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An application of grey model based on particle swarm optimization in power load forecasting

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ABSTRACT

Power load forecasting is an important part of power system planning and the basis of economic operation of power system. It is extremely important for power system planning and operation. The traditional grey forecasting model GM(1,1) can be applied to power load forecasting, but the forecasting accuracy will be greatly reduced when the power load changes with a faster growth rate are forecasted. In view of the limitation of the traditional grey prediction model GM(1,1), this paper will introduce particle swarm optimization algorithm, which combines it with the traditional grey prediction model GM(1,1) to solve the parameters of the grey model, thus a new prediction model is proposed. In order to verify the accuracy of the new forecasting model, three groups of different load data are selected to simulate GM(1,1) model and the improved model proposed in this paper. The results show that the model has high forecasting accuracy in forecasting the fast-growing power load.

Key words: power load forecasting; particle swarm optimization algorithm; grey model; forecasting accuracy; increment speed

INTRODUCTION

Electricity is the lifeblood of the national economy, which provides the necessary guarantee for the development of enterprises and institutions as well as the safety and stability of residents'lives. With the continuous improvement of the world economy and living electrification level, people's demand for electricity consumption continues to grow. Therefore, the power load forecasting technology which affects decision-making becomes more and more important. Power load forecasting is one of the important tasks of the power sector. Accurate load forecasting can economically and reasonably arrange the start-up and shutdown of generators within the power grid, maintain the security and stability of power grid operation, reduce unnecessary rotating reserve capacity, rationally arrange unit maintenance plans, ensure normal production and life of society, effectively reduce generation costs, and improve economic benefits and social benefits. Will benefit. The accuracy level of load forecasting directly affects whether the power sector can economically and optimally formulate power generation plans, formulate economic and reasonable power allocation plans, control the economic operation of power grids and arrange the installation and maintenance plans of units. Therefore, it is of great practical significance to explore effective methods to improve the accuracy of power load forecasting.

With the increase of energy consumption, it is more and more important to effectively improve the management level of power energy on the premise of the established total amount. More and more researchers have devoted themselves to the research of load forecasting technology, and new technologies have been put forward for many years. There are two common types of new load forecasting technologies, one is the basic forecasting methods represented by trend extrapolation, regression, time series and grey forecasting, the other is the integration of intelligent algorithm on the basis of the original forecasting technology to optimize the forecasting model. In most cases, a single prediction technology can not achieve the desired prediction accuracy. Combination forecasting with multiple methods has been widely used in recent years. At present, the representative forecasting methods in power load forecasting technology mainly include Delphi method, unit consumption method, elastic coefficient method, time series method, regression analysis method, trend extrapolation method, grey forecasting method, neural network method, wavelet analysis method, etc. Compared with other methods, the grey forecasting technology can establish a model in line with the forecast in the case of few data and poor information. Especially, short-term forecasting can achieve better results. It has the advantages of small sample size and high accuracy, and is widely used in power load forecasting technology. The grey forecasting method has many advantages, such as less sample data, no need to consider the distribution law and change trend, convenient operation, high forecasting accuracy, easy to test and so on, so it has attracted the attention of power system researchers. However, the GM(1,1) model has some limitations like other prediction methods. When the data is more discrete, that is, the grey level of data is larger, the prediction accuracy becomes worse, and it is not suitable for long-term backward prediction of power system for several years. Particle swarm optimization is a kind of swarm intelligence optimization algorithm, which has the characteristics of convenient parameter adjustment, fast convergence speed and strong global search ability. It can better deal with multi-dimensional space multi-peak problem optimization and dynamic target optimization. Moreover, the algorithm has fast processing speed, good solution quality and robustness, and has a wide range of applications in power load forecasting.

Based on particle swarm optimization and grey prediction model GM(1,1), considering that the precision of model fitting and prediction is poor when the absolute value of grey number a is large (i.e. when the data sequence changes unevenly), a grey model combining particle swarm optimization is proposed, and the implementation process of the model is discussed in detail. This paper uses the historical load data of a certain power grid to simulate and test the forecasting model, and verify its effect. The error analysis of the application results shows that the forecasting model constructed in this paper can achieve high forecasting accuracy in power load forecasting, which is superior to the traditional GM(1,1) model, expands the application scope of grey model, and has certain application value.

