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Short-term power load forecasting using grey correlation contest modeling

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ABSTRACT

Power load has the characteristic of nonlinear fluctuation and random growth. Aiming at the drawback that the forecasting accuracy of general GM(1,1) model goes down when there is a greater load mutation, this paper proposes a new grey model with grey correlation contest for short-term power load forecasting. In order to cover the impact of various certain and uncertain factors in climate and society on the model as fully as possible, original series are selected from different viewpoints to construct different forecasting strategies. By making full use of the characteristic that GM(1,1) model can give a perfect forecasting result in the smooth rise and drop phase of power load, and the feature that there are several peaks and valleys within daily power load, the predicted day is divided into several smooth segments for separate forecasting. Finally, the different forecasting strategies are implemented respectively in the different segments through grey correlation contest, so as to avoid the error amplification resulted from the improper choice of initial condition. A practical application verifies that, compared with the existing grey forecasting models, the proposed model is a stable and feasible forecasting model with a higher forecasting accuracy.

1. Introduction

Power load has the characteristic of typical nonlinear fluctuation, for it is comprehensively affected by various random and non-random factors including climate and society. Climatic factors refer to the change of temperature, humidity, season, etc. Social factors mainly involve human social activities, such as work, study, holidays and entertainment.

Early research efforts on short-term power load forecasting include ARMA model, recursive model, Kalman filter, multiple linear regression model, exponential smoothing model, state estimation model, and stochastic time series model. ARMA model has not taken factors such as weather conditions into consideration (Kurata & Mori, 2009). Recursive model can take the weather and other factors into consideration, but this forecasting model is linear and not applicable to forecasting for nonlinear problem (Kurata & Mori, 2009). In Kalman filter, because of the failure of avoiding the influence of observation noise on the forecasting, the error covariance matrix does not necessarily converge and prediction is sometimes impossible (Niu, Wang, & Wu, 2010). Multiple linear regression model, exponential smoothing model, state estimation model, and stochastic time series model use a large number of complex and non-linear relationships between the load and its influential factors, which requires a great amount of computational time and may result in numerical instabilities (Wang & Wang, 2008). In general, these early research efforts can not properly represent the complex nonlinear relationships between power load and its various influential factors.

During the last decades there has been lots of research work focusing on artificial neural network (ANN) and support vector machine (SVM). ANN shows good approximation capability for nonlinear function, and can select historical load, weather, day type, etc. as the input variables. However, many problems of ANN, such as network parameter selection, sub-optimization and low converging rate, still remain to be solved (Hinojosa & Hoese, 2010). Based on the structural risk minimization principle rather than the minimization of the training errors which is used by ANN, SVM is more efficient than ANN and could theoretically guarantee the global optimum. Nevertheless, SVM also has the network parameter selection problem (Wang et al., 2008).

Owing to these problems, the approach of grey forecasting has attracted an ever-increasing attention recently. Considering the random variable as the grey variable which varies within a certain range, the grey forecasting theory uses a data-generating technology to transform the irregular original data into the new data with strong regularity, so as to implement the original data analysis and forecasting. When power load keeps fluctuating in an exponential curve, forecasting in GM(1,1) grey model (Deng, 1982) has the advantages of high accuracy and fewer sampling data needed. However, the forecasting accuracy may drop when there is a greater load

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mutation. Many researchers have conducted research in improving the forecasting accuracy of GM(1,1) model. Niu, Zhang, Chen, and Zhang (2006) proposed to improve GM(1,1) model into GM(1,1,θ) model and utilize particle swarm optimization algorithm to solve the optimal vector θ. Wang, Sun, Yang, and Feng (2006) introduced the Markov state matrix into GM(1,1) model. Zhao (2007) introduced equivalent-dimension additional correction algorithm into GM(1,1) model. Yu, Feng, and Yang (2007) combined residual analysis with equivalent-dimension additional correction algorithm. These research efforts intended to increase the forecasting accuracy primarily from the viewpoint of internal optimization on the forecasting model itself. In fact, if we can provide an appropriate initial condition at the beginning of forecasting, it is possible to avoid the risk in which errors are introduced into the model and then gradually amplified during the forecasting process because of the improper choice of initial condition. This is essentially an external optimization mode which increases the forecasting accuracy by optimizing the external environment of forecasting model. Furthermore, if the two modes of internal and external optimization can be integrated with each other, the whole forecasting accuracy of GM(1,1) model may be dramatically improved.

