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Application of Optimized GM (1, 1) Prediction Model based on Ant Colony Algorithm in the Medium and Long Term Load Forecasting

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Abstract

The medium and long term load forecasting is the basis of power planning, investment, production, scheduling and trade, which plays an important role in electric power safety and economic operation. In China, it has the increasing uncertainty and the uncertainty of random variation to forecast the medium and long term load. Thus we can regard it as a typical grey system. However, the traditional grey prediction method cannot be adapt to the needs of the load forecasting gradually. It need to be rich and perfect with the continuous improvement of power system complexity and power marketization degree. This paper studied the modelling mechanism of grey prediction model. Then we analyzed the problems existing in the model, including the boundary value problem, the background value structure problem and the least squares parameter identification problem. This paper put forward an optimization method to directly identify the boundary value x(0)(1), the developing coefficient a and grey coefficient b using ant colony algorithm according to the time response expression of GM(1,1) model, so that it established an optimized GM(1,1) prediction model based on ant colony algorithm. This model can fix the impact of boundary value, and also avoid the errors brought by the background value construction and the least squares parameter estimation. It can verify the effectiveness of the proposed optimization model through the load data simulation. And it can improve the prediction accuracy effectively.

Keywords: *medium and long term load forecasting, grey prediction model, ant conoly algorithm*

1. Introduction

Power system load forecasting is one of the important work of the power sector. It is not only the premise to formulate reasonable power macroscopic planning, but also an important guarantee of electric power system safe and economic operation. It can keep the safety stability of the power grid operation, reduce unnecessary spinning reserve capacity, reasonably arrange the unit overhaul, ensure the normal production of society and people's normal life and improve the economic benefit and social benefit based on the accurate load forecasting [1]. Compared with other types of load forecasting, the medium and long term load forecasting has less samples. The forecast time span is larger. And the main influence factors are the macro economic and social factors which are mainly used in the macroscopic planning.

The development course of medium and long-term load forecasting technology is long. It gradually formed some mature methods. There are mainly two kinds of methods. One is the classic prediction method, including the time series method, regression analysis, correlation analysis, *etc.,* The other is the emerging prediction method, including the grey system theory, fuzzy prediction, expert system, support vector machine, *etc.*, In China, it

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has the increasing uncertainty and the uncertainty of random variation to forecast the medium and long term load [2]. Thus we can regard it as a typical grey system. However, the traditional grey prediction method cannot be adapt to the needs of the load forecasting gradually. It need to be rich and perfect with the continuous improvement of power system complexity and power marketization degree.

In this paper, GM (1,1) model were introduced. Besides, it analyzed the defects in modeling mechanism, determined key parameters of the model, optimized the parameters using ant colony algorithm, so that it established an optimized GM (1,1) prediction model based on ant colony algorithm. Finally, the optimized model was applied to the actual medium and long-term load forecasting to verify its effectiveness.

2. Grey GM (1, 1) Prediction Model

The grey system theory was put forward by the Chinese professor Deng JuLong in 1982, which was aimed to solve the partial information known, the partial information unknown problem with small sample, poor information system. Grey prediction model is one of the important contents of grey system theory [3]. And its core is the gray accumulation generation. In the prediction process of grey model, first of all, accumulate the system original sequence to get the approximate exponential law accumulation generation sequence. Then establish the differential equation and the difference equation based on the grey exponential rate of accumulation generation sequence. And to solve the accumulation generation sequence and predicted value of the fitting. Finally, the fitting values and predicted values of original sequence is obtained by the b-b reduction [4]. The grey GM (1,1) prediction model is the most commonly used grey forecasting model in the power system load forecasting. And this model has the advantages of low requirement of raw data, simple modeling process, convenient calculation and precision inspection, which has been widely used in load forecasting.

2.1. The Process of GM (1, 1) Model

Suppose $X^{0} = (x^{0}(1), x^{0}(2), \cdots, x^{0}(n))$, $X^{1} = (x^{1}(1), x^{1}(2), \cdots, x^{1}(n))$, and the original form of the model is

$$x^{(0)}(k) + ax^{(1)}(k) = b \tag{1}$$

$$Z^{1} = [z^{1}(2), z^{1}(3), \ldots, z^{1}(n)] \tag{2}$$

Among

$$z^{1}(k) = \frac{1}{2}[x^{1}(k) + x^{1}(k-1)] \tag{3}$$

And the basic form of the model is ：

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{4}$$

Suppose $X^{(0)}$ as a negative sequence

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)) \tag{5}$$

among,

$$x^{(0)}(k) \geq 0, k = 1, 2, \cdots, n \tag{6}$$

$X^{(1)}$ is the 1-AGO sequence of $X^{(0)}$ [5] .

