INTRODUCTION

The key to sustainable development is people-oriented and balanced with environmental conditions and resources. Unreasonable utilization and development of resources and serious urban pollution are the main problems hindering the sustainable and healthy development of cities. Therefore, it is necessary to speed up the improvement of resource utilization rate, develop new energy utilization, establish a scientific energy supply system, and promote the healthy development of the city. Low-carbon economy cities do not rely on clean energy and other single elements to achieve. Renewable energy and distributed energy supply system are the actual needs of every city and village. The environmental, energy, and low-carbon issues that plague us are essentially different aspects of a problem. To fundamentally solve these problems, we must rely on smart energy. The development of human society will prove that the construction of low-carbon economy city cannot do without our energy wisdom.

Abstract

With the continuous advancement of urbanization, the contradiction between urban development and environmental resources has become increasingly prominent, and environmental pollution has become increasingly serious. To fundamentally solve the problems of environment, energy, and low carbon, we must rely on the intelligence of energy. This paper aims to study the sustainable development of China’s intelligent energy industry based on artificial intelligence and low-carbon economy. In view of the problems existing in the optimization of power generation industry, this paper uses the annual load, electricity price, weather, and climate data of a southern power grid, uses the statistical variation particle swarm optimization algorithm, uses the historical runoff and rainfall data to optimize it, and studies the analysis methods, characteristics and laws of short-term load, electricity price and runoff, as well as the uncertain factors affecting their changes. The experimental results show that the predicted price is close to the actual price, and the median error of each period is <1% in statistical analysis, so the forecast value can be used to replace the actual value for scheduling. This method makes full use of the adaptive mutation in the late stage of particle optimization, and introduces the mechanism of particle size selection, which fully ensures the diversity of particles and improves the search ability of particles.

KEYWORDS

artificial intelligence, low-carbon economy, smart energy, sustainable development
With the rapid development of science and technology and artificial intelligence technology, the sustainable development of our country’s energy industry has also been solved to a certain extent. Many experts have done some research in this field. Among them, Lin CC, Deng DJ, Chen ZY, etc, aiming at the continuous increase of renewable energy and sustainable energy resources, and the application of low-carbon power and energy systems are facing different types of uncertainties, etc, they have been applied to the flexible evaluation of smart grid development so far. Real options (RO) methodology has been critically analyzed, and they hope to develop more practical reverse osmosis tools to be applied to the energy industry, so that the use of powerful “real options thinking” when making decisions under uncertain conditions is more widespread. Pisello Al, D’Alessandro, Antonella, Sambuco S, and others pointed out that new nanocomposite smart multifunctional materials are emerging as promising technological advancements in the construction industry, in which thermal energy efficiency requirements should meet environmental sustainability and mechanical performance requirements. They discussed the development and multi-purpose experimental characterization of cement-based materials mixed with different carbon nanostructures, and studied the morphology, optical properties, thermal properties, electrical properties, and strain sensing capabilities of different composite materials. In addition, low-carbon economic issues related to sustainable energy development have also been explored. Tong S, Zhizhen P, Shou C, and others believe that although the government, as the policy maker, has implemented many policies and actions in the disposal and recycling of waste products, such as financial policies such as increasing carbon emission taxes and subsidies for trade-in, but little gain. For this reason, they proposed two subsidy mechanisms: remanufacturing subsidies and tax rebates. Through their research, these incentive mechanisms have greatly encouraged customers to replace their existing products with new and remanufactured products, thereby promoting the development of a low-carbon economy. Although there are many studies on the sustainable development of our country’s low-carbon economy and energy industry every year, no active and effective research results have emerged so far. Therefore, this article hopes to combine artificial intelligence and low-carbon economy to discuss the sustainable development of China’s smart energy industry, hoping to provide a theoretical reference for the sustainable development of energy in our country.

In this paper, a bionic optimization algorithm based on swarm intelligence and neural network prediction model is established. The prediction accuracy of various intelligent models is improved by examples. Then, the intelligent prediction methods are combined properly to establish a comprehensive prediction model, and the bionic algorithm is applied to solve the problem. The performance of the model is verified by an example. The optimal operation model of power generation industry based on load, electricity price, and runoff forecast is established. Intelligent bionic optimization algorithm and intelligent combination algorithm are used to solve the problem. An example is given to verify the performance of swarm intelligence bionic optimization algorithm and intelligent combination algorithm in solving the high-dimensional nonlinear multi-objective optimization problem of “optimal operation model of power generation industry.”

