The Grey Forecasting Model for the Medium-and Long-Term Load Forecasting

To cite this article: Feng Song *et al* 2020 *J. Phys.: Conf. Ser.* **1654** 012104

The Grey Forecasting Model for the Medium-and Long-Term Load Forecasting

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Abstract. Load forecasting plays a particularly significant role in the stable operation of grid and the reasonable distribution of power resources. Based on grey model theory, this paper carries out load forecast of power system. In this paper, the grey model theory is used to realize the medium and long-term load forecasting, and the accuracy of the model to the load forecasting is tested by using the posterior difference method. Finally, an example is given to check the method's practicability.

1. Introduction

Load forecasting has a particular meaning for grid planning and construction. The accuracy of load forecasting [1] will directly affect the long term planning of power system, investment, green development and stable operation. Thus, load forecasting is an indispensable part of power system planning.

Accurate load historical data and statistical data is the premise of realizing the accurate load forecasting of power system. On this basis, the load forecasting is realized through scientific forecasting methods. Load forecasting is helpful to improve the operation of the power system and respond to the load fluctuation as soon as possible. Improving the accuracy of load forecasting can not only realize the reasonable distribution of resources, but also reduce the cost of power system operation. Therefore, in practice, it is necessary to carry out the corresponding load forecasting, whether it is to formulate power system planning or to realize the automation of power system operation.

Load forecasting is a process of estimating the load value for some time in the future by analyzing the load change rule and comprehensively considering the reasons that affect the load change according to the historical data of the load and its related factors. The method widely used in load forecasting is as follows: Regression analysis, Fuzzy prediction method [2, 3], Grey system theory [4], Neural network analysis and prediction method [5, 6], expert system theory.

Each method has its advantages and disadvantages. For instance, the neural network prediction method is suitable for solving the time series prediction problem and is applied to short-term load prediction. The problem of knowledge base formation and representation in expert system method has always puzzled the forecaster who tries to use it. In the power system load, it is difficult to obtain accurate and stable reference data, and the geographical, demographic and economic factors are often difficult to investigate. Large amount of empirical data is needed to forecast the large amount of historical load forecasting required by the multiple linear regression model. In contrast, the grey forecasting model needs to consider less external factors and does not rely too much on historical data, which is in line with the characteristics of "poor data" and "easy to fluctuate" of power system load.

All in all, for medium and long-term load forecasting, the grey model theory can obtain more accurate forecasting effect.

2. Data generation of grey prediction model

The gray prediction method is to enhance the order of the original sequence through gray generation, so as to get the forecast result of given original sequence through the reduction operation based on the fitting process of the generated sequence using various models. In the grey system, the grey data is not from a large number of samples to find the statistical law, but through the data generation method, and then find its potential law in the disordered data, and then through the law to seek the parameter model to establish the prediction model.

2.1. The accumulation generation

$\{x^{(0)}(k)\}$ is made up of the original sequence: $x^{(0)}(k)=(x^{(0)}(1),x^{(0)}(2),\cdots,x^{(0)}(n))$. Then accumulate the sequence, $x^{(1)}(k)=\sum_{m=1}^{k}x^{(0)}(m)\ k=1,2,\cdots,n$. By accumulating the given original sequence once, we can get a new number sequence:

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

$\{x^{(1)}(k)\}$ is expressed as 1-AGO. The latest obtained sequence is going to indicate better regular pattern after accumulation.

2.2. The generation of subtraction

The method of generating convergent is expressed as IAGO.

First, $\{x^{(r)}(k)\}$ is defined as r-generating sequence, and then the sequence was performed the i times subtraction, the new sequence is defined as i-IAGO. $a^{(i)}$ is used to indicate the obtained result. Then the following connections are as followed. 0 times of reduction is defined as 0-IAGO. The formula is

$$a^{(0)}(x^{(r)}(k))=x^{(r)}(k) \tag{2}$$

Notes: if the reduction is zero times, it means that there is no reduction. Therefore, the results obtained have not changed and are still the initial values

1 reduction expressed as 1-IAGO, its formula can be expressed as:

$$a^{(1)}(x^{(r)}(k))=a^{(0)}(x^{(r)}(k))-a^{(0)}(x^{(r)}(k-1)) \tag{3}$$

i times reduction expressed as I-IAGO, its formula can be expressed as:

$$a^{(i)}(x^{(r)}(k))=a^{(i-1)}(x^{(r)}(k))-a^{(i-1)}(x^{(r)}(k-1)) \tag{4}$$

Because $a^{(i)}[x^{(r)}(k)]=x^{(r-i)}(k)$, and when I =r, there is

$$a^{(r)}[x^{(r)}(k)]=x^{(r-r)}(k)=x^{(0)}(k) \tag{5}$$

$r^{(0)}$ can be acquired during the transformation from the r-AGO to r-IAGO.

