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Volatility forecasting for interbank offered rate using grey extreme learning machine: The case of China ☆

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ABSTRACT

Interbank Offered rate is the only direct market rate in China's currency market. Volatility forecasting of China Interbank Offered Rate (IBOR) has a very important theoretical and practical significance for financial asset pricing and financial risk measure or management. However, IBOR is a dynamics and non-steady time series whose developmental changes have stronger random fluctuation, so it is difficult to forecast the volatility of IBOR. This paper offers a hybrid algorithm using grey model and extreme learning machine (ELM) to forecast volatility of IBOR. The proposed algorithm is composed of three phases. In the first, grey model is used to deal with the original IBOR time series by accumulated generating operation (AGO) and weaken the stochastic volatility in original series. And then, a forecasting model is founded by using ELM to analyze the new IBOR series. Lastly, the predictive value of the original IBOR series can be obtained by inverse accumulated generating operation (IAGO). The new model is applied to forecasting Interbank Offered Rate of China. Compared with the forecasting results of BP and classical ELM, the new model is more efficient to forecasting short- and middle-term volatility of IBOR.

1. Introduction

The financial market is a very complex nonlinear dynamics system [1]. In recent years, with China's market-oriented interest rate continuing to accelerate the process, tools of the interest rate of China's macro-control were increasingly used. The interest rate risks of the commercial banks were more apparent. Interbank market as banks and other financial institutions for temporary, short-term lending market funds, is an important part of money market. The scale of their transactions of interbank market is increasing. With more and more frequent changes in interbank offered rate, for the commercial banks, the major players of the interbank market, the volatility risk cannot be underestimated. Therefore, accurate forecast trends interbank offered rate for commercial bank lending to guard against interest rate risk is significant.

The forecast of volatility has a very important theory and real meaning for the pricing of financial asset and the measure or the management of financial risk. At present, the method of volatility forecast can be divided into two classes, which are statistical method and artificial intelligence method. The statistical method is a parameter method. It is built by the method of deductive reasoning based on mathematical theory. The related form of the parameter is known by training samples and estimating the value of parameter. The common statistical methods have moving average, exponential smoothness and conditional heteroscedastic ARCH/GARCH class model method. In addition, it also has extensional stochastic volatility model (such as SV/LMSV),

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multivariant GARCH model method, autoregressive fractional integrated moving average model (ARIMA/ARFIMA) and so on. The artificial intelligence methods mainly include artificial neural network (ANN) and support vector machine (SVM) and so on.

Extreme learning machines (ELM) is provided by Dr. Huang and Zhu [2–4]. It is a single-hidden layer feedforward neural network (SLFN) and aims to break the barriers between the conventional artificial learning techniques and biological learning mechanism. The essence of ELM is that the hidden neurons of SLFN need not be iteratively tuned. It can generate connection weights between input layer and hidden layer and threshold of hidden layer neurons. Compared with those traditional computational intelligence algorithms, ELM provides better generalization performance at a much faster learning speed and with least human intervenes. ELM has good potential as a viable alternative technique for large-scale computing and artificial intelligence.

The grey model theory, proposed by Deng, is a method of dealing with uncertain and insufficient problems [5]. The grey forecasting model is often used to forecast the developing trend of system characteristic variables. Recently, grey prediction promotes grey theory progress in both theoretical breakthrough and real applications. The original idea of grey forecasting models, such as the one order and single variable grey forecasting model (GM(1, 1)), is to improve the simulating and forecasting accuracy, especially when sequence data are limited and statistical methods could not be constructed easily. Whether independent variables are added into the model or not, grey forecasting models are divided into single-variable grey forecasting models and multi-variable grey forecasting models. The GM(1, 1) model is a typical single-variable grey forecasting model, which is a useful forecasting approach for sequence data with equigap features [6].

The structure of this paper is as following: Section 2 firstly introduces related algorithms, such as ELM and grey model, and then presents the novel models, GrELM. Section 3 give results of different models in real dataset of Interbank Offered Rate of China. Finally, conclusions are presented in Section 4.

