A Wavelet Neural Network Model for Forecasting Exchange Rate Integrated with Genetic Algorithm

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Summary
Floating rate system has come into force in china, which will make exchange rate more fluctuant. As a result, participants within the insurance industry have frequently found themselves facing increased variable exchange rate negatively and dangerously affected the insurance industry and need to be pro-active instead of reactive to exchange risk. In this paper, a hybrid model is described, which integrates the Wavelet Neural Network with Genetic Algorithm and can predict Exchange Rate. Then the theory framework and algorithms are discussed. An empirical example is described. It shows that the proposed model can predict Exchange Rate with the scale of one day, one week and other intervals and the precision of prediction is not the decline trend when the forecasting scale is extended.

Key words:
Forecasting, Exchange rate, Wavelet neural network, Genetic algorithm.

Introduction

How to manage exchange risk is an austere issue for insurance industry. More and More companies have recognized it and have utilized many instruments, such as Hedging, BSI(Borrow-Spot-Invest), LSI(Lead-Spot-Invest) and so on, but every instrument relies on catching the fluctuant trends of future exchange rate. So Exchange rate forecasting is expected and there is a growing perception that financial economists' research on the models and systems of exchange rate forecasting (Bill Francis, 2001; Claudia Lawrenz, 2000; Wolfgang Polasek, 1999; Jerry Coakley, 2001; liuxiaobin, 2002;), above models and research prove that non-linear method based on time series analysis is a better and simple selection for forecasting exchange rate. But how to catch the short-term and long-term trends of future exchange rate without precision declining needs to be further discussed.

In this paper we describe a hybrid predication model based on time series analysis for Exchange Rate, which had Integrated Wavelet Neural Network Model with Genetic Algorithm. This paper is organized as follows. In section 1 describes the theory framework of the hybrid model. Section 2 emphasizes the adopted algorithms. Section 3 gives an empirical model of Exchange rate EUR and JPY. Then the last Section discusses and draws some conclusions.

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2. Framework of the Model

It is based on the theory of time series analysis to forecasting exchange rate. Figure 1 shows the theory framework (Li Guoqing, 1995).

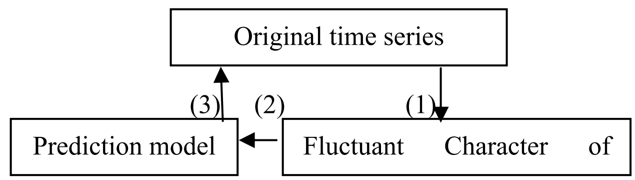

Fig.1. The framework of prediction theory

(1) Research the fluctuant character of series;
(2) Build model;
(3) Check up the model, iterate step (2) if the precision is not acceptant;

2.1 Fluctuant character of time series

Forecasting model relies on the fluctuant character of time series, this paper analyzes the fluctuant curve of different scales of time series to find the whole fluctuant rule. Research proves that exchange rate has the characteristic of multi-fractal. Figure 2 shows the result of the exchange rate EUR for example (others are omitted).

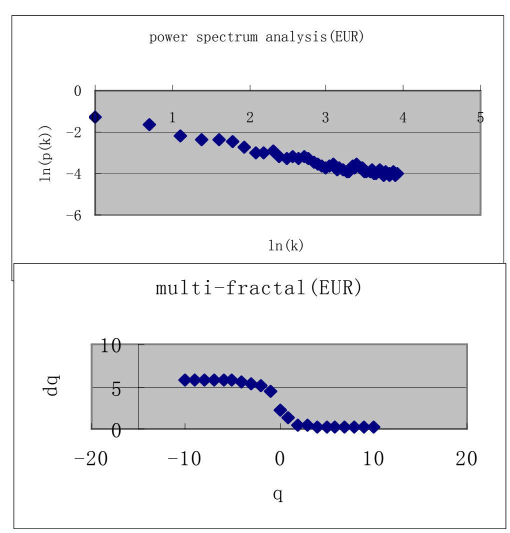

Fig. 2 Fluctuant character analysis

Above multi-fractal character shows that the main reason of exchange rate fluctuation is fluctuation of multi-gene, also called local fractional dimension. If the fluctuation rule of multi-gene can been distinguished and analyzed, we can simulate the exchange rate fluctuation regulation and r forecast the exchange rate trend (Peters E, 1994; Shu Jianping, 2003).