With the experience obtained from practical engineering projects, this paper proposes a hybrid optimization grey model (HOGM) with the integration of internal and external optimization mode for short-term power load forecasting. The internal optimization of HOGM consists of modeling feasibility test and parameter α correction. The external optimization of HOGM includes three aspects. First, original series are selected from different viewpoints to construct different forecasting strategies, so that the impact of various certain and uncertain factors such as climate and society on the model can be fully covered. Second, by making full use of the characteristic that GM(1,1) model can give a perfect forecasting result in the smooth rise and drop phase of power load and the feature that there are several peaks and valleys within daily power load, the predicted day is divided into several smooth segments for separate forecasting. Finally, the different forecasting strategies are implemented respectively in the different segments of the predicted day through grey correlation contest. In addition to the internal and external optimization, a data preprocessing mechanism is introduced to reduce the impact of abnormal data on the model. The flowchart of HOBM is shown in Fig. 1.

The rest of this paper is organized as follows. Section 2 introduces the basic GM(1,1) model. Section 3 describes the proposed HOGM based on segmented grey correlation and multi-strategy contest in detail. The forecasting method and steps of using HOGM are presented in Section 4. A practical verification and forecasting result comparison, concerning the application of HOGM and other three GM(1,1) models, are shown in Section 5. A conclusion is given in Section 6.

2. Basic GM(1,1) model

By performing the 1-accumulated generating operation (1-AGO), the original series $x^{(0)}$ is transformed into the following first-order series:

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

where

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i) \tag{2}$$

$x^{(1)}$ satisfies the following first-order differential equation:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = u \tag{3}$$

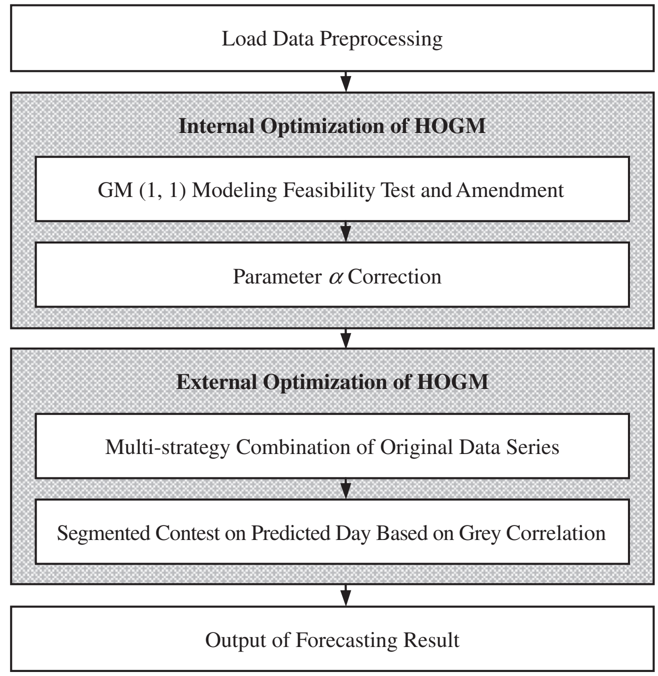

Fig. 1. Flowchart of HOBM.

The approximate values of parameter a and u are estimated by the least-squares method as:

$$\begin{bmatrix} \hat{a} \\ \hat{u} \end{bmatrix} = (B^{\mathrm{T}}B)^{-1}B^{\mathrm{T}}Y_n \tag{4}$$

where

$$Y_n = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, \quad B = \begin{bmatrix} -\frac{1}{2}[x^{(1)}(1) + x^{(1)}(2)] & 1 \\ -\frac{1}{2}[x^{(1)}(2) + x^{(1)}(3)] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}[x^{(1)}(n-1) + x^{(1)}(n)] & 1 \end{bmatrix} \tag{5}$$

The obtained $\hat{a}$ and $\hat{u}$ are substituted into Eq. (3) as follows:

$$\frac{dx^{(1)}}{dt} + \hat{a}x^{(1)} = \hat{u} \tag{6}$$

Then the one-step-ahead predicted value is calculated as:

$$x^{(1)}(k+1) = \left(x^{(1)}(1) - \frac{\hat{u}}{\hat{a}}\right)e^{-\hat{a}k} + \frac{\hat{u}}{\hat{a}} \quad (k = 0, 1, 2, \ldots) \tag{7}$$

By performing the 1-inverse accumulated generating operation (1-IAGO) on Eq. (7), the grey forecasting model of the original series $x^{(0)}$ is finally obtained as:

$$\begin{aligned} \hat{x}^{(0)}(k+1) &= \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \\ &= (e^{-\hat{a}} - 1)\left(x^{(0)}(1) - \frac{\hat{u}}{\hat{a}}\right)e^{-\hat{a}k} \quad (k = 0, 1, 2, \ldots) \end{aligned} \tag{8}$$

3. HOGM based on segmented grey correlation and multi-strategy contest

3.1. Overview

This paper presents a hybrid optimization grey model (HOGM) based on segmented grey correlation and multi-strategy contest, which is a forecasting model integrating the internal optimization with the external optimization. The external optimization on GM(1,1) model is proposed on the basis of an in-depth analysis that, among the various impact factors on power load such as climate and society, there are both lots of random factors and many regular ones. The internal optimization on GM(1,1) model is put forward against the drawbacks of the grey forecasting model itself. The block diagram of the whole HOGM is shown in Fig. 1.