PARTICLE SWARM OPTIMIZATION ALGORITHM

Particle swarm optimization (PSO) arises from the simulation of the behavior of birds and other groups. The Boids model proposed by C.W. Reynolds, a biologist, has great influence. The model interprets that individual behavior is only related to the behavior of its neighbors. Individuals follow three rules: collision avoidance, speed consistency and centripetal (average position) aggregation. In nature, many individual birds in the initial random state gradually organize into many smaller communities with the same speed and direction, and then integrate larger communities, which may disperse into many smaller communities. Biologist F. Heppner et al. studied the convergence behavior of birds, and found that birds fly synchronously on the basis of local perception, without a fixed coordinating organizer. E.O. Wilson, a biosociologist, concluded that in searching for unknown distribution of food, individuals gain more synergistic advantages through the experience of other members than the disadvantage of competition. P.J. Richerson and R. Boyd summarize the experiences people often use to make decisions based on their own experiences and those of others. After the study of bird swarm and human social system, the core idea of particle swarm optimization is summarized, that is, information sharing among groups is conducive to overall evolution.

To sum up the above research, American scholars J.Kennedy and R.C.Eberhart published an article entitled “Particle Swarm Optimization” at the IEEE International Neural Network Academic Conference, marking the formal establishment of particle swarm optimization. Subsequently, Y.Shi and R.C.Eberhart published an article entitled “A Modified Particle Swarm Optimizer” to further optimize and improve the particle swarm optimization algorithm. Practice shows that the particle swarm optimization algorithm can better deal with multi-dimensional space multi-peak problem optimization and dynamic target optimization, and the processing speed of the algorithm, the quality of the solution and robustness are good.

Particle swarm optimization initializes a group of particles randomly, and a single particle is considered as a feasible solution. The fitness function is used to judge whether the particle is good or bad. Common test functions include Sphere function, Rosenbrock function, Schwefel function, Rastrigin function, Quartic function

(Noise) function, Griewank function, Ackley function and Shaffer function. Each particle moves in the feasible solution space, and the velocity variable of the particle is composed of direction and distance components. Each particle follows the current optimal particle, searching and comparing generation by generation to get the optimal solution. In each iteration, the particle compares the optimal solution found by itself and the group optimal solution.

2.1 Parameter Setting

There are fewer parameters to be adjusted in particle swarm optimization, and the experience of parameter setting is as follows:

1. Number of particles: generally take 20-100, for most of the optimization process, often select 50 particles can get better results. When dealing with complex problems, the number of particles may reach 200 or more.
2. Particle length: The length of the solution of the problem to be solved is determined by the optimization problem itself.
3. The range of particles: the range of different dimensions is also determined by the optimization problem itself.
4. v_{max} : The maximum search speed of a particle determines the maximum displacement of the particle in each iteration. It is usually set to the range width of particles.
5. Learning factor: c_1 and c_2 are usually set to 2. In the existing literature records, generally c_1 is equal to c_2, and its range of variation is between 0 and 4.
6. Termination Conditions: Determined by specific problems, when the maximum number of iterations or a constraint condition is achieved, the algorithm search ends.

In addition, the parameter improvement of particle swarm optimization is mainly to innovate the velocity iteration formula in the algorithm, which mainly includes three aspects: the adjustment of inertia weight, the adjustment of learning factor and the adjustment of other parameters in the velocity iteration formula.

2.2 Implementation Steps

The implementation steps of particle swarm optimization are as follows:

Particle swarm optimization firstly randomly initializes the particle swarm in search space and velocity space, that is, to determine the initial position and velocity of the particle. Assuming the size of the initial population is *N*, the position and velocity of the first particle in the D-dimensional search space can be expressed as follows:

$$X_i = \left[x_{i1}, x_{i2}, \cdots, x_{iD}\right] \tag{1}$$

$$V_i = \left[v_{i1}, v_{i2}, \cdots, v_{iD}\right] \tag{2}$$

By evaluating the fitness of particles, the optimal fitness positions of each particle (pbest) at k-time and the best fitness positions experienced by all particles in the population (gbest) are determined, marked as P_i and P_g :

$$P_i = \left[p_{i1}, p_{i2}, \cdots, p_{iD}\right] \tag{3}$$

$$P_g = \left[p_{g1}, p_{g2}, \cdots, p_{gD}\right] \tag{4}$$

is the objective function, the optimum position of particle *i* is:

$$p_{i(k+1)} = \begin{cases} p_{i(k)} \cdots i = f \cdots f\left(x_i(k+1)\right) \geq f\left(p_i(k)\right) \\ x_{i(k+1)} \cdots i = f \cdots f\left(x_i(k+1)\right) < f\left(p_i(k)\right) \end{cases} \tag{5}$$