2 | PROPOSED METHOD

2.1 | Artificial intelligence method

Artificial neural network (ANN) is a very active frontier field at home and abroad. The application of artificial neural network in load, electricity price, and runoff forecasting is increasing gradually, but it is difficult to improve the accuracy of short-term load, electricity price and runoff forecasting.

BP neural network, radial basis function neural network, and fuzzy neural network have good nonlinear and self-learning ability, which are suitable for solving nonlinear problems such as short-term load, electricity price, runoff forecasting, and so on. However, BP neural network has some disadvantages, such as easy oscillation, slow convergence speed, easy to fall into local minimum, and difficult to determine the number of hidden neurons. Radial basis function neural network is simple, easy to operate and has fast convergence speed, but it also has its inherent shortcomings: the cost of obtaining data is very high, and the data often contains noise, and the reliability is not high; the number of hidden layer neurons is often determined by experience, and there is no theoretical basis; the results of fuzzy neural network K-means clustering algorithm are sensitive to the initial conditions, which often leads to some nodes Lack of learning. This paper mainly analyses the structure and algorithm of radial basis function neural network and fuzzy neural network.

1. Structure and algorithm of nonlinear RBF neural network

Radial basis function neural network is a three-layer neural network, which is composed of input layer, hidden layer, and output layer:

$$y = \sum_{i=1}^{n_i} w_i g \left( \| x - c_i \| / \sigma_i \right) + b \quad (1)$$
where \( x \in \mathbb{R}^d \) is the neural network input, \( w_i \) is the output layer weight, \( G(*) \) is the radial basis function, \( g_i \) is the center of the radial basis function, \( B \) is the output layer threshold, and \( n_c \) is the number of hidden layer neurons.

2. Structure and algorithm of fuzzy neural network

There are \( n \) sample sets to be trained, and each sample has \( m \)-Term eigenvalues of predictors, then there is eigenvalue matrix of predictors.

\[
A = (a_{ij})_{m \times n}
\]  

(2)

where \( i = 1,2,\ldots; j = 1,2,\ldots, N; a_{ij} \) is the measured value of characteristic value \( i \) of prediction factor \( j \) of training sample.

The sample set is composed of \( N \) prediction objects, and its eigenvectors are as follows:

\[
B = (b_1, b_2, \ldots, b_n)
\]  

(3)

The membership degree formula of prediction object is as follows:

\[
d_j = b_j / (\max b_j + \min b_j)
\]  

(4)

where \( \min b_j \) and \( \max b_j \) are the minimum and maximum eigenvalues of the prediction object, respectively.

2.2 Improved particle swarm optimization algorithm

The idea of the improved particle swarm optimization algorithm is as follows: on the basis of the traditional particle swarm optimization algorithm, according to the amplitude of particle flight speed, the new particles are divided into two categories: the particles with large amplitude are global optimization, and the other is local optimization. Advantages: It can avoid falling into local optimum and premature; it can improve the fine search and get the optimal solution quickly.20

The inertia factor \( \omega \) has a great influence on the optimization performance of the algorithm, and a larger value of \( \omega \) is conducive to improve the convergence speed of the algorithm. When the algorithm is small, the convergence accuracy of the algorithm is improved. Based on this, an adaptive adjustment strategy for \( \omega \) is proposed, that is, with the iteration going on, the \( \omega \) value is gradually reduced:

\[
\omega(k) = \frac{2}{1 + e^{\frac{k}{k_{max}}}} \cdot \left( \omega_{\max} + \omega_{\min} \right) / 2
\]  

(5)

Considering the advantages and disadvantages of new particles and previous particles, particle velocity in particle swarm optimization algorithm can be divided into two categories: one is that the new particles generated by the velocity vector are better than the previous particles, which is called the dominant particle speed; the other is called the inferior particle speed. The idea of particle speed update strategy is as follows: the advantage particle speed of improving particle quality is retained and global optimization is carried out, while the inferior particle speed participates in fine search.

The ergodicity of the basic PSO algorithm in the solution space cannot be guaranteed, so it cannot guarantee the convergence to the global optimal in theory. Based on the basic PSO algorithm, this paper introduces velocity variable coefficient and “neighborhood” selection algorithm to keep the diversity of particle swarm optimization and improve the ergodicity in the solution search space, so it is more likely to obtain the global optimal.