3.2. Load data preprocessing

There are usually two types of abnormal load data. One is the shortage data, which is shown as a straight line in Fig. 2. The other is the mutation data, which is shown as a peak or burr in Fig. 2.

Suppose the daily load consists of 96 sampling data-points. The preprocessing method for abnormal data is shown as follows.

(1) Preprocessing of shortage data

If the difference of load value between any two adjacent data-points on a day falls into the threshold λ as follows:

$$|l(i)-l(i-1)|<\lambda \quad (i=2,3,\ldots,96 \quad \lambda \in \text{constant}) \tag{9}$$

then the data on that day will be directly deleted.

If the difference of load value between any two adjacent data-points within consecutive two hours or more on a day falls into the threshold , then the data on that day will be preprocessed according to following principles.

For a holiday, the load value on the same holiday last year is taken as the load benchmark $L(y-1,d)$. The latest ordinary workday before the holiday is found out, and the difference of load value on that ordinary workday between last year and this year is taken as the annual load increase . Then the load correction value is calculated as:

$$L(y,d)=L(y-1,d)+\Delta \tag{10}$$

For an ordinary day, the day is marked as the Nth day where N is a constant. Given the normal load data from the first day to the $(N-1)$th day before the abnormal day and the k points of normal load data on the Nth day, then the load correction value is calculated as follows:

$$\begin{cases} P_{AVE}(t)=\frac{1}{N-1}\sum\limits_{i=1}^{N-1}P_R(i,t) \quad (t=1,2,\ldots,96) \\ \overline{P}_k=\frac{1}{k}\sum\limits_{i=1}^{k}P_R(N,t) \quad (t=1,2,\ldots,k) \\ \overline{P}_{AVEK}=\frac{1}{k}\sum\limits_{t=1}^{k}P_{AVE}(t) \quad (t=1,2,\ldots,k) \\ P_R(N,t)=P_{AVE}(t)-(\overline{P}_{AVEK}-\overline{P}_k) \quad (t=k+1,\ldots,96) \end{cases} \tag{11}$$

where $P_R(i,t)$ is the load datum at the time-point of t on the ith day among the $(N-1)$ days, $P_{AVE}(t)$ is the arithmetic mean of all load data at the time-point of t among the $(N-1)$ days, $\overline{P}_k$ is the arithmetic mean of the k points of normal load data on the Nth day, $\overline{P}_{AVEK}$ is the arithmetic mean of all load data at the k time-points among the $(N-1)$ days, and $P_R(N,t)$ is the load value at the correction time-point of t on the Nth day.

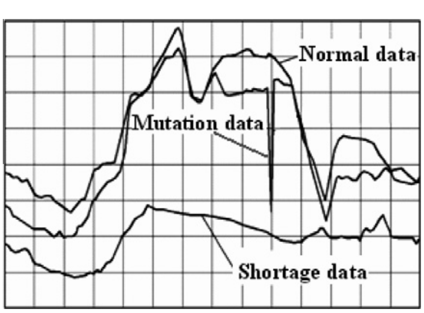

Fig. 2. Abnormal load data.

(2) Preprocessing of mutation data

$$\begin{cases} l(i)>(1+\alpha)\times l(i-1) \\ l(i)<(1-\alpha)\times l(i-1) \end{cases} \quad (i=2,3,\ldots,96 \quad \alpha \in \text{constant}) \tag{12}$$

If the load data of two points satisfy one of formula (12), then it is concluded that there is a load mutation. For the front-end of load, the right-adjacent class ratio generation is used for correction. For the back-end of load, the left-adjacent class ratio generation is used for correction. And for the middle section of load, the weighted mean before and after the load point is adopted for correction. The correction expressions are presented as follows:

$$\begin{cases} l(1)=[l(2)]^2/l(3) \\ l(i)=0.5\times[l(i-1)+l(i+1)] \quad (i=2,3,\ldots,95) \\ l(n)=[l(n-1)]^2/l(n-2) \quad (n=96) \end{cases} \tag{13}$$

3.3. Internal optimization of HOGM

3.3.1. GM(1,1) modeling feasibility test and amendment

The class ratio of $x^{(0)}$ can be used to determine the possibility of modeling GM(1,1) on a given series $x^{(0)}$ (Deng, 2002). For any $x^{(0)}(k)\in x^{(0)}$ $k=1,2,3,\ldots,n$, let $\sigma^{(0)}(k)$ be the class ratio of $x^{(0)}$. $\sigma^{(0)}(k)$ is defined as:

$$\sigma^{(0)}(k)=\frac{x^{(0)}(k-1)}{x^{(0)}(k)}, \quad k\geqslant 2 \tag{14}$$

The principle for GM(1,1) modeling feasibility analysis is described as follows. If

$$\sigma^{(0)}(k)\in(e^{\frac{-2}{n+1}},e^{\frac{2}{n+1}}) \tag{15}$$

then it is concluded that GM(1,1) could be modeled on $x^{(0)}$.

