TELKOMNIKA, Vol.11, No.11, November 2013, pp. 6862~6869
e-ISSN: 2087-278X

Short-term Power Load Forecasting based on Gray Theory

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Abstract

Power load forecasting provides the basis for the preparation of power planning, especially the accurate short-term power load forecasting. It can formulate power rationing program of area load reliably and timely, to maintain the normal production and life. This article describes the gray prediction method, and improves GM (1,1) model via processing the original data sequence smoothly, using the correction model of parameter α amending parameter values, adding the residual model, and also applying the idea of the metabolism. It conducts an empirical analysis of the 10KV large cable of Guigang Power Supply Bureau in Nan Ping, and verifies the limitations of ordinary gray theory. The improved gray model has a higher prediction accuracy than the conventional GM (1,1) model.

Keywords: *short-term load forecasting, the correction model of parameter α , the residual model, GM (1,1) model, the metabolism*

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1. Introduction

Power load forecasting is the premise of the real-time control, operation and development plan of power system. According to the period of forecasting, power load forecasting are usually divided into long-term, medium-term, short-term and ultra-short-term. Short-term load forecasting is to month, week, and day for the unit within a year. Accurate short-term load forecasting sets supplying and rationing power program timely and reliably in the peak area load of summer and winter, maintaining the normal production and life. It can also arrange the plan of starting or stopping and maintenance of generator sets in internal of the grid economically and reasonably, maintaining security and stability of the grid operation, reducing the costs of power generation, and improving the economic and social benefits.

Forecasting techniques can be divided into two categories, the first class is the method of visual prediction, and the second class is the method of mathematical model. Intuitive prediction methods typically include experts' prediction, the index conversion, the analogy and so on. Mathematical models of predicting mainly include regression model, time series model, and gray model. Among them, the ordinary gray GM (1, 1) model is a more effective model of load forecasting. However, when the electricity load curve fluctuations larger or the gray interval of predictive value becomes larger, the prediction error is usually larger. During the study of short-term power load forecasting, this article makes necessary improvements to the ordinary gray GM (1, 1) model, guaranteeing the accuracy of short-term power load forecasting.

2. The Construction of the Gray Model GM (1,1)

The gray system theory was first proposed by Professor of Deng Julong of Huazhong University of Science and Technology in 1982. It changes the processing method of the randomness in the concept, which would enable it use for the gray system whose information is unclear or incomplete. Its core idea is extracting law information from the non-law information. The gray theory overcomes the problem of large sample and sample statistical regularity in traditional regression analysis.

Grey Model refers the GM model. GM (1, 1) model is the most commonly used gray model, which contains a first order differential equation and one variable. Gray model is a more

Received May 12, 2013; Revised July 23, 2013; Accepted August 6, 2013

effective model of the power load forecasting. The substance of GM (1, 1) model is doing accumulated generating operation for the raw data. It is about to after it summing, original series generate data which presents exponential regularity, through establishing the differential equation, obtaining fitting curve, getting predictive values via regressive reduction [1]. The process of model construction is as follows

First, we should conduct the accumulated generating operation, and set the original data sequence as: $X^0 = [X^0(1),\ X^0(2),\ \ldots\ ,\ X^0(\mathrm{n})]$

After the first accumulated generating operation, the data sequence is: $X^1(k) = \sum_{i=1}^{k} X^0(i)$

After the second accumulated generating operation, the data sequence is: $X^2(k) = \sum_{i=1}^{k} X^1(i)$

After n times accumulated generating operation, the data sequence is: $X^n(k) = \sum_{i=1}^{k} X^{n-1}(i)$

Under normal circumstances, conducting cumulative to the original data sequence, accumulating more times, the regularity of the data series will be more apparent presented by the exponential growth. As the new data sequence with an exponential growth law, the solution of first-order differential equations is also a form of exponential growth, so that the sequence X^1 is considered to satisfy the first-order linear differential equations, that is, $X^1(t) = u/a + c*e^{-at}$ is the solution of the first-order differential equation $dX^1(t)/dt + a*X^1(t) = u$.

