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Long-term Load Forecasting in Power System: Grey System Prediction-based Models

[1]Mehdi Askari and [2]Abdolvahhab Fetanat
[1]Department of Engineering, Behbahan Higher Educational Complex, Behbahan, Iran
[2]Department of Electrical Engineering, Islamic Azad University, Behbahan Branch, Behbahan, Iran

Abstract: Long-term load forecasting is an important component for power system energy management and reliable power system operation. The Grey model GM (1, 1) based on the grey system theory has been extensively used as a powerful tool for load forecasting in recent years. In this study the accuracies of two different grey models include original GM (1, 1) and modified GM (1, 1) using Fourier series have been investigated. Also, the performance of these models with ARIMA as a conventional forecasting model has been compared. Numerical results show that the modified GM (1, 1) provides better performance in model fitting and model forecasting.

Key words: Long-term load forecasting, GM (1 ,1) model, grey prediction

INTRODUCTION

The system load is defined as the sum of all the consumers' load at the same time. Load forecasting is the problem of determining the future values of system load from the past and the current data points. Load forecasting has been essential for energy management and effective operation in power systems. Accurate load forecasting leads to important consequences such as efficient development of infrastructures, perfect electric power generation and so on (Song *et al*., 2005; Ghaderi *et al*., 2006). Power system load forecasting can be divided into three categories include long-term (with the lead time of more than one year), mid-term (with the lead time of one week to one year) and short-term (with the lead time shorter than one week) functions. In this study, long-term load forecasting method has been considered. A wide variety of load forecasting methods such as statistical models including linear regression and time series methods (Ismail *et al*., 2008; Charytoniuk *et al*., 1998; Song *et al*., 2005; Huang and Shih, 2003), artificial intelligent approaches (Ekonomou, 2010; Amjady, 2007; Hayati, 2007; Kandil *et al*., 2002; Song *et al*., 2005), data mining based model (Fan and Chen, 2006) and machine learning method (Bozic and Stojanovc, 2011; Al-Rashidi and El-Naggar, 2010) have been developed in the literatures.

In many situations such as long-term load forecasting, complexity of incomplete information has been taking placed. In other word some random factors such as time-varying parameters, social and economic factors and so on make it difficult to obtain an accurate model of system forecast. To improve the above problem and obtain high accuracy, we used Grey prediction model in this study.

Grey system theory, developed originally by (Ju-Deng, 1982). Main idea of this theory is to study uncertainly of system with small amount of data and incomplete data. It avoids the inherent defects of conventional methods such as probability theory and mainly works on poor incomplete or uncertain data to estimate the behavior of uncertain system or a time series.

In system theory, a system called a white system if its information is completely known and it called black system if its information is completely unknown. A grey system is a system with both known and unknown information.

The grey system has been successfully applied to systems analysis, prediction, data processing, modeling, decision making and control. The Grey Model (GM) based on the grey system theory is a forecasting dynamic model and has been widely used in many applications (Huang and Jane, 2009; Hsu and Chen, 2003; Kayacan *et al*., 2010; Bianco *et al*., 2010; Kung, 2005; Li and Wang, 2011). Grey prediction is able to consider as a curve fitting approach that has extremely good performance for real world data.

Corresponding Author: Mehdi Askari, Department of Engineering, Behbahan Higher Educational Complex, Behbahan, Iran

FUNDAMENTAL OF GREY THEORY

The GM (1, 1) model: The grey prediction is based on GM (n, m), where n is the order of grey difference equation and m is the number of variables. Among the family of grey prediction model, most of the pervious researchers have focused on GM (1, 1) model in their predictions. GM (1, 1) model ensure a fine agree between simplicity and accuracy of the results.

A non-negative sequence of raw data as:

$$X^{(0)}=(x^{(0)}(1),x^{(0)}(2),\ldots,x^{(0)}(n)), \qquad n\geq 4 \tag{1}$$

where, n is the sample size of data.

Accumulating Generation Operator (AGO) is used to smooth the randomness of primitive sequence. The AGO converting the original sequence into a monotonically increasing sequence. A new sequence $\mathbf{X}^{(1)}$ is generated by AGO as:

$$X^{(1)}=(x^{(1)}(1),x^{(1)}(2),\ldots,x^{(1)}(n)), \qquad n\geq 4 \tag{2}$$

Where:

$$x^{(1)}(1)=x^{(0)}(1)$$

and

$$x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i), \qquad k=1,2,3,..n \tag{3}$$

The generated mean sequence of $x^{(1)}$ is defined as:

$$Z^{(1)}=(z^{(1)}(1),z^{(1)}(2),\ldots,z^{(1)}(n)), \tag{4}$$

where, $z^{(1)}$ is the mean value of adjacent data, i.e.:

$$z^{(1)}(k)=0.5x^{(1)}(k)+0.5x^{(1)}(k\text{-}1), \qquad k=2,3,\ldots,n \tag{5}$$

