Expert Systems with Applications 37 (2010) 4318–4323

Contents lists available at ScienceDirect

Expert Systems with Applications

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

A genetic algorithm based nonlinear grey Bernoulli model for output forecasting in integrated circuit industry

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ARTICLE INFO

Keywords:
Forecast
Integrated circuit
Genetic algorithm
Nonlinear grey Bernoulli model
GM(1,1)
Grey Verhulst model

ABSTRACT

In this article, an improved nonlinear grey Bernoulli model by using genetic algorithms to solve the optimal parameter estimation problem of small amount of data used in the forecast is proposed. The time series data of Taiwan's integrated circuit industry (1990–2007) was used as the test data set. In addition, the mean absolute percentage error and the root mean square percentage error were used to compare the performance of the forecast models. The results showed that the improved nonlinear grey Bernoulli model is more accurate and performs better than the traditional GM(1,1) model and grey Verhulst model. Moreover, the optimum mechanisms indeed improve the grey model of prediction accuracy by using genetic algorithms approach.

1. Introduction

Since high-tech industries are faced with increasing global competitiveness and developing advanced technology, the product life cycles may get shorter and the volatility may increase. Accurate forecast demand will increase the competitiveness of enterprises. However, since the product life cycle is becoming shorter and shorter, the manager may not to gather enough observations, and the product may disappear from the market before collecting enough data. If managers only use a small amount of data using traditional statistical methods to forecast demand, the forecast error may increase. Therefore, how to use less data and be able to achieve good accuracy of the forecasts is a very important objective.

All forecasting methods can be classified according to the characteristics of qualitative forecast and the quantitative forecast (Archer, 1980; Bernstein, 1984; Waddell & Sohal, 1994). At present, there are a lot of the prediction models available, in which the well-known methods include Delphi method (Bollapragada, Gupta, Hurwitz, Miles, & Tyagi, 2008; Landeta, 2006; Paul, 2008), time series methods (Taylor, 2008), exponential smoothing methods (Altay, Rudisill, & Litteral, 2008; Gardner & Diaz-Saiz, 2008), regression methods (Badran, El-Zayyat, & Halasa, 2008; Jones & Cuzan, 2008), expert systems (Petropoulos, Nikolopoulos, & Assimakopoulos, 2008), and neural networks (Gutierrez, Solis, & Mukhopadhyay, 2008). Most of the above-mentioned methods require complex calculations and a large amount of experimental data, in order to have good prediction accuracy. Therefore, these methods are not being suitable for short-term forecasting problem with a limited data available.

The grey theory was first proposed by Deng (1982), mainly for a system with incomplete or uncertain information, to construct a grey model for forecasting and decision-making. Generally, the grey model is expressed as GM(α,β), which is the αth order partial differential equation of β variables. The most simple and commonly used grey model is the GM(1,1) model that denotes a signal variable and the first-order linear model. The GM(1,1) emphasizes that only a limited amount of data is required to construct the forecast model, and can be used to forecast the other unknown output data (Huang & Huang, 1997). It has been successfully applied to various fields, such as high-tech industry output forecast (Hsu, 2003; Hsu & Wang, 2007; Lin & Yang, 2003), tourism demand forecasting (Wang, 2004; Yu & Schwartz, 2006), electricity demand forecasts (Akay & Atak, 2007), and stock market prediction (Wang, 2002). Therefore, increased attention has been given to GM(1,1) in the forecast literature recently.

However, the study of how to improve the GM(1,1) model of forecasting accuracy has developed rapidly. For example, Trivedi and Singh (2005) proposed to improve the data modeling approach to reduce the variability of the data in order to effectively reduce GM(1,1) of the forecast error. Hsu and Wang (2007) used a Bayesian regression to estimate the grey forecasting model of development coefficient and grey input, and proposed an improved GM(1,1) model. Hsu (2003) and Zhou et al. (2006) combined the Marcov–Chain, Fourier function with the traditional GM(1,1) model, and build residual modification models to improve the forecast accuracy. Wang and Hsu (2008) used genetic algorithm to improve the traditional GM(1,1) model parameters estimated to increase forecast accuracy.

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doi:10.1016/j.eswa.2009.11.068

As described above the traditional GM(1,1) model is widely used in various grey systems for prediction application. However, the solution of traditional GM(1,1) model is an exponential curve (Chang, 2005), if the data series of the system with greater fluctuant, its forecast accuracy is lower. Therefore, if the system has a data series of random fluctuations, it's not necessarily a change in the monotony of the process. If it still uses the traditional GM(1,1) model to forecast, the forecast error will definitely increase. Therefore, the nonlinear grey prediction models, such as grey Verhulst model and nonlinear grey Bernoulli model, are widely used in various fields. For example, Zhang, Liu, Zhao, Sun, and Jiang (2003) and Wang, Li, and Yu (2006) used grey Verhulst model in the middle and long term load and road traffic accidents forecasting, respectively. Chen (2008) and Chen, Chen, and Chen (2008) used nonlinear grey Bernoulli model in the unemployment rate and exchange rate forecasts, respectively.