Applying the definition of derivative, the first item of the differential equation is made approximate dispose. Because the observation points are discrete values, the approximation process here does not exist the theory of defects.

$$dX^1(t)/dt = \lim_{\Delta t \to 0} \frac{X^1(t+\Delta t) - X^1(t)}{\Delta t} \approx \frac{X^1(k+1) - X^1(k)}{1} = X^0(k+1)$$

Finishing approximate treatment of the second of the differential equation, $aX^1(t) \approx 1/2*a*[X^1(k) + X^1(k+1)]$, the process is only in order to facilitate the calculation, and thus the improved gray model makes adjustment accordingly.

After approximate replacement, the original differential equation becomes:

$$X^0(k+1) + 1/2*a*[X^1(k) + X^1(k+1)] = u$$

The process of solving the differential equation is as follows:

When k=1, $X^0(2) + 1/2*a*[X^1(1) + X^1(2)] = u$

When k=2, $X^0(3) + 1/2*a*[X^1(2) + X^1(3)] = u$

When k=n-1, $X^0(n) + 1/2*a*[X^1(n-1) + X^1(n)] = u$

Then,

$$Y_n = \begin{bmatrix} X^0(2) \\ X^0(3) \\ \cdots \\ X^0(n) \end{bmatrix} \quad A = \begin{bmatrix} a \\ u \end{bmatrix} \quad B = \begin{bmatrix} -\frac{1}{2}(x^{(1)}(1) + x^{(1)}(2)) & 1 \\ -\frac{1}{2}(x^{(1)}(2) + x^{(1)}(3)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(x^{(1)}(n-1) + x^{(1)}(n)) & 1 \end{bmatrix}$$

The original equation written in matrix form is $Y_n = BA$ or $Y_n = B\hat{A} + E$. E is the residual matrix. Using the least squares method to estimate the parameter values of the matrix A, minimizing the value of residual matrix.

$$Q_e = \min \left\| Y_n - B\hat{A} \right\|^2 = \min (Y_n - B\hat{A})'(Y_n - B\hat{A})$$

$$\frac{\delta Q_e}{\delta A} = -2B'Y_n + 2B'B\hat{A} = 0$$

The solution is:

$$\hat{A} = (B'B)^{-1}B'Y_n = \begin{bmatrix} \hat{a} \\ \hat{u} \end{bmatrix}$$

Solving the parameter c, we adopt substituting a particular value. When t=1, $X^1(1) = \hat{u}/\hat{a} + \hat{c} * e^{-\hat{a}}$, we obtain that $\hat{c} = (X^1(1) - \hat{u}/\hat{a})e^{\hat{a}}$.

Putting the value c into the original equation, the prediction equation obtained is $X^1(t) = (X^1(1) - \hat{u}/\hat{a})e^{-\hat{a}(t-1)} + \hat{u}/\hat{a}$.

Finally, making $X^1(k)$ do regressive restoration, $X^0(k+1) = X^1(k+1) - X^1(k)$, we can get the GM (1, 1) prediction model as follows: $X^0(k+1) = (1-e^{\hat{a}})[X^1(1) - \hat{u}/\hat{a}]e^{-\hat{a}k}$, the equation is also known as time-response function [2].

3. Improved Gray GM (1,1) Model

Gray prediction model requires a few sample data, and only four historical data can determine a gray prediction equation. What's more, it does not take into account the distribution of the sample and trends, operating simple and easy to verify simultaneously. However, the gray prediction model has some limitations, for volatile data, when data grayscale becomes greater; the accuracy of prediction turns worse.

3.1. The Exponential Smoothing Process of Raw Data Series

Because the degree of dispersion of short-term power load value is relatively large, the original data is considered to do exponential smoothing process. On the one hand, the processed data weak the fluctuation of the data column, reducing the randomness; on the other hand, adjusting original changes in trend of the data columns, it will be better meet or more close to the decision-making needs [3].

The process of smoothing the raw data is as follows:

Set up the original data as $X^0 = [X^0(1), \quad X^0(2), \quad \ldots \quad , X^0(n)]$

Use the sliding average formula: $X^0(k) = \frac{1}{4}[X^0(k-1) + 2X^0(k) + X^0(k+1)]$ k=2,3, ⋯n-1

Make special treatment on both ends of the endpoint, $X^0(1) = \frac{3X^0(1) + X^0(2)}{4}$

$$X^0(n) = \frac{3X^0(n) + X^0(n-1)}{4}$$

The-moving average formula not only avoids excessive fluctuations in the data, but also increases the weight of that year's data. The randomness of new series is weakened, to some extent, the prediction accuracy of GM (1, 1) is also improved.

