cost and the public information of market price, but lacks of information on the rivals. Thus, the bidding process is a stochastic process. During this stochastic bidding process, each supplier will attempt to meet his/her objectives of:

- increasing his/her profit from day to day,
- satisfying the target utilization rate on his/her generator everyday,

as described in [8]. The utilization rate is defined as the ratio between the actual dispatched power and the expected dispatched power.

To achieve the objectives, we use the supplier's bidding price of the previous day to generate the bidding price of the next day in the following way, which is similar to the equation (3),

$$P_{new} = P_0 + \xi \quad \cdots\cdots (4)$$

where P_0 is the bidding price of the previous day, P_{new} is the bidding price of the next day, and ξ is an adjustment value that is generated according to the bidding strategy, which should take into account the supplier's business type and the tradeoff between the expected profit and risks.

The evolution process of the supplier bidding strategy is described as follows:

If the target utilization rate on the previous day is reached, then adds a random value to the P_0 to generate the bidding price of the next day P_{new},

$$P_{new} = P_0 + |N(0, \sigma_1^2)| \quad \cdots\cdots (5)$$

otherwise, subtracts a random value from P_0 to create P_{new},

$$P_{new} = P_0 - |N(0, \sigma_2^2)| \quad \cdots\cdots (6)$$

where $N(0, \sigma_1^2)$ and $N(0, \sigma_2^2)$ are normal distributions with mean 0 and standard deviations σ_1 and σ_2, respectively.

The standard deviations are determined by a sigmoid function as shown below,

$$\sigma_1 = \frac{c}{1 + e^{\frac{x}{T}}} \quad \cdots\cdots (7)$$

$$\sigma_2 = \frac{c}{1 + e^{\frac{-x}{T}}} \quad \cdots\cdots (8)$$

$$x = P_0 - P_{avg} \quad \cdots\cdots (9)$$

Here, c is a constant which represents the supplier's type – risk averse or opportunistic. When the supplier is risk averse, c should be small, and vice versa. T is a parameter that will change over the evolution process. Examples of σ_1 and σ_2 are shown in Fig.4.

As shown in Fig.4, when P_0 is larger than the market price P_{avg}, if the target utilization rate of the previous day is satisfied, the supplier will develop prudently the bidding price of the next day, using a normal distribution with smaller standard deviation to reduce the risk of losing in the market; If the target utilization rate of the previous day is not reached, the supplier will generate a smaller bidding price of the next day by subtracting a random value from the previous day's bidding price, using a normal distribution with larger standard deviation, to meet the target utilization rate firstly.

To ensure the supplier to be adaptive to the dynamically competitive environment, and be able to explore and exploit the optimal bidding strategy over the evolution process, we introduce the success rule [11] to evolve

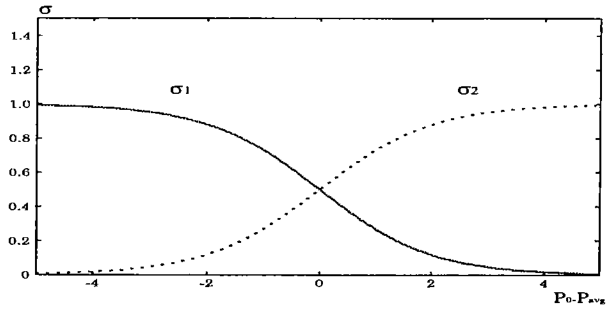

Fig. 4. Examples of σ_1 and σ_2 with parameters $c = 1.0$ and $T = 1.0$.

the bidding strategy by adjusting the parameter T during the bidding process. The success rule is applied every k trading days:

$$T = \begin{cases} c_i * T & if\ \ r(k) > Ratio \\ T & if\ \ r(k) = Ratio \\ c_d * T & if\ \ r(k) < Ratio \end{cases} \quad \cdots\cdots\cdots (10)$$

where $r(k)$ is the success ratio of satisfaction of target utilization rate on the generator during the last k trading days; $Ratio$ is the target success ratio to be satisfied; and $c_i = 1.22$ and $c_d = 0.82$ regulate the increase and decrease rates of the parameter T, respectively. In this first report, c_i and c_d are fixed for simplicity. To introduce the adaptation mechanism into c_i and c_d is a future work. The maximum and the minimum of parameter T are set to 8.0 and 0.01, respectively.

If the target success ratio is satisfied, the supplier will bid boldly with lager steps to maximize the profit; if not, the supplier will bid cautiously to meet his/her requirement on utilization rate of generator, and this will finally lead to meet his/her profit-maximizing goal in a long term.

4. Simulation results

We have developed a multi-agent based simulation method to test the bidding strategy we proposed in the above section. The application of multi-agent based simulation method to deal with issues in deregulated electricity industry is a newly promising research area [13][14]. In this paper, each adaptive agent represents a supplier participating in this day-ahead auction market, and is able to explore and exploit the optimal bidding strategy to meet his/her profit-maximizing goal in this competitive environment.