For the unqualified series by class ratio check, data transformation processing should be performed in order to make the class ratio of processed series fall into the accommodation area. The class ratio $\sigma_y(k)$ of the processed series should be close to 1. In other words, the class ratio deviation $\delta_y(k)$ should be as small as possible. Since $\delta_y(k)$ is defined as:

$$\delta_y(k)=\frac{\Delta_y(k)}{y(k)} \tag{16}$$

the mechanism of data amendment is to select proper processing series $y(k)$ in order to make the ratio of difference information $\Delta_y(k)$ to processing data $y(k)$ small enough. The main processing approaches include log transformation, square root transformation and translation transformation.

3.3.2. α Parameter correction for the accuracy improvement of GM(1,1) model itself

When the series development rate, namely the value of $|a|$, is larger, the forecasting accuracy of GM(1,1) model gets low. It is because the generation of background value in traditional GM(1,1) modeling adopts the following calculation equation:

$$z^{(1)}(k+1)=\frac{1}{2}(x^{(1)}(k)+x^{(1)}(k+1)) \tag{17}$$

It shows that this generation method simply calculates the mean of $x^{(1)}(k)$ and $x^{(1)}(k+1)$ by taking $\alpha=0.5$. The value of a is not taken into consideration.

Zhuang (1993) pointed out that the accurate calculation equation of the background value $z^{(1)}(k)$ should be defined as follows:

$$z^{(1)}(k+1) = \alpha x^{(1)}(k) + (1-\alpha)x^{(1)}(k+1) \tag{18}$$

Moreover, he gave out the relationship between a and α as follows:

$$\alpha = \frac{1}{a} - \frac{1}{e^a - 1} \tag{19}$$

By using L'Hopital's rule, it could be verified that the limit value of α is 0.5 when $a \to 0$. According to Eq. (19), we can calculate the corresponding values between a and α, which are shown in Table 1.

Table 1 indicates that α is very close to 0.5 when $|a|$ is smaller and α is far from 0.5 when $|a|$ is larger. Therefore, according to the different value of a, we can choose the different value of α to calculate the background value $z^{(1)}(k)$ so as to solve the problem of forecasting accuracy when $|a|$ is larger.

Based on the above analysis, this paper proposes a forecasting algorithm with parameter α correction for GM(1,1) model, which is described in steps as follows:

Step 1. Let $\alpha = 0.5$. The parameters a and u are calculated by the least-squares method according to Eq. (4).

Step 2. The obtained $\hat{a}$ is substituted into Eq. (19) and then $\hat{\alpha}$ is recalculated, which is marked as $\hat{\alpha}\ (m+1)\ m = 1, 2, \ldots$ Given an arbitrarily small positive integer ε, $\hat{\alpha}\ (m+1)$ and $\hat{\alpha}\ (m)$ is compared. If $|\hat{\alpha}(m+1)\text{-}\hat{\alpha}(m)| > \varepsilon$, go to Step 1 and substitute $\hat{\alpha}\ (m+1)$ into Eq. (18) to calculate background value $z^{(1)}(k+1)$. Then GM(1,1) is remodeled and forecasting is performed again. If $|\hat{\alpha}(m+1) - \hat{\alpha}(m)| < \varepsilon$, stop iteration cycle and go to Step 3.

Step 3. The GM(1,1) forecasting model is constructed according to Eq. (7). By performing 1-IAGO on $\hat{x}^{(1)}(k)$, the predicted value $\hat{x}^{(0)}(k)$ is obtained as shown in Eq. (8).

3.4. External optimization of HOGM

3.4.1. Preliminary concept

The basic idea of correlation degree is to judge the similarity degree between different curves. The greater the correlation coefficient is, the more optimal the corresponding forecasting model is (Chen, Jiang, Guo, & Deng, 2006; Xie, Dong, & Wang, 2002).

The predicted value curve is also called the comparison series. There are m predicted value curves, which are marked as:

$$x_i = \{x_i(1), x_i(2), \ldots, x_i(n) | i = 1, 2, \ldots, m\} \tag{20}$$

The actual value curve is also called the reference series, which usually consists of the data set on the last day before the predicted day or is a known actual curve. The actual value curve is marked as x_0.

