Simulation Analysis of Power Spot Market Based on Evolutionary Game

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Abstract. As a new round of deepening reform in power system goes on in China, establishing an effective and complete power spot market nationwide based on the construction and operation of eight power spot trials becomes an important task for China. This paper analyzes the competitive strategies and capabilities of different types of power generation enterprises under the operating rules of the electricity spot market by building an evolutionary game model based on an improved genetic algorithm using MATLAB, which provides a valuable scientific basis for the construction and development of the future electricity spot market.

Keywords: Spot electricity market; Improved genetic algorithm; Evolutionary game model; Power generation enterprise.

1. Introduction
China’s new round of electricity market reform, began in 2015, was aimed at establishing a sound market mechanism in the power industry to allow the market to play a full role[1,2]. Over the past four years, the reform of the electricity market has been progressing steadily and gratifying progress has been made in the construction of the electricity markets, the establishment of transmission and distribution prices, the reform of the power generation component, and the reform of the electricity sales area[3].

Many scholars have carried out research using evolutionary games to simulate the electricity spot market. Zhao Huiru et al. established the bidding strategy and equilibrium simulation model of the power market, and discussed the game strategy and game results of the generator and the seller [4]. Jiang Wei realized the prediction of short-term direct purchase electricity prices and direct purchase electricity by establishing a game model of both supply and demand under incomplete information [5]. Peng Chunhua et al. established a compound differential evolution game algorithm and discussed the quotation strategies of thermal power companies in different situations in market competition [6].

In terms of the application of genetic algorithms, scholars have also achieved notable research results. Wang Bei et al. proved that genetic algorithms can produce feasible solutions by applying genetic algorithms to classroom optimization problems[7]. Hao Fan et al. studied the scheduling problem of RGV workshop through improved genetic algorithm and traditional genetic algorithm, and found that the improved genetic algorithm can process the problem faster than traditional genetic algorithm[8]. In response to the problem of lunar rover path planning algorithm, Zhou Lanfeng et al. proposed a comprehensive genetic algorithm based on a virtual three-dimensional model. Through simulation experiments, it was found that the improved comprehensive genetic algorithm has better performance and higher stability[9].
The above research is mainly focused on optimizing the strategies of electric power generation companies in the electricity sales market to increase electricity sales revenue, but there is no related published research on the simulation-based analysis of the electricity spot market. In addition, there is insufficient research on the operating pressure of thermal power enterprises. In view of the limitations of previous research, this paper uses an evolutionary game model based on improved genetic algorithms, based on the logic and rules of electricity market transactions, to simulate the competitive pressures it faces when entering the electricity spot market, and focuses on the changes in supply and demand. At that time, the degree of change of the thermal power enterprise's income situation provides a valuable reference for the reform of the power marketization.

2. Construction of Evolutionary Game Model Based on Improved Genetic Algorithm

2.1. Algorithm Improvement

In this paper, an adaptive function is added to the crossover rate and mutation rate in the traditional genetic algorithm, so that the two can be adaptively adjusted in different situations\cite{8}. The specific formula is as follows:

\[
R_c = \begin{cases} 
  \frac{f_{\text{compare}} - \bar{f}}{f_{\text{compare}}}, & \text{if } f_{\text{compare}} \geq f_{\text{max}} - \bar{f} \\
  R_{c0}, & \text{if } f_{\text{compare}} < f_{\text{max}} - \bar{f} 
\end{cases}
\]

(1)

\[
f_{\text{compare}} = \max(f_a, f_b)
\]

(2)

\[
R_m = \begin{cases} 
  \frac{R_{m0}(f_{\text{max}} - f)}{(f_{\text{max}} - \bar{f})}, & \text{if } f > \bar{f} \\
  R_{m0}, & \text{if } f = \bar{f} \\
  \frac{R_{m0}(f_{\text{max}} - \bar{f})}{(f_{\text{max}} - f)}, & \text{if } f < \bar{f} 
\end{cases}
\]

(3)

Among them, \(R_c\) represents the crossing rate, \(R_m\) represents the mutation rate, \(f_{\text{max}}\) represents the highest fitness among all individuals in the population, \(\bar{f}\) represents the average fitness of all individuals in the population, \(f_a\) and \(f_b\) represent the fitness of the two individuals participating in the crossover, \(f_{\text{compare}}\) equals the larger of \(f_a\) and \(f_b\), \(\bar{f}\) represents the original fitness of the mutant individual.