3.2. Applying Parameter α to Correct Model's Estimate Value $\hat{a}$

Through predicting large amounts of data, we find that when the rate of columns of data is relatively fast (| a | is large), the prediction accuracy of GM (1, 1) model is relatively poor. In such cases, this article applies the correction model of parameter α, and the estimate value $\hat{a}$ is amended in the prediction equation.

In the traditional gray prediction method, $X^1(t) = 1/2 * [X^1(k) + X^1(k+1)]$, such replacement is only for convenience, thus from the perspective of a more general considerations, introducing a parameter α, $X^1(t) = \alpha X^1(k) + (1-\alpha)X^1(k+1)$. Consequently, it reduces the prediction error which the larger | a | brings, improves the prediction accuracy, and expands the scope of the prediction. Carrying out this substitution, the following relationship existing between the parameter α and a is as follows:

Set $X^0=[X^0(1),\ X^0(2),\ \ldots\ ,\ X^0(n)]$ as a non-negative sequence, and $X^1(t)$ is a cumulative sequence. For a given $X^1(t)=\alpha X^1(k)+(1-\alpha)X^1(k+1)$, the relationship between α and a is $\alpha=\frac{1}{a}-\frac{1}{e^a-1}$.

The Hospital's Rule can prove that $a\to 0$, the limit value of α is 0.5. $\lim_{a\to 0}\frac{1}{a}-\frac{1}{e^a-1}=\lim_{a\to 0}\frac{e^a-1-a}{a(e^a-1)}=\lim_{a\to 0}\frac{e^a-1}{ae^a+e^a-1}=1/2$

Therefore, depending on the value of a, we select different α to calculate $X^1(t)$, solving the problem of prediction accuracy because of the larger value of | a |.

The parameter α modification prediction algorithm of GM (1,1) model uses the idea of the iterative, the specific process which algorithm is based on is as follows:

First step, set the original data sequence of variable $X^0(t)$ as $[X^0(1),\ X^0(2),\ \ldots\ ,\ X^0(n)]$, and make the original data series do first accumulated generating operation, getting $X^1(t)=[X^1(1),X^1(2),\cdots,X^1(n)]$. Take α = 0.5, and solve the estimated value a according to the traditional gray model [4].

Second step, introduce $\hat{a}$ the first step in solving process obtained into $\alpha=\frac{1}{a}-\frac{1}{e^a-1}$, applying the new parameter α to recalculate $\hat{a}$, and note calculated parameter α as $\hat{\alpha}(m+1)$, m = 1,2, • • •, n.

Compared $\hat{\alpha}(m+1)$ with $\hat{\alpha}(m)$ the last step calculated, for any small positive number of ε, if $|\hat{\alpha}(m+1)-\hat{\alpha}(m)|$ > ε, it means the prediction accuracy may also be improved, and should again be transferred to the step 2. The process of iterative will be end, until the value of $|\hat{\alpha}(m+1)-\hat{\alpha}(m)|$ is less than ε.

Third step, establish the time response function $X^0(k+1)=(1-e^{\hat{a}})[X^1(1)-\hat{u}/\hat{a}]e^{-\hat{a}k}$, calculating the predicted value.

The iteration this method used is generally conducting 2 to 3 times. The level of increase of improved forecast accuracy is not large, but its predictive value is more accurate than the general model.

3.3. Residual Model

Through gray modeling, obtaining a set of forecast data series $\hat{X}^0=[\hat{X}^0(1),\ \hat{X}^0(2),\ \ldots\ ,\ \hat{X}^0(n)]$, the difference between the original series and the predict columns notes as the residuals, $e^0(k)=X^0(k)-\hat{X}^0(k)$, constituting a residual number as $e^0(k)$=[$e^0(1),e^0(2),\cdots,e^0(n)$].

