Bidding Feature Extraction and Bidding Strategy Optimization of Generation Companies Based on Big Data Analysis and Machine Learning

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Abstract. This paper introduces a method for optimizing bidding strategy for generation companies based on big data analysis and machine learning. This paper first proposes a bidding feature extraction model based on canonical correlation analysis, then proposes a generation company bidding prediction model, and finally solves the bi-level optimization model for generation companies bidding strategy optimization based on the simulated annealing method. A case scenario based on actual spot market data in China is provided to illustrate the relevant method. This paper optimizes the bidding strategy for a large coal-fired unit, and the profit of the unit increased by 76.6% after optimization. It is found that the key point of the bidding strategy for large coal-fired units is to keep the price of the first section low to ensure that the unit can always be turned on.

Keywords: electricity market; bidding strategy; big data analyze; canonical correlation analysis; simulated annealing algorithm

1 Introduction

The State Council issued the "Several Opinions on Further Deepening the Electricity System Reform"[1] in March 2015, which clearly defined the establishment of an effective and competitive electricity market structure. In 2022, "Guiding Opinions on Accelerating the Construction of a National Unified Electricity Market System"[2] further clarified the acceleration of the construction of a national unified electricity market system. Since the reform of the electricity market, the construction of the electricity spot market in South (starting with Guangdong) has been at the forefront of China. With the increase in the renewable portfolio standard and the advancement of market-oriented reforms[3-4], generation companies gradually enter the electricity spot market and offer bid in the spot market. However, generation companies lack bidding experience in the spot market, which will not only bring huge losses to the companies, but also reduce the efficiency of the power system. Therefore, it is important to extract bidding feature and optimize bidding strategy.

Extensive research has been conducted in past work on market structure and efficient bidding strategies for generation companies. In such efforts, a number of different methods are used. An effective method is to establish a forecast model of the electricity market. Literature [5]

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introduces the use of artificial intelligence neural network to establish a short-term price prediction model. Literature [6] uses a time series analysis method based on dynamic regression and transfer functions to create a price prediction model. Another bidding strategy model is expressed as a bi-level optimization model[7-11]. The upper layer of the bi-level optimization model is to optimize the bidding strategy by generation companies based on spot market conditions and generation profitability. The lower layer is the system clearing layer where power grid dispatching department minimizes generation costs based on bidding price using security-constrained unit commitment (SCUC) and security-constrained economic dispatch (SCED)[12]. In this case, it is important to predict the bidding price of generation companies by extracting bidding feature. On the other hand, solving the bi-level optimization model is also a huge difficulty. With advances in big data computing and machine learning methods, many complex problems that are difficult to solve with traditional methods can be solved with intelligent algorithm[13-15]. This paper proposes a big data computing method based on canonical correlation analysis (CCA) to extract bidding feature, and applies the simulated annealing algorithm to solve the bi-level optimization model of bidding strategy optimization.

The subsequent chapters of this paper are arranged as follows. Chapter 2 establishes mathematical model for bidding feature extraction and bidding strategy optimization based on canonical correlation analysis and machine learning. Chapter 3 proposes a bidding strategy optimization solution method based on simulated annealing algorithm. Chapter 4 presents case studies validating the proposed method. Chapter 5 concludes the entire paper.

2 Formulation of bidding feature extraction and bidding strategy optimization

2.1 Formulation of bidding feature extraction

In the actual spot market bidding, generation companies will offer their bidding price by analyzing information about the forecast load and the market price of the previous day. These multi-dimensional data constitute the known data set X. The actual bidding prices offered by generation companies form the data set Y. In order to extract bidding feature, we first analyze the correlation between X and Y using canonical correlation analysis (CCA).

