Bidding strategy of thermal power compound differential evolution game under the market mechanism of peak regulation auxiliary service

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Abstract
As the main provider of peak regulation auxiliary services, thermal power units are particularly important to ensure their revenue in an uncertain environment. To obtain the optimal bidding strategy for thermal power units, a thermal power peak regulation bidding model based on the Northeast Power Grid’s auxiliary service market bidding mechanism is established. Secondly, the evolutionary game theory is introduced into the bidding strategy of thermal power units. Meanwhile, in order to solve the multi-party game problem, a compound differential evolution game algorithm is constructed to solve the two-tiers bidding. Finally, based on the actual operating data of a typical day, the efficiency of the compound differential evolution game algorithm bidding strategy is verified, and the bidding strategy of thermal power units in different situations is discussed. The results show that when all units participate in peak regulation, the first-tier quotation is an optimal strategy at 0.19 yuan kWh$^{-1}$ and below, and the second-tier quotation is distributed between 0.6–0.8 yuan kWh$^{-1}$. When only some units are involved in peak regulation, the first-tier quotation of thermal power units adopts a high price strategy, mostly at 0.3 yuan kWh$^{-1}$, and the second-tier quotation is still based on a high price strategy.

1 | INTRODUCTION
In recent years, in order to solve the energy supply crisis and environmental pollution problems, China has vigorously promoted the development of renewable energy, and the installed capacity of wind power and photovoltaics has achieved rapid growth. In 2010, the cumulative installed capacity of wind power ranked first in the world [1]. As of the end of June 2020, the cumulative grid-connected capacity of wind power reached 216.75 GW. With a large number of grid-connected renewable energy sources, the problem of stable operation of the grid has become increasingly prominent, the consumption of renewable energy has encountered bottlenecks, and the phenomenon of wind curtailment has become more serious. In order to promote the consumption of clean energy such as wind power and nuclear power, and to ensure the safety, stability and economic operation of the power system [2], the Northeast Energy Regulatory Bureau issued a notice of “Northeast Electric Power Auxiliary Service Market Operation Rules (Trial)” in November 2016. Combining two years of market operation experience, the “Northeast Electric Power Auxiliary Service Market Operation Rules (Interim)” notice was issued in December 2018, and the market simulation operation was launched on 1 January 2019. In 2016, the wind curtailment rates in Liaoning, Jilin and Heilongjiang were as high as 13%, 30% and 19%, and in 2019 they dropped to 0.4%, 2.5% and 1.3%, respectively. In the first half of 2020, the curtailment of wind power in Northeast China decreased by 62.48% year-on-year, and the auxiliary service market achieved good results. At the same time, as the main provider of peak regulation auxiliary services, thermal power units are facing the problem of reduced power demand and large demand fluctuations [3]. How to obtain reasonable peak regulation compensation in an uncertain environment [4] and strive for the maximum benefit is a long-term consideration in the bidding strategy of thermal power units.
Regarding the bidding strategy of the electricity market, scholars at home and abroad have conducted many studies. In real-time market bidding, He and Zhang [5] used system dynamics simulation to predict dynamic real-time electricity price levels. Jia et al. [6] used deep reinforcement learning methods to dynamically learn incomplete information in the electricity market and predict the strategies of competitors. Wang et al. [7] combined reinforcement learning algorithms with system dynamics simulation, and obtained information and adapted to the environment through continuous interaction with the environment. Some scholars have proposed a solvable semi-qualitative procedure [8] to improve the reliability of real-time bidding. In order to improve the efficiency of bidding, scholars have proposed linear or second bidding [9], multi-level bidding [10], two-stage bidding strategy [11] and so on. Nazemi et al. [12] pointed out that in an on-demand auction, the marginal cost is no longer applicable and the Lerner index can be used for competitive bidding. Taking into account the bilateral bidding behaviour in the market, Moutinho et al. [13] combined cointegration analysis and causality analysis with the extended Cournot model, and Saéz-Gallego et al. [14] considered price-sensitive electricity consumer groups. When a large number of renewable energy sources are connected to the grid, De et al. [15] used an improved Benders decomposition algorithm to solve the model in order to solve the high-dimensional NP problem of the two-stage stochastic optimization model. Schaefer P et al. [16] believe that the balance between the ancillary service market and the spot market should be considered. This paper focuses on the peak regulation auxiliary service market for research, but the method to solve the problem of renewable energy consumption is not limited to this. Some scholars have proposed that the consumption of renewable energy can be improved through methods such as incentive compensation measures [17], joint dispatch [18], virtual power plants [19] and multi-micro grid systems [20].

For the solution of bidding problems, game theory is widely used, including evolutionary games [21], non-cooperative games [22], Nash equilibrium [23,24] etc. The bidding problem in the power auxiliary service market studied in this paper pursues an “evolutionary stable strategy,” so the evolutionary game method is selected for research. The evolutionary game method can be used not only in the bidding game in the electricity market, but also in the competition between online and offline retailers [25], and the two-level evolutionary game between enterprises and between enterprises and customers [26]. In addition, the game objects are not limited to two types. Shu et al. [27] established an evolutionary game model of three leadership structures in the supply chain. Liu et al. [28] constructed a game model among agricultural enterprises, governments, and farmers. Liu et al. [29] established a multi-agent evolutionary game model including carbon fibre industry manufacturing companies, application companies and governments.