Then the correlation coefficient between x_i and x_0 at the point of k is defined as:

$$\varepsilon_i(k) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \rho \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \max_i \max_k |x_0(k) - x_i(k)|} \tag{21}$$

where $|x_0(k) - x_i(k)|$ is the absolute difference between the actual value $x_0(k)$ and the predicted value $x_i(k)$ at the point of k, $\min_i \min_k |x_0(k) - x_i(k)|$ is the two-level minimum difference which means the minimum difference among both all the points of k $(k = 1, 2, \ldots, n)$ and all the predicted value curves $x_i(k)$ $(i = 1, 2, \ldots, m)$, $\max_i \max_k |x_0(k) - x_i(k)|$ is the two-level maximum difference which has the similar meaning of two-level to the minimum difference, and ρ is the resolution coefficient which value ranges from 0 to 1 and is normally taken as 0.5.

Integrating the correlation coefficient of each point, the correlation degree between the predicted value curve $x_i(k)$ and the actual value curve $x_0(k)$ is obtained as follows:

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \varepsilon_i(k) \tag{22}$$

3.4.2. Multi-strategy combination of original data series

The multi-strategy combination means selecting original series from many different viewpoints to construct different forecasting strategies so as to solve the comprehensive impact of various certain and uncertain factors such as climate and society on load changes. Because of the impact of some certain factors in climate and society, short-term power load change generally shows a daily load rhythm and a periodic load rhythm. As shown in Fig. 3, the daily load rhythm is usually presented as a number of peaks and valleys, and the periodic load rhythm includes not only the rhythm in a period of one day (24 h) but also the rhythm in a period of one week (7 days). Thus, in order to forecast the 24-h load on the future day, we can take the load data at the same hour within the last several days before the predicted day to compose 24 original data series. We can also take the load data at the same hour on the same day within the last several weeks before the predicted day to compose 24 original data series. We can even take the load data at the same hour on the same date within the last several months before the predicted day to compose 24 original data series. As for the impact of various uncertain factors in climate and society, it can be covered and reflected by the information which is contained in the above different original data series selected from many different viewpoints of time.

3.4.3. Segmented contest on predicted day based on grey correlation

According to the above analysis of daily load rhythm, the predicted day is divided into several smooth segments in terms of the time-points of load peaks or valleys, so that the intensity of load change could be effectively relieved for each segment and the forecasting accuracy of GM(1,1) model could be improved. With the verification of practical application, this paper proposes a simple and accurate segmentation method. This method divides the daily load into four segments: first, the midnight segment from 0:00 to the first peak; second, the morning segment from the first peak to the first valley; third, the afternoon segment from the first valley to the evening peak; and finally, the evening

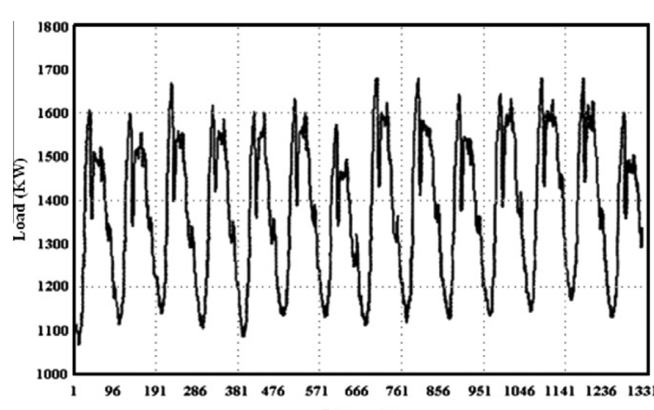

Fig. 3. Load curve of a power line within consecutive two weeks.

Table 1
Corresponding values between a and α.

a	0.001	0.01	0.1	0.2	0.3	0.5	1.0
α	0.4998	0.4992	0.4916	0.4833	0.4750	0.4585	0.4180
a	−0.001	−0.01	−0.1	−0.2	−0.3	−0.5	−1.0
α	0.5001	0.5008	0.5083	0.5166	0.5250	0.5414	0.5820

segment from the evening peak to 24:00. For each segment, the correlation coefficient of every forecasting strategy, which is designed in Section 3.4.2, is calculated according to the following equation:

$$\bar{\varepsilon}_i = \frac{\sum_{k=t_1+1}^{t_2} \varepsilon_i(k)}{t_2 - t_1}, \quad i = 1,2,3,4 \tag{23}$$

where t_1 and t_2 are the time-points of segmentation, i is the segment number of each segment. The strategy with the largest correlation coefficient is the winner of the contest for this segment and consequently it is determined as the forecasting strategy for this segment.

4. Forecasting algorithm based on HOGM

The working principle and forecasting steps of the forecasting algorithm based on HOGM are described as follows.

