

Application of Improved Grey Model in Medium and Long Term Load Forecasting

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Abstract. Grey model is a common method in medium and long-term power load forecasting, but it has great limitations. According to the characteristics of medium and long term power load forecasting, the method of sliding average and the principle of Markov model are introduced into the Grey forecasting theory, and the model is improved. This improvement can effectively improve the prediction accuracy of the model. Based on the load data of Qingdao City in the past ten years, it can be proved that the improved Grey model has improved the accuracy of the former.

1. Introduction

The power industry is a basic industry of the national economy, providing the energy security for economic development. Power load is closely related to the development of economy. Accurate and timely forecast of power load plays an extremely important role in the development of power industry and national economy. From a macro point of view, the accuracy of power load forecasting is directly related to the decision-making of the energy industry, and the overall investment of the power industry, and the layout of the entire power grid and the rationality of grid operation. From the microscopic point of view, the accuracy of power load forecasting is related to the stability of grid operation, and the production efficiency of power generation enterprises, and the daily work arrangements of power grid enterprises and power generation enterprises.

Load forecasting can be divided into super short-term, short-term, medium-term and long-term load forecasting. The selection of load forecasting method is the core of load forecasting. In broad sense, the load forecasting methods can be divided into empirical load forecasting and quantitative load forecasting. The former has expert forecasting model, analogy method and subjective probability model. The latter includes unit consumption method, elastic coefficient method, regression analysis method, time series method, artificial neural network method and Grey model method [1-3]. In recent years, the Grey model method has been deeply researched by many experts and has gained a certain degree of social recognition. Since the Grey model method requires less data and less computation in the application, it has been widely used in the long-term load forecasting. However, when the curve of load growth fluctuates greatly, the predicted load of Grey model often deviates greatly from the actual load, which has great limitations in practical application. Therefore, this paper improves the traditional Grey model, and introduces exponential smoothing method and Markov model to improve the accuracy of load forecasting, and provides a reference for medium and long-term load forecasting method selection in power system.



2. Grey correlation theory

Grey theory was first proposed by Chinese scholar Professor Deng Julong in 1982, and mainly applied to the analysis of the lack of data and the analysis of uncertainty data. Grey theory reveals the evolution law under the background of few data and information, based on analyzing the characteristics of few data, understanding the behavior of few data, exploring the potential mechanism and synthesizing the phenomena of few data [4]. The Grey models commonly used are GM (1, 1) and GM (1, N). GM (1, 1) is a first-order Grey model with only one variable, and GM (1, N) is a first-order Grey model with N variables[5-6]. The essence of the Grey model is to make the weak regularity series to be regular series by accumulating, decrementing or weighting the original data, then using the new series to generate GM (1,1) or GM (1,N) model, and establishing the related differential equation. By solving the differential equation, the parameters of the equation can be obtained. A Grey model of generating series is obtained, and then the prediction is made. Finally, the predicted result is restored to the original data result. The detailed method is as follows:

The known reference data is:

$$x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)) \quad (1)$$

Accumulate to generate the new sequence:

$$\begin{aligned} x^{(1)} &= (x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)) \\ &= (x^{(1)}(1), x^{(1)}(1) + x^{(0)}(2), \dots, x^{(1)}(n-1) + x^{(0)}(n)) \end{aligned} \quad (2)$$

Among them,

$$x^{(1)}(k) = \sum_{i=1}^k x^{(0)}(i) \quad (k=1, 2, \dots, n)$$

The mean sequence:

$$z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1) \quad (k=2, 3, \dots, n)$$

Namely,

$$z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(n)) \quad (3)$$

Build the grey differential equation as:

$$x^{(0)}(k) + az^{(1)}(k) = b \quad (k=2, 3, \dots, n) \quad (4)$$

Which $x^{(0)}(k)$ is called the Grey derivative, a is known as the development system, $z^{(1)}(k)$ is known as the whitening background value, b is known as the grey action.

Put the moment $k=2, 3, \dots, n$ in the above formula:

$$\begin{cases} x^{(0)}(2) + az^{(1)}(2) = b \\ x^{(0)}(3) + az^{(1)}(3) = b \\ \dots\dots\dots \\ x^{(0)}(n) + az^{(1)}(n) = b \end{cases}$$

$$\text{Make } Y_N = (x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n)),$$

$$u = (a, b)^T$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \dots & \dots \\ -z^{(1)}(n) & 1 \end{bmatrix}$$

Which Y_N is the data vector, B is the data matrix, u is the parameter vector, then GM (1,1) can be expressed as a matrix equation $Y_N = B \cdot u$.

The corresponding whitening differential equation is:

$$\frac{dx^{(1)}}{dt} + ax^{(1)}(t) = b \quad (5)$$

Substitute the data to solve the equation (Least squares method):

$$x^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a} \right) e^{-ak} + \frac{b}{a} \quad (k=1,2,\dots,n-1) \quad (6)$$

According to the above analysis results, we can establish the whitening model of GM (1,1):

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a} \right) e^{-ak} + \frac{b}{a} \quad (k=1,2,\dots,n-1) \quad (7)$$

The forecasting model of the original sequence can be obtained by doing the accumulated decrease

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \quad (k=1,2,\dots,n-1) \quad (8)$$

3. The improved Grey prediction model

The principle of Grey prediction model is very simple, and the required sample data is not a lot, and the calculation is more convenient. However, the general Grey model GM (1,1) also has some limitations. When the data dispersion is large, the prediction accuracy is poor. The Grey model is only suitable for medium and long-term prediction when the variables show a constant monotonicity, while for the curve without obvious variation, the prediction error is very large [7-9]. Therefore, the common Grey model GM (1,1) needs to be improved.