Assume that the data sets X and Y are two sets of multi-dimensional data sets, the number of samples is m, and they contain n_1 and n_2 features respectively. CCA will introduce two projection vectors a and b to project the data sets X, Y to one-dimensional data sets X', Y':

$$X' = a^T X, \quad Y' = b^T Y \tag{1}$$

The correlation coefficient ρ can be calculated for the projected vectors X' and Y'.

$$\rho(X,Y) = \frac{cov(X',Y')}{\sqrt{D(X')}\sqrt{D(Y')}} \tag{2}$$

Where D represents the variance of the data set and cov represents the covariance of two data sets. The correlation coefficient ρ will change with the change of the projection vector a and b. CCA requires finding the projection vector that maximizes the correlation coefficient. At this time, the correlation coefficient can represent the maximum correlation between the two multi-dimensional data sets, which can be described as:

$$\underbrace{\operatorname{argmax}}_{a,b} \frac{cov(X',Y')}{\sqrt{D(X')}\sqrt{D(Y')}} \tag{3}$$

The formula (3) can usually be solved by singular value decomposition (SVD) method. First the data sets X, Y can be normalized so that its mean is 0 and its variance is 1, and then it can be deduced that:

$$cov(X',Y') = a^T E(XY^T) b \tag{4}$$

$$D(X') = a^T E(XX^T) a \tag{5}$$

$$D(Y') = b^T E(YY^T) b \tag{6}$$

$$E(XX^T) = cov(X,X) \tag{7}$$

$$E(YY^T) = cov(Y,Y) \tag{8}$$

$$E(XY^T) = cov(X,Y) \tag{9}$$

$$E(YX^T) = cov(Y,X) \tag{10}$$

Record the covariance matrices $cov(X,Y)$, $cov(X,X)$, $cov(Y,Y)$ as S_{xy}, S_{xx}, S_{yy} respectively, and bring formulas (4)-(10) into formulas (3) to transform the objective function into:

$$\underbrace{\operatorname{argmax}}_{a,b} \frac{a^T S_{XY} b}{\sqrt{a^T S_{XX} a}\sqrt{b^T S_{YY} b}} \tag{11}$$

In formula (11), both the numerator and denominator contain a, b, so the correlation coefficient remains unchanged when a and b are enlarged or reduced proportionally. Therefore, formula (11) can be solved by fixing the denominator and to maximize the numerator, which is converted into an optimization problem:

$$\begin{gathered} \underbrace{\operatorname{argmax}}_{a,b} \quad a^T S_{XY} b \\ s.t. \begin{cases} a^T S_{XX} a = 1 \\ b^T S_{YY} b = 1 \end{cases} \end{gathered} \tag{12}$$

Let $a = S_{XX}^{-1/2} u, b = S_{YY}^{-1/2} v$, it can be deduced that:

$$a^T S_{XX} a = u^T u \tag{13}$$

$$b^T S_{YY} b = v^T v \tag{14}$$

$$a^T S_{XY} b = u^T S_{XX}^{-1/2} S_{XY} S_{YY}^{-1/2} v \tag{15}$$

Let $M = S_{XX}^{-1/2} S_{XY} S_{YY}^{-1/2}$, according to SVD, it can be deduced that:

$$M = U \Sigma V^T \tag{16}$$

Bring formulas (13)-(16) into (12), it can be deduced that:

$$\begin{gathered} \underbrace{\operatorname{argmax}}_{u,v} \quad (u^T U)\Sigma(V^T v) \\ s.t. \begin{cases} u^T u = 1 \\ v^T v = 1 \end{cases} \end{gathered} \tag{17}$$

According to formula (17), it can be seen that the maximum correlation coefficient is the maximum singular value of the matrix, and the optimal solution is the eigenvector corresponding to the maximum singular value. The maximum correlation coefficient and projection vector in the original problem (3) can be solved by using SVD.

After the CCA analysis, the one-dimensional projection value X' of the reference information can be calculated by the projection vector, which represents the typical feature of the multi-dimensional data sets. When the maximum correlation coefficient is greater than the threshold, it can be considered that the bidding strategy of the generation company is related to the typical feature, which can usually be fitted using a multi-segment linear fitting method.