Step 1. Let the current predicted day (CPD) be the day before the actual predicted day. According to the design idea presented in Section 3.4.1, the following original data series are selected from different viewpoints of time:

$$\begin{cases} x_{1t}^{(0)} = \{x_{1t}^{(0)}(k)|k = 1,2,\ldots,n\} \\ x_{2t}^{(0)} = \{x_{2t}^{(0)}(k)|k = 1,2,\ldots,n\} \\ x_{3t}^{(0)} = \{x_{3t}^{(0)}(k)|k = 1,2,\ldots,n\} \end{cases} \tag{24}$$

where $x_{1t}^{(0)}$ is the original data series at the time-point of t within the last five days before the CPD, which reflects the daily load rhythm at the same time point and is called Strategy 1; $x_{2t}^{(0)}$ is the original data series at the time-point of t on the same day within the last five weeks before the CPD, which reflects the weekly load rhythm at the same time point and is called Strategy 2; $x_{3t}^{(0)}$ is the original data series at the time-point of t on the same date within the last five months before the CPD, which reflects the monthly load rhythm at the same time-point and is called Strategy3; n is the data number of the original data series at every time-point of t and $n = 5$; t is the time-point of every hour per day and $t = 0, 1, \ldots, 23$.

Step2. According to Section 3.2, abnormality analysis is performed on the original data series, and then the abnormal data including the shortage data and the mutation data are preprocessed.

Step 3. According to Section 3.3.1, GM(1,1) modeling feasibility analysis is performed on the original data series. If the original data series are unqualified for modeling, they are correspondingly transformed to the new data series $y_{1t}^{(0)}$, $y_{2t}^{(0)}$ and $y_{3t}^{(0)}$.

Step 4. According to Section 3.3.2, the GM(1,1) model of the new data series $y_{1t}^{(0)}$, $y_{2t}^{(0)}$ and $y_{3t}^{(0)}$ is constructed with $\alpha = 0.5$. Then it is determined whether α satisfies the requirement for accuracy. If it does not, interaction cycle is started until the requirement for accuracy is satisfied.

Step 5. The GM(1,1) model introduced in Section 2 is used for forecasting. For the above three strategies, the corresponding predicted values at the time-point of t on the CPD are respectively obtained as the following $\widehat{y}_{1t}^{(0)}(k+1)$, $\widehat{y}_{2t}^{(0)}(k+1)$ and $\widehat{y}_{3t}^{(0)}(k+1)$:

$$\begin{cases} \hat{y}_{1t}^{(0)}(k+1) = \hat{y}_{1t}^{(1)}(k+1) - \hat{y}_{1t}^{(1)}(k) = (e^{-\hat{a}_1} - 1)\left(y_{1t}^{(0)}(1) - \frac{\hat{b}_1}{\hat{a}_1}\right)e^{-\hat{a}_1 k} \\ \hat{y}_{2t}^{(0)}(k+1) = \hat{y}_{2t}^{(1)}(k+1) - \hat{y}_{2t}^{(1)}(k) = (e^{-\hat{a}_2} - 1)\left(y_{2t}^{(0)}(1) - \frac{\hat{b}_2}{\hat{a}_2}\right)e^{-\hat{a}_2 k} \\ \hat{y}_{3t}^{(0)}(k+1) = \hat{y}_{3t}^{(1)}(k+1) - \hat{y}_{3t}^{(1)}(k) = (e^{-\hat{a}_3} - 1)\left(y_{3t}^{(0)}(1) - \frac{\hat{b}_3}{\hat{a}_3}\right)e^{-\hat{a}_3 k} \end{cases} \tag{25}$$

Let:

$$\begin{cases} z_1(t) = \hat{y}_{1t}^{(0)}(k+1) \\ z_2(t) = \hat{y}_{2t}^{(0)}(k+1) \\ z_3(t) = \hat{y}_{3t}^{(0)}(k+1) \end{cases} \tag{26}$$

then the three predicted value curves on the CPD, which are obtained by using the above three strategies, are z_1, z_2 and z_3 as follows:

$$\begin{cases} z_1 = \{z_1(t)|t = 0,1,\ldots,23\} \\ z_2 = \{z_2(t)|t = 0,1,\ldots,23\} \\ z_3 = \{z_3(t)|t = 0,1,\ldots,23\} \end{cases} \tag{27}$$

Step 6. The same days on every week within the last month before the CPD are statistically analyzed and then the load means at every time-points of 24 h are calculated. According to the obtained load means of every hour and the segmentation method for the predicted day described in Section 3.4.2, the CPD is divided into four segments.

Step 7. The correlation coefficients between the three predicted value curves and the actual value curve of the CPD are respectively calculated. By comparing the correlation coefficients of the three strategies for each segment, the strategy with the largest correlation coefficient is determined as the forecasting strategy for this segment. Thus, the modeling process based on HOGM is completed.