The global optimum position of all the particles in the population is:

$$p_g \in \begin{cases} \left[P_1(k), P_2(k), \cdots, P_D(k)\right] \\ f\left(P_g\right) = \min\left(f\left(P_1(k), P_2(k), \cdots, P_D(k)\right)\right) \end{cases} \tag{6}$$

In each iteration of particle swarm optimization, the particle updates its speed and position by tracking pbest and gbest. The specific updating formulas are as follows:

$$\begin{aligned} V_{i,j}(k+1) = \omega V_{i,j}(k) + c_1 r_1\left[P_{i,j}(k) - X_{i,j}(k)\right] \\ + c_2 r_2\left[P_{g,j}(k) - X_{i,j}(k)\right] \end{aligned} \tag{7}$$

$$\begin{aligned} X_{ij}(k+1) = X_{ij} + V_{ij}(k+1), i = 1,2,\cdots,N, \\ j = 1,2,\cdots,D \end{aligned} \tag{8}$$

In formula (7) and formula (8), ω is inertia weight factor, c_1 and c_2 are positive acceleration constants which usually between 0 and 2, r_1 and r_2 are random numbers between 0 and 1. In addition, by setting the velocity range $[-v_{\max}, v_{\max}]$ and position range $[x_{\min}, x_{\max}]$ of particles, the movement of particles can be appropriately restricted.

GREY PREDICTION MODEL

In 1979, Professor Deng Julong, a Chinese scholar, opened the prelude of the study of grey system theory with a paper entitled "Minimum information stabilization of systems with incomplete parameters". In 1982, Professor Deng published the first paper on grey system theory "The Control Problems of Grey Systems" in the magazine "Systems and Control" of the Northern Netherlands Publishing Company, and published a paper entitled "Grey Control System" in the Journal Journal of Central China Institute of Technology, marking the establishment of grey system theory since then. Since then, many scholars at home and abroad have done a lot of research on Grey Theory and its practical application, with fruitful results. In addition to a large number of high-level academic papers, the integration of grey system theory and other disciplines has formed a series of new branches of disciplines, such as grey breeding, grey medicine, grey geology and so on. So far, the application of grey system theory has been extended to many fields, such as industry, agriculture, energy, transportation, geology, ecology, environment, meteorology, education, medicine, law, sports, military, economic, financial, management and so on. After more than 30 years of development, grey system theory has formed a relatively perfect theoretical system. Based on Grey algebraic system, grey equation and grey matrix, the whole set of theory forms an analysis and evaluation model system based on grey correlation space, grey clustering and grey statistical evaluation. Based on the five-step method (analyzing and sorting out the original data, weakening the impact disturbance system through grey sequence generation and operator, mining the potential law of the system, transforming difference equation and differential equation, establishing dynamic differential equation with original data), the method system is based on sequence grey prediction, catastrophic grey prediction, interval grey prediction and topological grey prediction. Prediction system based on grey prediction of measurement and system; decision model system marked by grey target decision, grey relational decision, clustering decision and grey hierarchical decision; grey combination model system characterized by multi-method integration and innovation, and optimization model system with grey programming, grey game, Grey Input-output and grey control as its theme; system analysis and evaluation Estimation, modeling, prediction, decision-making, control and optimization are the main technical systems.

In the research of grey system theory, all kinds of systems are divided into white, black and grey systems. "White" means that the information is completely known, "black" means that the information is completely unknown, "gray" means that the information is partly known, partly unknown, or incomplete. In real life, there are always incomplete information in various systems in the fields of economy, energy and so on. Common information such as parameter, structure and relationship is incomplete. Such systems belong to grey system. The research of grey system is to extract the valuable part of the known information, and then form the recognition of the system's operation law.