1. Elastic adaptive particle swarm optimization algorithm.

Elastic particle swarm optimization (PSO) is to introduce the elastic velocity adjustment factor to adaptively reduce or enlarge the position of particles on the basis of the basic particle swarm optimization algorithm and the improved particle swarm optimization algorithm, so as to avoid all particles gathering near an extreme point in the later stage of the algorithm, so as to avoid particles falling into local optimum and premature phenomenon. Elastic particle swarm optimization (PSO) can avoid strong “convergence” in the process of particle swarm optimization by adjusting the inertia factor adaptively, so as to improve the convergence accuracy of the algorithm.21

2. Adaptive variable coefficient particle swarm optimization algorithm.

The basic principle of adaptive variable coefficient particle swarm optimization algorithm is as follows: on the basis of traditional particle swarm optimization and elastic adaptive particle swarm optimization algorithm, the adaptive decreasing factor or adaptive increasing factor is introduced to modify the position change, and then the flight speed of the next-generation particle is adaptively adjusted; meanwhile, the inertia factor is expressed as a function of the average fitness variance reflecting the diversity of particle swarm. Its advantages: the adaptive increasing factor multiplied by the position change of I particle can increase the speed of the next generation of I particle, so as to speed up the convergence speed of the algorithm; the adaptive decreasing factor multiplied by the position change of the previous generation of I particle can reduce the speed of the next generation of I particle, so as to improve the search accuracy, so as to effectively avoid particle swarm optimization falling into local optimum and premature phenomenon. The adaptive inertia
factor can avoid strong “convergence” in the process of particle swarm optimization and improve the convergence accuracy of the algorithm.

3. Adaptive particle swarm optimization algorithm.

The basic principle of adaptive particle swarm optimization is: on the basis of basic particle swarm optimization, improved particle swarm optimization and adaptive variable coefficient particle swarm optimization algorithm, the inertia factor \( \omega \) is properly combined with the maximum fitness value of the K-L generation particle swarm, the minimum fitness value of the K-L generation particle swarm, the average fitness value of the K-1 generation particle population, the average fitness value of the K-2 generation particle population and the adaptive control parameters of the K-generation particle swarm. The \( \omega \) value is adaptively adjusted by inheriting and utilizing the population information of the first two generations of the particle swarm. Its advantages: realize the information sharing of particle swarm optimization, make the particle flight speed adaptive adjustment, and avoid particles falling into local optimum and premature phenomenon.

4. Adaptive particle swarm optimization algorithm.

The basic principle of adaptive particle swarm optimization algorithm is as follows: on the basis of traditional particle swarm optimization, adaptive variable coefficient particle swarm optimization and adaptive adjustment particle swarm optimization algorithm, the compression factor \( \lambda \) is introduced to adjust the global particle flight speed; the position adjustment factor is introduced to adjust the position of the next-generation particle; the inertia factor is expressed as the average fitness variance function reflecting the diversity of particle swarm. The advantages of the PSO algorithm are that the particle position and flight speed are adjusted adaptively, the global search ability of PSO algorithm is improved, and the convergence accuracy of PSO algorithm is improved.

5. Dynamic adjusting particle swarm optimization algorithm.

The basic principle of dynamically adjusting particle swarm optimization algorithm is as follows: on the basis of traditional particle swarm optimization, improved particle swarm optimization and adaptive particle swarm optimization algorithm, particle scale screening mechanism is introduced to adjust the flight speed of new generation particles. Through the screening mechanism, particles are divided into three categories: particles with high speed participate in global optimization; those with low speed participate in local optimization; those between the larger and smaller ones. In the later stage of particle operation, some of them are transformed into particles with higher speed to participate in adaptive global optimization; the other part is evolved into particles with low speed to participate in local optimization. The inertia factor \( \omega \) is coupled with the maximum and minimum velocities of particles and the number of iterations. Its advantages are as follows: it ensures the diversity of particles, improves the convergence speed and accuracy, and avoids particles falling into local optimum and premature phenomenon.

6. Implementation of mutation particle swarm optimization algorithm for solving optimal operation model of thermal power plants.