Step 8. Let the CPD be the actual predicted day. According to the design idea in Section 3.4.1 and the determined forecasting strategy for the segment which each predicted time-point belongs to, the corresponding original data series is selected. Then the GM(1,1) model introduced in Section 2 is used for forecasting and the predicted load values of the 24 time-points on the actual predicted day are obtained in turn.

Step 9. The forecasting result is output.

5. Verification in an engineering project

By taking the load data from Pingnan 10 kV Line, Guifang Civic Power Supply Bureau, Southern Power Network, Guangxi Province, China, from January to June in 2009 as a sample, the HOGM proposed in this paper and general GM(1,1) model are applied respectively into the load forecasting. The forecasting strategy based on HOBM is described in detail in Section 4. The forecasting schemes based on general GM(1,1) model include three ones: first, Scheme 1 which selects the original data series at the same time-point within the last five days before the predicted day in order to reflect

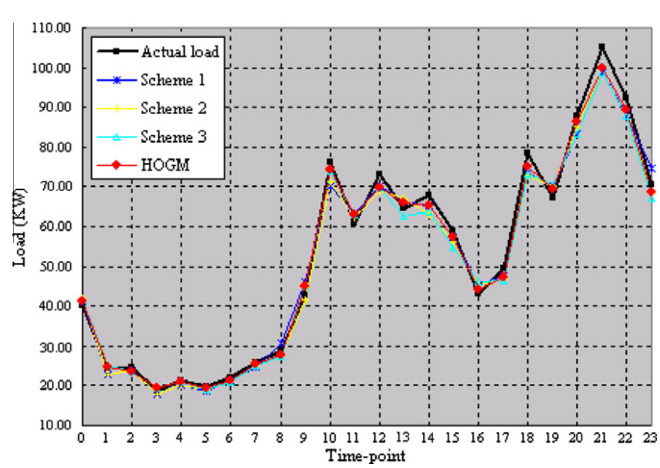

Fig. 4. Curves of forecasting results.

Table 2
Data of forecasting results.

Time-point	Actual value (KW)	General GM(1,1) model						HOGM	
		Scheme 1		Scheme 2		Scheme 3			
		Predicted value	Error (%)	Predicted value	Error (%)	Predicted value	Error (%)	Predicted value	Error (%)
00:00	40.12	41.26	2.84	42.08	4.89	41.45	3.32	41.05	2.32
01:00	24.14	22.66	6.12	22.96	4.88	25.02	3.65	24.81	2.78
02:00	24.76	23.77	4.00	23.90	3.48	23.56	4.85	23.69	4.32
03:00	18.52	17.90	3.35	17.78	3.97	19.25	3.94	19.24	3.89
04:00	21.32	20.04	6.01	20.31	4.74	20.73	2.77	21.05	1.27
05:00	19.82	18.63	5.98	18.84	4.95	19.21	3.08	19.54	1.41
06:00	22.18	21.23	4.27	21.15	4.65	21.09	4.91	21.23	4.28
07:00	25.88	24.61	4.90	24.85	3.97	25.15	2.82	25.44	1.70
08:00	28.80	30.80	6.94	27.51	4.49	27.33	5.10	27.54	4.38
09:00	42.76	46.23	8.12	41.59	2.74	44.90	5.00	44.86	4.91
10:00	76.08	70.03	7.95	71.16	6.47	73.97	2.77	74.40	2.21
11:00	60.86	63.55	4.42	62.43	2.58	62.93	3.40	62.90	3.35
12:00	73.06	70.30	3.78	69.12	5.39	69.81	4.45	69.86	4.38
13:00	64.60	66.47	2.89	67.01	3.73	62.46	3.31	65.93	2.06
14:00	67.78	65.14	3.90	63.12	6.88	63.67	6.06	65.30	3.66
15:00	58.94	57.19	2.97	56.13	4.77	54.73	7.14	57.34	2.71
16:00	43.16	45.31	4.98	45.47	5.35	46.01	6.60	44.39	2.85
17:00	49.40	47.52	3.81	46.68	5.51	46.42	6.03	47.07	4.72
18:00	78.58	73.41	6.58	72.88	7.25	73.18	6.87	74.89	4.70
19:00	67.16	70.33	4.72	70.01	4.24	70.69	5.26	69.41	3.35
20:00	87.70	83.45	4.85	85.30	2.74	83.34	4.97	86.16	1.76
21:00	105.02	98.88	5.85	99.74	5.03	98.57	6.14	99.86	4.91
22:00	92.20	88.16	4.38	89.21	3.24	87.72	4.86	89.42	3.02
23:00	70.66	74.74	5.77	68.40	3.20	67.15	4.97	68.83	2.59
Maximum forecasting error (%)		7.95		7.25		6.87		4.91	
Average forecasting error (%)		4.98		4.55		4.68		3.23	

Table 3
Calculation result of segmented correlation coefficient.