In the early stage of the electricity deregulation process, electricity consumers in many markets are protected by capped price, as did in the California's electricity market. Consumers have little awareness that they should alter their consumption patterns and manage their power demand. The market demand shows little elasticity at the current stage. Therefore, two cases of market power load forecasted by the ISO are used here for simulations. One is a fixed load case, in that the forecasted load is the same as shown in Fig.2 and remains unchanged during the evolution process. To show the increasing power demand in reality, the other is a changing load case, in that the forecasted load of each hour shown in Fig.2 will increase 3 (MW) everyday during the simulation. As a result, the hourly power load of everyday will be larger than the power supply in this case when the evolution is over 667 trading days.

Table 1. Max. generation capacities and initial bidding prices of 10 rivals

agent	0	1	2	3	4
Max. generation capacity (MW)	300	400	300	400	500
initial bidding price ($/MWh)	10.0	12.0	9.0	13.0	12.0

agent	5	6	7	8	9
Max. generation capacity (MW)	500	400	500	600	600
initial bidding price ($/MWh)	10.0	11.0	11.0	14.0	12.0

It should be pointed out that all agents in our simulations will bid their maximum generation capacity as their bidding quantity on every trading day. The unit cost C_i of each supplier is set to 8.0 ($/MWh). The target utilization rate and success ratio of all agents are specified to 1.0 and 0.8, respectively. The success rule is applied every 10 trading days. The ceiling price of the market is set to 20.0 ($/MWh). And the bidding strategy is allowed to evolve for 1000 trading days.

4.1 Simulation case 1:

To test the feasibility of the proposed bidding strategy, we show an example of an agent A, who use the proposed supplier bidding strategy to develop his/her bidding price to compete against 10 rivals. All rivals in this simulation case are assumed to just bid their initial bidding prices everyday with a variation range of $\pm 10\%$. The maximum generation capacity of agent A is set to 300 (MW). The maximum generation capacities and initial bidding prices of 10 rivals are given in Table 1. As can be seen from the generation levels of all agents, no supplier possesses the market power since no agent has the dominant market share.

The bidding prices of agent A in both power load cases are shown in Fig.5. As shown in this figure, agent A is forced to bid price in the range of 11$/MWh - 12$/MWh in the fixed load case, which is a stationary noise environment; while, in the changing load case, agent A is successful in exploring and exploiting the optimal bidding strategy, which varies with the change of power load, to meet his/her profit-maximizing goal. The result shows that the proposed bidding strategy is capable of developing optimal bidding strategy in stationary and non stationary environment.

Table 2 shows the effect of business type, which is represented here by the parameter c, on the reward of agent A in this simulation case. Each reward shown in Table 2 is the average of average everyday reward of agent A from 100 simulations. As shown in this table, business type plays a very important role in achieving the profit-maximizing goal of agent A. When c is too large, that is , agent A is of opportunistic type, reward obtained decreases since agent A faces larger risk of not being accepted by the ISO. If c is too small, reward obtained also decreases because agent A bids prices close to the public available market price and has little ability of exploring optimal bidding strategy for himself.

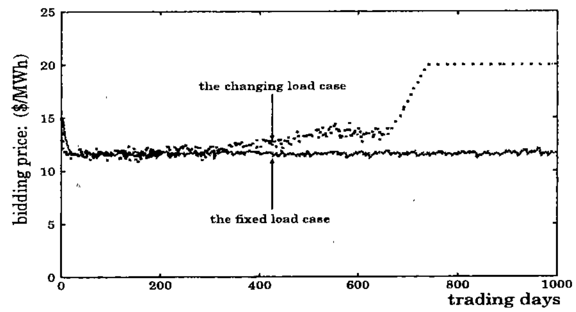

Fig. 5. The bidding prices of agent A in the fixed load case and the changing load case. The parameter c in these two load cases are set to 0.25 and 0.75, respectively.

Table 2. Average everyday reward of agent A

c	0.1	0.25	0.5	0.75	1.0
reward ($) in fixed load case	22183	22393	22182	21807	21357
reward ($) in changing load case	42397	45462	46460	46666	46579

4.2 Simulation case 2: In this case, we investigate the effect of business type on the market price. We assume that agent A is still competing with the 10 rivals, whose maximum generation capacities are shown in Table 1. But this time, all rivals are assumed to use the proposed supplier bidding strategy to develop their bidding prices. All the initial bidding prices of agent A and his rivals are set to 15$/MWh here. The simulation results are plotted in Fig.6 and Fig.7.

In Fig.6 and Fig.7, all the parameters c of agents in curve 1 are set to 0.25, and 1.0 in curve 3, respectively. And the parameters c of agents in curve 2 are randomly selected from the range of [0.2, 1.2] to represent a simulation in heterogeneous agents environment.

Fig.6 shows that, even under the discriminatory pricing rule, in the fixed load case, where power supply is bigger than the power demand, intense competition among the agents forces the market price down to a lower price level, which is close to the agents' truly unit cost C_i (8.0$/MWh). We can also see from this figure that the curve 3 has the quickest decrease of the market price and largest oscillation at the end of the evolving process than two others because agents in curve 3 are opportunistic. On the other hand, competition among the agents with small parameters c=0.25 leads to a slow decrease and lower market price at the end of the trading days, because of the prudently bidding of all agents.

