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Time Series Grey System Prediction-based Models: Gold Price Forecasting

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ABSTRACT

The Grey Model GM (1, 1) based on the grey system theory has been extensively used as a powerful tool for data 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. So, the performance of these models has been compared with ARIMA as a conventional forecasting model. For this purpose, gold price as a high noisy data has been used. Numerical results was showed that the modified GM (1, 1) provides better performance in model fitting and model forecasting.

Key words: Grey forecasting, GM (1, 1) model, gold prediction, improved grey model, ARIMA model

INTRODUCTION

Time series prediction is the problem of determining the future values of a system from the past and current data points. Time series prediction models are broadly used in financial area, such as stock marketing, foreign currency exchange rates and so on (Mukherjee *et al.*, 2011a; Raja and Selvam, 2011; Mukherjee *et al.*, 2011b). In many situations, 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 time series systems (Ekpenyong, 2008; Lin *et al.*, 2006; Uysal, 2007). In present study a grey prediction model has been proposed to improve the above problem.

Grey system theory, developed originally by Ju-Deng (1982). Main idea of this theory is to study uncertainty 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 (Li *et al.*, 2007).

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 (Kayacan *et al.*, 2010).

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; 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.

One of most important time series is gold price. Gold is an essential traded product and forecasting its price, has theoretical and practical significance (Ismail *et al.*, 2009). The information restricted in this study is believed to be valuable for financial managers. In fact, the knowledge of oncoming gold price allows financial actors to make best decision on trading. The accurate prediction of gold price has been considered in this study. For this purpose, two GM model include ordinary GM (1, 1) model and Fourier series modified GM (1, 1) model have been presented. Also, the performance of above GM models has been compared with ARIMA as a Conventional model.

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:

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

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 $X^{(1)}$ is generated by AGO as:

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

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:

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

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

$$Z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k\text{-}1), \quad K = 2,3,..., n \tag{5}$$

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:

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

where, $\hat{x}^{(1)}(k+1)$ 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:

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

In that:

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

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

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

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

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

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

Where:

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

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

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

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, $x^{(0)}$ and the model predicted values, $\hat{x}^{(0)}(1)$. The residual sequence has been denoted as:

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

where,

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

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:

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

where, T = n-1, $z = (\frac{n-1}{2}) - 1$ and the result only take integer number (Guo *et al.*, 2005).

Eq. 15 can be rewritten as:

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

where, P and C matrixes are defined as:

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

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

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:

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

Error analysis and validation: Prediction accuracy is a vital criterion for evaluating forecasting authority. In present 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 (Ismail *et al.*, 2008). This indicator is calculated as:

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

where,

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

SIMULATION RESULTS

To show the efficiency of proposed method, Gold Prices (GP) from the London PM Fix (Noon fixing time) has been used in this study. The prediction of the gold price is a very important topic in financial area. Accurate prediction of gold price is very difficult. In fact because of the time-varying statistical properties of the gold price, mathematical modeling of its behavior is not easy. Figure 1 shows gold price between the dates 01.02.2011 and 28.04.2011. According to Fig. 1, the data are highly nonlinear, noisy and nonstationary.

In order to compare with above models, the most widely used ARIMA (1, 0, 0) model (Han, 1994) as a conventional model, has been presented in this study. Table 1 shows the AMPE values for original GM (1, 1) model (OGM), Fourier series modified GM (1, 1) model (FGM) and ARIMA model prediction. The AMPE of the OGM model, FGM model and ARIMA model for interpolation data are 0.3212, 0.1531 and 0.4380%, respectively. Also, the AMPE of the OGM model, FGM model and ARIMA model for extrapolation data are 0.5621, 0.2101 and 0.5510%, respectively. So, FGM (1, 1) model has better performance when compared to OGM model and ARIMA model as expected. Also, the performance of interpolation is giving better in compared with extrapolation.

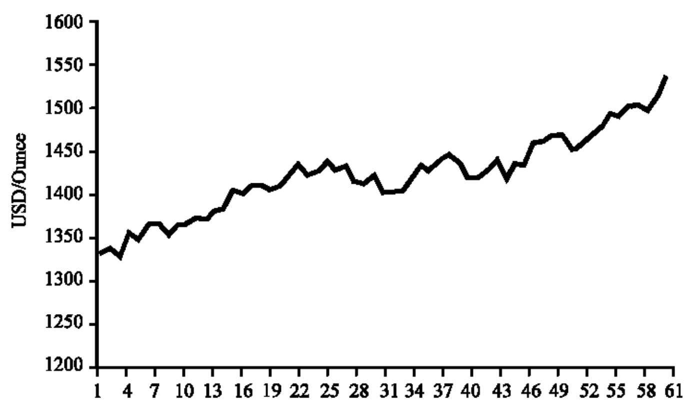

Fig. 1: Gold price chart as data set

Table 1: The accuracy of the studied models

Model	AMPE% (interpolation)	AMPE%(extrapolation)
OGM	0.3212	0.5621
FGM	0.1531	0.2101
ARIMA	0.4380	0.5510

CONCLUSION

Gold price prediction is an important factor in economic decision making. In the other hand, grey prediction model is a widely used forecasting model that has been applied to many forecasting fields. In present study the performance of the various prediction models include Original GM (1, 1) model, Fourier series modified GM (1, 1) model and conventional ARIMA method have been compared in gold prediction forecasting area. Results of the study demonstrate that modified GM(1,1) model has better performances not only on model fitting but also on model forecasting.

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