

# Study on the load forecasting of power system based on gray forecasting model

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## Abstract

This paper analyzes the impact of power system load in various areas, and studies the necessity of the forecasting on it in detail. It gets a reasonable control of the power system load, and conducts a forecasting of medium and long term on it, which have a very significant impact on society and economy. Then this paper conducts forecasting and testing on power system load based on gray forecasting model, obtains corresponding predicted value by taking some of the data for example, compares the value with the actual value, and finally finds out that the accuracy of forecasting is good by using posterior variance examination.

Key words: GRAY THEORY, GRAY FORECASTING MODEL, POWER SYSTEM, LOAD FORECASTING

## 1. Introduction

Electric power, as an important basic industry for the country, is an important resource in life and also an important guarantee for the normal operation of

economy. Load forecasting of power system is an important basis of power planning, production and operation, and accurate load forecasting can enhance the security and stability of power grid operation, and

improve the reliability of power supply, and effectively reduce the cost of electricity generation, thus enhancing economic and social benefits. Just because load forecasting plays such an important role in power system, how to further improve the accuracy of load forecasting is very important.

In today's global economic integration, national productivity directly determines the level of comprehensive national strength. As electric power is an important resource of industry and life of each country, it plays an important role in economic development. Therefore, how to deal with power system load and conduct prediction of medium and long term on it plays a decisive role in the conservation and security of electricity.

There are numerous power load forecasting methods, which are usually divided into the traditional load forecasting methods and new load forecasting method. Because of the simple and practical model of traditional forecasting models, the parameters have relatively clear physical meaning, which is widely used in the actual system. However, traditional methods rely mostly on expert experience to judge, so its prediction accuracy is often low. In recent years, with the increasing complexity of system as well as the emergence of some new cross-disciplinary subjects and application theories, many new load forecasting models appear, to accommodate the increasing requirements for load forecasting accuracy. Among these, the gray forecasting method of power load based on Gray Theory is one of the forecasting methods that are the most widely used and has the best effect in current load forecasting of medium and long term. This paper sets up model on the issue of power system load, conducts forecasting on power system load of medium and long term, and studies and analyzes its accuracy.

## 2. Gray system theory and gray forecasting system model

### 2.1. Gray system theory

Gray system theory calls the known information as «white» information, the completely unknown information as «black» information, and the information between the two information as «gray» information.

Gray forecasting method develops on the basis of gray theory model, which applies gray generation to weaken the randomness of the original series, so as to obtain the prediction result of the original series through reduction operation on the basis of applying various models to conduct fitting process on the series generated. This kind of model requires less original series, considers no distribution law, operates easily, has high short-term forecasting accuracy, and

is easy to inspect, but the end forecasting results in forecasting period are not ideal. Therefore, there are many literature making a number of improvements for the defects of gray forecasting model, and many improved gray forecasting models are formed, which are hereinafter discussed in detail.

### 2.2. Grey forecasting model

Gray system is to establish a better model by gray forecasting system and selecting some of the information, when it contains less data or information data contains uncertain factors.

The core of gray system theory is gray dynamic modeling, and its idea is to directly convert time series into differential equations, so as to establish a dynamic model of system development and change. Currently, the commonly used model in power load forecasting is GM (1,1) model, its essence is to do a cumulative generation on the raw data, the data generated shows exponential law, fitting curve is obtained by establishing differential equation model, and the predicted value is restored by repeatedly minus division.

First, data conversion is conducted. Because sub-factor data have different dimensions, they are not comparable. In order to ensure the accuracy of the modeling results, data conversion must be conducted to eliminate the dimensions of factors. The method is shown as follows.

Ordered series  $x = (x(1) \ x(2) \ \cdots \ x(n))$ , mapping  $f: x \rightarrow y \ f(x(k)) = y(k) \ k = 1, 2, \cdots, n$  is called as the data conversion from series  $x$  to series  $y$ , and their data conversion are: initial value conversion, equalization conversion, percentage conversion, multiple conversion, normalization conversion, range maximization conversion, interval value conversion and so on. And initial value conversion is applied here.

$$f(x(k)) = \frac{x(k)}{x(1)} = y(k) \ k = 1, 2, \cdots, n, x(1) \neq 0 \quad (1)$$

That is the initial value conversion of  $f$ . Conduct initial value conversion on matrix  $A$ , and use matrix transformation. The model obtained by fitting is the first order differential equation of time series, and gray system is to establish differential equation on discrete sequence.