According to the formula, it can be seen that when performing crossover and mutation operations, the crossover rate and the mutation rate are related to the difference between the maximum fitness and the average fitness of the current population, and this difference can reflect the discrete state of the population fitness, when the population Individuals are not similar. When the gap is large, the difference will be relatively large; while when the dispersion of the population is weak and the similarity of the individuals in the population is high, the difference will be relatively small.

On this basis, the large population is divided into multiple sub-populations for parallel operation, and the individual exchanges and information exchange between the sub-populations are controlled during the genetic process. This algorithm improves the algorithm without affecting the speed of the algorithm. The accuracy rate further avoids the algorithm entering the local optimal solution.

2.2. Model Building

2.2.1. Power allocation. For the \(j\) th power generator, its power generation in a certain period will be derived according to the following conditions:

If the generator's quotation combination includes a clearing power price of \(P_n\), the corresponding
reported electricity capacity is $Q_m$ during this period, $P_t$ is the corresponding electricity price for all generators, the total power generation reported by $P_t$ is $Q_a$. At this time, the power generation capacity of the generator is:

$$Q_j = \sum_{i=1}^{n} Q_i + \frac{Q_a}{Q_t} (D - \sum_{i=1}^{n} Q_i)$$  \hspace{1cm} (4)

If the generator's quotation combination does not include the clearing price $P_t$, in its quotation combination, the quotation closest to $P_t$ and less than $P_t$ is $P_u$ then its power generation during this period is:

$$Q_j = \sum_{u=1}^{k} Q_u$$  \hspace{1cm} (5)

Ultimately the power market achieves a balance between supply and demand:

$$D = \sum_{j=1}^{k} Q_j$$  \hspace{1cm} (6)

2.2.2. Quotation Rules. Assume there are $k$ generators in the power grid, for the $j$th generator, when reporting the bidding curve of time period $t$, the power generator will report $n$ sets of data $[p_{j1}, Q_{j1}], [p_{j2}, Q_{j2}], ... [p_{jn}, Q_{jn}]$, where $p_{ji}$ represents the price quoted in paragraph $i$, $Q_j$ represents the power generation of the generator that is relative to the generation increase of the clearing price at $P_{j(i-1)}$ when the market clearing price reaches $p_{ji}$ in this period. For this data, electricity price $p_{ji}$ and electricity $Q_{ji}$ need to meet the following constraints:

$$p_{j(i-1)} < p_{ji} < p_{j(i+1)}, i \in [1, m]$$  \hspace{1cm} (7)

$$\sum_{i=1}^{m} Q_j < Cap_j \times T$$  \hspace{1cm} (8)

Among them, $Cap_j$ represents the installed capacity of the $j$ power generator, $T$ represents the specific duration of each settlement time period in the electricity market, and $Cap_j \times T$ represents the upper limit of the amount of electricity that can be issued by the $j$th generator during the single settlement period of the electricity spot market.

2.2.3. Cost fitting. According to the characteristics of the cost structure of power generation enterprises, the power generation costs of power generation enterprises are expressed as follows:

$$C = C_u + C_v$$  \hspace{1cm} (9)

$$C_u = \lambda \times Cap$$  \hspace{1cm} (10)

$$C_v = \alpha P^2 + \beta P + \gamma$$  \hspace{1cm} (11)

Among them, $C$ represents the total cost of the generator; $C_u$ represents the fixed cost of the generator; $C_v$ represents the variable cost of the generator. $\lambda$ represents the fixed cost per unit capacity of different units; $Cap$ represents the assembled unit capacity; $\alpha$, $\beta$, and $\gamma$ represent the variable cost parameters of the units, and the parameters of different units are different; $P$ represents the generating power of the generator.
2.2.4. Thermal power company quote strategy. The generator's unit load is divided into 4 gradients: \([0, Q_1], [Q_1, Q_2], [Q_2, Q_3], [Q_3, Q_4]\).

In terms of pricing, we divide the generator's price strategy into six nodes and five steps: \([0, c_1], [c_1, c_2], [c_2, c_3], [c_3, c_4], [c_4, c_5]\).

In order to simplify the analysis process, we choose two representative quotation strategies as the starting strategy of the game: 'low price strategy' and 'high price strategy'. And 'low-priced strategy' corresponds to one to four steps of capacity strategy, 'high-priced strategy' corresponds to two to five steps of capacity strategy.

3. Modeling of Evolutionary Game Model Based on Improved Genetic Algorithm

In order to simulate the multi-party participation in the power market competition, this paper combines evolutionary game theory and genetic algorithm to calculate the fitness of the genetic algorithm according to the background design of the evolutionary game.

