Bidding Simulation Methods of Multi-input Decision Factors for Power Suppliers based on Intelligent Agent

Heng Feng, Zhenglin Yang and Huichao Wang

ABSTRACT

With the development of electric power industry, it has become an urgent problem of deregulation of the industry. From monopoly to free competition, the market participants’ bidding decisions will undergo great change. Because of difference of market participants’ cost, risk preference, relationship of supply and demand, bidding behaviors of market participants show a more perplexing situation. In this paper, a multi-input decision factors algorithm based on intelligent agent is used to simulate the behavior of generators. The influence of subordinate objective of decision and risk preference on the bidding behavior of generators is considered in the model. The case analysis shows that generator's intelligent agent model established in this paper can well simulate generators of different characteristics; through learning the historical experience, generators can improve their bidding behaviors, update the selection probability of each bidding strategy, and finally achieve good returns.

Keywords: decision behavior; intelligent agent; multi-input decision factor; risk preference; dynamic evolution.

INTRODUCTION

The construction and operation of electricity market is a complex system engineering. The cost of trial and error is huge, so it is necessary to make a forward-looking study to reduce the risk of market model selection. At present, a variety of electricity market experimental environments have been established both at domestic and abroad [1-3], which not only require the establishment of market rule and market model, but also have the ability to simulate the decision-making behavior of market participants. At present, there are a lot of simulation methods to study the bidding decision behavior of market participants, but most of them are only limited to the static analysis, which can’t reflect the decision-making process of market participants [4].

China Electric Power Research Institute (Nanjing), Nanjing 210003, Jiangsu Province, China
Email: 915266332@qq.com
This work was supported by the Science and Technology Project of State Grid Corporation of China under Grant (DZN17201600244.)
The intelligent agent rising in recent years is a kind of intelligent entity that can continuously acquire knowledge from the environment and gain maximum benefit by improving its own ability[5]. It can operate independently in a certain environment, act on external environment and also be affected by it. It can use the limited external information to make the best decision, especially suitable for the modelling and simulation of market participants in the early stage of electricity market, promote the rapid establishment of the electricity market mechanism and relevant rule [6].

At present, many researches have been done on bidding simulation methods for generators based on intelligent agent both at domestic and abroad. The paper [7] develops a bidding decision procedure module based on the intelligent learning algorithm (Q-learning), and simulates it on the 5 node test system. However, due to the limitation of the current version of ISO program module in AMES, only one round of bidding can be processed every day, and the load fluctuation is not taken into account during the decision process, but the market load demand is the main external factor that should be considered in the decision-making process of generators. The literature [8] uses the simulation system as a based technology platform, carries out the research of generators on the intelligent agent algorithm under different levels of supply and demand, but does not consider the characteristics of generators’ bidding behavior under the condition of changing supply and demand. In order to deal with the benefit maximization problem of generators, the papers [9]-[11] build the bidding strategy model of generators using Q learning algorithm. In the literature [9], the sole objective of generators’ decision making is the profit, and the subordinate decision-making objectives, such as the utilization of units and risk preference, have not been considered. The literature [10] uses generator's immediate income and relative market share as the utility function to maximize its generator’s profit and increase the market share at the same time. In order to optimize the bidding decision of generators, the paper [11] takes the profit and the continuous use rate of generators as the goal.

The existing literature analysis modelling is mostly based on single factor, where the decision-making factor of intelligent algorithms is mostly generators’ income [12]. However, in the electricity market environment, the bidding decision behavior of generators is affected by many factors, and the single decision factor can’t effectively simulate the bidding decision-making behavior of rational generators [13]. The existing literature is limited to the static market analysis under certain supply and demand[14], and can’t simulate the influence of electricity supply and demand changing over time period and abnormal shutdown of equipment on the bidding behavior of generators [15].

The model in this paper first extracts key factors to implement classification modelling from different effective factors and then uses the multi input decision factor algorithm based on intelligent agent to model generators’ bidding behavior and their dynamic behavior evolution process under changing relationship between supply and demand.