There are six basic principles of grey system theory, namely, the principle of difference information, the principle of uncertainty of solution, the principle of cognitive basis, the principle of minimum information, the principle of new information priority and the principle of grey immortality. Specific explanations are as follows: the principle of difference information indicates that difference is information, and there must be difference in all information; the principle of uncertainty of solution indicates that the problem has non-unique characteristics due to incomplete information, which is the basic principle of grey system theory to solve practical problems; the principle of cognitive basis reflects that information is the basis of cognition; the principle of minimum information, because of grey system theory. Small samples and poor information of the system have the characteristics of uncertainty, so the solution of grey system theory is based on making full use of the least known information. The new information priority principle shows that the new information has better guiding significance for the cognition of things and the change of future development than the old information. Therefore, in the practical application process, researchers often provide new information. Given more weight, this method can achieve better results in grey modeling, grey prediction and grey evaluation. The principle of grey immortality shows that "incomplete information" is absolute and complete information is relative.

Grey forecasting is a quantitative forecasting based on GM(1,1) model. According to its functions and characteristics, it can be divided into sequence forecasting, waveform forecasting, interval forecasting, catastrophe forecasting and system forecasting. Grey prediction is an important part of grey system theory. GM(1,1) model is the core content of grey prediction model. The model is generated by accumulating historical data series. Because the accumulated sequence has exponential growth law, combined with the solution of first-order differential equation has the characteristic of exponential growth, the model parameters are solved by least square method, and the homogeneous index is established for the accumulated generated sequence. The model is fitted by number, and the target value is obtained by cumulative reduction. For power load system, the situation of power supply units, power grid capacity and so on is known, but other factors affecting the load, such as weather conditions, regional economic activities and so on, are difficult to know accurately. Therefore, power load can be defined as a grey system, and the use conditions of GM(1,1) model for power load forecasting can be defined.

3.1 Modeling process

The specific modeling process of grey prediction model is as follows:

The original data of electricity load in previous years are:

$$x^{(0)} = \left[x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\right] \tag{9}$$

Let one accumulated generating operation (1-AGO) of Sequences be:

$$x^{(1)} = \left[x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\right] \tag{10}$$

Among it: $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$

Because of the exponential growth of sequence $x^{(1)}$, we consider that sequence $x^{(1)}$ satisfies the first order linear differential equation with exponential growth as its general solution:

$$\frac{\mathrm{d}x^{(1)}}{\mathrm{d}t} + ax^{(1)} = u \tag{11}$$

The differential term in discrete form can be expressed as $x^{(0)}(k+1)$. $x^{(1)}$ takes the average values at k and k+1:

$$x^{(1)} = \frac{1}{2}\left[x^{(1)}(k) + x^{(1)}(k+1)\right] \tag{12}$$

So the equation is transformed to:

$$x^{(0)}(k+1) + \frac{1}{2}a\left[x^{(1)}(k+1) + x^{(1)}(k)\right] = u \tag{13}$$

The above results are written in matrix form as follows:

$$\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} = \begin{bmatrix} -\frac{1}{2}\left[x^{(1)}(1) + x^{(1)}(2)\right] & 1 \\ -\frac{1}{2}\left[x^{(1)}(1) + x^{(1)}(2)\right] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left[x^{(1)}(1) + x^{(1)}(2)\right] & 1 \end{bmatrix} \begin{pmatrix} a \\ u \end{pmatrix} \tag{14}$$

By solving the equation, we can get: $\left(B^T B\right)^{-1} B^T Y_n = \begin{bmatrix} \hat{a} \\ \hat{u} \end{bmatrix}$. By taking the parameters back to the original equation, we can get:

$$\hat{x}^{(0)}(k+1) = \left(1 - e^{\hat{a}}\right)\left[x^{(0)}(1) - \frac{\hat{u}}{\hat{a}}\right]e^{-\hat{a}k}, (k = 1,2,\cdots,N) \tag{15}$$

3.2 Parameter Significance

The development coefficient a and grey action u in GM(1,1) model respectively reflect the development trend of the accumulative generated sequence and the fitting value of the original sequence and the relationship between the data changes in the background value. Grey action u is used to distinguish general input-output modelling from grey modelling. It is also an important symbol to distinguish grey box viewpoint from grey system viewpoint. The GM(1,1) model can be established after the variables a and u are determined, and the scope of application of the model is determined. It has been proved by literature that when the development coefficient $|a| \geq 2$, the GM(1,1) model is meaningless. The smoother the original data changes, the smaller the development coefficient $|a|$, and the higher the prediction accuracy of the corresponding GM(1,1) model. The applicability of GM(1,1) model varies with the range of value of $|a|$. It can be summarized as follows:

1. When $-a \leq 0.3$, GM(1,1) model is suitable for

medium and long term prediction,

2. When $-3 < -a \le 0.5$, GM(1,1) model is not suitable for medium and long term prediction,
3. When $0.5 < -a \le 0.8$, GM(1,1) model should also be used cautiously for short-term prediction,
4. When $0.8 < -a \le 1$, residual correction GM(1,1) model should be adopted,
5. When $-a > 1$, GM(1,1) model was no longer suitable for use.

A large number of examples show that GM(1,1) model can better fit the exponential growth curve, and can achieve higher prediction accuracy in power load forecasting. However, when the data is more discrete, that is, the greater the gray level of data, the prediction accuracy will be greatly reduced.

ESTABLISHMENT OF GREY MODEL FOR DYNAMIC PARTICLE SWARM OPTIMIZATION

Over the years, scholars have done a lot of research on Optimization and improvement of grey prediction model, but there are still some defects and improvement space in grey prediction model. When the traditional grey forecasting model GM(1,1) is used to predict the fast-growing load, the forecasting accuracy will be deviated. The reason for the sharp decrease of prediction accuracy is that the background value is simply defined as the form of formula (12) in the process of solving. In order to avoid errors caused by inappropriate background values, it is particularly important to use appropriate methods to find the appropriate a value. Formula (14) and formula (15) show that there is a high degree of non-linear relationship between a and error. It is difficult to solve the optimal value a by traditional optimization methods. Therefore, this paper uses particle swarm optimization to solve GM(1,1) model, and constructs a grey prediction model based on particle swarm optimization.

4.1 Implementation Steps

The algorithm of the model is described as follows:

Step 1: Initialize particles: Randomly generate *N* particles, set the initial position and velocity of particles.

$$Y_i = [a_i, u_i](i = 1,2,\cdots,N) \tag{16}$$

$$V_i = [v_{i1}, v_{i2}](i = 1,2,\cdots,N) \tag{17}$$

Step 2: Calculate the fitness of each particle: Substitute a_i into formula (12) to get $x^{(1)}$, and then substitute its value into formula (14) and formula (15) to get the fitting value of the original data of the particle.

Set the sum of squares of errors $\sum_{k=1}^{n}\left(x^{(0)}(k) - x^{(0)}(k')\right)^2$ as the objective function to calculate the fitness value.

$$f(Y_i) = \frac{1}{2}\sum_{k=1}^{n}\left[x^{(0)}(k) - x^{(0)}(k')\right]^2 \tag{18}$$

$x^{(0)}(k)$ and $x^{(0)}(k')$ are the k-th actual and predicted values of the load respectively.

Step 3: Use formula (7) and formula (8) to determine the new position and velocity of each particle. If the particle fitness is better than the corresponding fitness of pbest, set it to the new pbest. If the particle fitness is better than the corresponding fitness of gbest, set it to gbest. Assuming that the number of iterations is greater than the maximum number of iterations or the objective function achieves the set ideal threshold, the iteration process ends and the final gbest and pbest are output to get the value of *a*.

4.2 Parameter Setting

In addition, the optimized parameters are as follows:

1. *D*: The number of particles in the population is set to 40.
2. *X*: The position of each particle is initialized by the program according to the difference between the upper and lower bounds of the function.
3. *V*: The maximum velocity is set at 15% of the range of change per dimension. In addition to the randomly generated range of r_1 and r_2 in the velocity formula, the random variable r_3 in the range of (0,1) is introduced. When the search stagnation speed of PSO algorithm tends to zero, r_3 can regain a certain speed of particles and continue to search.
4. *w*: inertia weight: Because the inertia weight affects the optimization effect of the algorithm, the larger the inertia weight, the better the global optimization; on the contrary, the smaller the inertia weight, the better the local optimization.

Therefore, a linear descending method is used to set the inertia weight, which can give full play to the global search ability of the algorithm, converge to a certain region quickly, and then obtain a higher precision solution through local precise search.