Obtaining the absolute value of this residual column, that is, $|e^0(k)|$=[$|e^0(1)|,|e^0(2)|,\cdots|e^0(n)|$], and constructing gray prediction model GM (1,1) for $|e^0(k)|$, we can get the predicted value of the absolute value of the residuals $|\hat{e}^0(k)|$. Then in accordance with the positive or negative of original residuals, the absolute value sign of the predictive value of the residuals is removed, and make them fit to the original predictive values, improving the prediction accuracy. Namely,

$$X^0(k+1)=(1-e^{\hat{a}})[X^1(1)-\hat{u}/\hat{a}]e^{-\hat{a}k}+\hat{e}^0(k+1)$$

Through using the residual model to revise the original gray model, the prediction accuracy will be improved obviously [5-7].

3.4. Metabolic Modeling

Under normal circumstances, when the common gray model GM (1, 1) is applied to predict, we will find only the first 1 to 2 points have high accuracy, and the more to the future development, the predictive significance of the subsequent value turns weaker. Because in the gray model, Clipping plane between the upper and lower bounds of future projections, known as the gray plane, this plane commences shaping a horn, that is, the farther the next moment, the greater the gray interval, which means the larger of the grayscale, therefore, the practical significance of the predictive value becomes smaller. Thus, in practical applications, we should consider the impact factor entered into the system over time continuously. With the

development of the system, the information the old data represented becomes weaker, so we should remove the old information timely, making the sequence being modeled better reflect the characteristics of the system.

The steps of GM (1, 1) metabolic modeling are as follows:

First step, take the first five values of the original data sequence the smooth index processed as the sequence being modeled [8, 9].

Second step, Use the built model to predict the back of 1~2 data (applying these improved methods to predict). If the prediction error is large, the existing sequence is restarted the metabolism modeling, creating a new sequence being modeled. If the prediction error is very small, the predictive value of the first data will be recorded, and new data will be added to the original sequence being modeled, which acts as a new modeling sequence. Note: in general, when the number of data series is over seven, the old data should be removed.

Third step, the second step will be repeated, until the modeling is completed, outputting the best predictive value. Because a mode is built each time, we will calculate the following two data, leading the different predicted values which is calculated by two modeling data, and the data closed to the raw data should be chosen as the modeling results.

Via metabolic modeling, the accuracy of the predictive value will increase, and the average relative error will be about 5% [10].

3.5. The Posteriori Differential Test

The posteriori differential test is a calibration method, according to the statistics of forecast and actual values. The ratio of the posteriori difference determines the advantages and disadvantages of the method. The specific steps are as follows:

Calculate the mean and variance of the residuals [11].

The value of the residuals: $e^0(k) = X^0(k) - \hat{X}^0(k)$

The variance of the residuals: $S_2^2 = 1/n * \sum_{k=1}^{n} (e^0(k) - \bar{e}^0)$

Gray predicted fitting curve goes across the geometric center of the historical data, so the sum of residuals is 0 and the mean of the residuals $\bar{e}^0$ = 0.

At the same time, calculate the mean and variance of the raw data.

The mean of the original data: $\bar{X}^0 = 1/n * \sum_{k=1}^{n} X^0(k)$

The variance of the original data: $S_1^2 = 1/n * \sum_{k=1}^{n} (X^0(k) - \bar{X}^0)$

The ratio of the posteriori difference: c=S_2/S_1, meaning the degree of dispersion between the predicted values and the actual values.

The smaller value of the index c will be more beautiful, indicating that the degree of dispersion between the forecast value and actual value is not large. Under normal circumstances, c <0.35 means the prediction accuracy is good, and 0.35 <c <0.45 means the prediction accuracy is reluctant [12].

4. Empirical Analysis

Table 1. The Power Load Values of 24 hours of 10KV Cable in Nanping

Time point	Actual value	Time point	Actual value
0:00	166.000	12:00	239.000
1:00	132.000	13:00	267.000
2:00	119.500	14:00	242.500
3:00	137.000	15:00	268.000
4:00	125.500	16:00	267.500
5:00	135.000	17:00	427.500
6:00	171.500	18:00	347.000
7:00	168.400	19:00	533.000
8:00	223.250	20:00	563.000
9:00	231.900	21:00	478.000
10:00	326.900	22:00	369.500
11:00	253.000	23:00	272.000

This article analyzes the 10KV large cable of Guigang Power Supply Bureau in Nanping, selecting the values of power load of a working day which is in April, 2010. Respectively use the gray prediction model GM (1, 1) of the corrected parameter α, the gray prediction model of joining the residual model and the gray model which applies residuals and metabolism to improve simultaneously to forecast. By comparing the actual values with the predicted values, we analyze the prediction accuracy of each model. The power load values of 24 hours of 10KV cable in Nanping shown in Table 1.