By analysing domestic and foreign articles on evolutionary games, it can be found that most scholars study two-party evolutionary games or three-party evolutionary games. When only the evolutionary game model is used, there are rarely more than three-party games. In this paper, when studying the game bidding between multiple thermal power units, a single evolutionary game is more difficult to solve. Combining the research experience of domestic and foreign scholars, the differential evolution algorithm [30] can be introduced to solve the problem. Evolutionary game theory has been gradually applied to analyse and predict network attacks [31] and defence [32] to maintain network security. It can also be used to solve multi-objective problems [33], and the effectiveness of the algorithm can be guaranteed. In addition, there are few literature studies on the bidding strategy of thermal power units in the power auxiliary service market, and the literature on the operation mechanism of the latest auxiliary service market is even rarer. Therefore, this paper takes the power auxiliary service market in Northeast China as an example, establishes a thermal power peak regulation bidding model, and applies the compound differential evolution game algorithm (CDEG) to solve the two-level bidding. In addition, on the basis of empirical analysis, the bidding strategies of thermal power units in different situations are discussed. This research not only provides a theoretical basis for the bidding strategy of thermal power units in the auxiliary service market, but also reveals the main reasons that affect the bidding strategy.

2 BIDDING MODEL OF THERMAL POWER PEAK REGULATION

2.1 Regulation auxiliary service market bidding mechanism

Due to the inconsistent development progress of the peak regulation auxiliary service market in various regions, the market operation mechanism is also different. This article takes the earlier developed Northeast region as an example to study its real-time deep peak regulation auxiliary service market bidding mechanism (hereinafter referred to as the “Northeast Mechanism”) [34].

In the Northeast mechanism, power peak regulation auxiliary services are divided into basic obligation peak regulation auxiliary services and paid peak regulation auxiliary services. Real-time in-depth peak regulation transaction is a kind of paid peak regulation auxiliary service, which refers to the transaction of providing auxiliary service when the power generating unit of a thermal power plant reduces the output within the day so that the average load rate of the thermal power plant unit is less than or equal to the paid peak regulation benchmark. The paid peak regulation benchmarks of thermal power plants under the Northeast mechanism are shown in Table 1.

The average load rate refers to the average load rate of start-up units in the unit statistical period of thermal power plant, which is counted in 15 min. The calculation method is as follows:

$$\lambda_{i,t} = \frac{P_{i,t}}{C_{i}} \times 100\%.$$  (1)
TABLE 1  Paid peak regulation benchmarks for thermal power plants under the Northeast mechanism

| Period       | Type of thermal power plant | Paid peak regulation compensation benchmark |
|--------------|----------------------------|-----------------------------------------------|
| Non-heating  | Pure condensate thermal power unit | Load rate 50% |
|              | Thermal power unit          | Load rate 48% |
| Heating      | Pure condensate thermal power unit | Load rate 48% |
|              | Thermal power unit          | Load rate 50% |

Among them, \( \lambda_{i,t} \) is the average load rate of unit \( i \) in the \( t \)-th statistical period; \( P_{i,t} \) is the average output of unit \( i \) in the \( t \)-th statistical period; \( C_i \) is the installed capacity of unit \( i \).

The real-time in-depth peak regulation transaction adopts a “stepped” quotation method and price mechanism. Power generation companies have two floating quotations in different periods. The specific tiers and the upper and lower limits of the quotation are shown in Table 2.

When the real-time deep peak regulation transaction is called within a day, the power dispatching organization shall give priority to the use of free auxiliary peak regulation services according to the actual needs of grid operation. If the free peak regulation auxiliary service can’t meet the demand of peak regulation, it will be called from low to high according to the results of the day ahead bidding. The compensation cost of real-time deep peak regulation transaction is calculated according to the paid peak regulation electricity quantity of each tier and the clearing price of the corresponding auxiliary service market, and the power generation cost is calculated according to the total generating capacity and the benchmark on-grid price of thermal power.

2.2  Thermal power generation cost function

The power generation costs of thermal power units mainly include fixed costs and variable costs. Fixed costs do not change with the amount of power generation, and mainly include fixed asset depreciation, maintenance costs, wages and benefits and other expenses. Variable costs vary with the change in power generation, and mainly include fuel, water and material costs.

Among variable costs, fuel costs account for 80–90% of total costs, so the cost of thermal power generation is greatly affected by coal prices. This article assumes that the price of coal is stable for a certain period of time, and a second-order polynomial can be used to simulate the cost of power generation (the cost of power generation per hour):

\[
C(P_{i,t}) = a + bP_{i,t} + cP_{i,t}^2.
\]  

(2)

Among them, \( a, b, c \) is the fuel coefficient, which is related to the installed capacity of the thermal power plant; \( P_{i,t} \) is the active power of the thermal power unit \( i \) in the \( t \)-th statistical cycle.