The price quotations of thermal power companies will follow the rules of tiered quotations. Renewable energy companies follow the principle of low prices. This article assumes that the quoted price of renewable energy generators is always 0.

The price quoted by each power producer is an independent population, and each individual in the population is a possible quote curve for the power producer. The initial population of each power producer will include two bidding strategies: low price and high price. The number of individuals who choose each strategy will account for half of the total population.

For the \(j\)th power generator, the installed capacity \(C_{j}\) (unit: 10 MW) is the number of its genes. In the quotation curve, if two adjacent genes have the same quotation, they can be merged. And combined with the length \(T\) of each period in the market, the genetic structure of the \(i\)th individual \(G_i\) in the population \(j\) corresponds to the \(j\)th generator is finally obtained as follows:

\[
    G_i = \left[ p_{j1}^i, p_{j2}^i, p_{j3}^i, \ldots, p_{jm}^i \middle| q_{j1}^i, q_{j2}^i, q_{j3}^i, \ldots, q_{jm}^i \right], \quad i \in [1, N]
\]

In the above formula, \(G_i^j\) represents the primary gene of the \(i\) individual in the \(j\)th population, which is the first initial quotation curve of the \(j\)th generator, \(N\) is the size of the population, \(p_{j1}^i, p_{j2}^i, p_{j3}^i, \ldots, p_{jm}^i\) is the different quotes for that individual, \(q_{j1}^i, q_{j2}^i, q_{j3}^i, \ldots, q_{jm}^i\) represents the reported power corresponding to different quotes.

After determining the population, according to the requirements of the improved genetic algorithm, the population should be divided randomly. And then, according to the evolutionary game theory, the fitness of individuals in the algorithm is calculated. And through the improved genetic algorithm, genetic operations are performed in small population units, that is, the process of selection, crossover, and mutation. After the genetic operation, the individual's genes in the population have been greatly updated. At this time, the fitness is recalculated to remember the information exchange of the small population. The genes of some individuals have changed here, so far all the genetic steps involving individual genes have been completed, and the algorithm is about to enter the next generation iteration.

4. Simulation and Analysis of Evolutionary Game Model Based on Improved Genetic Algorithm

In this paper, typical examples are constructed with reference to the electric power structure characteristics of most provinces in China. The power structure is mainly composed of thermal power, wind power and photovoltaic.

We assume that the power market has twenty-four clearing times in one day, that is, the power market clearing is performed every hour. This example introduces two thermal power generators that are quite different. A generator is a traditional small unit thermal power generator; B generator is a new technology large unit generator.

The installed capacity of each power supplier is shown in the table below:
Table 1. Installed capacity of each power supplier.

| Generator | Thermal power A | Thermal power B | Wind power | Solar power |
|-----------|----------------|----------------|------------|------------|
| Installed capacity (10,000 kW) | 60 | 100 | 30 | 20 |

The generation technology used by generators A and B differs. The parameters of A and B thermal power generator units are as follows:

Table 2. Thermal power unit parameters.

| Thermal power parameters | Thermal power A | Thermal power B |
|--------------------------|----------------|----------------|
| Fixed cost $\lambda$ (Yuan / 10,000 kW) | 1.345 | 1.230 |
| $\alpha$ (10,000kW) | 60 | 100 |
| Variable costs $\beta$ | -1.85 $\times 10^{-03}$ | -1.04 $\times 10^{-03}$ |
| $\gamma$ | 0.3423 | 0.3253 |
| Output Power $P_{\text{max}}$ (10,000kW) | 60 | 100 |
| $P_{\text{min}}$ (10,000kW) | 18 | 20 |

4.1. Renewable Energy unit Output Simulation

Based on previous research by scholars [10], in this paper, when simulating the output of renewable energy, the wind speed obeys the Weibull distribution and the light intensity obeys the beta distribution. The simulation results are as follows:

Figure 1. Day-to-day output of renewable energy.

According to the calculation of the above simulation data, the annualized average utilization hours of the solar power unit is about 1224.0 hours, and the annualized average utilization hours of the wind turbine unit is about 1871.4 hours. The above data is basically consistent with the national average utilization hours of renewable energy in the past years for which data is available.

4.2. Single-period Thermal Power unit Bidding Simulation

Through calculation, the single-period demand of the electricity market is about 800,000 kW · h. This article focuses on the standard supply and demand background. In the bidding simulation, the genetic algorithm will run 2,000 generations to observe whether the bidding strategy of each thermal power generator has reached an evolutionary stable state.