3.1. Weakening the original data

Weakening the original data, we must first observe the dispersion of the original data, if the original data is smoother, then the effect of weakening is not obvious, if the original data is not smooth discrete sequence, the original data can be smoothed to reduce the outlier influences. In this paper, we use the Grey model to accumulate the original data and then move and smooth the newly-produced series. The formula is as follows:

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \quad (k=1,2,\dots,n-1)$$

$$t = 2, 3, \dots, n-1 \quad (9)$$

The two endpoints respectively are:

$$\hat{x}^{(0)}(1) = \frac{3x^{(0)}(1) + x^{(0)}(2)}{4} \quad (10)$$

$$\hat{x}^{(0)}(n) = \frac{3x^{(0)}(n-1) + x^{(0)}(n)}{4} \quad (11)$$

The series processed by the moving-smoothing method can weaken the influence of the interference sequence and make the prediction result more accurate. The prediction results can be obtained by reversing the results from the grey model prediction.

3.2. The residual value correction based on the principle of Markov model

For the common Grey model GM (1,1), the test method commonly used is the residual value test. The

$$\varepsilon(k) = \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \quad (k=1,2,\dots,n)$$

residual is $\varepsilon(k)$, then calculating

If $\varepsilon(k) < 0.2$, it can be considered as meeting the general requirements;

If $\varepsilon(k) < 0.1$, it can be considered as meeting the higher requirements;

However, this residual value test only tests the accuracy of the predicted value, and does not correct the predicted value from the perspective of the residual value. Therefore, this paper establishes the Markov correction model based on the principle of Markov model.

First, define the residual sequence as $q^{(0)}$:

$$q^{(0)} = (q^{(0)}(1), q^{(0)}(2), \dots, q^{(0)}(n),)$$

Which $q^{(0)}(k) = x^{(0)}(k) - \hat{x}^{(0)}(k)$, and $k=1,2,\dots,n$.

For the sequence of residual values, the aforementioned grey relational model is still used for the prediction. By comparing the residual values, we can see that the symbols of the residual values have positive and negative differences. Suppose the residual value is positive with state 1, and the residual value is negative with state 2. P_{ij} is the probability from the state i at the time t to the state j at the next moment $t+1$. Then the probability of residual values may be as follows: $P_{11}, P_{12}, P_{21}, P_{22}$, according to

the Markov theory, it can be known that the annual load forecasting, $P_{ij} = \frac{N_{ij}}{N_i}$, $i=1,2; j=1,2$.

Among N_{ij} is the number of years from the state i at the time t to the state j at the next moment $t+1$ of load residual value. N_i is the number of years at the state i at the time t .

Therefore, the transition probability matrix can be established as follows:

$$P = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix}$$

after m times of transformation, the probability that the residual value of load is state 1 and 2 after m years are respectively P_1^m and P_2^m . If P_1^m is greater than P_2^m , it can be judged that the residual value of load after m years is positive; if P_1^m is smaller than P_2^m , the residual value of load after m years can be judged as negative.

If the residual value of the load also meets the requirements of the general Grey model $\varepsilon(k) < 0.2$, or the judgment $\varepsilon(k) < 0.1$, the residual value and the predicted load value may be superposed to obtain the revised load predicted value.

4. Example analysis

The power load of Qingdao City from 2006 to 2015 (the data is from the Qingdao Statistical Yearbook) is predicted by General Grey model GM (1,1) and improved grey model. It is calculated by matlab7.0, and the detailed results are shown in Table 1.

Table 1. Forecast results and error rates

Year	Actual value	General GM(1,1) model		Improved GM(1,1) model	
		Predictive value	Error rate	Predictive value	Error rate
	10^8 KW h	(10^8 KW h)	(%)	(10^8 KW h)	(%)

2006	174.2649	181.1484	3.95	169.4029	-2.79
2007	175.7868	182.9589	4.08	180.6737	2.78
2008	186.9992	194.7036	4.12	188.3456	0.72
2009	195.075	202.6244	3.87	198.1572	1.58
2010	292.9716	308.1182	5.17	299.5927	2.26
2011	313.4403	325.5077	3.85	308.0177	-1.73
2012	318.3560	329.0845	3.37	324.0545	1.79
2013	339.2702	349.2786	2.95	344.6306	1.58
2014	337.8197	345.4882	2.27	334.6779	-0.93
2015	342.2929	358.6545	4.78	339.6572	-0.77

By comparing the prediction results of the general model and the improved model, we can see that the average prediction error rate of the general model is 3.84%, while the average error of the improved model is only 1.69%, much lower than the error rate of the general model. This shows that the prediction accuracy of the improved Grey model based on Markov theory is higher than the general prediction model. Therefore, this improvement is effective.

5. Conclusion

It can be seen from the above analysis that the general Grey GM (1,1) model has a large error for long-term load forecasting, but the error rate of the Grey model can be effectively reduced by using the moving smoothing method and the Markov model. Although the Markov model is usually used for short-term load forecasting, combining it with the Grey model and applying it to long-term load forecasting can effectively reduce the error rate of the forecasting model. Therefore, the Markov model can be applied to medium-long-term load forecasting.

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