The original data is conducted to do the smoothing index processing, getting the revised data sequence is:

X^0 = [157.50, 137.38, 127.00, 129.75, 130.75, 141.75, 161.60,182.89, 211.70, 253.49, 284.68, 267.98, 294.50, 253.88, 255.00,261.50, 307.63, 367.38, 413.63, 494.00, 534.25, 472.13, 372.25, 296.38]

Use matlab to build the GM (1, 1) model for the revised original sequence. After three iterations, we get the estimate value of the parameter $\hat{a}$, that is, $\hat{a}$ =0.4581, and parameter $\alpha(3)$ =0.4619; in the second iteration, parameter $\alpha(2)$ =0.4585;

$\forall \varepsilon > 0$,setε=0.01,obtaining $|\alpha(3) - \alpha(2)| = 0.0034 < 0.01$,so end the iterative process. The predictive value and relative error are shown in Table 2.

Table 2. The Predictive Value of the Gray Model Correcting Parameter α

Time point	Actual value	Predictive value	Relative error	Time point	Actual value	Predictive value	Relative error
0:00	166.000	157.500	5.12%	12:00	239.000	262.433	-9.80%
1:00	132.000	141.262	-7.02%	13:00	267.000	277.634	-3.98%
2:00	119.500	149.444	-25.10%	14:00	242.500	293.715	-21.10%
3:00	137.000	158.101	-15.40%	15:00	268.000	310.728	-15.94%
4:00	125.500	167.258	-33.27%	16:00	267.500	328.726	-22.89%
5:00	135.000	176.946	-31.07%	17:00	427.500	347.767	18.60%
6:00	171.500	187.195	-9.15%	18:00	347.000	367.911	-6.03%
7:00	168.400	198.038	-17.60%	19:00	533.000	389.221	26.98%
8:00	223.250	209.509	6.15%	20:00	563.000	411.766	26.86%
9:00	231.900	221.645	4.42%	21:00	478.000	435.616	8.87%
10:00	326.900	234.483	28.27%	22:00	369.500	460.848	-24.72%
11:00	253.000	248.065	1.95%	23:00	272.000	487.542	79.24%

Use matlab to make the image, and we can see that the application of the above model has relatively large error intuitively, verifying the gray model is only able to accurately forecast the subsequent two values.

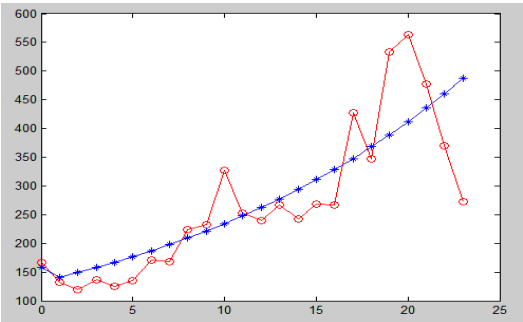

Figure 1. The Predictive Value of the Gray Model Correcting Parameter α

Get absolute value of the above model residuals, and constitute the residual series. After the introduction of the residual model, the predictive value and relative error are shown in Table 3.

Table 3. The Predictive Value of the Gray Model Introducing the Residual

Time point	Actual value	Predictive value	Relative error	Time point	Actual value	Predictive value	Relative error
0:00	166.000	157.500	5.12%	12:00	239.000	262.433	-9.80%
1:00	132.000	141.262	-7.02%	13:00	267.000	277.634	-3.98%
2:00	119.500	149.444	-25.10%	14:00	242.500	293.715	-21.10%
3:00	137.000	158.101	-15.40%	15:00	268.000	310.728	-15.94%
4:00	125.500	167.258	-33.27%	16:00	267.500	328.726	-22.89%
5:00	135.000	176.946	-31.07%	17:00	427.500	347.767	18.60%
6:00	171.500	187.195	-9.15%	18:00	347.000	367.911	-6.03%
7:00	168.400	198.038	-17.60%	19:00	533.000	389.221	26.98%
8:00	223.250	209.509	6.15%	20:00	563.000	411.766	26.86%
9:00	231.900	221.645	4.42%	21:00	478.000	435.616	8.87%
10:00	326.900	234.483	28.27%	22:00	369.500	460.848	-24.72%
11:00	253.000	248.065	1.95%	23:00	272.000	487.542	79.24%

Apply matlab to make the image similarly, and we can see that, relative to the gray model correcting the parameter α, the prediction accuracy of the GM (1, 1) model adding residuals has been significantly improved. Through the posteriori difference test, we can obtain the posteriori difference C = 0.3506. In accordance with the usual standards, the prediction accuracy is reluctant.