2.2 Architecture of the hybrid model

2.2.1 Wavelet Analysis

Due that the wavelet transform can analyze signal in different scales and extract local time-frequency character, we have distilled local fractional dimension of exchange rate fluctuation via wavelet analysis.

2.2.2 Neural network

As for the non-linear relation between local fractional dimension (wavelet analysis coefficient) and exchange rate future data, we obtained it via neural network. So a wavelet neural network is constructed.

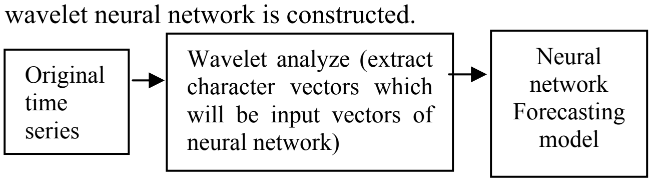

Fig.3. Wavelet neural network structure

For coupling of wavelet analysis and neural network, there are two main methods (Hiroaki Katsuragi, 2000):

- Using time as benchmark. Using wavelet analysis coefficients of different scales in same time as input character vectors of neural network to predict future data.
- Using scale as benchmark. Using wavelet analysis coefficients of different time in same scale as input character vectors of neural network to predict future data.

Exchange rate has been proved to present multi-fractal, it means any above method could not reflects and grasps data fluctuation character accurately, so this paper integrates above two methods, input character vectors of neural network comprise not only wavelet analysis coefficients of different scales in same time but also wavelet analysis coefficients of different time in same scale.

2.2.3 Genetic Algorithm

It basically uses experience to confirm structure of neural network (Liu jin, 1994). When design a neural network, generally confirm its structure in advance or by the means of increase by degrees or degression. Increase by degrees becomes from a simple network, and make it complex gradually according to needs of problem until discover the best structure. Degression is reverse which start with a complex network, and make it simple gradually until find the best structure. The two methods are also difficult to confirm the best structure. In order to solve the above limitation, we adopted genetic algorithm to help search the best length of Wavelet analysis coefficients and parameters of neural network.

2.2.4 Architecture framework

Based on above theory, the working flow is as follows:

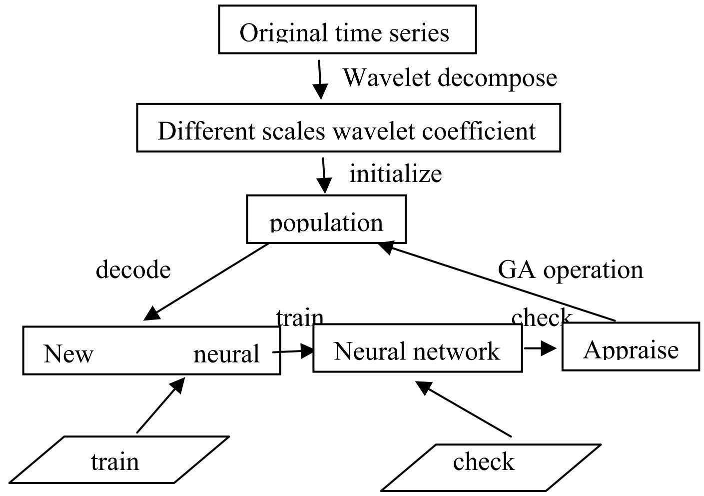

Fig.4. Working flow

3. Algorithm of the Model

In the methods of Wavelet transformation, this paper selects Wavelet quick analysis measure, which is simple and prompt without special Wavelet function involved. During this measure, there are two common methods, the Mallat algorithm and A Trous algorithm.