The GM (1, 1) model can be constructed by establishing a first order differential equation for $x^{(1)}(k)$ as:

$$\frac{dx^{(1)}(k)}{dk}+ax^{(1)}(k)=b. \tag{6}$$

The solution, also known as time response function, of above equation is given by:

$$\hat{x}^{(1)}(k+1)=[x^{(0)}(1)\text{-}\frac{b}{a}]e^{-ak}+\frac{b}{a} \tag{7}$$

where, $x^{(1)}(k+1)$ denotes the prediction x at time point k+1 and the coefficients $[a,b]^T$ can be obtained by the Ordinary Least Squares (OLS) method:

$$[a,b]^T=(B^TB)^{-1}B^TY \tag{8}$$

In that,

$$Y=[x^{(0)}(2),x^{(0)}(3),\ldots,x^{(0)}(n)]^T, \tag{9}$$

$$B=\begin{bmatrix}-z^{(1)}(2) & 1\\ -z^{(1)}(3) & 1\\ \vdots & \vdots\\ -z^{(1)}(n) & 1\end{bmatrix} \tag{10}$$

Inverse AGO (IAGO) is used to find predicted values of primitive sequence. By using the IAGO:

$$\hat{x}^{(0)}(k+1)=[x^{(0)}(1)\text{-}\frac{b}{a}]e^{-ak}(1\text{-}e^{a}) \tag{11}$$

Therefore, the fitted and predicted sequence $\hat{x}^{(0)}$ is given as:

$$\hat{X}^{(0)}=(\hat{x}^{(0)}(1),\hat{x}^{(0)}(2),\ldots,\hat{x}^{(0)}(n),\ldots), \quad \text{and } \hat{x}^{(0)}(1)=x^{(0)}(1) \tag{12}$$

Where:

$$\hat{x}^{(0)}(1),\hat{x}^{(0)}(2),\ldots,\hat{x}^{(0)}(n)$$

are called the GM (1, 1) fitted sequence, while

$$\hat{x}^{(0)}(n+1),\hat{x}^{(0)}(n+2),\ldots,$$

are called the GM (1, 1) forecast values.

Improved grey prediction model: Residual modification model of GM (1, 1) developed as the difference between the real values $x^{(0)}(k)$ and the model predicted values, $\hat{x}^{(0)}(1)$ The residual sequence has been denoted as:

$$\varepsilon^{(0)}=(\varepsilon^{(0)}(2),\varepsilon^{(0)}(3),\ldots,\varepsilon^{(0)}(n)), \tag{13}$$

Where:

$$\varepsilon^{(0)}(k)=x^{(0)}(k)\text{-}\hat{x}^{(0)}(k), \qquad k=2,3,\ldots,n \tag{14}$$

The residual GM (1, 1) model has been developed to improve the modeling accuracy of original GM (1, 1) model. In this study the Fourier series has been used to modify the grey system.

Fourier series modification of residual model: The error residual in Eq. 14 can be expressed in Fourier series as:

$$\varepsilon^{(0)} \cong \frac{1}{2}a_0 + \sum_{i=1}^{z}[a_i \cos(\frac{2\pi i}{T}k) + b_i \sin(\frac{2\pi i}{T}k)], \quad k = 2, 3, ...n \tag{15}$$

where, T = n−1, z = (n−1/2)−1 and the result only take integer number (Guo *et al*., 2005).

Equation 15 can be rewritten as:

$$\varepsilon^{(0)} \cong PC \tag{16}$$

where, P and C matrixes are defined as:

$$P = \begin{bmatrix} \frac{1}{2} & \cos(2\frac{2\pi}{T}) & \sin(2\frac{2\pi}{T}) & \cos(2\frac{2\pi 2}{T}) & \sin(2\frac{2\pi 2}{T}) & \cdots & \cos(2\frac{2\pi z}{T}) & \sin(2\frac{2\pi z}{T}) \\ \frac{1}{2} & \cos(3\frac{2\pi}{T}) & \sin(3\frac{2\pi}{T}) & \cos(3\frac{2\pi 2}{T}) & \sin(3\frac{2\pi 2}{T}) & \cdots & \cos(2\frac{2\pi z}{T}) & \sin(2\frac{2\pi z}{T}) \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \frac{1}{2} & \cos(n\frac{2\pi}{T}) & \sin(n\frac{2\pi}{T}) & \cos(n\frac{2\pi 2}{T}) & \sin(n\frac{2\pi 2}{T}) & \cdots & \cos(2\frac{2\pi z}{T}) & \sin(2\frac{2\pi z}{T}) \end{bmatrix} \tag{17}$$

$$C = [a_0, a_1, b_1, a_2, b_2, \ldots, a_n, b_n]^T \tag{18}$$

By using ordinary least squares method, Eq. 16 can be solved and matrix C has been calculated as:

$$\hat{C} \cong (P^T P)^{-1} P^T \varepsilon^{(0)} \tag{19}$$

Therefore, the Fourier series modification can be denoted as follow:

$$\hat{x}_F^{(0)}(k) = \hat{x}^{(0)}(k) - \hat{\varepsilon}^{(0)}(k), \qquad k = 2,3,\ldots,n+1. \tag{20}$$

