Electrical Power and Energy Systems 33 (2011) 809–816

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

A research on short term load forecasting problem applying improved grey dynamic model

Guo-Dong Li [a,*], Chen-Hong Wang [b], Shiro Masuda [a], Masatake Nagai [c]

[a] Department of System Design, Tokyo Metropolitan University, 191-0065 Hino City, Japan
[b] Department of Microbiology, Hebei North University, 075000 Zhangjiakou City, China
[c] Department of Engineering, Kanagawa University, 221-8686 Yokohama City, Japan

ARTICLE INFO

Article history:
Received 22 June 2006
Received in revised form 8 January 2007
Accepted 24 November 2010
Available online 23 February 2011

Keywords:
Short term load forecasting (STLF)
Grey dynamic model GM(2,1)
Grey number
Cubic spline function
Taylor approximation method

ABSTRACT

The grey dynamic model GM(1, 1), which is based on the grey system theory, has recently emerged as a powerful tool for short term load forecasting (STLF) problem. However, GM(1, 1) is only a first order single variable grey model, the forecasted accuracy is unsatisfactory when original data show great randomness. In this paper, we propose improved grey dynamic model GM(2, 1), a second order single variable grey model, to enhance the forecasted accuracy. Then it is applied to improve STLF performance. We provide a viewpoint that the derivative and background value of GM(2, 1) model can be expressed in grey number. Then cubic spline function is presented to calculate the derivative and background value in grey number interval. We call the proposed model as 3spGM(2, 1) model. Additionally, Taylor approximation method is applied to 3spGM(2, 1) for achieving the high forecasted accuracy. The improved version is defined as T-3spGM(2, 1). The power system load data of ordinary and special days are used to validate the proposed model. The experimental results showed that the proposed model has better performance for STLF problem.

© 2011 Published by Elsevier Ltd.

1. Introduction

The short term load forecasting (STLF) problem has been widely studied in the fields of electrical power and energy systems. The reason is that accurate forecasting can help in the real-time power generation, efficient energy management, and economic cost saving [1]. Up to present, proposed methods for STLF problem can be roughly divided into four types: time series method, regression method, expert-based method and neural network based method. However, the successes of these methods rely on a law for the distribution of original series or a large amount of observed data [2]. Therefore, they are often difficult to carry out and are not even feasible due to cost considerations [3].

We can change our attribute and look at the real world from a different angle, system dynamics can be treated from the viewpoint of the degree of information availability, we would walk out from the shadow of large sample statistics. In modern control theory, system dynamics are classified by the degree of information completeness. In 1982, Deng proposed grey system theory [4] to study the uncertainty of system. In grey system theory, according to the degree of information, if the system information is fully known, the system is called a white system, while the system information is unknown, it is called a black system. A system with partial information known and partial information unknown is grey system. It avoids the inherent defects of conventional, large sample statistical methods, and only requires a limited amount of discrete data to estimate the behavior of a system with incomplete information.

The grey model (abbreviated as GM) based on the grey system theory is a forecasting dynamic model and has been applied to many forecasting fields. The GM has three properties: first, it does not need a large amount of sample data. Second, its calculation is simple. Third, it can use random sample data. Since 1980s, the methods based on GM is getting more and more attention for its promising results in STLF. In the beginning, researchers are trying to demonstrate the feasibility of applying GM to STLF problem in power engineering. Recently, efforts are put to improve the forecasting performance of GM. A wide variety of methods to improve STLF performance have been reported as in [5–15] which include combining with ARIMA model or neural network, error compensation and data preprocessing etc. However these methods are only proposed based on GM(1, 1) which stands for the first order grey model with one variable. It has been pointed out that GM(1, 1) is unsatisfactory when original data shown great randomness [16]. Up to present, GM(2, 1), a single variable second order grey model, has been not yet applied to resolve STLF problem in power engineering. It has been indicated that GM(2, 1) model has very serious

* Corresponding author. Tel./fax: +81 42 585 8631.
E-mail address: guodong_li2006@yahoo.co.jp (G.-D. Li).

0142-0615/$ - see front matter © 2011 Published by Elsevier Ltd.
doi:10.1016/j.ijepes.2010.11.005

morbidity problem [17]. This is the reason that GM(2, 1) model has been not widely applied.

In this paper, we propose improved GM(2, 1) model to enhance the forecasted accuracy, then it is applied to perform load forecasting. We provide a viewpoint that the derivative and background value of GM(2, 1) model can be expressed in grey number. Then cubic spline function is presented to calculate the derivative and background value in grey number interval. We call the proposed model as 3spGM(2, 1) model. Additionally, Taylor approximation method is applied to 3spGM(2, 1) for achieving the high forecasted accuracy. The improved version is defined as T-3spGM(2, 1). The power system load data of ordinary and special days are used to validate the effectiveness of proposed model. The experimental results show that the proposed T-3spGM(2, 1) model has better performance for STLF problem.

This paper is organized as follows: Section 2 describes the grey system theory. Section 3 introduces proposed T-3spGM(2, 1) model. In Section 4, the case study is described. Finally, conclusions are drawn in Section 5.