It is necessary to find a power change sequence to maximize the power generation benefits of thermal power plants under various constraints. When the model is solved by mutation particle swarm optimization algorithm, each particle represents a kind of operation mode of thermal power plant group. The power of each period of thermal power plant is set as the element of particle position vector \( \mathbf{x} \), and the climbing speed of final power of thermal power plant in each period is the element of particle velocity vector \( \mathbf{v} \). The change of final power in each period of thermal power plant group must meet various constraints in the above model.

According to the mathematical model of maximum power generation benefit of thermal power plants, the power is discretized into several points, and the combination of each power discrete point in each period is defined as the position represented by artificial particles, each position represents a solution of the problem, and the change of power is the particle velocity of particle swarm optimization. M artificial particles and their initial positions were randomly initialized.

In order to overcome the premature phenomenon of traditional particle swarm optimization (PSO), mutation particle swarm optimization (PSO) automatically adjusts mutation control parameters according to the individual fitness and the dispersion degree of the population. The particles are divided into two categories: the large particles participate in the global optimization, and the small particles participate in the local optimization. With the iteration, the adaptive particles are automatically selected to participate in the global optimization, which can not only maintain the diversity of the population, but also accelerate the convergence speed and improve the stability of the global convergence of the algorithm.

Based on the forecasting results of load and electricity price, and considering the constraints of output and power balance of thermal power plants, the optimal operation model of thermal power plants is established. Using the mutation particle swarm optimization algorithm to solve the model, the power price output curve of the thermal power plant group in each period of the day is obtained.
2.3 Sustainable development theory of smart energy industry

1. Connotation of sustainable development of smart energy industry.

In this paper, the definition of sustainable development of intelligent energy industry is summarized as: on the premise of not exceeding the ecological and social carrying capacity, providing energy and products to meet the needs of economic and social development, realizing the benign interaction between the development of intelligent energy industry and environmental protection, sustainable utilization of resources and social development, and realizing the coordinated development of economy, ecology, and society from the industrial level.

2. Theory of sustainable development of smart energy industry.

Sustainable development emphasizes the overall coordination of “economy, ecology and society,” reveals the operation essence of “development, coordination and sustainability,” and embodies the organic unity of “power, quality and fairness.” In other words, sustainable development is a process of positive interaction. On the one hand, industrial development drives the development of economy, society, and ecology; on the other hand, the three systems provide power for industrial development. Sustainable development is to achieve coordination in this interaction, while paying attention to the sharing of development quality and development results. Specifically, the sustainable development of intelligent energy industry includes the following aspects:

First of all, economy, society, and ecosystem are important supports for the sustainable development of intelligent energy industry. The industrial system operates in a certain socio-economic ecological environment, and a good socio-economic ecological environment provides power for the sustainable development of the industry. The development of social economy improves the purchasing power of consumers and increases the demand for products. Enterprises expand production through investment, including investment in natural resources and environment, production capital, labor force and infrastructure. In addition, industrial development also needs the support of upstream and downstream industries and government policies. Therefore, a country’s natural capital, production capital, social capital, human capital and their reasonable allocation, optimization and upgrading are important support for industrial development.

Secondly, the sustainable development of intelligent energy industry is based on its own development. Sustainable development opposes the traditional growth mode of pursuing economic benefits, but it does not deny economic growth. Economic growth provides the material basis for social wealth accumulation and technological innovation. Sustainable development advocates a development model based on environmental carrying capacity and aimed at improving people’s quality of life. For a single industry, industrial development is a process of scale expansion, technological progress, organizational change, and efficiency improvement. The development of intelligent energy industry is to expand the scale of intelligent energy industry to meet the needs of economic and social development through rational development and utilization of intelligent energy, improve market competitiveness through technological innovation, realize sustainable development, and improve industrial efficiency through industrial organization evolution.

Third, the sustainable development of intelligent energy industry should give full play to its ecological and environmental benefits. The development of intelligent energy industry is a double-edged sword, which has both positive and negative effects on the development of ecosystem. On the one hand, the production of energy equipment causes environmental pollution, and the repeated construction of large-scale intelligent energy projects causes resource waste; on the other hand, intelligent energy is generally renewable and clean, which ensures the stability of energy supply, reduces energy pressure and reduces environmental pollution. The sustainable development of intelligent energy industry should reduce resource consumption and replace pollution factors in the production of new energy equipment through the innovation of production technology and production process, so as to realize the replacement of traditional energy by intelligent energy and give full play to the advantages of intelligent energy.