The marginal cost of thermal power generation can be expressed as:

\[
MC = \frac{dC(P_{i,t})}{dP_{i,t}} = b + 2cP_{i,t}.
\]  

(3)

The average cost of thermal power generation is:

\[
AC = \frac{C(P_{i,t})}{P_{i,t}} = \frac{a}{P_{i,t}} + b + cP_{i,t}.
\]  

(4)

When \( MC = AC \), the economic load point is reached, as shown in Figure 1.

FIGURE 1  The average cost and marginal cost curve of thermal power generation

TABLE 2  Quotation mechanism rules under the Northeast mechanism

| Period       | Quotation tier | Type of thermal power plant | Thermal power plant load rate | Lower quotation limit (yuan kWh\(^{-1}\)) | Quotation ceiling (yuan kWh\(^{-1}\)) |
|--------------|---------------|----------------------------|-------------------------------|------------------------------------------|-------------------------------------|
| Non-heating  | First-tier    | Pure condensate thermal power unit | 40% < load factor ≤ 50% | 0 | 0.4 |
|              |               | Thermal power unit          | 40% < load factor ≤ 48% | 0.4 | 1 |
|              | Second-tier   | All thermal power units     | Load factor ≤ 40% | 0.4 | 1 |
| Heating      | First-tier    | Pure condensate thermal power unit | 40% < load factor ≤ 48% | 0 | 0.4 |
|              |               | Thermal power unit          | 40% < load factor ≤ 50% | 0.4 | 1 |
|              | Second-tier   | All thermal power units     | Load factor ≤ 40% | 0.4 | 1 |
2.3 Bidding model of thermal power auxiliary service market

The goal of each thermal power unit is to maximize its own profit. When the trading day is divided into \( T \) periods, and \( Z_i \) represents the profit of the thermal power unit, the competitive power generation model of thermal power is:

\[
\max : Z_i = \frac{24}{T} \sum_{t=1}^{T} v_t \times p_{i,t}^{\text{bid}} + \frac{24}{T} \sum_{t=1}^{T} a_t \times p_{i,t}^{\text{paid}} - \frac{24}{T} \sum_{t=1}^{T} C_i(p_{i,t}).
\]  

(5)

Among them, \( v_t \) represents the benchmark on-grid electricity price of the thermal power unit in the period \( t \) (a fixed constant within a certain period of time); \( p_{i,t}^{\text{bid}} \) represents the bid-winning power of thermal power unit \( i \) in period \( t \); \( a_t \) represents the paid peak regulation clearing price of period \( t \); \( p_{i,t}^{\text{paid}} \) represents the paid peak power capacity of thermal power unit \( i \) in period \( t \).

The constraints of the model are as follows:

1) System power balance constraints.

\[
\sum_{i=1}^{K} p_{i,t}^{\text{bid}} + p_{i,t}^{R} = p_{i,t}^{D}.
\]

(6)

Among them, \( K \) is the number of thermal power units participating in the auxiliary peak regulation bidding; \( p_{i,t}^{R} \) is the total output of renewable energy in period \( t \); and \( p_{i,t}^{D} \) is the system load demand in period \( t \).

2) Output constraints of thermal power units.

\[
\begin{cases}
P_{i,t}^{\text{min}} \leq p_{i,t}^{\text{bid}} \leq P_{i,t}^{\text{max}} \\
p_{i,t}^{\text{bid}} - p_{i,t-1}^{\text{bid}} \leq P_{i,t}^{\text{r}} \times \frac{24}{T}.
\end{cases}
\]

(7)

Among them, \( P_{i,t}^{\text{min}} \) represents the minimum technical output of the thermal power unit; \( P_{i,t}^{\text{max}} \) represents the maximum technical output of the thermal power unit \( i \); \( P_{i,t}^{\text{r}} \) is the maximum climbing rate per hour of the thermal power unit \( i \).

3 THERMAL POWER COMPOUND DIFFERENTIAL EVOLUTION GAME ALGORITHM

3.1 Introduction to evolutionary game principles

The evolutionary game improves the classical game, and at the same time introduces the dynamic evolution theory, which makes the evolutionary game theory more practical. The core content of the researcher is to solve the “evolutionary stability strategy” [35]. The analysis shows that the game of thermal power plants has two characteristics: “bounded rationality” and “learning adjustment strategy.” The classical game model requires stricter requirements and requires the research object to have completely rational characteristics. However, in practice, the goal of enterprise management for thermal power plants during the game is to maximize the profits of the power plant. In the peak regulation game, thermal power plants are not completely rational. At this time, the main goal of business operations is to maximize their own economic benefits after assuming the corresponding social responsibilities. Thermal power units need to unconditionally obey the demand for peak regulation. The second feature is mainly reflected in the fact that each thermal power plant only decides whether to win the bid the next day. The thermal power plants are a long-term game process. Each power plant's strategy selection in each game must consider the external environment and the strategies selected by the competitors in the previous rounds of the game so that their strategies can obtain greater benefits in this round of the game.