5. c_1, c_2 : learning factor, take $c_1 = c_2 = 1.49445$.
6. MaxIter: Maximum number of iterations. After many calculations, MaxIter is 1500.

APPLICATION CASE ANALYSIS

This paper collects the historical load data of a district in Beijing to test the forecasting effect of the grey power load forecasting model based on particle swarm optimization. All the data are collected from the dispatching and marketing department of Beijing National Grid Corporation. Beijing National Grid Power Company is a provincial power unit, which is responsible for the construction and operation of Beijing Electric Grid. Besides providing safe and reliable power supply for customers in the area under its jurisdiction, the company also undertakes the important mission of ensuring the reliable use of electricity by the central authorities and various political, economic and cultural activities in the capital. By the end of 2012, the company had supplied power to 16 districts in Beijing, covering a total area of 16 410 square kilometers, providing power security to 20.693 million permanent residents. The capacity of power generation equipment in Beijing area is 7.3419 million kW. Including power generation capacity of 508,800 kW self-contained power plant and unified power generation capacity of 683,740,000 kW. The power transmission line of Beijing power grid is 227.15 kilometers with a transformer capacity of 3286,000 kilovolt-amperes. 419 substations and 1029 transformers with a total transformer capacity of 94324.4 MVA are operating in Beijing. Including 9 500 kV substations, 26 transformers, the total transformer capacity reached 25 206 MVA; 220 kV substations 70, 181 transformers, transformer capacity 31605 MVA. Among them, there are 62 substations, 158 transformers, transformer capacity 30130 MVA; 8 user substations, 23 transformers, transformer capacity 1475 MVA; 340 110 kV substations, 822 transformers, transformer capacity 37513.4 MVA. Among them, the company's 286 substations, 704 transformers, transformer capacity 33500.5 MVA; user substations 54, 118 transformers, transformer capacity 4012.9 MVA. The company has 474 overhead lines with a total length of 6338.492 km, including 6 500 kV overhead lines with a length of 223.06 km, 183 220 kV overhead lines with a length of 2648.132 km, 285 110 kV overhead lines with a length of 3467.3 km, 773 110 kV and above lines with a total length of 1426.356 km, 109 220 kV cables with a length of 339.554 km and 664 110 kV cables with a length of 1086.802 km. The load status of Beijing power grid is a typical representative of the industry in the whole country. Therefore, it is of practical significance to select load data of Beijing power grid to test the model.

In order to correctly evaluate the accuracy of the forecasting model, three sets of historical load data in recent three years are selected to simulate GM (1,1) model and the improved model proposed in this paper. The original test data is shown in Table 1. The data corresponding to the first seven year numbers in Table 1 will be used as the original data sequence of the test. The data with the year number 8 is the load value corresponding to k=8. This value will be used as the accurate value of the year to be predicted to evaluate the accuracy of the predicted results. The three groups of data in Table 1 grow in an approximate exponential manner, and the growth trend is shown in Figure 1.

Tab. 1 The power load data for testing

Number	Load1	Load2	Load3
1	1.2637	1.2845	1.6408
2	1.3073	1.3522	2.1456
3	1.3125	1.4520	2.7413
4	1.3512	1.6703	3.4952
5	1.4521	1.8255	4.4522
6	1.5846	2.1075	5.3712
7	1.6254	2.3215	7.4561
8	1.7145	2.4763	9.4812

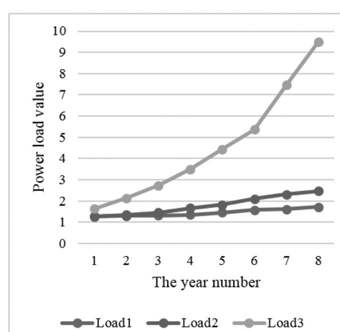

Fig. 1 Electricity consumption curves of certain regions in 7 years

In the actual test of the model, the number of randomly generated particles N=500, the maximum number of iterations is 300, the change of decreases from 1.2 to 0.2, $C_1 = C_2 = 2$, and $V_{\max}$ is set to 10% of the range of change per dimension. The posterior difference ratio, small error probability and the relative error between the predicted value and the actual value of the two models are tested respectively. Among them, the posterior difference ratio represents the ratio of residual variance to historical data variance, the smaller the value, the better. The probability of small error is defined as the probability that the absolute value of each residual and its mean value is less than 0.6745 times of the root mean square of the variance of historical data, and the larger the value, the better . The test results are shown in Table 2 and Figure 2.