$$\frac{dx}{dt} + ax = \mu \quad (2)$$

From the definition of derivative,

$$\frac{dx}{dt} = \lim_{\Delta t \rightarrow 0} \frac{x(t + \Delta t) - x(t)}{\Delta t}, \text{ when } \Delta t \text{ tends to}$$

0,  $\Delta t$  uses the approximate value of unit 1, obtaining

$$x(t+1) - x(t) = \frac{\Delta x}{\Delta t}, \text{ its discrete form is}$$

$$\frac{\Delta x}{\Delta t} = x(k+1) - x(k) = \Delta^{(1)}(x(k+1)) \quad (3)$$

Assuming  $X^{(0)} = (x^{(0)}(1) \ x^{(0)}(2) \ \dots \ x^{(0)}(3))$  is non-negative series, conduct accumulation on  $X^{(0)}$ , and the generated series obtained is

$$X^{(1)} = (x^{(1)}(1) \ x^{(1)}(2) \ \dots \ x^{(1)}(3)) \quad (4)$$

In which,

$$x^{(1)}(k) = \sum_{i=0}^k X(i), \quad x^{(0)}(k) + a^{(1)}(k) = b, \text{ by}$$

simplifying, obtaining

$$x^{(0)}(k) = \beta - \alpha x^{(1)}(k-1) \quad (5)$$

In which,

$$\beta = \frac{b}{1+0.5a}, \quad \alpha = \frac{a}{1+0.5a}, \text{ thus}$$

$$\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} = \begin{bmatrix} -\frac{1}{2}(x^{(1)}(1) + x^{(1)}(2)) & 1 \\ -\frac{1}{2}(x^{(1)}(2) + x^{(1)}(3)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(x^{(1)}(n-1) + x^{(1)}(n)) & 1 \end{bmatrix} \quad (6)$$

Assuming

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, B = \begin{bmatrix} -\frac{1}{2}(x^{(1)}(1) + x^{(1)}(2)) & 1 \\ -\frac{1}{2}(x^{(1)}(2) + x^{(1)}(3)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(x^{(1)}(n-1) + x^{(1)}(n)) & 1 \end{bmatrix}$$

### 3. Improved method of gray model

In the practical application of gray model in load forecasting, it is found that the forecasting accuracy will be significantly reduced when data dispersion is relatively large, and especially in the load forecasting of medium and long term for longer time span, the end prediction effect of forecasting period is not ideal. The main reasons are as following: taking no consideration on the impact on system growth rate; not introducing new information into the model, and removing the old information.

For above reasons, GM (1,1) model can be modi-

fied to achieve higher accuracy. There are three commonly seen improvements: first, modifying raw data, such as index weighting method, moving average method, policy addition factor method, 20% average repair method; second, modifying the model itself, such as residual gray forecasting model, interference factor gray model, gray forecasting - correction model; Third, improving technology, such as gray hierarchical forecasting method, combination model method, forecasting model of filling vacancies of equidimensional new information, and gray model group modeling method.

#### 3.1. Applying moving average method to pre-process raw data

This method is the commonly used improved method of gray model, and generally is the first step to conduct improvement. The purpose of conducting moving average processing on the raw data is mainly to weaken the impact of extreme value (bad data) among the data, weaken the volatility of the data series, and reduce randomness at the same time, thereby strengthening the trend of raw data, and modifying raw data into series of incremental change as far as possible, to match or be close to the decision-making needs.

After conducting moving average processing on raw data, random error and human error of data decrease in the statistics, thus weakening the interference of human subjectivity and occasionality of data, so as to improve model accuracy. However, this method still cannot resolve the error caused by defects in the model itself.

#### 3.2. Residual processing

If the residual test of the gray model built based on raw data or the raw data after being preprocessed fails or has large error, GM (1,1) model of residual can be built to modify the original model.

Assume  $k=i, i+1, \dots, n$ , build residual series  $Q^{(0)} = (Q^{(0)}(i) \ Q^{(0)}(i+1) \ \dots \ Q^{(0)}(n))$ , and apply residual series to build GM(1,1) model before adding into the original model. The model accuracy after residual modifying is greatly enhanced. However,  $\alpha$ ,  $\mu$  variation after treatment on the residual still exists.