2. Grey system theory

In recent years, grey system theory has become a very effective method of solving uncertainty problems under discrete data and incomplete information. The theory includes five major parts, which include grey forecasting [18], grey relation [19], grey decision [20], grey programming [21] and grey control [22]. The grey dynamic model has the advantages of establishing a model with few data and uncertain data and has become the core of grey system theory.

2.1. Grey system, grey set and grey number

According to the concept of the black box, a grey system is defined as a system containing uncertain information presented by grey numbers and grey variables [23]. Suppose A is a grey subset of universal set U. A is defined by its two membership functions $\underline{\mu}_A(x)$ and $\bar{\mu}_A(x)$, which associates with each element x [24]:

$$\begin{cases} \underline{\mu}_A(x): & U \to [0,1] \\ \bar{\mu}_A(x): & U \to [0,1] \end{cases} \tag{1}$$

where $0 \leqslant \underline{\mu}_A(x) \leqslant \bar{\mu}_A(x) \leqslant 1,\ x \in U,\ \underline{\mu}_A(x)$ and $\bar{\mu}_A(x)$ are the lower and upper membership functions in A respectively. For an arbitrary element x_0,x_0 can also be a vector. If $\underline{\mu}_A(x_0) = \bar{\mu}_A(x_0)$, then x_0 degenerates into a fuzziness element whose degree of greyness is zero. It shows that grey system theory can more flexibly deal with the fuzziness situation.

A grey number is such a number whose exact value is unknown but a rough range of the value is known. In applications, a grey number in general is an interval or a general set of numbers [25]. If the lower and upper limits of x can be estimated and x is defined as interval grey number.

$$\otimes x = x|_{\underline{\mu}}^{\bar{\mu}} = [\underline{x},\quad \bar{x}] \tag{2}$$

A grey number can be described with a white number as its "representative", where the white number is determined by using either previously known information or through some other means. Here, the whitening method for the grey number is given as

$$x = (1-\lambda)\underline{x} + \lambda\bar{x}, \quad \lambda \in [0,1] \tag{3}$$

where λ is called whitening coefficient (or weight). When $\lambda > 0.5$, the generation of x is said to have "emphasis more on new and less on old information". When $\lambda < 0.5$, the generation of x is said to have "emphasis more on old and less on new information". And when $\lambda = 0.5$, the generation of x is said to be "no preference".

2.2. Grey 1-AGO and 1-IAGO

Forecasting is to analyze the developing tendency in the future according to the past facts. Most of the forecasting methods need a large amount of history data, and use the stochastic and statistic method to analyzes the characteristics of the system [26]. Furthermore, because of additional noises from outside and the complex interrelations among the system or between it and its environment, it is more difficult to analyze the system [27]. The GM can be established on the basis of a small amount of data. The most critical feature of GM is the use of grey generating approaches to reduce the variation of the original data series by transforming the data series linearly. The most commonly applied grey generating approaches are the accumulated generating operation (AGO) and the inverse accumulated generating operation (IAGO). The AGO converts a series lacking any obvious regularity into a strictly monotonically increasing series to reduce the randomness of the series, increase the smoothness of the series, and minimize interference from the random information.

It is assumed that the uncertain behavior of system can be represented by the grey process, denoted by $x^{(0)}$. Where $x^{(0)} = \{x^{(0)}(0), x^{(0)}(1), \ldots, x^{(0)}(n)\}$ is original data series of real numbers with irregular distribution. Then 1-AGO generation series $x^{(1)}$ for $x^{(0)}$ is given by

$$x^{(1)}(j) = \sum_{i=0}^{j} x^{(0)}(i) \tag{4}$$

Then $x^{(1)} = \left\{\sum_{i=0}^{0} x^{(0)}(i), \sum_{i=0}^{1} x^{(0)}(i), \ldots, \sum_{i=0}^{n} x^{(0)}(i)\right\}$, which is the first order AGO series obtained from $x^{(0)}$.

From Eq. (4), it is obvious that the original data $x^{(0)}(i)$ can be easily recovered from $x^{(1)}(i)$ as

$$x^{(0)}(i) = x^{(1)}(i) - x^{(1)}(i-1) \tag{5}$$

where $x^{(0)}(0) = x^{(1)}(0)$. This operation is called first order IAGO (1-IAGO).

2.3. GM(1, 1) model

The grey forecasting GM(1, 1) model can be expressed by one variable, and first order differential equation as

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

where the coefficients a and b are called developing and grey input coefficient, respectively. Let sampling time $\Delta t = 1$, then by least-square method, the coefficients a and b can be obtained as

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (A^{\top}A)^{-1}A^{\top}X_n \tag{7}$$

where

$$A = \begin{bmatrix} -z^{(1)}(1) & 1 \\ -z^{(1)}(2) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{8}$$

$$X_n = \begin{bmatrix} x^{(0)}(1) \\ x^{(0)}(2) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \tag{9}$$

Download English Version:

https://daneshyari.com/en/article/400086

Download Persian Version:

https://daneshyari.com/article/400086

Daneshyari.com