Strategy	Segment (time)			
	S1 (0:00–10:00)	S2 (11:00–16:00)	S3 (17:00–21:00)	S4 (22:00–23:00)
Strategy 1	0.6953	0.8012	0.7153	0.6598
Strategy 2	0.7529	0.7762	0.7439	0.8564
Strategy 3	0.8009	0.7062	0.6317	0.7583
Determined strategy for this segment	Strategy 3	Strategy 1	Strategy 2	Strategy 2

the predicted active power obtained from the daily load rhythm; second, Scheme 2 which selects the original data series at the same time-point on the same day within the last five weeks before the predicted day in order to reflect the predicted active power obtained from the weekly load rhythm; and finally, Scheme 3 which selects the original data series at the same time-point on the same date within the last five months before the predicted day in order to reflect the predicted active power obtained from the monthly load rhythm. The forecasting results and a comparison between the predicted values and the actual value are shown in Fig. 4 and Table 2.

Due to the different selection of the original data series, three different forecasting schemes are constructed for general GM(1,1) model and then three forecasting results are obtained. It can be seen from Fig. 4 that, when the power load steadily fluctuates in an exponential curve, each of the three forecasting schemes can make a good fit to the original data series and obtain a satisfactory forecasting result. However, with the increase of load mutation, forecasting error also increases. And the forecasting error of each of three forecasting schemes goes to the maximum at one of the load peaks. It is shown in Table 2 that the maximum forecasting error of the three forecasting schemes is 7.95%, 7.25% and 6.87%. This is the very weakness that GM(1,1) forecasting model has.

As for the forecasting strategy based on HOGM, the segmentation result along with the calculated value of the correlation coefficient for each segment are presented in Table 3. It can be seen from Fig. 4 that the forecasting error based on HOGM also goes to the maximum at one of the load peaks. Table 2 shows that the maximum forecasting error based on HOGM is 4.91%, which is significantly better than that of the three general GM(1,1) forecasting model. Owing to the decrease of forecasting errors during great load mutations, the average forecasting error based on HOGM is reduced to 3.23%, which is much lower than that of the three general GM(1,1) forecasting model. Meanwhile, it can be seen from Fig. 4 and Table 2 that, dissimilar to the general GM(1,1) model, the forecasting result of HOGM does not depend on the selection method of the original series and thus it is a stable forecasting model.

6. Conclusion

Since power load is comprehensively affected by various certain and uncertain factors in climate and society, it shows the characteristics of nonlinear fluctuation and random growth. Consequently, power load is regarded as a typical grey system. In this paper, the original series are selected from the different viewpoints of time to construct several different forecasting strategies, which aims at fully covering the impact of various certain and uncertain factors on the forecasting result, such as climatic factors including the change of temperature and humidity, and social factors including weekends and holidays. The predicted day is divided into several smooth segments according to the time-points of load peaks or valleys, which is proposed by considering the characteristic that general GM(1,1) model can give a perfect forecasting result in the smooth rise and drop phase of power load, and the drawback that the forecasting accuracy of general GM(1,1) model goes down when there is a greater load mutation. Owing to the different adaptability of different forecasting strategies to different time-segments, the contest of correlation coefficient between different forecasting strategies in each time-segment is adopted to determine the practical forecasting strategy for this segment. The essence of the ideas mentioned above is to optimize the external initial condition of the forecasting model so as to avoid the risk in which errors are introduced into the model and then gradually amplified during the forecasting process because of the improper choice of initial condition. Besides the external optimization, the proposed HOGM integrates some internal optimization algorithms, including load data preprocessing, modeling feasibility test and amendment, and parameter α correction. The application in an engineering project illustrates that, compared with the existing GM(1,1) models, HOGM has a higher forecasting accuracy and the independency on the choice of initial value. At the same time, this application also demonstrates that, compared with ANN and SVM, HOGM does not require users to have in-depth knowledge for model parameter selection. Therefore, HOGM is also a feasible forecasting model.

Power load forecasting is complex system engineering. With respect to the external optimization of the forecasting model, this paper considers the impact of various factors on the original series mainly from the time dimension and puts forward the selection of multiple original series in different time periods for the construction of forecasting model. In fact, as the further research of the external optimization on grey model, it is needed to take some special and known events such as National Day and Soccer World Cup into account so as to give more accurate forecasting result for special days with these special events. This is also one of our research focuses for the next stage. Moreover, with the applications in many provincial or civic projects and the integration of the local load characteristic, this proposed forecasting model is to be further improved.

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