#### 3.3. Equidimensional new information processing

Since GM (1,1) model does not consider the impact of  $\alpha$ ,  $\mu$  varying with time, the prediction error is large. The idea of equidimensional new information processing is to send the new information obtained from predictive model into the original data series, removing a stale data, and repeat the cycle until it reaches the intended target. The specific approach is to use known series to establish GM (1,1) model and

predict a value; add this predicted value after the known series, remove the first data of the series to ensure the equal dimension of series, create a new GM (1,1) model, predict the next value, add the result after the series, and then remove the oldest data, repeat the procedure, forecast one by one, and fill vacancies in order of precedence until the forecasting target is completed or predetermined accuracy is achieved.

This improvement not only overcomes the problem of fixed mathematical model in simple gray prediction, but also takes advantage of high short-term forecasting accuracy of gray forecasting method. Therefore, the prediction model has been effectively corrected and its forecasting accuracy has improved significantly. Although applying equidimensional new information processing can weaken the prediction error due to  $\alpha$ ,  $\mu$  to some extent, this method can only better predict the recent data, but can not solve the problem of large error in medium and long term prediction.

### 3.4. Forecasting improved method of load in medium and long term based on $\beta$ value

Reference [3] proposes an improved method based on  $\beta$  value, after referring to residuals processing, raw data moving average processing and equidimensional new information processing.  $\beta$  is defined as the ratio of development index to annual power consumption.

GDP development index is the comparable price index of GDP of 100 in 2014. The steps of the improved method are as follows.

**Step 1** The relationship between annual power consumption and GDP index in the same year constitutes  $\beta$  value series.

**Step 2** Based on gray forecasting theory, use GM (1,1) model and equidimensional new information technology to build forecasting model, to predict  $\beta$  value.

**Step 3** Set macro GDP index and predicted  $\beta$  value according to the national economic development, to predict power consumption in reverse.

Based on related data, different methods are applied in modeling, to predict the future electricity demand. The results show that a variety of methods can process raw data perfectly; but in terms of prediction accuracy, using only GM (1,1) model has the largest prediction error, applying GM (1,1) modeling theory with equidimensional new information technology and moving average processing technology to conduct forecasting can greatly reduce prediction error, and using the proposed method has the minimum prediction error.

Improved method based on  $\beta$  value is proposed

aiming at the feature of medium and long term electricity demand forecasting in power system, which is actually based on GM (1,1) modeling theory. It conducts reconstruction on the original data at the same time, and the impact of the national economic development on the annual electricity consumption is added to the prediction model in the process of constructing new data. For this reason, using this method to conduct medium and long term load forecasting method can achieve good results both in the accuracy of the model and the results of prediction.

### 4. Other improvements of gray model

In addition to the above improved methods and  $\beta$  value improved methods based on common methods, there are some other improved models, such as integral optimization model, white index coincident model, same response model and strict differential fitting model. Reference [8] analyzes and compares these types of improved models.

The above four models are all obtained by modifying the background value and parameter estimation of traditional GM (1,1) model. Except that the calculation methods of background value and parameter estimation are different, other modeling steps are the same with GM (1,1) model, and the specific improvements are as follows.

#### 4.1. Integral optimization model

Model background value

$$z^{(1)}(k) = \frac{x^{(1)}(k) - x^{(1)}(k-1)}{h x^{(1)}(k) - h x^{(1)}(k-1)}, k = 2, 3, \dots, n \quad (7)$$

#### 4.2. White index coincident model

Assume

$$C = \begin{pmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ \vdots \\ x^{(1)}(n) \end{pmatrix}, A = \begin{pmatrix} x^{(1)}(1) & 1 \\ x^{(1)}(2) & 1 \\ \vdots & \vdots \\ x^{(1)}(n-1) & 1 \end{pmatrix}, \text{ obtaining by the}$$

least square method

$$\beta = (A^T A)^{-1} A^T C \quad (8)$$

Among them,

$$\beta = \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix}$$

The estimated values of parameters  $a$ ,  $b$  are

$$\hat{a} = -\ln \hat{\beta}_1, \hat{b} = \frac{\hat{\beta}_2}{1 - \hat{\beta}_1} \hat{a} \quad (9)$$

4.3. Same response model

Assume

$$B = \begin{pmatrix} -x^{(1)}(1) & 1 \\ -x^{(1)}(2) & 1 \\ \dots & \dots \\ -x^{(1)}(n-1) & 1 \end{pmatrix}, Y_n = \begin{pmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \dots \\ x^{(0)}(n) \end{pmatrix}, \text{ and estimate}$$

parameters  $c_1, c_2$ , by the least square method, thus

$$\begin{bmatrix} \hat{c}_1 \\ \hat{c}_2 \end{bmatrix} = (B^T B)^{-1} B^T Y \tag{10}$$