Error analysis and validation: Prediction accuracy is a vital criterion for evaluating forecasting authority. In this study Absolute Mean Percentage Error (AMPE) criterion has been used to estimate model performances and reliability. AMPE is a general accepted percentage measure of prediction accuracy. This indicator is calculated as:

$$AMPE = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{e(k)}{x^{(0)}(k)}\right| \times 100\% \tag{21}$$

Where:

$$e(k) = x^{(0)}(k) - \hat{x}^{(0)}(k).$$

RESULTS AND DISCUSSION

To show the efficiency of proposed method, the power consumption in Taiwan has been used according to Hsu and Chen (2003). Table 1 shows the values of Taiwan's power consumption for the duration of the years 1985 to 2000. In this study, the historical annual power demands of Taiwan from 1985 to 1998 are used for model fitting. Then, power demand of years 1999 and 2000 have been forecasted and compared with general data.

The predicted results from original GM (1, 1) model are plotted in Fig. 1. According to Fig. 1, it is obvious that GM (1, 1) model cannot exactly match the system dynamics. This problem is more observable for posterior predicted data (1999-200).

Figure 2 shows the predicted results for Fourier series modified GM (1, 1) model. It is obvious that predicted curve is following closely the actual load.

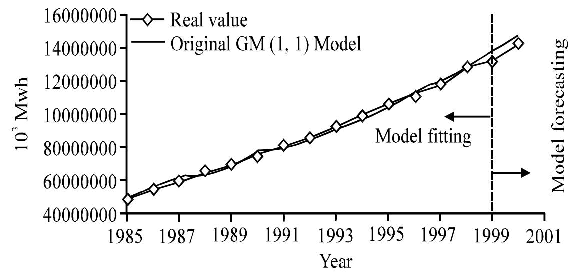

Fig. 1: Real values and original GM (1, 1) model values

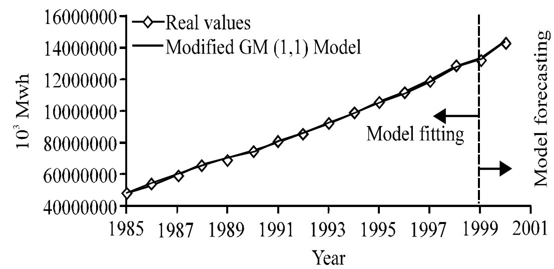

Fig. 2: Real values and modified GM (1, 1) model values

Table 1: Power consumption of Taiwan from 1985-2000

Year	Power consumption value
1985	47919102
1986	53812862
1987	59174751
1988	65227727
1989	69251809
1990	74344947
1991	80977405
1992	85290354
1993	92084684
1994	98561004
1995	105368193
1996	111139816
1997	118299046
1998	128129801
1999	131725892
2000	142412887

Table 2: The accuracy of the studied models

Model	AMPE (1986-1998)	AMPE (1999-2000)
Original GM (1,1)	1.58	3.90
Modified GM (1,1) using Fourier series	0.46	0.98
ARIMA	4.24	2.27
Modified GM (1,1) using neural network	0.57	1.29

In order to compare with proposed models, the most widely used ARIMA (1, 0, 0) model Fig. 2 shows the predicted results for Fourier series modified GM (1, 1) model. It is obvious that predicted curve is following closely the actual load.

In order to compare with proposed models, the most widely used ARIMA (1, 0, 0) model (Han, 1994), as a conventional model and a modified GM (1, 1) model using neural network (Hsu and Chen, 2003), have been used in this study. Table 2 shows the AMPE values for original GM (1, 1) model, modified GM (1, 1) model using Fourier series, modified GM (1, 1) model using neural network and ARIMA model prediction. According to this table, the Absolute Mean Percentage Error (AMPE) of modified GM (1, 1) model using Fourier series is 0.46% for fitted data and is 0.98% for predicted data. The AMPE of the original GM (1, 1) model, modified GM(1, 1) model using neural network, and ARIMA model from 1999 to 2000 are 3.9, 0.98 and 2.27%, respectively. So, modified GM (1, 1) model has better performance when compared to other models as expected. However, model fitting part (1985-1998) in all models is giving better performance than posterior forecasting part (1999-2000).

CONCLUSION

Accurate load forecasting in one of the vital factors for economic operation of power systems. In the other hand, grey prediction model is a widely used forecasting model that has been applied to many forecasting fields. In this study, the performance of the various prediction models has been compared in long-term load forecasting field. These models are Original GM (1, 1) model, modified GM (1, 1) model and conventional ARIMA method. Study results demonstrate that modified GM (1, 1) model has better performances not only on model fitting but also on model forecasting.

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