This article assumes that the peak regulation game of thermal power plants is a non-cooperative game. The power plant formulates its strategy based on the output range of its own units and the strategies of other power plants in the area. Due to the difference between power plant unit models, the revenue of each power plant is different. When the quotation is the same, the operating costs of the units are different, and the income of each power plant will also be different, but the thermal power manufacturers are all enterprises, and they will maximize their profits as their business goals. Driven by profits, the power plants in the region will inevitably adjust each round of game strategy to make their profits increase or remain unchanged. Therefore, this article establishes the following game evolution process:

Supposing that there are \( K \) game groups, each group \( k (k = 1, 2, \ldots , K) \) has \( N \) kinds of strategies distinguished by subscript labels \( i = 1, 2, \ldots , N \). The \( N \)-dimensional vector corresponding to the population \( k \):

\[
\vec{s}^k = \left\{ x^k = (x_1, \ldots , x_N)|x_i \geq 0, \sum x_i = 1 \right\}.
\]

(8)

Any vector \( \vec{r}^k \) with this form represents the mixed strategy of any individual of the population \( k \), and the vector \( \vec{r}^k \) with this form represents the proportion of individuals in the population \( k \) that adopt each strategy in the population. Therefore, the Cartesian product \( S = S^1 \times \cdots \times S^K \) of \( K \) such \( N \)-dimensional spaces represents both the policy set and the state space.

Evolutionary game theory uses the fitness of the individual in each population to describe the game strategy. The fitness of the individual is a function of the individual’s strategy and the current state. The fitness function is a mapping

\[
f^k : S^k \times S \rightarrow R.
\]

(9)

where \( k = 1, 2, \ldots , K \). It can also be written as \( f^k(\vec{r}, s) = \left( f^1(\vec{r}, s), \ldots , f^K(\vec{r}, s) \right) \). And suppose that the function is a linear function of the first variable (own strategy) \( \vec{k}^k \in S^k \), and \( s \in S \).
is continuously differentiable for the second variable (population state).

The basic model of evolutionary games is a dynamic structure that describes how state $S$ evolves over time. For the case of continuous time, the derivative of state with respect to time is defined as: $\dot{S} = (\dot{S}_1, \ldots, \dot{S}_N)$, where

$$\dot{S}^k = \left( \frac{dS_1}{dt}, \ldots, \frac{dS_N}{dt} \right), \quad (k = 1, \ldots, K).$$

Therefore, the evolutionary game process can be expressed by a certain function $F : S \to \mathbb{R}^N$, namely $S = F(s)$. This is a differential equation system. Given initial conditions $(0) \in S$, the curve corresponding $S = F(s)$ to the solution of the system depicts the evolution of all populations. If a certain solution of the system is known to be stable according to stability analysis, the solution is an evolutionary stable strategy.

### 3.2 Bidding strategy of thermal power evolution game

In the ancillary service market, thermal power plants participating in the bidding game will set multiple bidding strategies according to their actual conditions, and each bidding strategy consists of bidding electricity and bidding electricity prices. When studying this type of problem, starting from the simplest scenario, construct a $2 \times 2$ asymmetric evolutionary game model. The two types of thermal power plants ($k = 1$; $k = 2$) respectively represent the installed capacity of two types of thermal power plants. The power plant quotation strategy in the regulation system is mainly high price and low price. For the convenience of the following description, define strategy 1 as the power plant reporting high price online ($i = 1$), and define strategy 2 as the power plant reporting base price online ($i = 2$). The selection of the quotation strategy of power plants is relatively random when bidding online, and the quotation strategy is different, and the income is different.

Assuming that $C_{ij}$ represents the paid peak regulation income of thermal power plants after providing corresponding peak regulation and other services, then $C_{1j}$ and $C_{2j}$ respectively represent the peak regulation auxiliary service income of the first and second types of thermal power plants, and there is

$$C_{1j} \geq 0, C_{2j} \geq 0, \text{ and } (\alpha_{1j}, \alpha_{2j}) \text{ represent the power generation revenue when the first and second thermal power plants do not participate in auxiliary peak regulation in the four bidding situations. The specific revenue of the two thermal power plants under each quotation strategy is shown in Table 3.}

Let $p$ denotes the proportion of thermal power plants using strategy 1 in the first type of power generation company, and $q$ denotes the proportion of thermal power plants using strategy 1 in the second type of thermal power plants. Then the state,

$$s = \{(p_1, p_2, (1-p)q, 1-q))\}. \quad (11)$$

**Table 3** Thermal power plants bidding game considering peak regulation ancillary services income

| Coal plant classification/ quotation strategy | $k = 2, i = 1$ | $k = 2, i = 2$ |
|---------------------------------------------|-----------------|-----------------|
| $k = 1, i = 1$                             | $a_{11} + C_{1j}$, $a_{12} + C_{1j}$ | $a_{12} + C_{1j}$, $a_{22} + C_{2j}$ |
| $k = 1, i = 2$                             | $a_{21} + C_{1j}$, $a_{22} + C_{2j}$ | $a_{22} + C_{2j}$ |

can be described by a point $(p, q)$ in the $[0, 1] \times [0, 1]$ area, and $(p, q)$ reflects the dynamics of the evolution of the bidding system of power generation enterprises. $r^1 = (1, 0)$ indicates that the probability of the power plant choosing the high price strategy is 100%, and $r^2 = (0, 1)$ indicates that the power plant choosing the strategy of reporting the base price is 100%. Then for the first type of power plant: the adaptability of strategy 1 is chosen as in the following Equation (8):

$$f^1(r^i, s) = q(a_{11} + C_{1j}) + (1 - q)(a_{12} + C_{1j}). \quad (12)$$

The fitness of selecting strategy 2 is shown in Equation (9).