After substitution, the estimated values of  $a$  and  $b$  are

$$\hat{a} = -\ln(1 - \hat{c}_1), \hat{b} = -\ln(1 - \hat{c}_1) \frac{\hat{c}_2}{\hat{c}_1} \tag{11}$$

4.4. Strict differential fitting model

Assume

$$Z = \begin{pmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ \dots \\ x^{(1)}(n) \end{pmatrix}, A = \begin{pmatrix} -x^{(1)}(2) \dots 1 \\ -x^{(1)}(3) & 1 \\ \dots & \dots \\ -x^{(1)}(n) & 1 \end{pmatrix}, \theta = \begin{pmatrix} \xi \\ \eta \end{pmatrix}, \text{ then}$$

$$A^\theta = Z \tag{12}$$

Conduct the least square method on the above formula:

$$\theta = (A^T A)^{-1} A^T Z \tag{13}$$

Estimated values of  $\xi$  and  $\eta$  can be obtained, and the estimated values of parameters can be obtained by substitution.

$$\hat{a} = \ln(1 + 1/\xi), \hat{b} = \eta \ln(1 + 1/\xi) \tag{14}$$

GM (1,1) and the above four improved models are applied to conduct modeling and accuracy test on five types of load series of different growth laws, and the

results show that: (1) When the original series change according to exponentially function law, if its growth rate is less than 30%, the prediction accuracy of the above gray models is high, and meets the following law. When the growth rate of load is greater, prediction error is greater, but in annual electricity demand forecasting, since it generally may not grow at the annual growth rate of more than 30% in 20 consecutive years, all GM (1,1) models are applicable; (2) for the average annual growth rate of 6.1837%, approximate the load of exponential growth law, except integration optimization model, the accuracy of the other three models are higher than that of traditional GM (1,1), and the variance of accuracy is little, in which the accuracy of white index coincident model and same response model is the same; (3) for the average annual growth rate of 10.5171% and 28.4025%, approximate the load of exponential growth law, the accuracy of the four models are higher than that of traditional GM (1,1), and the accuracy of white index coincident model and same response model is the highest, followed by strict differential fitting model and integral optimization model; (4) When the original series change on non-exponential function law (Gompertzlan-curve and S-curve), the accuracy of all gray forecasting models deteriorate. To further improve the annual electricity demand forecasting accuracy of GM (1,1) model, it is necessary to have a correct estimation on the development status and stage of the city and have a correct understanding on the regularity that the future development of annual electricity consumption follows.

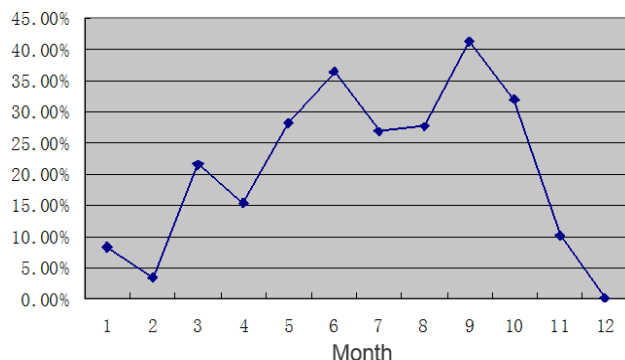
5. The test on gray forecasting model in the load forecasting of power system

Using the model to test the power system in a certain area, the predicted and actual value is obtained as follows in Table 1.

Table 1. The predicted and actual value

	Predictive value	The actual value	The absolute value of the difference	Impact rate
January	585960	541019	44941	8.3067323%
February	495280	479208	16072	3.3538672%
March	544340	694372	150032	21.606862%
April	573480	677586	104106	15.364249%
May	511870	713699	201829	28.2792886%
June	480750	756600	275850	36.4591594%
July	548250	749327	201077	26.834346%
August	541220	748495	207275	27.6922358%
September	521030	888568	367538	41.362957%

According to the data in the table, draw the line graph of month and affection rate, which is shown in Figure 1,



**Figure 1.** The line graph of month and affection rate in 2014

Conduct test on gray forecasting model according to the posterior variance examination, and grade test table of accuracy test is shown in Table 2.