THEORETICAL MODEL

With the power industry going from monopoly to competition, the decision-making of market participants will change greatly, especially for generators: the traditional power suppliers only need to arrange the unit output and the unit maintenance plan according to the scheduling, but in the electricity market environment, the generators are based on marginal cost, and utilize the market information to optimize the bidding behavior [16]. However, generators’ own limited external information at the early stage of electricity market, and many different factors influence bidding of generators in electricity market environment; for the generators themselves, their bidding decision have different decision-making preference
and risk preference. The above factors increase the uncertainty of bidding behaviors; therefore, the bidding behavior should be considered in many dimensions.

However, there are many factors affecting the bidding behavior in the market environment, if all the relevant factors are modelled in a unified model, it is possible to have a curse of dimensionality in the solution or leads to a non-convergence of the simulation results. Therefore, it is necessary to classify and analyze the influencing factors and refine the key influencing factors for modelling.

At present, the factors that affect the bidding of generators can be broadly divided into two categories: The first one is market factors, including market supply and demand, market historical price, historical average return, market rules, fuel price trends and release of information about the market; The other is generator's own behavior factors, they mainly include risk preference, decision-making preference, the rationality degree of the agent, the marginal cost of the unit itself and the installed capacity. In the market factors, the market supply and demand and market rules are the most basic external data for the bidding. The bidding power and bidding price of generators are released by the electricity trading institution, and the market clearing result is decided by bidding price of each generator, the market clearing rule and market supply and demand. Therefore, the key influencing factors extracted from market factors are market supply and demand and the market clearing rule.

In its own behavioral factors, the unit marginal cost and the installed capacity are the main basis for generators to bid [17]. Because the supply and demand fluctuates constantly, the generators will inevitably encounter various risk aversion problems in the bidding. At the same time, generators have different decision-making preference. Therefore, the key influencing factors extracted from its behavioral factors are risk preference, subordinate decision-making objective, marginal cost and installed capacity of generators.

In this model, the key influencing factors refined above are analyzed and modelled, and the validity of the extracted influencing factors is verified by a 5 node case.

**Intelligent Agent Model**

In order to maximize the benefit, rational generators will continue to learn from the experience of competitive bidding in order to improve the profit level of the next auction. The intelligent agent can use the past historical experience to optimize the follow-up strategy, and characterize the dynamic learning ability of generators; the bidding behavior of generators changes from centralized decision under planning system to decentralized decision in competitive market, intelligent agent can make use of limited external information to make decisions autonomously, and interact well with other intelligent agents. Intelligent agent can represent different types of generators through the setting of related factors in the algorithm. Based on the above reasons, this paper uses the intelligent agent method to simulate the bidding behavior of generators.

The intelligent agent model proposed in this paper first needs to establish a reasonable set of bidding strategies for generators, give each element in the bidding strategy space a certain initial probability and propensity coefficient. Then, through the roulette algorithm, the bidding strategy of the generator is continuously selected. After the ISO clearing, a timely return is generated, and the probability and propensity coefficient of each element are updated by immediate return. After several rounds of rotation, the generator will converge on the strategy that will maximize the revenue. In this paper, VRE-learning algorithm is used to simulate the bidding behavior of generators. The algorithm was put forward by Roth and Erev [13] in 1995. The algorithm and the corresponding decision module are presented in document [7].