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)) \quad (7)$$

among,

$$x^{1}(k) = \sum_{i=1}^{k} x^{0}(j); k = (1, 2, \cdots, n) \quad (8)$$

$Z^{(1)}$ is the near to the average generated sequence of $X^{(1)}$.

$$Z^{(1)} = (z^{(1)}(1), z^{(1)}(2), \cdots, z^{(1)}(n)) \quad (9)$$

among,

$$z^{1}(k) = \frac{1}{2}\left[x^{(1)}\mathrm{k} + \mathrm{x}^{(1)}(\mathrm{k}-1)\right], k = 2, 3, \cdots, n \quad (10)$$

If $\hat{A} = \left[\hat{a}, \hat{b}\right]$ is parameters of the column, and

$$Y = \begin{bmatrix} x^{0}(2) \\ x^{0}(3) \\ \cdots\cdots \\ x^{0}(11) \end{bmatrix}, \quad B = \begin{pmatrix} -z^{1}(2) & 1 \\ -z^{1}(3) & 1 \\ \cdots & \cdots \\ -z^{1}(11) & 1 \end{pmatrix} \quad (11)$$

then the least squares estimate parameter list of $x^{(0)}(\mathrm{k}) + \mathrm{a}z^{(1)}(\mathrm{k}) = \mathrm{b}$ should meet $\hat{A} = (\mathrm{B}^{\mathrm{T}}\mathrm{B})^{-1}\mathrm{B}^{\mathrm{T}}\mathrm{Y}$.

Suppose $X^{(0)}$ as a negative sequence, $X^{(1)}$ is the 1-AGO sequence of $X^{(0)}$. $Z^{(1)}$ is the near to the average generated sequence of $X^{(1)}$. $\hat{A} = (\mathrm{B}^{\mathrm{T}}\mathrm{B})^{-1}\mathrm{B}^{\mathrm{T}}\mathrm{Y}$. Then we can get that $\frac{dx(1)}{dt} + ax^{(1)} = \mathrm{b}$ is the albino differential equation of GM(1，1) model.

i)The solution of albino differential equation $\frac{dx(1)}{dt} + ax^{(1)} = \mathrm{b}$, which is called Time response function: $x^{(1)}\mathrm{t} = (\mathrm{x}^{(1)}(\mathrm{t}) - \frac{b}{a})\mathrm{e}^{-\mathrm{at}} + \frac{b}{a}$.

ii)The time corresponding sequence of $x^{(0)}(\mathrm{k}) + \mathrm{a}z^{(1)}(\mathrm{k}) = \mathrm{b}$ in GM(1,1) model is $\hat{x}^{(1)}(\mathrm{k}+1) = (\mathrm{x}^{(1)}(1) - \frac{b}{a})\mathrm{e}^{-\mathrm{ak}} + \frac{b}{a}, k = 1, 2, \cdots, n$

iii) The b-b reduced value is

$$\hat{x}^{(0)}(\mathrm{k}+1) = \hat{x}^{(1)}(\mathrm{k}+1) - \hat{x}^{(1)}(\mathrm{k}) = (1-\mathrm{e}^{\mathrm{a}})(\mathrm{x}^{(0)}(1) - \frac{b}{a})\mathrm{e}^{-\mathrm{ak}}, k = 1, 2, \cdots, n \quad (12)$$

among, call the parameter –a as the development coefficient, b as the grey action.