The sustainable development of intelligent energy industry should continuously improve its social benefits. The development of intelligent energy industry to achieve social benefits is to achieve equity and share the fruits of industrial development. Through reasonable resource allocation, contemporary people can enjoy the benefits brought by the expansion of current industrial scale and efficiency, realize employment growth, provide rich intelligent energy products, meet the energy demand of backward regions, change the energy consumption structure, and solve the energy security problems. While meeting the needs of contemporary people, we should not deprive future generations of the ability to meet the needs, maintain a certain quality of resources and environment, and realize equal emphasis on intragenerational and intergenerational equity.

Finally, the sustainable development of intelligent energy industry should realize the unity of development, sustainability, and coordination. Development emphasizes the improvement of productivity, ecological protection, and social progress; sustainability emphasizes the long-term rationality...
in the process of development, which does not exceed the carrying capacity of social ecosystem, and seeks the driving force of sustainable industrial development; coordination emphasizes the organic unity of current interests and long-term interests, economic interests and social ecological interests, overall interests and local interests, and emphasizes protection, development, and efficiency The balance between rate and fairness.  

2.4 Smart energy construction environment

1. Social environment.

China’s energy consumption is mainly coal and oil, more and more use will lead to the shortage of fossil energy, which will lead to a substantial increase in production costs. These costs will increase the cost of living of consumers and affect people’s daily life. Smart energy can reduce energy consumption, reduce production and consumption costs of new energy by improving various energy systems and innovative energy technologies, promote the large-scale and commercial application of new energy, ensure the sustainable, safe and stable supply of energy, reduce people’s dependence on and use of fossil energy such as coal, so that we can enjoy cleaner and cheaper energy. Thus, smart energy can meet the needs of human development, improve our quality of life, and can get the support of the whole society.

2. Technical environment.

Intelligent energy application technology includes traditional energy conservation and emission reduction technology, new energy technology, and Internet technology, which are combined and applied with each other. It is an open, transparent and systematic integrated management system. It uses the Internet and modern communication technology to monitor, count and analyze the energy production, use, scheduling and efficiency in real time, and uses big data and cloud computing technology for real-time detection, monitoring report and optimization processing, so as to achieve the best state of an open, transparent and systematic comprehensive management system. The advent of the era of artificial intelligence can be said to provide a once-in-a-lifetime historical opportunity for promoting the energy revolution. The formation of intelligent energy will become the key symbol of substantial progress of energy revolution, which indicates that the energy revolution is highly integrated with information technology and industrial technology and is gradually becoming mature. At the same time, the substitution of energy forms is highly related to the transformation of civilization, and ultimately meets the requirements of civilization transformation, and establishes a new energy form from wisdom to wisdom. With the continuous advancement of energy revolution, the continuous breakthrough of energy technology, the continuous improvement of energy system and the sustainable development of intelligent energy, it can not only meet the requirements of safety, cleanliness, economy and sustainability, but also gradually develop into a similar human brain. According to the new trends and requirements of human cultural evolution, it has created a new era of intelligent energy.

3 EXPERIMENTAL DESIGN OF ENERGY OPTIMIZATION IN THERMAL POWER PLANT

3.1 Data collection and processing

Thermal power plants A, B, and C belong to the State Power Corporation and are dispatched by the same home appliance network company. The installed capacity of thermal power plant C is 150,000 kW, and the fitted coal consumption characteristics of four thermal power plants are $0.495p^2 + 28.245p + 148.0$; 4 sets of installed capacity of thermal power plant B are 300,000 kW, and the fitted coal consumption characteristics of four thermal power plants are $0.288p^2 + 24.649p + 228.0$; the installed capacity of thermal power plant A is 4 sets of 300,000 kW, 1 set of 600,000 kW, and the fitted coal consumption characteristics of 5 sets are $0.184p^2 + 16.726p + 420.0$; The load of each period of the system is obtained from the forecast, and the market clearing price on that day is obtained from the forecast. According to the optimal operation model of thermal power plant group, the dispatching plan of thermal power plant group is arranged, that is, the power price output curve is arranged, and the maximum benefit, minimum cost and minimum pollution discharge are considered.