Suppose that the number of segments of the piecewise linear function is M, the dividing point of the function is g_m, the slope of each linear function is k_m, and the intercept is b_m. The samples recorded in the m segment are recorded as set $\mathcal{A}_m$, then the piecewise linear fitting model can be transformed into an optimization model with the minimum mean square error (MSE) of all sample points as the objective function:

$$\begin{gathered} min \quad \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \\ s.t. \begin{cases} k_m g_m + b_m = k_{m+1} g_m + b_{m+1} & m = 1, 2, ..., M-1 \\ \underset{x_i \in \mathcal{A}_m}{\hat{y}_i} \;\; = k_m x_i + b_m \end{cases} \end{gathered} \tag{18}$$

The key issue of the multi-segment linear fitting model is to determine the number of segments and the corresponding function dividing points. After the number of segments and dividing points are determined, the optimization model (18) is a convex optimization model and can be solved directly by commercial solver such as Gurobi.

2.2 Formulation of bidding strategy optimization

After extracting bidding feature by CCA and multi-segment linear fitting model, we can then forecast bidding price from other competitor companies and optimize target unit bidding strategy. The lower layer contains security-constrained unit commitment (SCUC) and security-constrained economic dispatch (SCED). SCUC ignoring network constrains is formulated as follows:

$$\min \sum_{i=1}^{N} \sum_{t=1}^{T} [B_{i,t}(P_{i,t}) + C_{i,t}^{U}] \tag{19}$$

Subject to:

$$\sum_{i=1}^{N} P_{i,t} = D_t \tag{20}$$

$$\alpha_{i,t} P_{i,t}^{\min} \le P_{i,t} \le \alpha_{i,t} P_{i,t}^{\max} \tag{21}$$

$$\begin{gathered} P_{i,t} - P_{i,t-1} \le \Delta P_i^U \alpha_{i,t-1} + \\ P_{i,t}^{\min}(\alpha_{i,t} - \alpha_{i,t-1}) + P_{i,t}^{\max}(1 - \alpha_{i,t}) \end{gathered} \tag{22}$$

$$\begin{gathered} P_{i,t-1} - P_{i,t} \le \Delta P_i^D \alpha_{i,t} - \\ P_{i,t}^{\min}(\alpha_{i,t} - \alpha_{i,t-1}) + P_{i,t}^{\max}(1 - \alpha_{i,t-1}) \end{gathered} \tag{23}$$

$$T_{i,t}^{D} - (\alpha_{i,t} - \alpha_{i,t-1}) T_D \ge 0 \tag{24}$$

$$T_{i,t}^{U} - (\alpha_{i,t-1} - \alpha_{i,t}) T_U \ge 0 \tag{25}$$

$$T_{i,t}^{U} = \sum_{k=t-T_U}^{t-1} \alpha_{i,k} \tag{26}$$

$$T_{i,t}^{D} = \sum_{k=t-T_D}^{t-1} (1 - \alpha_{i,k}) \tag{27}$$

$P_{i,t}$ denotes the generation power of unit i in period t, and D_t denotes the load in period t. Formulation (20) expresses that generating power is equal to load power in each period and formulation (21) limits the generated power between the maximum power and the minimum power where $\alpha_{i,t}$ denotes the binary status of each unit. Formulation (22)-(23) limit the unit ramp constraints where ΔP_i^U and ΔP_i^D denote the maximum ramp up power and the maximum ramp down power respectively. Formulation (24)-(27) limit the minimum startup time T_U and the minimum downtime T_D. The objective according to formulation (19) is to minimize the total generation cost, where $B_{i,t}(P_{i,t})$ denotes the bidding price offered by generator companies and $C_{i,t}^{U}$ denotes the startup costs.

SCUC can obtain the binary status $\alpha_{i,t}$, and after fixing $\alpha_{i,t}$, the formulation (19)-(27) can represent the SCED model. When network constrains are ignored, the Lagrange multiplier of the load balancing constraint (20) can represent the spot market price at each period.