$$f^1(r^2, s) = q(a_{21} + C_{2j}) + (1 - q)(a_{22} + C_{2j}). \quad (13)$$

Equation (10) indicates the average fitness:

$$f^1(p, q) = pf^1(r^1, s) + (1 - p)f^1(r^2, s). \quad (14)$$

Similarly, we can express fitness of the second group of thermal power plants selecting strategy 1, as shown in Equation (11).

$$f^2(r^1, s) = p(r_{11} + C_{2j}) + (1 - p)(r_{12} + C_{2j}). \quad (15)$$

The fitness of strategy 2 is shown in Equation (12),

$$f^2(r^2, s) = p(r_{21} + C_{2j}) + (1 - p)(r_{22} + C_{2j}). \quad (16)$$

Its average fitness is shown in Equation (13).

$$f^2(p, q) = qf^2(r^1, s) + (1 - q)f^2(r^2, s). \quad (17)$$

As long as the fitness of a strategy in the group is higher than the average fitness of the group, the strategy will develop. Then the adjustment equation of the first group of thermal power plants to $p$ can be expressed by

$$\frac{dp}{dt} = p[(f^1(r^1, s) - f^1(p, q))]. \quad (18)$$

as shown in the following Equation (14):

$$\frac{dp}{dt} = p[(f^1(r^1, s) - f^1(p, q)) = p(1 - p)[a_{11} - q(a_{11} + a_{12})]. \quad (19)$$
where

\[ u_1 = u_{12} + C_{1j}' - u_{22} - C_{1j}''', \]

\[ u_2 = u_{21} + C_{1j}'' - u_{11} - C_{1j}', \]

\[ v_1 = v_{21} + C_{2j}'' - v_{22} - C_{2j}''', \]

\[ v_2 = v_{12} + C_{2j}''' - v_{11} - C_{2j}'. \]

Similarly, the adjustment equation of the second group of thermal power plants to \( q \) could be expressed by Equation (15),

\[ \frac{dq}{dt} = q[(f^2(r^1, s) - f^2(q, s)] = q(1 - q)[v_1 - p(v_1 + v_2)]. \tag{24} \]

Therefore, the system dynamics of thermal power plants’ peaks regulation can be expressed by differential Equation (14) and Equation (15). Equation (14) indicates that the proportion of thermal power plants using Strategy 1 of the first type of thermal power plant is stable when and only when \( p = 0; p = 1, \) or

\[ q = u_1 / (u_1 + u_2). \tag{25} \]

Similarly, the proportion of the second type of thermal power plant using the strategy 1 thermal power plant bidding online is stable when and only when \( q = 0; q = 1, \) or

\[ p = v_1 / (v_1 + v_2). \tag{26} \]

When studying the dynamics of a system group, for a system described by a differential equation system, the stability study at the equilibrium point can be judged by studying the Jacobian matrix of the system. The differential equations are shown as Equation (16):

\[
\begin{align*}
\frac{dp}{dt} & = p(1 - p)[u_1 - q(u_1 + u_2)] \\
\frac{dq}{dt} & = q(1 - q)[v_1 - p(v_1 + v_2)]
\end{align*}
\]

The first-order derivative of \( p \) and \( q \) leads to a Jacobian matrix \( J \), as shown in Equation (17):

\[
\begin{pmatrix}
(1 - 2p)[u_1 - q(u_1 + u_2)] & -p(1 - p)(u_1 + u_2) \\
-q(1 - q)(v_1 + v_2) & (1 - 2q)[v_1 - p(v_1 + v_2)]
\end{pmatrix}. \tag{28}
\]

At this point, the expressions of the determinant and trace of the five partial equilibria are shown in Table 4.

With calculation and analysis about stable points of equations, five local equilibrium points are drawn out as: \((0,0), (0,1), (1,0), (1,1), (u_1 / (v_1 + v_2), u_1 / (u_1 + u_2))\). Stability of these five local equilibrium points can be judged by the Jacobian matrix.

### Table 4 The calculation method of local stability under the compensation of peak adjustment auxiliary service is considered

| Equilibriums | Determinant of \( J \) (sign) | Trace of \( J \) (sign) | Results |
|--------------|-------------------------------|------------------------|---------|
| \( p = 0, q = 0 \)  | \(+\)                          | \(+\)                   | Unstable |
| \( p = 0, q = 1 \)  | \(+\)                          | \(-\)                   | ESS     |
| \( p = 1, q = 0 \)  | \(+\)                          | \(-\)                   | ESS     |
| \( p = 1, q = 1 \)  | \(+\)                          | \(+\)                   | Unstable |
| \( p = \alpha / (v_1 + v_2), q = \alpha / (u_1 + u_2) \) | \(-\)                        | 0                       | Saddle point |

The discrimination rules are set as follows. When the matrix’s determinant is greater than zero and its trace is less than zero, we call it ESS. When the matrix’s determinant and trace are both greater than zero, it is a saddle point. When the matrix’s determinant is less than zero, it is called as a saddle point. Table 5 illustrates the analysis results of one of them, and the specific dynamic evolution process is shown in Figure 2.