Tab. 2 Comparison of the simulation results with GM(1,1) model and PSOGM(1,1) model

Load	Model	The value of a	Forecast annual actual load value	Forecast value of forecast year	posterior error ratio	Small error probability	Relative error
Load1	GM（1,1）	0.4736	1.7145	1.7287	0.009	1	0.221
	PSO-GM（1,1）	0.4803	1.7145	1.7132	0.007	1	0.178
Load2	GM（1,1）	0.4353	2.4763	2.4678	0.005	1	0.345
	PSO-GM（1,1）	0.4420	2.4763	2.4703	0.003	1	0.248
Load3	GM（1,1）	0.7102	9.4812	9.4722	0.008	1	0.562
	PSO-GM（1,1）	0.7464	9.4812	9.4801	0.004	1	0.102

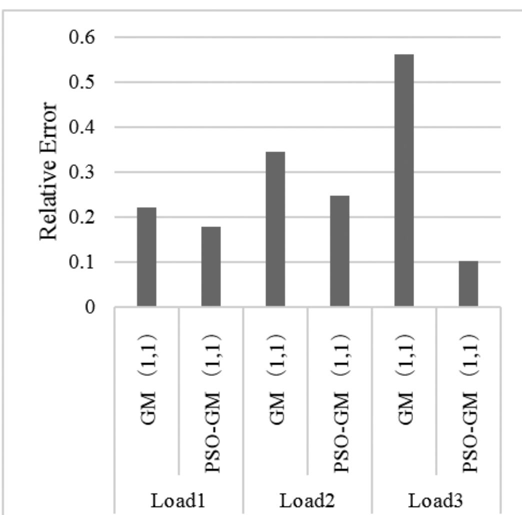

Fig. 2 The forecasting error comparison of three groups power load

From the comparison of the prediction errors between the data in Table 2 and those in Figure 2, it can be seen that the advantages of GM(1,1) with PSO are not obvious when the load increases slowly (as shown in the first column in Figure 2), because the GM(1,1) model itself has achieved a good prediction accuracy for the data with slower growth. For the load data with larger increment (as shown in column 3 of Figure 2), the prediction accuracy of the new model is better than that of the pure GM(1,1) model because of the participation of particle swarm optimization.

SUMMARY

Based on the traditional GM(1,1) algorithm and aiming at the problem that the prediction accuracy decreases when the power load forecasting data increases rapidly, the particle swarm optimization algorithm is used to solve the parameters of GM(1,1) model instead of the traditional least squares method. A new prediction model is proposed, and the realization process of the model is discussed in detail. The simulation results of the model are tested by the actual survey data of Beijing Power Grid. The error analysis proves that the prediction accuracy of the model is obviously improved when forecasting the power load data with fast growth. In theory, the accuracy of the grey model is improved, the adaptability of the model is enhanced, and the application scope of GM(1,1) model is extended. The model is applied in power load forecasting. It can achieve good prediction results, and has certain theoretical significance and application value.

With the prominence of energy shortage and the further advancement of China's green energy strategy, the forecasting work provides important guidance for the effective allocation of established resources. With the increase of attention, more and more researchers have devoted themselves to the research of power load forecasting. The current research on load forecasting should be more realistic and systematic, which poses new challenges to our research ability. More load forecasting problems are waiting for us to solve. There is still room for further optimization in this paper. For example, whether there is a general data transformation method that can minimize the error of the prediction model, whether there are some shortcomings of the particle swarm optimization algorithm itself, whether it is necessary to improve the algorithm, can better improve the prediction accuracy of the model, and so on, these aspects are the direction that we need to continue to work on. In addition, the forecasting data are replaced by the same dimension, and the variables A and u are regarded as functions of t, so the forecasting model can be used for long-term load forecasting.

With the further study of management science theory and the improvement of human's cognitive ability, more advanced and complex research methods will be used to solve the existing problems. The research of power load forecasting technology will develop towards more intelligent direction, and more accurate forecasting technology will guide the efficient operation of the power sector.

Biographical Notes

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