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An optimized Nash nonlinear grey Bernoulli model for forecasting the main economic indices of high technology enterprises in China

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A R T I C L E I N F O

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A B S T R A C T

To accurately predict the main economic indices of high technology enterprises in China with nonlinear small sample characteristic, a new method for optimizing Nash nonlinear grey Bernoulli model (Nash NGBM(1,1)) is proposed in this study. Meanwhile, an optimized model is constructed to fully employ the predictive functions of original data information and solve optimum parameters. The process is indicated as follows: First, the merits and the disadvantages of the various approaches for ascertaining the initial conditions of the grey model are analyzed. Then, an optimized predictive function of the NGBM(1,1) is obtained by minimizing the error in the summed squares. Based on the function thus obtained, a nonlinear optimization model is developed to calculate the unknown parameters in the Nash NGBM(1,1). The results from a fluctuating sequence example and an actual case from the opto-electronics industry in Taiwan indicate that the optimized Nash NGBM(1,1) proposed in this paper gives a superior modeling performance. Finally, the main economic indices pertinent to high technology enterprises in China are forecasted using the optimized Nash NGBM(1,1) and relevant suggestions are made.

1. Introduction

The 21st century is an era characterized by global competition in high technology products and services. High technology industries are focused on technological innovation and are a crucial factor in the economic development of the region and the nation in particular. At the Chinese Science and Technology Conference in 2006, China was targeted to be an innovative nation for the future. Promoted by the conference, high technology industries have rapidly expanded and now make a major contribution to the national economy. Research by the National Statistics Bureau shows that the gross product of these high technology industries increased by 24.6% in 2010 corresponding to 7615.6 billion Yuan, which is 10.8% of the total industrial gross product.

High technology enterprises are the economic entities that make up high technology industry. They have received a great deal of attention from the Chinese Government. Forecasting the trends in the chief economic indices of these enterprises is essential for the development of projects and policy making. As Chinese high technology enterprises are neonatal, and so the data relating to existing economic indices are limited, it is difficult to apply existing statistical methods of analysis and forecasting to them. As a result, little research has been conducted on quantitative forecasting of Chinese high technology enterprises.

Grey forecasting (Deng, 2002a,b) is an effective method for modeling and forecasting small sample time series. In the early 1980s, Deng proposed the grey model GM(1,1) based on control theory, which is the core model used in the grey forecasting model. This model utilizes an operator obtained by first-order accumulation to operate on the non-negative original sequence. It demonstrates the approximate exponential growth laws and achieves short-term forecasting accuracy. The GM(1,1) has been validated and widely used in the community (Hao, Yeh, Gao, et al., 2006; Hsu, 2003, 2011; Li, Chang, Chen, & Chen, 2012; Li, Yeh, & Chang, 2009; Lu, Lewis, & Lin, 2009; Wang, 2002, etc.). The model achieved significant improvements in prediction accuracy particularly with regards the following aspects: the sequence generation (Li, Yamaguchi, & Nagai, 2005; Liu & Lin, 2006; Yeh & Lu, 1996), the background value (Lin, Chiu, Lee, et al., 2012; Tan, 2000; Wang, Dang, Liu, et al., 2007), parameter estimation (Wang & Hsu, 2008), the time response function (Dang & Liu, 2004; Liu, Liu, & Zhai, 2003; Wang, Dang, Li, et al., 2010), the differential equations (Deng, 2002a,b; Wang, Dang, & Liu, 2009; Xie & Liu, 2009; Xue & Wei, 2008), and non-equigap grey model (He & Sun, 2001; Deng 2002a,b; Li, Chang, Chen, & Chen, 2010; Li, Chang, Chen, & Chen, 2011). In addition, many hybrid models based on GM(1,1) were proposed. These include the grey econometric model (Liu & Lin, 2006), the grey Markov model (Dong, Chi, Zhang, et al., 2012; Hsu, Liu, Yeh, & Hung, 2009), and the grey fuzzy model (Lin et al., 2012), etc. However, no matter how much improvement is made to the GM(1,1), the predictive function of the grey model is

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always monotonic. As a result, GM(1,1) is not suitable for original data which contains significant fluctuations.

The recently developed nonlinear grey Bernoulli model NGBM(1,1) (Chen, 2008) is a new grey forecasting model. It has a power exponent n that can effectively manifest the nonlinear characteristics of real systems and flexibly determine the shape of the model' curve. Unlike GM(1,1) and the grey Verhulst model which rely on a constant number such as 0 or 2, the NGBM(1,1) does not require such a number. Therefore, forecasting of the fluctuation sequence can be performed by the fluctuation features as long as the power exponent and structural parameters in the model are known. The NGBM(1,1) was successfully used to simulate and forecast the values of the annual unemployment rates of ten selected countries and foreign exchange rates of Taiwan's major trading partners (Chen, 2008; Chen, Chen & Chen, 2008). This success indicates that the NGBM(1,1) significantly improves the accuracy of the simulation and forecasting predictions of the traditional GM(1,1). Zhou, Fang, Li, et al. (2009) selected the value of n by using a particle swarm optimization algorithm and used the model to forecast the power load of the Hubei electric power network. Hsu (2010) used the genetic algorithm to optimize parameters of the NGBM(1,1) and applied it to forecasting the economic trends in the integrated circuit industries in Taiwan. Chen, Hsin, and Wu (2010) proposed a Nash NGBM(1,1) in which an interpolated coefficient in the background value is introduced into the NGBM(1,1) and the parameters solved for based on the Nash equilibrium concept. This strengthens the adaptability of the model towards the original data and eventually improves the accuracy of the model. Later, Wang, Hipel, Wang, et al. (2011) proposed a nonlinear model to optimize the interpolated coefficient for the background value of the NGBM(1,1) and used the optimized model to forecast the standard reaching rate of the industrial waste water in 31 administrative areas in China. Pao, Fu, and Tseng (2012) forecasted CO_2 emissions, energy consumption, and economic growth in China based on ARIMA and NGBM(1,1). Performance evaluation results showed that the NGBM(1,1) can be used safely for future projection of these indicators in clean energy economy.