### 3.3 Compound differential evolution game algorithm

Section 3.2 lists the evolutionary stability strategies of two players. When the number of players reaches three or more, the
FIGURE 3  Schematic diagram of game between populations

FIGURE 4  Flow chart of compound differential evolution game

process of solving the replicated dynamic equations and its stable point is too complex. Therefore, this paper proposes a method of combining evolutionary game theory with a modern intelligent optimization algorithm [36] to realize the dynamic evolutionary game process of thermal power plant bidding power generation. In this paper, combined with the differential evolution algorithm, each thermal power plant is regarded as a group. By analysing the game results of different strategies among the groups, the population is updated and sorted, and then the differential evolution game algorithm (CDEG) [37] is proposed.

In the CDEG, it is assumed that there are $K$ thermal power plants participating in the game bidding, and $F_i$ represents the $i$-th bidding player. There are $N$ individuals in each population. Each individual is represented by $(P, f, s)$, which represents the bidding strategy of the game party. $P$ is the bidding quantity, $f$ is the first-tier bidding price, and $s$ is the second-tier bidding price. The game process of the population is shown in Figure 3.

The process of CDEG mainly includes the following steps (Figure 4):

1) Initialize the game population. Each thermal power plant determines the range of bidding power according to the peak regulation demand on the next day and the estimation of competitors (it can be obtained through repeated simulation games in a single period). And randomly generate two tiers bidding prices, and finally, each population generates $N$ bidding individuals to form the initial game population.

2) Competitive game among populations. Randomly select an individual from each population to play the game. And randomly generate two tiers bidding prices, and finally, each population generates $N$ bidding individuals to form the initial game population.

3) Repeat the game until the specified number of times.

4) Calculate the average return of each individual game.

5) Sorting the average income of individuals in the population.

6) The population is divided into good parts and bad parts.

7) The population is recombinated.

8) Enter the next round/the next period.

9) Calculate the average return of each individual game.

10) Sorting the average income of individuals in the population.

11) The population is divided into good parts and bad parts.

12) The population is recombinated.

13) Enter the next round/the next period.

14) Calculate the average return of each individual game.

15) Sorting the average income of individuals in the population.

16) The population is divided into good parts and bad parts.

17) The population is recombinated.

18) Enter the next round/the next period.

19) Calculate the average return of each individual game.

20) Sorting the average income of individuals in the population.

21) The population is divided into good parts and bad parts.

22) The population is recombinated.

23) Enter the next round/the next period.
3) Population compound differential evolution. Based on the compound differential evolution algorithm (CDE), each population independently evolves and improves its own bidding strategy. The CDE optimization process of each population mainly includes the following operations:

a. Individual sort operation. According to the average return value of the individual, the population is sorted internally.

b. Population segmentation operation. Set the degree of division $d(0 < d < 1)$ and divide the population into superior and inferior populations based on the individual ranking results.

c. Compound differential evolution operation. The DE/rand/1 mutation strategy is adopted for the superior population, and individuals are randomly selected as the mutation basis vector to improve individual diversity; the DE/best/1 mutation strategy is adopted for the inferior population, and the current best individual is selected as the mutation basis vector. In order to improve evolutionary convergence (detailed mutation process see ref. [38]).

d. A reorganization operation. Synthesize the updated superior and inferior populations into a new generation of populations, and enter the next round/next period of the game iteration process.

4 | EMPIRICAL ANALYSIS

4.1 | Basic data

This paper uses the typical daily actual operating data of a certain province in the Northeast as a basic construction example. Each bidding scheduling period is 15 min, and there are 96 periods per day. The actual load curve, wind power output curve, and net load curve of a typical day in a provincial power grid are shown in Figure 5.

Table 6 shows the data of 41 thermal power units started on a typical day in a provincial power grid. When all 41 units are in operation, the total maximum output is 14565 MW, the minimum output is 4461 MW, and the maximum ramp rate is 160.8 MW/min (the set of $a, b, c$ fuel factor, see ref. [39]).