The nonlinear grey Bernoulli model proposed to select a real number into the equation to find the estimated parameters in order to obtain the minimum prediction error (Chen, 2008; Chen et al., 2008). However, the estimated parameters of the proposed method cannot be the optimum value and the minimum prediction error. Therefore, this article by optimum theory of genetic algorithm as the optimal parameter estimation methods to improve forecasting performance of the nonlinear grey Bernoulli model, proposed by genetic algorithm base nonlinear grey Bernoulli model.

Hsu and Wang (2007) showed that Taiwan's IC industry with a short product life cycle was rapidly progressing and without much historical data on the properties, and could be a good system to be applied in the grey forecast model. In this article, the genetic algorithm based nonlinear grey Bernoulli model in a small amount of data has been verified using the data from the Taiwanese IC industry. The empirical results are compared with the grey Verhulst model and the traditional GM(1,1) model in order to find the lowest prediction error of the model, and to build a suitable model for the IC industry. By the model to get the forecast as the IC industry to develop a strategy of production, but also can aid manager in the decision making process with both target setting and portfolio decisions.

2. Methods

This article has utilized the genetic algorithm for optimization problem, and then constructed the GA based nonlinear grey Bernoulli model, as described in the following.

2.1. Genetic algorithm

Genetic algorithm (GA) is a powerful stochastic search and optimization method based on the mechanics of natural selection and natural genetics (Goldberg, 1989). It was first published by Holland (1975) and popularized by Goldberg (1989). In recent years, the GA is used in large solution sets to find the optimal solution. The GA has been widely applied to many fields, such as forecasting atmospheric corrosion of metallic materials (Fang, Wang, Qi, & Zheng, 2008), forecasting air carrier financial stress and insolvency (Gritta, Davalos, Adrangi, & Goodfriend, 2005), rainfall forecasting (Nasseri, Asghari, & Abedini, 2008), and forecasting flood disasters (Jin, Cheng, & Wei, 2008).

The main advantage of GA is that it can search the whole parameter space with the ability to skip local-optimal points. Therefore, the GA has been applied to parameter estimation problems (Aksoy, Zhang, & Nielsen-Gammon, 2006; Hashemi, Barani, & Ebrahimi, 2008; Lee, Park, & Chang, 2006). In order to solve a parameter estimation problem, genetic algorithm must have the following components: (1) a chromosomal representation of solution to the problem, (2) an initial population and the choice of population size, (3) an appropriate fitness function to guide well in the genetic search, (4) genetic operators (initialization, mutation, crossover, and comparision) for the representation, and (5) define stopping criteria. The solution provided by GA is more optimal and global in nature (Sheta, 2006).

The genetic algorithm used in this article is successfully applied to many combinatorial optimization problems (Michalewicz, 1992), and the results more robust and accurate (Sheta, 2006). Moreover, Wang and Hsu (2008) showed that genetic algorithm can improve the traditional GM(1,1) model of forecasting accuracy. Therefore, the use of genetic algorithm for nonlinear grey Bernoulli model of the optimal parameter estimation method is appropriate.

2.2. GA based nonlinear grey Bernoulli model

Liu, Dong, and Fang (2004) developed a nonlinear grey Bernoulli model (NGBM(1,1)) by combining both the traditional GM(1,1) model and the Bernoulli equation. This model still has the same advantages of a GM(1,1) model, that is, it provides a good prediction accuracy for limited number of samples. This article builds a GA based nonlinear Bernoulli model, called the GANGBM(1,1). The GANGBM(1,1) model is constructed as in the following.

Step 1: Let the original data sequence is defined as

$$x^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(k)\right). \tag{1}$$

Step 2: A new sequence $x^{(1)}$ is generated by the accumulated generating operation (AGO),

$$x^{(1)} = \left(\sum_{k=1}^{1} x^{(0)}(k), \sum_{k=1}^{2} x^{(0)}(k), \sum_{k=1}^{3} x^{(0)}(k), \ldots, \sum_{k=1}^{n} x^{(0)}(k)\right). \tag{2}$$

Step 3: The NGBM(1,1) model of the first-order differential equation (whitening equation) is established as $\frac{dx^{(1)}}{dt} + ax^{(1)} = b(x^{(1)})^{\gamma}$, where $x^{(1)}$ is the background value of $dx^{(1)}/dt$, a and b are the parameters, and γ belongs to the real number (Chen, 2008). The differential equation in a discrete system could be written as

$$\lim_{\Delta t \to 0} \frac{x^{(1)}(k) - x^{(1)}(k-1)}{\Delta t} + a\frac{x^{(1)}(k) + x^{(1)}(k-1)}{2} = b\left[\frac{x^{(1)}(k) + x^{(1)}(k-1)}{2}\right]^{\gamma}. \tag{3}$$

Let $\Delta t = 0$ and $x^{(1)}(k) - x^{(1)}(k-1) = x^{(0)}(k)$, and the difference equation will be

$$x^{(0)}(k) + az^{(1)}(k) = b\left[z^{(1)}(k)\right]^{\gamma}, \tag{4}$$

where $z^{(1)}(k) = [x^{(1)}(k) + x^{(1)}(k-1)]/2$, $k = 2, 3, 4, \ldots, n$

Step 4: The optimized solution of the parameters a and $b$can be determined by the least-square method as:

$$\hat{A} = [a, b]^T = (B^T B)^{-1} B^T Y, \tag{5}$$

where