Within 2,000 generations, thermal power generator A and B fully competed to determine the market clearing price through a common quotation. The bidding spectrum of power generator A and B is shown in Figure 2. Through this figure, we can see the bidding situation of generator A and B in the 2,000 rounds of inheritance. Different color temperatures represent different quotes. The black line in the figure represents the power generation rights obtained by the unit through competition according to the corresponding algebraic formula.
Figure 2. Atlas of generator quotes. Figure 3. Revenue graph of power generators.

See Figure 3 for the benefits of A and B power generators during the game. Based on the above data analysis, the situation that occurred after the 800th generation will be a more common situation in the spot electricity market competition under standard supply and demand conditions. Due to its good technical indicators and relatively low cost, power producer B has a strong competitiveness in the electricity market and will find it easy to obtain market initiative.

4.3. Competitiveness Analysis of Generating Units under Different Demand Curves

To discuss the impact of demand curves of different types and with different amount required on the profitability of power generators, a benchmark standard demand curve needs to be set first as the basis for change. Therefore, we simulated the demand curve of the industrial type and the demand curve under the condition of loose supply and requirement for comparison. The volatility of the standard curve is the normalized result of the demand curve within a day at a randomly selected area, as shown in Figure 4.

Figure 4. Demand curve normalization coefficient.

We can calculate the requirement of the standard curve according to the standard output of different types of units. The annual average utilization hour of solar power units is about 1,224.0 hours, the annual average utilization hour of wind power units is about 1,871.4 hours and the average annual utilization hour of thermal power units is about 4,361 hours. Through calculation, the total requirement within one day of the standard demand curve is 2,013.24 million kwh. This article assumes that the power requirement of the industrial-type demand curve is the same as the standard curve, and the total requirement of the demand curve under loose supply and requirement conditions is 10% lower than the standard curve. From this, the daily demand curves of the three curves can be obtained as shown in Figure 5, 6, and 7.
Figure 5. Daily demand curve under standard conditions.

Figure 6. Intra-day demand curve of industries.

Figure 7. Daily demand curve under loose supply and demand.

In this case, the price of clearing electricity within the day is shown in Figures 8, 9, and 10.

Figure 8. Daily clearing price chart under standard conditions.

Figure 9. Intra-day clearing price of similar industrial curve.

In this case, the revenue of each power producer is as follows:

Table 3. Revenue table of generators under the standard demand curve.

| Generator | Wind power | Solar power | Thermal power A | Thermal power B |
|-----------|------------|-------------|-----------------|----------------|
| Revenue (10,000 yuan) | 3.09 | 2.77 | 17.4 | 23.3 |

Table 4. Revenue table of power producers with a type of industrial curve.

| Generator | Wind power | Solar power | Thermal power A | Thermal power B |
|-----------|------------|-------------|-----------------|----------------|
| Revenue (10,000 yuan) | 3.62 | 2.49 | 14.58 | 38.09 |

Table 5. Revenue table of generators under loose supply and demand.

| Generator | Wind power | Solar power | Thermal power A | Thermal power B |
|-----------|------------|-------------|-----------------|----------------|
| Revenue (10,000 yuan) | 2.33 | 2.39 | -3.69 | 8.29 |

Comparing to the standard curve, the wind energy revenue has increased while the solar energy revenue has decreased under the industry-like demand curve. Among the thermal power generators, the revenue of generator A has declined while that of generator B has increased significantly.
Under the loose supply and demand situation, the revenues of all power producers have significantly decreased, and the revenues of wind energy as renewable energy has been greatly affected. The electricity price during solar working hours has been slightly reduced, but the relative impact is small. Among thermal power companies, the revenue of power generators $A$ in a day becomes negative, and the revenue of power producers $B$ has also declined to a certain extent. In summary, the change in the total demand in the market has a great impact on the revenue of power generators. When the demand in the market decreases, the competition pressure of power generators suddenly increases and power generators with lower production efficiency will face the risk of loss throughout the process.

5. Conclusion
This paper proposes a game model of the electric power spot market according to an improved genetic algorithm and evolutionary game theory, and discusses the impact of changes in the daily demand curve on the revenue of power generation companies by simulating the quotation strategies adopted by power generation companies in electric power spot market. When the total demand corresponding to the demand curve is unchanged, the type of the demand curve will slightly affect the total revenue of the power generation industry, mainly affecting the distribution of benefits between different types of power generators. When the category of the demand curve remains unchanged, the total demand will have a great impact on the total revenue of the power generation industry, and in fact may cause big losses to traditional low-efficiency thermal power companies with relatively high variable costs. The simulation results of the electricity spot market provide a scientific basis for the construction and development of the nationwide electricity spot market in the future.

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