3.2 Research object

The mutation particle swarm optimization algorithm is used to solve the optimal operation model of thermal power plants. Firstly, the load combination forecasting model is used to forecast the system load of each period on 1 January 2020 (without considering the network loss load). Then, using the load, weather, clearing electricity price data, load and meteorological data of the first two weeks, the clearing price of each period of the day is predicted by using the electricity price forecasting model. Then, the mutation particle swarm optimization algorithm is used to solve the optimal operation model of thermal power plant, and the power price output
curve, income curve and cost curve of thermal power plant are obtained.

4 | EXPERIMENTAL RESULT

4.1 | Artificial intelligence electricity price forecast

The comparison between the forecast price and the actual price on 1 January 2020 is shown in Figure 1. It can be seen from the figure that the predicted price is quite close to the actual price, and the median error of each period of the day is <1%, so the predicted value can be used to replace the actual value for scheduling.

The predicted system demand output of each period on 1 January 2020 and the output process of thermal power plants and thermal power stations in each period are shown in Figure 2. It can be seen from the figure that the output of thermal power plant group in each period is slightly higher than that of system demand in each period. The reason is that when arranging the output of thermal power plant group, considering the system network loss, the system network loss rate is tentatively set as 0.975%. Generally speaking, the output of thermal power plant group in each period can meet the system demand, output, and network loss balance.

According to the analysis of energy consumption characteristic curves of three thermal power plants, when the total output of thermal power plant is less than 290,000 kW, the operation of thermal power plant C is more favorable; when the total output of thermal power plant is greater than 290,000 kW and less than 430,000 kW, the operation of thermal power plant B is more favorable; when the total output of thermal power plant is greater than 430,000 kW, thermal power plant a is more favorable. It can be seen from the figure that thermal power plant C is basically operating at about 100,000 kW, thermal power plant B is basically operating between 100,000 kW and 200,000 kW, and thermal power plant a is basically operating between 190,000 kW and 300,000 kW.

The actual total output of the thermal power system, including the network loss, can fully meet the demand of the system. The output of each period of the thermal power plant makes up for each other, which not only meets the demand of system output, but also meets the requirement of minimum daily operation cost. It also shows that according to the change law of market clearing electricity price, the load distribution among thermal power plants can make the daily power generation revenue of thermal power plants maximum, and at the same time achieve the goals of minimum cost and minimum pollution discharge. Thermal power plants and thermal power plants generate more power when the electricity price is high, but less when the electricity price is low. According to the law of electricity price change, the dispatching under the condition of meeting the system demand at the same time, whether the single output and benefit of thermal power plants, or the output, benefit and market clearing price of the whole thermal power plant group are consistent in the time period, which fully meets the requirements of short-term optimal dispatching of thermal power plants.

4.2 | Thermal power plant optimization model

The comparison of the total output, revenue cost, and generation revenue of the scheduling model with mutation particle swarm optimization is shown in Figure 3.

The comparison of total output and power generation benefits of thermal power plants at each punctual time is shown in Figure 4.

The output, income, cost, and benefit of power plant group optimization model solved by mutation particle swarm optimization algorithm are affected by market factors, as shown in Table 1, and fluctuate with the change of market price.

It shows that the mutation particle swarm optimization algorithm is suitable for solving this kind of nonlinear combinatorial multi-objective optimization problems. Both the precision and the time of solving the optimization function are better. From the calculation and analysis of the above examples, it can be seen that for the optimal operation and scheduling of thermal power plants, the constraints of each generating unit should be met, and the load demand and network loss balance of the power system should be met. Then,
The constraints of the power industry and energy conservation and emission reduction should be followed, and according to the law of the electricity industry's clearing price, when the load demand of the power system is low, the power system should meet the constraints. The thermal power plant units with small capacity and low coal consumption rate should be arranged as far as possible to operate in a stable base load state; on the contrary, when the load demand of the power system is high, the thermal power plant units with large capacity and low coal consumption rate should be arranged as far as possible. When the load change is large, the large unit should undertake peak load regulation. Following the change of electricity market clearing price, it is necessary to adjust the stable operation of thermal power plants as far

**FIGURE 2** System demand output and output process of thermal power plants and thermal power stations in different periods

**FIGURE 3** Comparison of total output and whole day generation revenue, output and cost of each power station in 96 period of scheduling model based on mutation particle swarm optimization