The upper layer is the bidding strategy optimization layer for each generator companies. Each unit calculates its profit in the spot market based on the market price π_t and unit output

$P_{i,t}^{cleared}$ obtained from the lower layer. The lower layer objective function is formulated as follows:

$$\max \sum_{t=1}^{T}[P_{i,t}^{cleared}\pi_t - C_{i,t}(P_{i,t}^{cleared}) + C_{i,t}^{U,cleared}] \tag{28}$$

$C_{i,t}$ denotes the operating cost of the unit and $C_{i,t}^{U,cleared}$ denotes the actual startup cost of the unit. Unit bidding price $B_{i,t}$ is usually a five-segment bidding in China, which is formulated as follows:

$$0 \le B_{i,t}^{j} \le B_{i,t}^{j+1} \le B_{i,t}^{max} \quad j=1,2,3,4 \tag{29}$$

$$\underline{S}_{i,t}^{1} = P_{i,t}^{\min} \tag{30}$$

$$\bar{S}_{i,t}^{5} = P_{i,t}^{max} \tag{31}$$

$$\bar{S}_{i,t}^{j} = \underline{S}_{i,t}^{j+1} \tag{32}$$

$B_{i,t}^{j}$ denotes the j segment bidding price, which is constrained by formulation (29), and $B_{i,t}^{max}$ is the maximum bidding price in the spot market. $\bar{S}_{i,t}^{j}$ and $\underline{S}_{i,t}^{j}$ denote the cap capacity and the floor capacity in the j segment. Formulation (30)-(32) restrict the bidding capacity of each segment to be connected end to end.

3 A bidding strategy optimization solution method based on simulated annealing algorithm

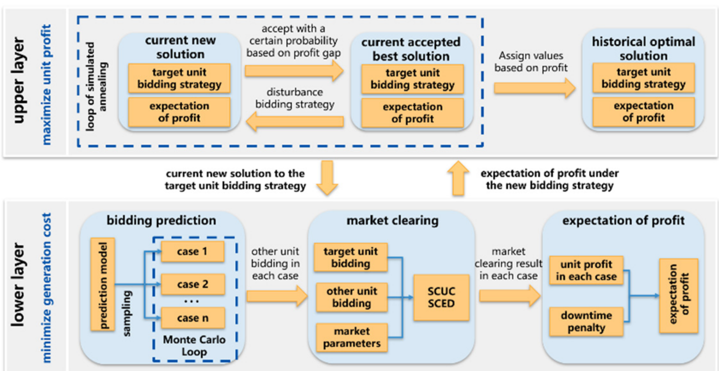

Fig. 1. The framework of simulated annealing algorithm.

One solution algorithm for the bi-level optimization model is mathematical programming with equilibrium constrains (MPEC), but MPEC cannot consider the binary variables of thermal units in the lower layer market clearing model, which will bring great errors to the optimization of the thermal units bidding strategy. This paper proposes an intelligent optimization algorithm based on simulated annealing algorithm to solve the bi-level optimization model. The algorithm framework is shown in Figure 1.

The upper layer simulated annealing algorithm stores three groups of bidding strategies and their corresponding profit. According to the principle of simulated annealing algorithm, the current accepted best solution is disturbance to obtain current new bidding strategy, which will then be entered into the market clearing layer to obtain the corresponding profit. If the new bidding strategy is better than current accepted bidding strategy, then the new bidding strategy will replace the current accepted bidding strategy, otherwise the new bidding strategy will be accepted with a certain probability whose expression is as follows:

$$p = exp\left[\frac{-(W_{current} - W_{new})}{\beta \times T}\right] \tag{33}$$

$W_{current}$ and W_{new} denote the profit of the new solution and current accepted solution respectively, T denotes the temperature of the annealing algorithm at current time, and β is a constant parameter whose purpose is to control the order of magnitude of the profit difference. The higher the profit corresponding to the current bidding strategy, the greater the probability of it being accepted, and as the temperature T gradually decreases, the probability of the algorithm accepting poorer bidding strategy will also become lower, which ensures that the algorithm has a stronger desire to explore at the beginning and tends to converge at the end. Since the current accepted bidding strategy may be replaced by poorer bidding strategy, the algorithm will also store the historical optimal solutions as the optimization results of the final bidding strategy.

The lower layer will generate a set of bidding scenarios based on bidding features extracted from other units, and then calculate the profit of the target unit under each set of scenarios through the spot market clearing procedure, and return the expectation of profit to the upper layer unit company.