2. Methods and materials

2.1. Methods

2.1.1. Extreme learning machines

Extreme learning machines(ELM) is a new neural network algorithm. It was firstly proposed by Huang in 2004. Compared with SVM and the traditional neural network, ELM has fast learning speed and requires less artificial intervening. Generalization ability of ELM is very strong for heterogeneous data sets [7–9].

From the perspective of the structure of neural network, ELM is a simple SLFN (single hidden layer feedforward neural network). SLFN schematic diagram is given in Fig. 1.

The SLFN only includes three layers, input layer, hidden layer and output layer. Input layer has d-dimensional vector. Hidden layer comprises L hidden neurons. Generally L is much less than the number of samples N. Output layer outputs m-dimensional vector.

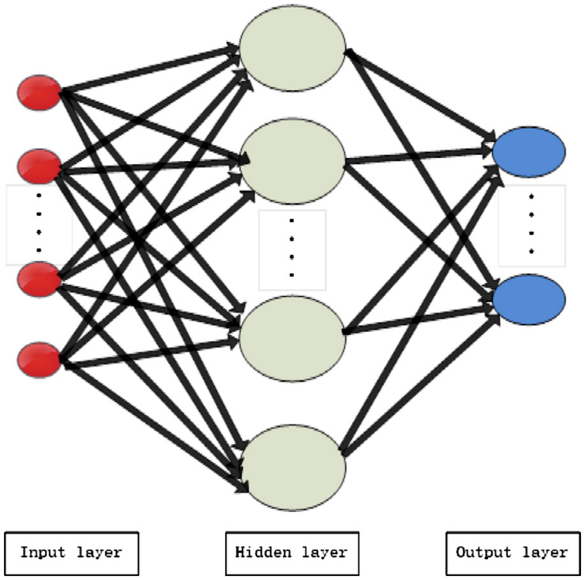

Fig. 1. Single-hidden layer feedforward network.

ELM is a single hidden-layer feedforward neural networks (SLFN). For N different samples $(x_i,\ t_i)$, 2, $t_i = (t_{i1}, t_{i2}, \ldots, t_{im})^T \in R^m$, the number of hidden layer nodes is M. The mathematical model $g(x)$'s SLFN's activation function is as follows [10]:

$$\sum_{i=1}^{M} \beta_i g(x_j) = \sum_{i=1}^{M} \beta_i g(a_i \cdot x_j + b_j) = t_j (j = 1, 2, \ldots, N) \tag{1}$$

Among them, a_i connects the ith input nodes in the hidden layer weights, which are $a_i = (a_{i1}, a_{i2}, \ldots, a_{in})^T$. b_i connects the ith deviation from the hidden layer nodes. β_i connects the ith output nodes in the hidden layer weights, which are $\beta_i = (\beta_{i1}, \beta_{i2}, \ldots, \beta_{im})^T$. The activation function $g(x)$ can be "sigmoid" or "sine" function and so on. The above N matrix's equations can be written as:

$$H\beta = T \quad H(a_1, \ldots, a_M, b_i, \ldots, b_M, x_1, \ldots, x_N) = \begin{bmatrix} g(a_1 \cdot x_1 + b_1 \cdots g(a_M \cdot x_1 + b_M)) \\ \vdots \\ g(a_1 \cdot x_N + b_1 \cdots g(a_M \cdot x_N + b_M)) \end{bmatrix}_{N\times M}$$
$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_M^T \end{bmatrix}_{M\times N} \quad T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{N\times M} \tag{2}$$

Set $E(W)$ represents the error sum of squares between the expected and actual values. The problem can be transformed into solving the optimal weights $W = (a, b, \beta)$, which minimizes the $E(W)$. Mathematical expressions can be written as:

$$\begin{cases} \arg\min E(W) = \arg\min \|\varepsilon\|^2 \\ \text{s.t.} \sum_{i=1}^{M} \beta_i g(a_i \cdot x_j + b_i - y_j = \varepsilon_j \\ (j = 1, 2, \ldots, N) \end{cases} \tag{3}$$

$\varepsilon_j = [\varepsilon_{j1}, \varepsilon_{j2}, \ldots, \varepsilon_{jm}]$ is the jth sample error.