**FIGURE 4** Comparison of total output and power generation benefits of thermal power plants at different punctual times based on mutation particle swarm optimization scheduling model

**TABLE 1** Comparison of total output and power generation benefits of thermal power plants at different punctual times based on mutation particle swarm optimization scheduling model

| On schedule | Predictive electricity | General Dispatching | Power plant A | Power plant B | Power plant C |
|-------------|------------------------|---------------------|--------------|--------------|--------------|
| time        | Price (yuan/ MWh)     | Force (MW)         | Total output (MW) | Total benefit (yuan) | Total output (MW) | Total benefit (yuan) | Total output (MW) | Total benefit (yuan) |
| 1:00        | 140                    | 400                 | 165           | 3400         | 160          | 3050         | 80           | 1260         |
| 11:00       | 360                    | 520                 | 260           | 12 000       | 176          | 8900         | 70           | 3260         |
as possible, and select the appropriate optimization model, which can achieve the purpose of maximizing benefits, minimizing costs and minimizing emissions.

The optimal operation of thermal power plant is a three-dimensional objective optimization problem with strong constraints, nonlinearity, and multi-stage. In this paper, according to the requirements of optimal operation of thermal power plant industry, the optimal operation model of thermal power plant industry under the power market environment is established, and the model is solved by mutation particle swarm optimization algorithm. The results show that the proposed method makes use of the adaptive mutation in the late stage of particle optimization, introduces the particle size screening mechanism, fully ensures the diversity of particles and improves the search ability of particles; the introduction of nonlinear adaptive adjustment inertia weight factor avoids the "convergence" in the process of particle swarm optimization, and improves the convergence speed and accuracy of the algorithm. A practical example shows that the algorithm is suitable for solving the three-dimensional objective optimization model.

5 CONCLUSIONS

In recent years, with the rapid development of China's economy, energy consumption is increasing. How to make full use of the discharge and inflow time of the reservoir and accurately predict the inflow of the reservoir is a difficult problem. How to coordinate hydropower generation and thermal power generation while pursuing the maximum comprehensive benefit is also an urgent problem to be solved. In the environment of power industry, the essence of power load forecasting is to forecast the power demand of power market. Short-term load forecasting is an important part of load forecasting, which is of great significance to optimal combination dispatching of power plants, economic operation of power system, optimal power flow distribution of power grid, and power market transaction.

According to the characteristics of hydropower industry and various constraints, this paper studies the optimal operation model and intelligent solution method of hydropower station under the environment of power industry, aiming at maximizing the power generation income of hydropower industry. Considering the characteristics of cascade hydropower stations and the demand of hydropower stations, the optimization model of cascade hydropower stations is established to meet the demand of hydropower stations. According to the requirements of industrial optimal operation of thermal power plant, the optimal operation model of thermal power plant under the power market environment is established, and the intelligent solution method is studied. According to the characteristics of hydrothermal power plants and various constraints, aiming at maximizing power generation benefits, minimizing wastewater and minimizing operating costs, a joint optimal operation model of hydrothermal power plants under the power market environment is established to reduce the start-up and shutdown costs as much as possible and reduce pollution emissions. At the same time, the balance between the total output of the hydropower station in each period to meet the system output demand and the power grid loss in each period is studied, and the intelligent solution method is studied.

In this paper, an optimal operation model of power industry based on artificial intelligence and low-carbon environmental protection is established. The complex optimal operation strategy of thermal power plant is transformed into a strongly constrained, nonlinear, multi-stage ternary combinatorial optimization problem, and the model is solved by mutation particle swarm optimization algorithm. In order to ensure the diversity of particle swarm optimization, improve the search ability of particles, avoid the "convergence" in the process of particle swarm optimization, and improve the convergence speed and accuracy of the algorithm, the particle selection mechanism and nonlinear adaptive inertia weight adjustment are introduced. Numerical examples show that the proposed mutation particle swarm optimization algorithm is suitable for solving the nonlinear ternary combination optimization model and can quickly obtain the load curve and benefit curve of electricity price.

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**How to cite this article:** Shi C, Feng X, Jin Z. Sustainable development of China’s smart energy industry based on artificial intelligence and low-carbon economy. *Energy Sci Eng*. 2022;10:243–252. [https://doi.org/10.1002/ese3.856](https://doi.org/10.1002/ese3.856)