2.3. The mean generation
Non-adjacent mean generation and adjacent mean generation are two main methods to generate mean. Even the original sequence like $\{x\}=[x(1),x(2),\cdots,x(n)]$ can generate mean value. The generated value of point K is marked a as $z(k)$, represented as:

$$z(k)=0.5x(k)+0.5x(k-1) \tag{6}$$

It's called $z(k)$ as the adjacent mean generation value.

Both are the original sequence: $\{x\}=[x(1),x(2),\cdots,x(k-1),\Phi(k),x(k+1),x(n)]$. The $\Phi(k)$ here is the hole, and marking the generated value of point k as $z(k)$, and now

$$z(k)=0.5x(k-1)+0.5x(k+1) \tag{7}$$

$z(k)$ is referred to as the non-adjacent mean generated value.

3. Grey prediction model modelling
Grey system modelling is to reduce the uncertainty of information by mining and collating the initial data, and then carry out mathematical modelling on this basis.

3.1. Modeling mechanism of grey prediction model
Grey theory with differential equation as the main form is based on grey number. The method is called GM. When power system load forecasting is carried out, the GM (1, 1) model is widely adopted, it is appropriate for the explosive growth of data. It is the data verified that this model requires fewer amounts of data, no need to do a lot of data calculation and the prediction is very accurate. It is essentially a process of accumulating and generating the initial data, so the sequence obtained is inerratic and convenient for the following modeling.

Marking the $x^{(0)}$ as the modelling sequence of GM (1,1): $x^{(0)}=\{x^{(0)}(1),x^{(0)}(2),\cdots,x^{(0)}(n)\}$.

Marking the $x^{(1)}$ as the first-order accumulation generated sequence of $x^{(0)}$

$$\begin{aligned}&x^{(1)}=\{x^{(1)}(1),x^{(1)}(2),\cdots,x^{(1)}(n)\}\\&x^{(1)}(1)=x^{(0)}(1)\end{aligned} \tag{8}$$

$$x^{(1)}(k)=\sum_{m=1}^{k}x^{(0)}(m)\ k=1,2,\cdots,n \tag{9}$$

Marking the $z^{(1)}$ as the mean sequence of $x^{(1)}$:

$$z^{(1)}(k)=0.5x^{(1)}(k)+0.5x^{(1)}(k-1)\ \text{k=2,3,}\cdots\text{,n} \tag{10}$$

Then, the definition of GM (1,1) which is of the grey differential equation is:

$$x^{(0)}(k)+az^{(1)}(k)=u \tag{11}$$

Where, a is the expansion coefficient; u is the grey action; $z^{(1)}(k)$ is the sequence of white background value.

GM (1,1) grey differential equation agrees with the following differential equation for albinism

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=u \tag{12}$$

Where, a and u are parameters, expressed as $P=[a,u]^T$, and refer to the least square method, the solution of $y_n = BP$ is: $P=[a,u]^T = (B^T B)^{-1} B^T y_n$.

The parameters a and u of GM (1,1) can be identified by the above equation. In fact, $(B^T B)^{-1} B^T$ can be understood as the generalized inverse of the data matrix B. And then:

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} = \begin{bmatrix} -0.5*[x^{(1)}(1)+x^{(1)}(2)] & 1 \\ -0.5*[x^{(1)}(2)+x^{(1)}(3)] & 1 \\ \vdots & \vdots \\ -0.5*[x^{(1)}(n-1)+x^{(1)}(n)] & 1 \end{bmatrix} \tag{13}$$

$$y_n = [x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n)]^T \tag{14}$$

B is the data matrix, y_n is the data vector, and P is the parameter vector.