The difference of market prices in the changing load case, which is resulted from the competition among agents with different business types, is shown in Fig.7. It is very interesting to find that, due to the strategic bidding of agents, the market prices go up to the market ceiling price on about 400 trading day, even though the power supply at this time is still bigger than the power demand.

4.3 Simulation case 3: We compare the proposed bidding strategy with another simple bidding strategy for suppliers, which is a simplified version of

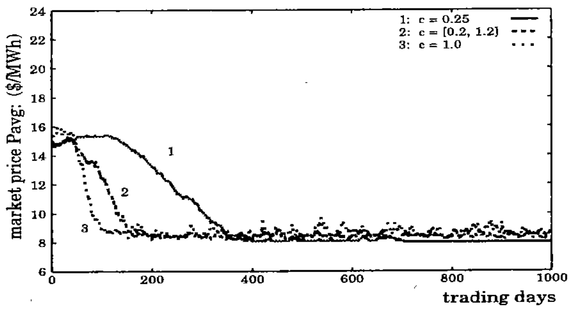

Fig. 6. The market prices over the evolution process in the fixed load case.

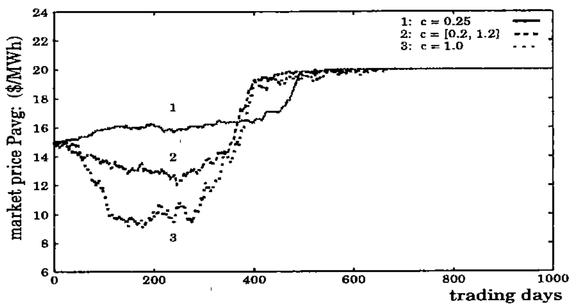

Fig. 7. The market prices over the evolution process in the changing load case.

the "naive reinforcement learning algorithm" used in [8]. The simple bidding strategy can be summarized as follows: if the supplier fails to achieve his/her target utilization rate on the previous trading day, then subtracts a random value from the previous bidding price; otherwise, adds a random value to previous bidding price to create the next day's bidding price. The random value is generated from a normal distribution with mean 0 and standard deviation σ_3.

In this simulation, all participants compete against others in the changing load case. There are four maximum generation capacity levels, 300MW, 400MW, 500MW and 600MW. At each capacity level, there are four suppliers, two using the proposed bidding strategy and two others using the simple bidding strategy. This makes for a total of 16 agents participating in the electricity auction market. All parameters c of the agents using the proposed bidding strategy are set to 1.0. The σ_3 of all the agents using the simple bidding strategy are specified to 0.5 so that the majority of the variation of bidding prices in two consecutive days are within the range of $\pm 15\%$. Simulation results are given in Table 3. As shown in this table, the proposed bidding strategy can lead to a better reward for suppliers from the auction market. However, simulation results also show that, when the parameters c remains unchanged and σ_3 decreases to 0.1, agents using simple bidding strategy will win over those using the proposed bidding strategy due to their cautiously bidding.

5. Conclusion and future work

Based on the (1+1)-ES algorithm, we proposed a bid-

Table 3. Average daily rewards of agents at different Max. generation capacity levels using different bidding strategies in the electricity auction market

Max. generation capacity (MW)	Proposed Strategy Average daily rewards ($)	Simple Strategy Average daily rewards ($)
300	24944	20213
400	32495	26399
500	39554	33545
600	45339	38342

ding strategy for suppliers in a day-ahead electricity auction market. Suppliers' types were included in this approach, and their effects on the market price were analyzed. Simulation results, which were based on a multi-agent approach, have shown the validity of the proposed bidding strategy.

Although the proposed strategy is some kind of simple at the current stage and a practical strategy may need to take into consideration many constraints and parameters, it will still provide us some valuable information on market design and the supplier bidding strategy. It is believed that developing bidding strategy under different market designs can provide a deep insight into the complex new electricity markets and identify how rules can be designed to improve the performance of the market. How to extend our methodology to study markets where uniform pricing rule is adopted will be our future work.

In this paper, we developed the bidding strategy from a supplier's point of view, without considering the demand-side bidding. In practice, the demand from the consumers is a function of the market price. When the market price goes up, the demand will decrease to some extent. When this relationship is considered, there should be an impact on the profits of suppliers and will eventually affect the suppliers' bidding strategies.

Moreover, we just used the bidding data of the previous day to develop the bids of the next day. In reality, historical bidding data, including the publicly available information of the market, play a very important role in developing the optimal bidding strategy for suppliers. It is believed that combining the technique of artificial intelligence with the proposed bidding strategy, such as using the neural network to predict the market price and power demand, will decrease risks facing the suppliers and increase greatly the profits for them in this daily repeated auction market.

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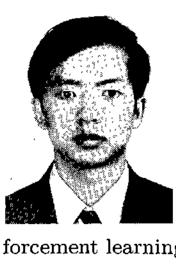

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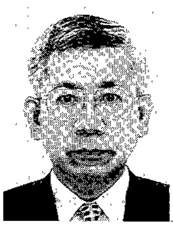

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