4 Case study

In order to better understand the proposed measures, we use the actual bidding data during a spot market in Province X in China for example analysis.

4.1 Bidding Feature Extraction

In a certain month, the daily load and the actual bidding data of a certain unit A are shown in Figure 2. It can be seen from Figure 2 that the relationship between daily load and the actual bidding price is vague. Therefore, it is necessary to use CCA to conduct big data analysis on reference information and historical bidding to extract the largest correlation. The maximum, average, and minimum values of the load, electricity price, predicted load on the operating day and the day before are used as the data set X, and the average value of the actual bidding price is used as the data set Y. Conducting a typical correlation analysis on X and Y, the relationship between the reference information projection values and the average bidding price of all units can be divided into four cases, as shown in Figure 3. When the correlation coefficient is less than 0.7, there is no obvious change trend in the average bidding price as the projection value changes, and the correlation is very small. When the correlation is greater than 0.7, there are three typical relationships between the projection value and the average price: clustering into two categories, linear and piecewise linear. These three typical relationships can be fitted using the three-segment linear fitting method. After determining the number of segments is three, the dividing points and the segmented function can be found by exhaustive method, with the goal of minimizing the MSE in the formula (18). The fitting results of three typical situations are shown in Figure 3.

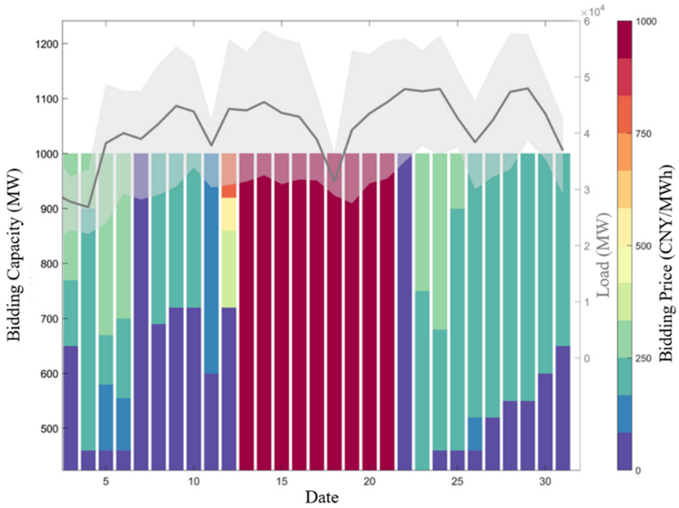

Fig. 2. The daily load and the actual bidding data of the unit A in a certain month.

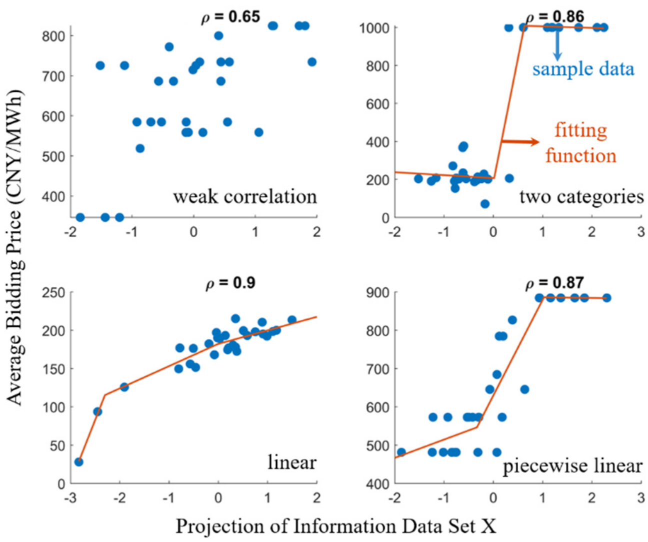

Fig. 3. Four typical relationships and piecewise linear fitting function

K-means cluster analysis is performed on the historical bidding of each generating unit, and the bidding strategies are clustered into three categories: low-price strategy, medium-price strategy, and high-price strategy. The clustering situation of the unit A is shown in Figure 4. It can be seen that the low-price strategy is not much different from the mid-price strategy, while the high-price strategy is a bidding of 1000 CNY/MW for the entire segment. According to the clustering results, in the historical bidding data, the probability of this unit adopting the low-price strategy, the medium -price strategy, and the high-price strategy are 25.8%, 45.2%, and 29.0% respectively. If the reference information of the unit is not relevant to the actual bidding, the unit bidding will be sampled according to the historical bidding strategy probability.

