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Multi-variable weakening buffer operator and its application

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ABSTRACT

To weaken the disturbances of multi-variable and reveal the real situation, it is proved that the essence of the weakening buffer operator (abbreviated as WBO) can weaken the disturbance of one variable. According to this, the multi-variable weakening buffer operator is put forward. The multi-variable weakening buffer operator can satisfy the desire to use the freshest data and its buffer effect is obvious when the sample size is small. Four real cases show that the proposed multi-variable weakening buffer operator has higher forecasting performances.

1. Introduction

Forecasting the future values of time series data plays a very important role in our research. Superior forecasting ability is an important characteristic of successful managers in complex and uncertain environments. With the rapid developments of science and technology, managers can better understand the future situation and make right strategies and plans by getting more information in advance. Thus, some forecasting methods have been developed, for example, moving average, support vector clustering, neural networks and time series [7,24]. However, these methods require a large amount of data and must meet some assumptions, and they are invalid when the observed data available is of a small sample size.

Moreover, in some cases, the time series may exhibit a jumping phenomenon due to the changing of policy. Therefore, it is difficult to fit a reasonable mathematic model. In such a case, it is most important to weaken the impact of policy. Considering the above reasons, based on the fact that the recent data could provide more information than the distant data (More recent data are typically more relevant, especially for short-term forecasts [9]), more emphasis has been placed on data which is more recent. Take the energy demand in China from 1985 to 2006 as an example. Actually, the growth rate of energy demand in China from 1985 to 2002 is tempered. From 2003 to 2006, Chinese total energy demand increased abruptly.(During this period, China has already entered into the heavy chemical industry stage, becoming one member of World Trade Organization. The rapid development of heavy and chemical industry accelerates Chinese economic growth. The growth rate of Chinese economy was above 10%. The rapid development of economy accelerates Chinese energy demand growth.) To obtain better forecasting results from 2004 to 2006, we must give more weight to the data of 2003.

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Grey weakening buffer operator is proposed to cope with the disturbance. It was first introduced in early 1990s by Liu [23]. Since then, WBO has been widely and successfully applied to various systems [5,15–17,26]. Its improved form appeared simultaneously [1,3,4,6,8,13,14,19,22,25]. However, traditional WBOs can only deal with a single variable, and little research has been conducted on multiple variables. The multi-variable weakening buffer operator model is put forward by giving more weight to newer information in this paper.

The rest of this paper is organized as follows. In Section 2, the essence of a variable WBO is introduced. In Sections 3, the multi-variable weakening buffer operator model is proposed. In Section 4, the advantages of the new model over the traditional model is clarified by four real cases. The conclusions of this work are discussed in Section 5.

2. The essence of a variable WBO

With the changes of economic development, the historical data tends to deviate from the current situations. Gray buffer operator can weaken these disturbances and reveal the real situation. Its definition is as follows.

2.1. GM(1,1) model with the WBO

Definition. [13] Given a raw data sequence $X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\},\ X^{(0)}D = \{x^{(0)}(1)d, x^{(0)}(2)d, \dots, x^{(0)}(n)d\}$, where

$$x^{(0)}(k)d = \frac{x^{(0)}(k) + x^{(0)}(k+1) + \cdots + x^{(0)}(n)}{n-k+1}, \tag{1}$$

D is a first order WBO.

The sequence $\{x^{(0)}(1)d, x^{(0)}(2)d, \dots, x^{(0)}(n)d\}$ is given by WBO of Eq. (1). A new series $X^{(1)}D = \{x^{(1)}(1)d, x^{(1)}(2)d, \dots, x^{(1)}(n)d\}$ can be generated by the first-order accumulated generating operator as $x^{(1)}(k)d = \sum_{i=1}^{k} x^{(0)}(i)d, k = 1, 2, \dots, n$. Since the original form of GM(1,1) model $x^{(0)}(k)d + az^{(1)}(k) = b$, where $z^{(1)}(k) = \frac{x^{(1)}(k)d + x^{(1)}(k-1)d}{2}, k = 2, 3, \dots, n$. [11,20]. The least squares estimate of a and b can be obtained by

$$\begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = (B^T B)^{-1} B^T Y,$$

where

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

The prediction expression of GM(1,1) model can be obtained as $\hat{x}^{(1)}(t) = [x^{(0)}(1) - \frac{\hat{b}}{\hat{a}}]e^{-\hat{a}t} + \frac{\hat{b}}{\hat{a}}$ by solving the differential $\frac{dx^{(1)}}{dt} + ax^{(1)} = b$. The prediction at $k+1$ can be obtained as $\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k)$.

2.2. The essence of WBO

A lemma is given in order to discuss the essence of WBO.

Lemma 1. [2] *Assume that $A \in C^{n \times n}$, $\delta A \in C^{n \times n}$, $b \in C^n$, $\delta b \in C^n$, vector norm $\|\cdot\|$ and matrix norm $\|\cdot\|$ are tolerant. If a matrix norm $\|\cdot\|$ followed $\|A^{-1}\|\|\delta A\| < 1$, then the solutions of linear system equations $AX = b$ and $(A + \delta A)(X + \delta x) = b + \delta b$ satisfy*

$$\frac{\|\delta x\|}{\|x\|} \le \frac{\|A\|\|A^{-1}\|}{1 - \|A\|\|A^{-1}\|\frac{\|\delta A\|}{\|A\|}} \left(\frac{\|\delta A\|}{\|A\|} + \frac{\|\delta b\|}{\|b\|} \right)$$

Theorem 1. *For the GM(1,1) model of original data $\{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\}$ based on WBO, if the rth data is disturbed, that is $\hat{x}^{(0)}(r) = x^{(0)}(r) + \epsilon_r, r = 1, 2, \dots, n$. L_r is the $\|\delta B\|_2$ resulted from this disturbance, T_r is the $\|\delta Y\|_2$ resulted from this disturbance, the relative perturbation bound of the parameter estimation is $\frac{\|B\|\|B^{-1}\|}{1 - \|B\|\|B^{-1}\|\frac{\|L_r\|}{\|B\|}}(\frac{\|L_r\|}{\|B\|} + \frac{\|T_r\|}{\|Y\|})$ by Lemma 1. Then the relative perturbation bound of the parameter estimation is larger while the more recent data is perturbed.*