| Unit parameters | Maximum technical output/MW | Minimum technical output/MW | Climbing rate/hour |
|-----------------|-----------------------------|-----------------------------|-------------------|
| Thermal power unit number | 1 | 135 | 60 | 90 |
| 2 | 135 | 60 | 90 |
| 3 | 135 | 60 | 180 |
| 4 | 150 | 60 | 120 |
| 5 | 220 | 88 | 132 |
| 6 | 220 | 88 | 132 |
| 7 | 270 | 100 | 180 |
| 8 | 270 | 100 | 180 |
| 9 | 300 | 70 | 240 |
| 10 | 300 | 100 | 180 |
| 11 | 300 | 90 | 300 |
| 12 | 300 | 90 | 300 |
| 13 | 300 | 90 | 300 |
| 14 | 300 | 120 | 180 |
| 15 | 300 | 120 | 180 |
| 16 | 320 | 120 | 192 |
| 17 | 330 | 80 | 240 |
| 18 | 330 | 80 | 240 |
| 19 | 330 | 80 | 240 |
| 20 | 330 | 120 | 210 |
| 21 | 330 | 120 | 210 |
| 22 | 330 | 120 | 210 |
| 23 | 330 | 95 | 180 |
| 24 | 350 | 70 | 210 |
| 25 | 350 | 60 | 210 |
| 26 | 350 | 120 | 210 |
| 27 | 350 | 120 | 210 |
| 28 | 350 | 120 | 210 |
| 29 | 350 | 105 | 222 |
| 30 | 350 | 130 | 210 |
| 31 | 350 | 100 | 360 |
| 32 | 350 | 135 | 210 |
| 33 | 350 | 150 | 210 |
| 34 | 600 | 90 | 360 |
| 35 | 600 | 90 | 360 |
| 36 | 600 | 180 | 360 |
| 37 | 600 | 180 | 360 |
| 38 | 600 | 180 | 360 |
| 39 | 600 | 170 | 360 |
| 40 | 600 | 170 | 360 |
| 41 | 600 | 180 | 360 |
initial bidding power of the unit is less than 75% of the maximum output. In the end, the power of the thermal power unit won the bid is less than or equal to the power of its bid, and some units have failed to bid. The thermal power unit needs to continuously change the bidding strategy and seek to maximize its revenue. In this paper, the average value of the unit’s first-period bidding revenue and the deep peak regulation revenue is used as the unit’s average period revenue throughout the day to simplify the peak regulation process and make a rough estimate of the bidding power. Figure 6 shows the sum of the optimal bidding power for 41 units of 200 simulations. It can be seen that the total bidding volume is in a fluctuating upward trend. In the 200th game, the total optimal bidding volume reached 10881.55 MW. Even when supply exceeds demand, each unit will continue to increase bidding power in order to maximize its revenue.

This article lists the changes in the optimal bidding volume of Unit 32 and Unit 37 that converge quickly as shown in Figure 7. It can be seen that around the 50th generation, the optimal strategy of the two units is basically stable, slightly less than 75% of the unit’s maximum output.

4.3 Multi-period bidding price determination

As shown in the previous section, since there are a total of 41 thermal power units, there are a total of 41 populations. In this paper, the number of iterative updates of the population is set to 100 generations, the population size is 20, the number of games between the populations in each generation is 1000, and the population division degree is 0.5.

Figure 8 shows the bidding strategy for 41 units of the 100th generation. In the first-tier quotation, red is the superior strategy and blue is the inferior strategy. In the second-tier quotation, the yellow is the superior strategy and the green is the inferior strategy. It can be seen that there is a clear dividing line for the first-tier quotation, and quotations of 0.19 yuan kWh$^{-1}$ and below are mostly excellent strategies, that is, the low-price strategy for all units will be more dominant and the profit will be higher. The second-tier quotation has no dividing line, and the quotations are relatively random, distributed between 0.4-1 yuan kWh$^{-1}$. The second quotation has little effect on the revenue of the unit.

Figure 9 shows the evolution process of the optimal quotation for 41 units. It can be seen that starting from the 10th generation, the first-tier optimal quotation is basically below 0.20 yuan kWh$^{-1}$. With the increase in the number of iterations, the best price for the first-tier has stabilized between 0.16 and 0.19 yuan kWh$^{-1}$, mostly at 0.18 yuan kWh$^{-1}$, and will not continue to decline. The optimal quotation of the second-tier is widely distributed and does not change regularly with the increase of the number of iterations. It is basically distributed between 0.6-0.8 yuan kWh$^{-1}$, and there are some higher quotations and lower quotations.

Figure 10 and Figure 11 show the clearing price statistics of 1000 games in each generation, including the evolution of the highest clearing price, the lowest clearing price, and the average clearing price. It can be seen from Figure 10 that the lowest clearing price of the first-tier stabilized at 0.19 yuan kWh$^{-1}$...
FIGURE 8  The 100th generation of various group bidding strategies

FIGURE 9  The optimal bidding strategy for 41 populations in each generation

FIGURE 10  The first-tier clearing price statistics

FIGURE 11  The second-tier clearing price statistics
after the 40th generation; the highest clearing price fluctuated around 0.35 yuan kWh\(^{-1}\); the average clearing price dropped rapidly in the first 10 generations, and finally fluctuates slightly at 0.25 yuan kWh\(^{-1}\). It can be seen from Figure 11 that the highest clearing price of the second-tier is basically the highest price of 1 yuan kWh\(^{-1}\), and the average clearing price is also on the high side. The minimum clearing price fluctuates greatly between 0.75 and 0.9 yuan kWh\(^{-1}\).

Figure 12 lists the highest and expected returns that the 41 units can obtain during each period when the 41 units are updated to 100 generations. It can be seen that the highest revenue that the same type of unit can obtain is basically the same, but due to different bidding strategies, the expected revenue is slightly different.