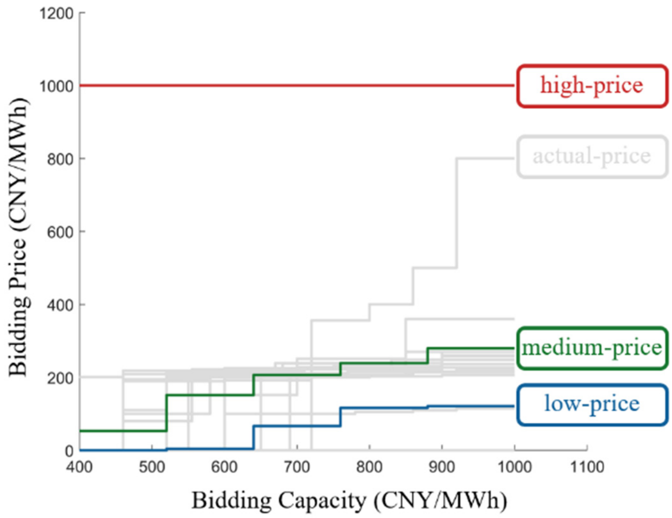

Fig. 4. Clustering result of historical bidding price of the unit A

4.2 Bidding strategy optimization

In this section, bidding strategy of unit A will be optimized by simulated annealing algorithm. The technical parameters of unit A are shown in Table 1. We optimize the bidding strategy of unit A for the 31 operating days of the month based on the previous bidding strategy optimization model. Table 2 summarizes the values of total unit profit, unit profit per MWh, total power generation and total startup time before and after optimization, which can generally reflect the optimization effect after optimizing the bidding strategy.

Table 1. The technical parameters of unit A.

minimum output (MW)	400
maximum output (MW)	1000
marginal cost (CNY/MWh)	220.71
minimum start up time (h)	120
minimum shut down time (h)	120
maximum ramp up rate (MW/h)	540
maximum ramp down rate (MW/h)	540
startup cost (CNY)	360000

Table 2. Comparison of data before and after optimization.

	before optimization	after optimization	growth percentage
sum profit (million CNY)	15.99	28.24	76.57%
profit per MWh (CNY/MWh)	45.56	48.01	5.37%
power generation (GWh)	351	588	67.57%
startup time (period)	1632	2966	81.74%

The total profit of the unit before optimization is 15.99 million CNY, which is above the average level. After the optimization of the bidding strategy, the total profit reaches 28.24 million CNY, an increase of 76.57%. Although the unit's profit per MWh only increases by 5.37%, its total power generation increases by 67.57%, and its total startup time increases by 81.74%, indicating that this large coal-fired unit can significantly increase its profit by increasing the startup time and power generation. Since the minimum shutdown time of large coal-fired units is long, once the unit is shut down, it will lose the opportunity to generate when market price is high in the future. Therefore, large coal-fired units need to lower the first-segment bidding price to ensure that the unit can always be turned on.

5 Conclusion

In this paper, we have discussed a set of methods for extracting the bidding feature of generation company and optimizing the bidding strategy. First, we calculate the maximum correlation coefficient between the bidding reference information and the bidding price through CCA algorithm, and obtain the projection vector of the bidding reference information. Then, we use a piecewise linear function to fit the unit's bidding price, and combined with the K-means clustering algorithm, we predict the unit's bidding strategy in the future operating days. Finally, we proposed a simulated annealing algorithm to solve the bi-level optimization model of generation companies' bidding strategy and obtain the optimal bidding strategy for the target unit. Our research found that for large coal-fired units, appropriately reducing the first-section bidding price to ensure that the unit is started up is the key to the bidding strategy.

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