The differential equation of bleaching formula is solved, and then the prediction model of GM (1,1) is obtained.

$$\hat{x}^{(1)}(k+1) = (x^{(0)}(1) - \frac{u}{a})e^{-ak} + \frac{u}{a} \quad \text{k=1,2,}\cdots\text{,n} \tag{15}$$

Doing the accumulation and subtraction to generate the $\hat{x}^{(1)}(k)$ reduction, and getting the predicted results of $\hat{x}^{(0)}(k)$. Then, the forecasting model of GM (1,1) is:

$$\begin{aligned} \hat{x}^{(0)}(k+1) &= \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \\ &= (x^{(0)}(1) - \frac{u}{a})(1-e^{a})e^{-ak} \quad k = 1,2,\cdots n \end{aligned} \tag{16}$$

3.2. The test of grey prediction model

The accuracy of the model is an important index to measure the level of prediction. This paper uses the method of posterior difference to examine the precision of the model.

The posterior difference test is on account of the residuals (absolute errors) ε, According to the absolute value of the residual difference in each cycle, the probability of the point with the smaller residual and the size of the prediction error variance index are investigated. The specific steps are as follows:

Labelling the $x^{(0)}$ as the original sequence: $x^{(0)} = (x^{(0)}(1),\ x^{(0)}(2),\ \cdots,\ x^{(0)}(n))$, $\hat{x}^{(0)}(k)$ as the predicted value sequence, $k = 1,2,\cdots,n$.

Then, $\overline{x} = \frac{1}{n}\sum_{k=1}^{n} x^{(0)}(k)$ is the average value of the original data $x^{(0)}(k)$; $S_1^2 = \frac{1}{n}\sum_{k=1}^{n}(x^{(0)}(k) - \overline{x})^2$ is the variance of $x^{(0)}(k)$; $\overline{\varepsilon} = \frac{1}{n}\sum_{k=1}^{n}\varepsilon^{(0)}(k)$ is the average value of $\varepsilon^{(0)}(k)$; $S_2^2 = \frac{1}{n}\sum_{k=1}^{n}(\varepsilon^{(0)}(k) - \overline{\varepsilon})^2$ is the variance of $\varepsilon^{(0)}(k)$; $C = \frac{S_2}{S_1}$ is the posterior difference ratio; $P = \{\varepsilon^{(0)}(k) - \varepsilon < 0.6745 S_1\}$ is the small error probability.

In the prediction, it is required that C is as small as possible, and P is as large as possible. Due to the difference of parameters P and C, the preciseness of grey model prediction is divided into four types, and Table 1 shows four types of classification basis.

Table 1. Prediction accuracy criteria

level 1	Good (level 1)	Qualified (level 2)	Barely (level 3)	Unqualified (grade 4)
P	>0.95	>0.8	>0.7	≤0.7
C	<0.35	<0.45	<0.5	≥0.65

3.3. The specific steps of grey prediction

(1) Obtaining original sequence: $x^{(0)} = (x^{(0)}(1),\ x^{(0)}(2),\ \cdots, x^{(0)}(n))$; (2) Calculating the accumulated generated value $x^{(1)}(k)$ of the original sequence on the basis of formula (9); (3) Calculating a and u parameters on the basis of the differential equation (12); (4) The GM (1,1) prediction model $\hat{x}^{(1)}(k+1)$ is acquired by applying formula (15). The result $\hat{x}^{(0)}(k+1)$ is obtained by the gradual reduction of the GM (1,1) model; (5) Calculating the forecasting data errors and identifying the accuracy of the forecasting model.

4. Examples of load forecasting

4.1. The medium-and long-term load forecast data

In this case, the gray prediction model will be used to predict the electricity consumption of a town. The town has a large number of enterprises engaged in mechanical processing and metal smelting, and the quantity of load is relatively higher than that of the surrounding cities, so the factors that affect the load are very uncertain. The Table 2 display the load changes in the region from 2001 to 2011.

Table 2. Annual electricity consumption unit of a city from 2001 to 2011 (100 million kilo watt hours)

The serial number	year	Electricity consumption	The serial number	year	Electricity consumption
1	2001	711.3	7	2007	1487.7
2	2002	724.9	8	2008	1917.5
3	2003	736.1	9	2009	2125.2
4	2004	813.4	10	2010	2556.6
5	2005	1093.1	11	2011	3027.0
6	2006	1294.4			

By processing the data in Table 2, we can obtain the original data trend chart from 2001 to 2011 shown in Figure 1. This curve reflect the original quantity of electric charge. It can be seen from the figure that the overall quantity of load from 2001 to 2011 shows an upward trend, which conforms to the conditions of the grey forecast model.