**Table 2.** Accuracy inspection level checklist

Prediction accuracy class	$P$	$C$
Good	$> 0.9$	$< 0.35$
Qualified	$\geq 0.8$	$< 0.45$
Reluctantly	$\geq 0.7$	$0.5$
Failure	$< 0.7$	$\geq 0.65$

Solve time residual  $S_1$  and original data  $S_2$  in a period of time interval, according to posterior variance ratio formula

$$c = \frac{S_1}{S_2} \quad (15)$$

Solving error probability  $P$ , according to formula

$$P = P \left\{ \left| \varepsilon_{(1)}^{(0)} - \bar{\varepsilon} \right| < 0.6745 S_2 \right\} \quad (16)$$

In the formula,  $\bar{\varepsilon}$  is the residual average.

Based on  $C$  value and  $P$  value, conduct test according to grade test table of accuracy test. The conclusion obtained is that the prediction accuracy is good and can provide reference for power system load forecasting.

### 6. Conclusions

This paper applies gray theory as one of the power load forecasting methods. Although its application has some limitations, its forecast accuracy is generally higher and can meet the requirements through

continuous improvement of the model, so that this method is widely used. Common improved methods on traditional GM (1,1) model are moving average method, residuals processing method and equidimensional new information processing method. These three improved methods conduct modification on different aspects of traditional model, and the integrated use of these three methods in modeling can usually get a higher prediction accuracy. The above-mentioned three improved forecasting methods are not satisfactory in making medium and long term load forecasting, so improved method of  $\beta$  value is introduced to suit the requirements of medium and long term load forecasting. In addition, improved models obtained by using different calculation methods of background value and parameter estimation are fit for different annual growth rates. Apply gray forecasting model to predict and test power system load, take the data in 2008 as an example to get corresponding predicted value, compare it with the actual value, and finally obtain that the forecasting accuracy is good by using posterior variance examination and can provide reference for power system load forecasting.

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### References

1. Zhigang Qi, Xiaohui Yuan (2014) New method for long term load forecasting in power system. *Power System Engineering*, 36(11), p.p.77-81.
2. Sergio Jurado, Ángela Nebot (2015) Hybrid methodologies for electricity load forecasting: Entropy-based feature selection with machine learning and soft computing techniques. *Energy*, 86(15), p.p.276-291.
3. Quanyou Zhang (2012) A medium and long term electricity demand forecasting model based on Grey System Theory. *Power System Technology*, 23(8), p.p.99-103.
4. Ming Gao, Fangzhu Li (2011) Medium and long term load forecasting based on Grey Theory. *Electric Power*, 36(4), p.p.48-57.
5. YU Ming-sheng, FENG Gui-hong, YANG Xiang (2008) Application of combined optimization grey model in medium and long term electric load forecasting. *Journal of Shenyang University of Technology*, 8(5), p.p.112-121.
6. San Cristóbal, José Ramón (2015) A Cost Forecasting Model for a Vessel Drydocking. *Journal of Ship Production and Design*, 31(1), p.p.58-62.
7. G. Sudheer, A. Suseelatha (2015) Short term load forecasting using wavelet transform combined

- with Holt–Winters and weighted nearest neighbor models.*Journal of Electrical Power & Energy Systems*, 64(1),p.p.340-346.
8. Gopinathan Sudheer, Annamareddy Suseelatha(2015) A wavelet-nearest neighbor model for short-term load forecasting.*Energy Science & Engineering*, 3(1),p.p.51-59.
  9. Rainer Göb, Kristina Lurz, Antonio Pievato(2015) More Accurate Prediction Intervals for Exponential Smoothing with Covariates with Applications in Electrical Load Forecasting and Sales Forecasting.*Quality and Reliability Engineering International*, 31(4),p.p.669-682.
  10. Morita Hironobu, Tamura Yasuo(1995) Long-term load forecasting using grey system theory.*Electrical Engineering in Japan*, 115(2),p.p.11-20.
  11. Hamed Chitsaz, Hamid Shaker(2015) Short-term electricity load forecasting of buildings in micro-grids.*Energy and Buildings*, 99(15),p.p.50-60.
  12. Hsu CC, Chen CY.(2003) Applications of Improved Grey Prediction Model for Power Demand Forecasting.*Energy Conversion and Management*, 44(14),p.p.2241-2249.
  13. Liu Sifeng, J Forrest(2007) The current development status on grey system theory.*Journal of Grey System*, 19(2),p.p.111-123.



### Variable selection procedures in linear regression models with selection consistency property

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