2.2. The Defects and Optimization of GM (1,1) Model

i)The model boundary value problem

According to the derivation process of the model, the precondition of GM(1.1) is $\hat{x}^{(1)}(1) = x^{(0)}(1)$. In addition, $x^{(0)}(1)$ do not participate in the structure of B and Y. So it has nothing to do with the model parameters [6]. However, the correction effect of $x^{(0)}(1)$ on the index of forecast results cannot be ignored. Set the boundary value correction formula is $x^{(1)}(1) = x^{(0)}(1) + \varepsilon$, among, ε is the boundary value correction term.

$$\tilde{x}^{(1)}(k) = [x^{(0)}(1) + \varepsilon - \frac{b}{a}]e^{-a(k-1)} + \frac{b}{a} \tag{13}$$

$$\tilde{x}^{(0)}(k) = (1 - e^{a})(x^{(0)}(1) + \varepsilon - \frac{b}{a})e^{-a(k-1)} \tag{14}$$

And then

$$\tilde{x}^{(1)}(k) = \hat{x}^{(1)}(k) + b e^{-a(k-1)} \tag{15}$$

$$\tilde{x}^{(0)}(k) = \hat{x}^{(0)}(k) + b(1 - e^{a}) e^{-a(k-1)} \tag{16}$$

At the same time, the predicted results of GM(1,1) model is a fitting curve under the least square sense without the point of $(1, x^{(0)}(1))$. So to force the system boundary value as $x^{(0)}(1)$, namely, to determine fitting curve after the point of $(1, x^{(0)}(1))$ is the lack of theoretical basis which is one of the main error sources of GM(1,1) model [7].

ii) The background value problem

The background values of parameters –a and b of the GM(1,1) model are closely related to the structure of $Z^{(1)}$. We integrate both sides of the equation. We can get that:

$$\int_{k-1}^{k} \frac{dx^{(1)}(t)}{dt} dt + a\int_{k-1}^{k} x^{(1)}(t)\,dt = \int_{k-1}^{k} b\,dt \tag{17}$$

And then get:

$$x^{(1)}(k) - x^{(1)}(k-1) + a\int_{k-1}^{k} x^{(1)}(t)\,dt = b \tag{18}$$

By contrast, we can get that:

$$z^{(1)}(k) = \int_{k-1}^{k} x^{(1)}(t)\,dt \tag{19}$$

In addition, in the derivative differential process of $X^{(1)}$ at the point of k. According to laser mean value theorem,

$$\exists \xi_k \in (k-1, k),\ x^{(1)}(k) - x^{(1)}(k-1) = \frac{dx^{(1)}}{dt}\Big|_{t=\xi_k} \tag{20}$$

and

$$x^{(1)}(\xi_k) = a_k x^{(1)}(k-1) + (1 - a_k) x^{(1)}(k), a_k \in (0,1) \tag{21}$$

Accordingly, in the model of GM(1,1), the grey derivative $x^{(0)}(k) = x^{(1)}(k) - x^{(1)}(k-1)$ is the derivative at the point of ξ_k, whose corresponding background value is

$$x^{(1)}(\xi_k) = a_k x^{(1)}(k-1) + (1 - a_k) x^{(1)}(k) \tag{22}$$

Namely, the general form of the background value structure is

$$z^{(1)}(k) = a_k x^{(1)}(k-1) + (1 - a_k) x^{(1)}(k) \tag{23}$$

From the above two aspects, It is not reasonable to simply set

$$z^{(1)}(k) = \frac{1}{2}[x^{(1)}(k) + x^{(1)}(k-1)] \tag{24}$$

which is one of the main error sources of GM(1,1) model.

iii)The least squares parameter estimation problem

In the model of GM(1,1), according to the least squares criterion, to calculate the value of the parameter $\hat{A} = [\hat{a}, \hat{b}]$. Namely, the sum of error squares of predicted results is the smallest:

$$\min_{a,b} \sum_{i=1}^{n} [\hat{x}^{(0)}(i) - x^{(0)}(i)]^2 \tag{25}$$

However, in the actual error inspection, we tend to be more important to get a minimum of the average relative error of predicted results:

$$\min_{a,b} [\frac{1}{n} \sum_{i=1}^{n} \frac{\left|\hat{x}^{(0)}(i) - x^{(0)}(i)\right|}{\left|x^{(0)}(i)\right|} \%] \tag{26}$$

The guidelines are not the same which is one of the main error sources of GM(1,1) model [8].

3. The Model Parameters Optimization Based On Ant Colony Algorithm

Ant colony algorithm is put forward by the Italian scholar M. Dorigo which is a new type of simulated evolutionary swarm optimization algorithm [9]. In this method, it artificial simulates the ant colony to search for food. In this process of searching, individual ants find the shortest path from the principle of ant colony to the food source based on pheromones of exchanges and cooperation. It is aimed to solve a series of discrete combination optimization problems [10].