All these improvements focus on the model parameters and the background value. In fact, the initial condition is also an important factor determining the grey modeling accuracy. This is because the initial condition is a part of the predictive function. The current paper aims to develop an approach to increase the predictive precision of the Nash NGBM(1,1) by optimizing the initial condition. Subsequently, we apply the optimized model to forecasting the chief economic indices with nonlinear small sample characteristics.

The remainder of this paper is organized as follows. A brief introduction to the Nash NGBM(1,1) and the method of optimization of the initial condition are given in Section 2. Section 3 proves the advantages of using the proposed optimized Nash NGBM(1,1) put forward in this paper over existing NGBM models by considering a numerical example of fluctuating data and a real test case taken from the opto-electronics industry in Taiwan. Predictions concerning the economic indices for Chinese high technology enterprises are presented in Section 4 and, finally, the paper concludes with some comments in Section 5.

2. Methodology

2.1. A brief introduction to the Nash NGBM(1,1)

The Nash nonlinear grey Bernoulli model NGBM(1,1) is a first-order single-variable grey Bernoulli model with an interpolated coefficient in the background value (Chen et al., 2010). For predications involving nonlinear small sample time series, its performance is better than that of the traditional grey forecasting models and NGBM(1,1) itself. The procedures involved for using the Nash NGBM(1,1) can be summarized as follows.

Step1: Let an original non-negative time series be

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(m)). \tag{1}$$

In Eq. (1), $x^{(0)}(k)$ represents the behavior of the data at the time index k for $k = 1, 2, \ldots, m$.

Step 2: The 1-AGO (accumulated generating operation) series of $X^{(0)}$ can obtained by imposing the first-order accumulating generator operator to $X^{(0)}$. Let

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(m)), \tag{2}$$

where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$.

Step 3: The grey differential equation of the NGBM(1,1) is defined as

$$x^{(0)}(k) + az^{(1)}(k) = b(z^{(1)}(k))^n \quad \text{for} \quad k = 2, 3, \ldots, m, \tag{3}$$

where $x^{(0)}(k)$ is called a grey derivative, and $z^{(1)}(k) = (1 - p)x^{(1)}(k) + px^{(1)}(k - 1)$ is referred to the background value of the grey derivative. When p is equal to 0.5, the above equation is called the nonlinear grey Bernoulli model. Its abbreviation is denoted as NGBM(1,1) (Chen, 2008). When p is an indefinite value in the interval [0,1], the model is called the Nash nonlinear grey Bernoulli model. Its abbreviation is denoted as NNGBM(1,1) (Chen et al., 2010).

Step 4: The least squares estimation of a and b can be evaluated according to Eq. (3) as follows:

$$(a, b)^T = (B^T B)^{-1} B^T Y, \tag{4}$$

where

$$B = \begin{bmatrix} -z^{(1)}(2) & (z^{(1)}(2))^n \\ -z^{(1)}(3) & (z^{(1)}(3))^n \\ \vdots & \vdots \\ -z^{(1)}(m) & (z^{(1)}(m))^n \end{bmatrix} \text{ and } Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(m) \end{bmatrix}.$$

Step 5: The whitenization differential equation of the NNGBM(1,1) is a first-order differential equation. It can be established based on the monotonically increasing series $X^{(1)}$ as follows:

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b(x^{(1)}(t))^n, \tag{5}$$

where a is the development coefficient and b is the grey factor for $n \neq 1$.

Step 6: Set the initial value $\hat{x}^{(1)}(0) = x^{(0)}(1)$. Then, Eq. (5) is equivalent to

$$\hat{x}^{(1)}(k+1) = \left\{ \frac{b}{a} + \left[(x^{(0)}(1))^{1-n} - \frac{b}{a} \right] e^{-(1-n)ak} \right\}^{\frac{1}{1-n}}. \tag{6}$$

Step 7: Apply the first-order inverse accumulation operation (1-IAGO) to $\hat{x}^{(1)}(k)$ to obtain the simulation and forecasting value

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1) \quad \text{for} \quad k = 2, 3, \ldots \tag{7}$$

Step 8: Modeling error analysis: The relative percentage error (RPE) compares the real and forecast values and is used to evaluate the precision at a specific time instant k. The RPE is defined as

$$RPE(k) = \left| \frac{\hat{x}^{(0)}(k) - x^{(0)}(k)}{x^{(0)}(k)} \right| \times 100\%. \tag{8}$$

The total model precision can be evaluated by the average relative percentage error (ARPE) as follows:

$$ARPE = \frac{1}{m-1} \sum_{k=2}^{m} RPE(k). \tag{9}$$