The update formula for the propensity coefficient in the VRE algorithm is as follows:
Where $q_{t+1}$: update for propensity coefficient for round $t+1$; profit $t$: immediate gains for round $t$; $t$: for the bidding round; $m$: the policy number selected in a round; $M$: policy number for policy space; $r$ is a forget factor, weakening the influence of previous experience and increase the impact of new strategies on behavioral tendencies; $e$ is an empirical parameter. The update formula for the selection probability is as follows:

$$p_{t}(m) = \frac{\exp[q_{t}(m)/c]}{\sum_{j=1}^{M} \exp[q_{t}(j)/c]}$$

Where, $p_{t}(m)$ represents the probability of the $t$ round update of policy $m$; $c$ is the cooling factor, which determines the influence degree of the propensity coefficient on the selection probability, the selection of parameter $c$ is dynamically adjusted according to the coefficients of each round strategy, as follows:

$$c_{t} = \frac{k}{M} \sum_{m} q_{t}(m)$$

Where, $k$ is a real number greater than 0, and its value varies in different systems.

**Multi-input Decision Factor Bidding Model**

After deregulation of power industry, generators usually take the lead in becoming the main player of electricity market for independent decision-making, operation and settlement. There are many types of generators in power market, and the decision-making characteristics and management mode of each generator is different. In order to model the bidding decision behavior that meets the actual requirements of generators, the key factors that can characterize the bidding behavior of generators need to be extracted first, multi-input decision factor model proposed by this paper summarizes the key factors from the market factors and behavior factors affecting bidding decision of generators, the key factor combining into multi-input decision factors and classification, and then use the intelligent agent to simulate different characteristics of generators bidding behavior.

**RISK PREFERENCE**

In the market environment, how to optimize the bidding strategy and maximize the profit is the most important issue for generators. But generators in the early market master the limited external information, the system load fluctuation and many uncertain factors exist in the market, making the bidding decision facing great risk. Generators in the model are rational generators, their modeling problem of risk characteristics are different from the general literature, but the rational generators also have different risk attitudes: some generators like to pursue risk, make good use of the original bidding experience and limited external information to explore a better strategy. After a long time of learning and exploration, they will reach a mature state; others resist taking risk, they are not easy to accept the change in the external environment and sensitive to the earning response, after a short time study and exploration, they will reach a mature state. Risk characteristics is not corresponding to
business income, the risk-seeking generators’ income is not necessarily better than the risk
averse generators’ income, risk characteristics mainly reflected in the degree of sensitivity to
their turn volatility and change in the market environment.

How to characterize the generators with different risk characteristics is a question to be
considered in this section. All kinds of generators in the model are rational and in the early
operation of the market, how the risk characteristics of both generators is, they will learn to
use the past auction experience in order to obtain better gains at the next auction. In VRE
algorithm, the formula of propensity coefficient update (1), e is an adjustable parameter with
a range of (0, 1). By the formula (1) shows that the bigger e means instant income is the
smaller proportion in the updates of the tendency coefficient formula, after repeated learning
and exploration, generators will reach maturity; the smaller e means that timely gains in the
formula is in the larger proportion of generators, is easily into the steady state, after
convergence strategy. Therefore, factor e can be used to simulate the risk characteristics of
generators.

SUBORDINATE DECISION GOAL

Decision-making target of generators in the existing literature is only instant revenue,
which is only a major goal for evaluating generator's decision, and other decision-making
objectives include the relative utilization of subordinate units, the unit market share and other
factors. In the day ahead market, generators submit the bidding data to the electricity trading
center, but after clearing the bid result does not necessarily satisfy the best operation power
generators, power generation units and the Chamber of Commerce in income relative
utilization between compromises. In the algorithm, the probability of the element selected in
the strategy space is updated by the utility function. The decision-making of generators must
take the relative utilization rate of power producers and instant income units into account. In
this paper, the model draws on the method in document [18], and gives some weights to the
relative utilization of the generator in the utility function to characterize the subordinate
decision goal. In the algorithm, poss is the unit relative utilization factor. In the formula, Q is
the winning electricity for the generator, G is the installed capacity of the generator, the \(B_{eq}\)
is the load, and the \(G_w\) is the total installed capacity of the market.

\[
poss = \frac{Q}{G} \left( \frac{B_{eq}}{G_w} \right) \quad (4)
\]

utility function \[ profit = (mcp * Q - C)^i \times poss \] \quad (5)\n
Where MCP is the market clearing price: Q is the winning electricity for the generator, C is
the variable cost of the unit, and I is the subordinate goal of the decision, and the weight in
the utility function.