4.4 Sensitivity analysis

Section 4.3 discusses the scenario where each thermal power unit actively participates in auxiliary peak regulation services and the supply exceeds demand. However, when some large-capacity units cannot participate in peak regulation or peak regulation is not active, the bidding situation of the remaining 33 units is shown in Figure 13. It can be seen that the first-tier quotation strategy of each thermal power unit is no longer a low-price strategy, and is widely distributed, mostly at 0.3 yuan kWh\(^{-1}\), which is a high-price strategy. The second-tier quotation is not much different from the quotation in the scenario of oversupply, and the high price strategy is still the main one.

Figures 14 and 15 show the clearing price statistics of 1000 games of each generation in the new situation. It can be seen that the average clearing price of the first-tier is basically 0.39 yuan kWh\(^{-1}\), and the minimum clearing price is also above 0.30 yuan kWh\(^{-1}\). The second-tier highest clearing price is basically the highest price of 1 yuan kWh\(^{-1}\), and the average clearing price is also high. Therefore, when the peak regulation enthusiasm of some thermal power units is not high, and the peak regulation demand is greater than the peak regulation supply, the two quotations of the units participating in the peak regulation will gradually adopt the high price strategy.
5 | CONCLUSIONS

This paper combines the CDE with the evolutionary game algorithm to study the bidding strategy of thermal power units under the auxiliary service market mechanism. The thermal power unit adopts a two-tiers bidding strategy to bid in the auxiliary service market before the day, in order to maximize the sum of the revenue from power generation and the peak regulation auxiliary service. The results show that the computational efficiency of the CDEG is higher, and the bidding strategy converges faster. Finally, through sensitivity analysis, the key factors affecting the bidding strategy are obtained. This article draws the following conclusions:

(1) The CDEG is suitable for solving the bidding strategy of multiple thermal power units. It can achieve rapid convergence and continue to evolve to seek better strategies.

(2) When thermal power units participate in peak regulation auxiliary services, even when supply exceeds demand, each unit will continue to increase bidding power in order to maximize its revenue.

(3) In the case of oversupply, the first-tier quotation of thermal power units at 0.19 yuan kWh\(^{-1}\) and below is an excellent strategy, and the second-tier quotation is basically distributed at 0.6–0.8 yuan kWh\(^{-1}\). The clearing price of the first-tier is about 0.25 yuan kWh\(^{-1}\), and the clearing price of the second-tier is about 0.95 yuan kWh\(^{-1}\).

(4) When supply is less than demand, the first-tier quotation of each thermal power unit adopts the high-price strategy, mostly at 0.3 yuan kWh\(^{-1}\), and the second-tier quotation is still based on the high-price strategy. The clearing price of the first-tier is finally around 0.39 yuan kWh\(^{-1}\), and the clearing price of the second-tier is around 0.97 yuan kWh\(^{-1}\).

(5) In the case that all thermal power units can be turned on to meet the demand for peak regulation, the willingness of thermal power units to participate in peak regulation assistance has become a key factor affecting peak regulation bidding. The auxiliary service market can encourage thermal power plants to participate in peak regulation by improving the peak regulation bidding mechanism, thereby reducing the cost of peak regulation auxiliary service compensation and enabling the healthy development of the auxiliary service market.

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CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

NOMENCLATURE

- \(P_{i,t}\): Active power of unit \(i\) in the \(t\)-th statistical cycle
- \(AC\): Average cost of thermal power generation
- \(\lambda_{i,t}\): Average load rate of unit \(i\) in the \(t\)-th statistical cycle
- \(P_{i,t}\): Average output of unit \(i\) in the \(t\)-th statistical cycle
- \(r_{i}\): Benchmark price of thermal power unit on grid in time \(t\)
- \(P_{\text{bid}}\): Bid winning capacity of thermal power unit \(i\) in time \(t\)
- \(P\): Bidding power
- \(f\): Fitness function
- \(a, b, c\): Fuel factor
- \(C_i\): Installed capacity of unit \(i\)
- \(q, p\): Low price strategy ratio
- \(MC\): Marginal cost of thermal power generation
- \(P_{i}^{\text{m}}\): Maximum climbing rate per hour of thermal power unit \(i\)
- \(P_{i}^{\max}\): Maximum technical output of thermal power unit \(i\)
- \(P_{i}^{\text{min}}\): Minimum technical output of thermal power unit \(i\)
- \(N\): Number of strategies
- \(K\): Number of thermal power units participating in the auxiliary peak regulation bidding
- \(\alpha_t\): Paid peak regulation clearing price of time \(t\)
- \(P_{\text{bid}}\): Paid peak regulation of thermal power unit \(i\) in time \(t\)
- \(C_{ij}\): Peak regulation ancillary service income
- \(d\): Population segmentation
- \(Z_{i}\): Profit of thermal power unit
- \(s\): Second quotation
- \(P_{i}^{P}\): System load demand at time \(t\)
- \(u\): The first category of thermal power plant revenue
- \(\varepsilon\): The proportion of individuals in population \(k\) who adopt each strategy in the population
- \(v\): The second category of thermal power plant revenue
- \(P_{R}\): Time period \(t\) Total output of renewable energy
- \(CDE\): Compound differential evolution algorithm
- \(CDEG\): Compound differential evolutionary game algorithm
- \(DE\): Differential evolution algorithm

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