So we choose the ant colony algorithm to optimize the model parameters a, b and ε. And specific steps are as follows:

Step 1: Select the number of ants s.

Step 2: Estimate the scope of parameters a, b and ε.

$x_{a\min} \le a \le x_{a\max}$, $x_{b\min} \le b \le x_{b\max}$, $x_{\varepsilon\min} \le \varepsilon \le x_{\varepsilon\max}$

Among, $x_{\min}$ and $x_{\max}$ are the lower limit and upper limit of variable value separately.

In the actual operation, we can get the traditional GM (1, 1) model firstly, then to solve the estimates of parameters a and b. Then select the appropriate scope accordingly.

Step 3: Segment the value interval.

Set the number of value interval is M. Rectangular coordinate system with a, b, and ε to coordinate axis is divided into $M \times M \times M$ matrixes. The coordinate of every small square is the coordinate of every ant's location [11].

$$(a_i, b_j, \varepsilon_p) = (x_{a\min} + \frac{(x_{a\max} - x_{a\min})}{M} i, x_{b\min} + \frac{(x_{b\max} - x_{b\min})}{M} j, x_{\varepsilon\min} + \frac{(x_{\varepsilon\max} - x_{\varepsilon\min})}{M} p) \quad (27)$$

Among, $i, j, p = 1, 2, \cdots, M$

Step 4: At the beginning, the pheromone concentration of matrixes are equal and constant. Namely, the pheromone concentration $\tau_{ijp}(0) = c$. And randomly assign the initial position of the ants.

Step 5: Calculate the position $(a_i, b_j, \varepsilon_p)$ of ants and the corresponding target $objD$. The target is the average relative error function:

$$f(a, b, \varepsilon) = \min_{a,b,\varepsilon} [\frac{1}{n} \sum_{i=1}^{n} \frac{\left| \hat{x}^{(0)}(i) - x^{(0)}(i) \right|}{\left| x^{(0)}(i) \right|} \%] \quad (28)$$

All the ants, the minimum target ant is the optimal one. And the minimum value is $\min D$.

Step 6: Update the pheromone concentration. Principle is that the bigger target value, the stronger the pheromone concentration in the optimum box. The update formula is:

$$\tau_{ijp}(t+1) = \tau_{ijp}(t) + Q / objD(i) \quad (29)$$

Among, Q is the constant. $\tau_{ijp}(t+1)$ is the pheromone concentration at the $t+1$ cycle. And with the time going, the pheromones evaporate gradually, which increases the randomness and autonomy of subsequent ants selecting[12].

Step 7: Ant-foraging rules. Every ant search for the food in the range of perception (position is $(a_i, b_j, \varepsilon_p)$). The ants choose the walking direction according to the pheromone concentration [13]. The stronger the pheromone concentration, the greater the probability of ant select. The probability formula is:

$$P(i, j, p) = \tau_{ijp} / \sum_{i,j.p} \tau_{ijp} \quad (30)$$

And ants randomly select other directions with a minimum probability of error. At the same time, the ants can remember the path to avoid walking the repeat line.

Step 8: Judge the best ant whether meet the requirements of the precision, or the largest number of iterations. If meet, then output the optimal objective function value and the optimal decision-making location. If not, go back to step 5.

The above is ant colony optimization of GM (1, 1) model, shorthand for ACOGM model.

4. The Empirical Analysis

To verify the effectiveness and practicability of the model in this paper, we predict with the two models GM (1, 1) and ACOGM (1, 1). Select eight years of power consumption in the three regions as the experimental data [14]. As shown in Table 4-1.

Table 4-1. Historical Load Data and Growth Rates of Four Kinds

Year	Load 1/GW	Load 2/GW	Load 3/GW
1	1.2025	0.8059	0.2223
2	1.3073	0.9518	0.2824
3	1.3145	1.2629	0.3637
4	1.4173	1.5483	0.5662
5	1.5556	1.5520	0.7481
6	1.7149	1.6368	0.9223
7	1.8112	1.8167	1.2476
8	1.9628	2.2168	1.7962
Growth rates /%	6.3161	13.483	29.846

The growth trend of three kinds load curve is as shown in the figure below. From Figure 4-1, we can know that the data of Load 1, Load 2 and Load 3 are approximate exponential growth. However, the growth rate is different. Set the data of the first seven years as the original data in Table 4-1. And set the 8th year data as the predicted data to verify the effect of fitting and forecasting.