"i=0" shows that the unit pays only attention to the revenue; "i>0" indicating the weight of
the unit utilization in the utility function.

CASE ANALYSIS

The case in this paper is supported by integrated experimental platform for electricity
market which is built by Key Laboratory of State Grid Corporation of China which is
electricity market operation technology laboratory. This platform is designed in three
dimensions from the electricity transaction operation simulation, the market participant
behavior simulation and the power grid operation simulation as the overall design, the 5 node
system is built on the experimental platform to illustrate the intelligent agent model and learning algorithm used in the electricity market simulation. The network topology is shown in Figure 1, the simulation system has three independent generators and six transmission lines, each generator bids using intelligent agent. The marginal cost data of generating units are shown in Table 1. Because we only consider the day ahead market bidding, the fixed cost according to the average utilization hours allocates the bidding cost in the day ahead market, this paper uses processing method of the [9] model about cost data of generators. In accordance with the corresponding calculation rules, the generator's strategic space is

\[ s = [0.8, 0.9, 1.1, 1.2, 1.22, 1.28, 1.29, 1.3, 1.31, 1.33, 1.35, 1.38, 1.4, 1.42, 1.44, 1.5, 1.6, 1.7, 1.8, 1.9] \]  

In order to simplify the processing, three generators in this paper use the same policy space, and the intelligent decision module of generators is the same. The intelligent algorithm factor is set as follows: k=2, r=0.09.

<table>
<thead>
<tr>
<th>generators</th>
<th>a/$(\text{MW.h})^{-1}$</th>
<th>b/$(\text{MW}^2\text{h})^{-1}$</th>
<th>$P_{\text{MAX}}$/MW</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.3</td>
<td>0.22</td>
<td>250</td>
</tr>
<tr>
<td>2</td>
<td>1.2</td>
<td>0.17</td>
<td>300</td>
</tr>
<tr>
<td>3</td>
<td>1.0</td>
<td>0.245</td>
<td>300</td>
</tr>
</tbody>
</table>

Figure 1. Topology of 5-bus electric system. Figure 2. Real time load of a certain period of 300 days.

The generator offers only one bid per day, and system load is a period of load during 300 days. Figure 2 is the load data for the selected 100 days period at this time, the average load value was 427MW, and the variance was 14.6 $(\text{MW})^2$. In the model, the load of this period is set up as random fluctuation, its purpose is to verify that the intelligent agent, which represents the generators, has the learning characteristics under the change of market supply and demand.

3.1 Multi-input Decision Factors

This module set 4 case to indicate its effectiveness of the intelligent agent model. Because generators use the same strategy space and the same intelligent decision-making module, the following analysis refer to the generator 2, although it has been simplified, but it will not affect the rationality of example.
Case 1: intelligent agent decision-making factors: $e=0.9$, $i=0$, $k=2$, $r=0.09$, which illustrate generators seeking risk, and only focusing on immediate gains.

By calculation, the average income of the generator will be 3976 dollars in 300 days. As can be seen from Figure 3, bidding behavior of generator 2 reaches a relatively stable state after a certain number of study rounds, then proceeding in a small range of fluctuation, this is because the generator bidding based on historical experience of learning have found a more mature strategy. The market reached a balance state, the load change is the only factor affecting generators return volatility at this time.

Figure 4 shows the choice of bidding strategy of generator 2 in each bidding process. As can be seen from Figure 4, the bidding behavior reaches a relatively stable state in about 150 rounds, and the stable strategy of generator 2 focus on the relatively high price factor, which is because the generator only focus on immediate benefits.

Case 2: intelligent agent decision-making factors: $e=0.9$, $i=3$, $k=2$, $r=0.09$; which illustrate generators seeking risk, meanwhile focusing on decision-making subordinate goals in a large proportion.