4.2. The grey prediction simulation design

The GM (1,1) model was used for load forecasting, and the data were processed to reduce the dimension and disorder to obtain the required forecast data. After the gray prediction, the model is verified by posterior error. Table 3 shows the error analysis of load forecasting using grey model.

Table 3. Load prediction error analysis table (100kwh)

year	The original data	Forecast data	Absolute error	The relative error
2001	711.3	711.3	0	0.0%
2002	724.9	617.2	107.7	- 14.9%
2003	736.1	740.4	4.3	0.6%
2004	813.4	888.3	74.9	9.2%
2005	1093.1	1065.7	27.4	- 2.5%
2006	1294.4	1278.5	15.9	- 1.2%
2007	1487.7	1533.9	46.2	3.1%
2008	1917.5	1840.2	77.3	- 4.0%

In Figure 2, the prediction results and original data are shown. The model accuracy posterior: the calculated variance of the original data is 412.7; The residual error is 55.9; The posterior difference ratio C is 0.135<0.35. The probability of small mistake P is 1>0.95.

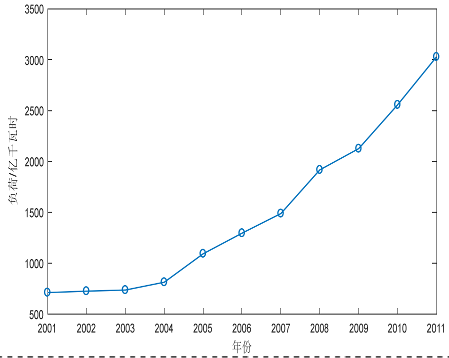

Figure 1. Raw data trend chart from 2001 to 2011

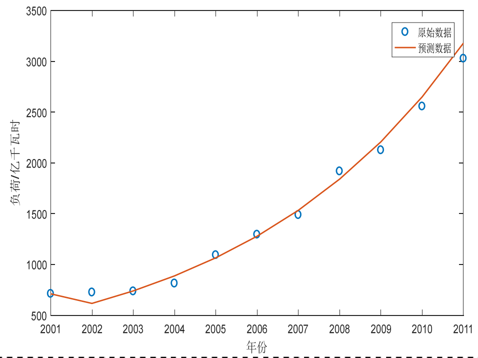

Figure 2. Original data and forecast data trend chart from 2001 to 2008

Through the calculation of the range of parameters C and the size of P, it can be concluded that the accuracy of load forecasting using GM (1,1) model theory is level 1. Therefore, it is feasible to use GM(1,1) model to forecast the regional load. Table 4 shows that the GM (1,1) model is used to predict the electricity consumption in the region from 2009 to 2011 and tests the accuracy of the prediction

Table 4. Load prediction error analysis table (100kwh)

year	The original data	Forecast data	Absolute error	The relative error	Prediction accuracy
2009	2125.2	2207.7	82.5	3.9%	96.1%
2010	2556.6	2648.6	92.0	3.6%	96.4%
2011	3027.0	3177.6	150.6	5.0%	95.0%

Through the load forecasting and forecasting error analysis of this area, it can be concluded that the GM (1,1) forecasting model is effective. Through the error analysis, the error does not affect the accuracy of the prediction results. Therefore, the GM (1,1) model can effectively make a reasonable forecast of the regional electricity load.

5. Conclusion

The characteristic of grey prediction is expressed in the form of differential equation. When the load data is not processed, it is difficult to find the universal law of its existence. In the grey prediction, We need to generate and process the data, after processing the regularity of the processed data will be strengthened. The development coefficient and grey dosage are calculated by using the least square method, and the operation of whitening differential equation and reduction is adopted to GM (1,1) model for prediction. Although the load forecasting model based on grey theory is consistent with the theoretical basis, it may not have prediction effect in practical application, so it is necessary to test the accuracy of the model. The posterior error check is used here, and the posterior is obtained through various calculations of the residual. The accuracy of the model is determined by difference ratio C and small mistake probability P.

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