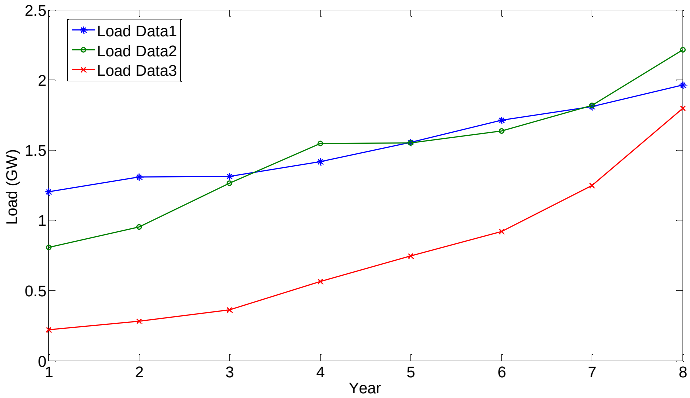

Figure 4-1. The Growth Trend of Three Kinds Load Curve

When to determine the model parameters of ant colony optimization algorithm, set the value range of the development coefficient a to [-1, 0]. Set the grey action b to [0, 2]. Set the boundary value correction term to [-1, 1]. Set the number of ants is 50. The activity range of every ant is $3\times3\times3$ matrixes [15]. The proportion of disappearing is 10%. The probability of error is 5%.

The simulation results of model is as shown in Table 4-2.

Table 4-2. The Results of Simulation

Load Type	Prediction model	a	b	ε	The average error of fitting/%	Step prediction error/%
Load 1	GM(1,1)	-0.0735	1.1201	0	1.9386	-0.6868
	ACOGM	-0.0683	1.1619	0.9665	0.6791	-1.2045
Load 2	GM(1,1)	-0.1021	0.9778	0	6.3721	-7.0870
	ACOGM	-0.1355	0.7795	0.4340	4.9116	-3.1735
Load 3	GM(1,1)	-0.2831	0.1968	0	5.1275	-8.0431
	ACOGM	-0.2875	0.1919	0.7158	2.5218	-7.4073

From the simulation results of Table 4-2, we can get that:

i) For the slower growth of load sequence, the fitting effect of ACOGM is better than GM(1,1). However, the step prediction error is bigger. The whole optimization effect is not obvious. The reason is that it has been achieved a high prediction accuracy based on GM(1,1) model for the slower growth load sequence. And the GM(1,1) is enough for this kind sequence.

ii) For the faster growth of load sequence, the fitting effect and optimization effect of ACOGM are better than GM(1,1). And the effects are very obvious. So for the faster growth load sequence, the traditional GM(1,1) is not suitable, which reflect the superiority of ant colony algorithm to optimize GM (1, 1) model.

5. Conclusions

This paper analyzed the rational modeling machine defect of GM (1, 1) model. And put forward the model that using ant colony algorithm parameters optimization method in view of the effect of traditional GM (1, 1) model is not stable, the fitting effect is not good, or better fitting effect and prediction effect is not good, and so on. The conclusion of this article is as follows.

i) This paper studied the modeling mechanism of GM (1, 1). And analyzed the machine rational defects of GM (1, 1) model. And first was the boundary value problem, the second was the background value structure problem, the 3th was the least squares estimation problem.

ii) Based on the above analysis, this paper selected development coefficient, grey action and the boundary correction term as model parameters, to optimize the model directly. On the one hand, this method overcome the GM (1, 1) model boundary defects, on the other hand, avoided the background value structure and the least square parameter estimation, and avoided the traditional model in the process of solving parameters some machine rational problems. And this method improved the predictive accuracy of the model which had a certain theoretical significance.

iii) This paper chose the three kinds load sequence with different growth rates as simulation analysis. Results show that it had high fitting and forecasting precision of faster growth load sequence, extending the scope of GM (1, 1) model. And the programming calculation process is simple. It has certain actual application value in the medium and long-term load forecasting.

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