By calculation, the average income of the generator will be 2661 dollars in 300 days. As can be seen from Figure 5 and Figure 6, the bidding behavior of the generator has reached a relatively stable state after about 80 rounds of study. Comparative analysis of Case 1 and Case 2: when the risk parameter of $e$ phase are the same, the final strategy of generators of different subordinate decision factors is different, this is because the utility function of generator 2 in Case 2 is the immediate revenue and unit utilization rate, the final strategy in stable increase factor strategy is relatively low in order to get more power for reaching the expected unit utilization rate. Compared with other strategies, although the generation profit
is reduced, the relative utilization rate of the unit is relatively large, and the overall utility function is better than other strategies.

Case 3: intelligent agent decision factors: e=0.5, i=0, k=2, r=0.09; that is, the generator resisted the risk and focused only on immediate gains.

As can be seen from Figure 7 and Figure 8, the electricity supplier's bidding earnings are probably in the 20 round or so, reaching a relatively stable state. Figure 8 and Figure 4 comparative analysis: when the decision dependent target parameters I phase at the same time, the learning behavior of power suppliers with different risk preferences are different. Figure 8 generation companies in the bidding process soon reached a steady state; Figure 4 generation after a long time of learning to reach steady state. This is because changes in risk resist generators is not easy to accept external conditions, is sensitive to the fluctuation of income, get some profit will reach maturity, change and risk loving power suppliers receptive environment and returns, after a long time of learning will reach maturity.

Case 4: intelligent agent decision factors: e=0.5, i=3, k=2, r=0.09; that is, the generator resisted the risk, while only a larger proportion of attention to the unit subordinate goals.

Can be seen from Figure 9 and Figure 10, bidding revenue in about 20 rounds or so reached a relatively stable state, the average income of generators for $3638, this is because the power producers resist risk, learning some experience after the auction will choose a suboptimal strategy as a final strategy at the same time; see the final strategy in stable increase factor is relatively low, this is because the power producers pay more attention to making subordinate objectives.

Four case comparative analyses show that the model can simulate the dynamic
evolution behavior of power suppliers. The generators with different characteristics in the model can finally reach maturity through intelligent agents. The early market, bidding experience generator's rational and effective historical data are extremely rare, so power companies continue to try new price strategy to look forward to the return at the same time as the next price quotation accumulated learning experience, so the volatility is relatively large, with the exploration process and learning constantly, gradually accumulated power suppliers the historical data and experience, began to gradually reduce the probability of exploring new bidding and more on the use of the original bidding data and experience. Its subsequent bidding behavior tends to be rational and accurate, and this bidding process conforms to the characteristics of dynamic behavior evolution.

CONCLUSION

In this paper, a bidding simulation method of multi-input decision factors for power suppliers based on intelligent agent is proposed. This method can effectively simulate the bidding behavior in the day-ahead electricity market, which is conducive to rapid establishment of the early electric power market mechanism and rules.

Example analysis shows that:
1. The learning time of generators with different risk characteristics is different, and risk-seeking generators will have to study for a long time to achieve the final stability strategy.
2. The target of generators focusing on subordinate objectives is not only the instant revenue, generators will also take the utilization of units into account and bid at a low price in order to get more power for maximizing the overall utility function in the electricity market.
3. This model can simulate the dynamic evolution behavior of power suppliers. Through the study of the history bidding experience, bidding behaviors of generators eventually evolve to a stable state.

EXPECTATION

1. The rational decision-making of generation companies must consider many factors: the size of competition electricity, the installed capacity, supply and demand ratio, generating cost, fuel price trend, and marginal unit estimation. Only by taking more relevant factors into account, it can better simulate the bidding behavior of electricity market members.
2. How the ancillary service cost and fixed cost allocate in the day-ahead electricity market can continue to serve as the future direction of further study.

REFERENCES