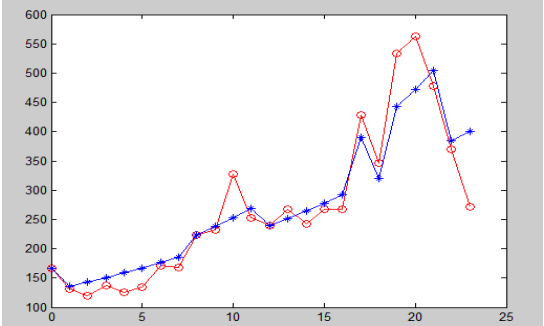

Figure 2. The Predictive Value of the Gray Model Introducing the Residual

Put the metabolic thought into the gray model introducing the residuals. The predicted value and the relative error are shown in Table 4

Table 4. The Predictive Value of the Gray Model Adding the Metabolic Thought

Time point	Actual value	Predictive value	Relative error	Time point	Actual value	Predictive value	Relative error
0:00	166.000	166.000	0.00%	12:00	239.000	249.321	-4.10%
1:00	132.000	129.901	1.59%	13:00	267.000	256.590	3.90%
2:00	119.500	123.776	-3.57%	14:00	242.500	254.656	-5.01%
3:00	137.000	130.921	4.44%	15:00	268.000	260.107	2.57%
4:00	125.500	120.004	4.38%	16:00	267.500	253.596	5.02%
5:00	135.000	128.125	5.10%	17:00	427.500	404.826	5.31%
6:00	171.500	174.652	-1.84%	18:00	347.000	364.001	-4.90%
7:00	168.400	168.420	-0.01%	19:00	533.000	501.554	5.90%
8:00	223.250	223.185	0.03%	20:00	563.000	530.015	5.86%
9:00	231.900	240.153	-3.56%	21:00	478.000	467.259	2.25%
10:00	326.900	302.125	7.58%	22:00	369.500	350.661	5.10%
11:00	253.000	264.317	-4.47%	23:00	272.000	262.416	3.53%

Use matlab do the plot processing for the above-mentioned data, we can see that the prediction accuracy of the the GM (1, 1) model introducing the ideal of metabolism has been improved further. The average relative error MAPE is 3.89%, and the posteriori difference C is

0.106. In accordance with the standards given above, the prediction accuracy of the method is better. It also proves that this method can better predict and analyze.

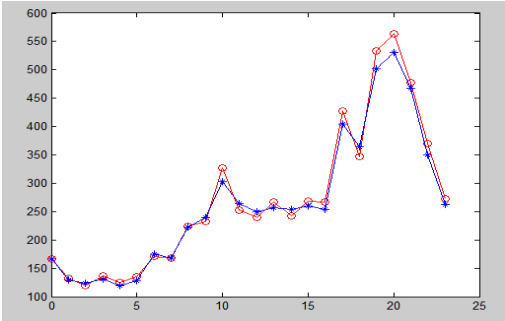

Figure 3. The Predictive Value of the Gray Model Adding the Metabolic Thought

5. Conclusion

Through the analysis of three improved gray models, we can see the ordinary gray model often only accurately predicts the subsequent two values. There exists big error, and it doesn't meet the actual needs. This article aims at the limitations of the gray model in theory, using the parameter α to correct the model's estimate value $\hat{a}$, conducting residual processing for the gray model, and introducing the idea of metabolism at the same time, and gets more accurate prediction results. But in essence, the power load of system can't be controlled. It is influenced by the factors of economic, time, climate and the random interference, leading any kind of prediction methods exist a certain degree of error. Therefore, in order to find the load forecasting method that suits the actual system, the power load forecasting should be based on the actual situation and the existing data.

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