The Mallat algorithm requires double extraction, which makes the length of the analysis coefficients to be half. As the analysis scales increasing, the sub-wave function must be sampled by increasing dots (Yucheng Zhang, 1995). Thus the Wavelet coefficients are gradually decreased and the amount of calculation is greatly increased. As to the Wavelet coefficients with variable length, it makes trouble for the input of the ANN (Artificial Neural Network). So the method of Mallat is not available for the requirements in this paper.

Therefore the method of A Trous is introduced, which cancels the double extraction in the algorithm of Mallat . The formula for the analysis sequence in detail is as follows:

$$C_i(t) = \sum_l h(l) C_{i-1}(t + 2^i l) \tag{1}$$

$$d_i(t) = C_{i-1}(t) - C_i(t) \tag{2}$$

Where, $h(l)$ is discrete lowpass. Suppose the original time series data as $C(t)$ and $C_0(t) = C(t)$, then define the set $W = \{d_1(t), d_2(t), \cdots, d_p(t), C_p(t)\}$ as the Wavelet transformation under the scale of p. The reconstruction formula of the original time series data is as follows:

$$C(t) = C_p(t) + \sum_{i=1}^{p} d_i(t) \tag{3}$$

A Trous algorithm is quick and simple, and its key is to determine the lowpass $h(l)$. In this paper, $h_3(\frac{1}{16}, \frac{1}{4}, \frac{3}{8}, \frac{1}{4}, \frac{1}{16})$ is adopted.

It can be seen from formula 4 that the problem of boundary prediction arises when the signal $C_i(t)$ of low frequency is calculated.

The problem of boundary prediction is that given a limited time series $x(t), t \le T$, according to Formula $C_i(t) = \sum_l h(l) C_{i-1}(t + 2^i l)$. When the Wavelet coefficient $C_i(\tau)$ is calculated at the time of τ, the data at the time of $\tau + 2^i l$ are required. And when the time of τ is exactly at the boundary or close to the boundary, the calculation of $C_i(\tau)$ will use the data outside the boundary, that is, $x(t)$ with $t \succ T$. As for the Wavelet analysis which takes aim at the prediction, the $x(t)$ with $t \succ T$ is an unknown value to be predicted.

To reduce the effect of the boundary, the measure of Enantiomorphous Delay Development is used, which is the most common in the field of signal processing. That means we suppose $x(N+t) = x(N-t), t = 1, 2, \cdots, N$, and N is the length of the sequence. This method has been adopted by Aussum Alex (Aussum, 1997) to analyze the effect of the prediction and validate its feasibility. Thereby it is also adopted in this thesis.

4. Empirical model and result analysis

This paper showed the checking result of the exchange rate EUR (others are omitted). All data used in this paper is derived from the web of the People's Bank of China, www.pbc.gov.cn. The data were collected day-by-day from 2003 to 2006 except weekend. The former 3-year-data was used to train the prediction model and rear year data was used to validate the model.

4.1 Wavelet Analysis

A Trous algorithm is taken to decompose the original time serial data in five scales and the wavelet coefficients are showed in Figure 5,

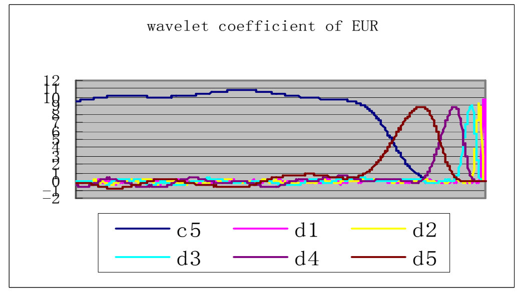

Fig.5 A Trous wavelet analysis coefficients

Where, d_1, d_2, d_3, d_4, d_5 are high frequency signals (detail signals) in different scales, and c_5 is low frequency (background signals) in the fifth scale. According to formulation (6), original signals is composed by d_1, d_2, d_3, d_4, d_5 and c_5.

4.2 Parameter of ANN model

Instructed as figure 4, initialized a random population, and then ANN is trained via samples to confirm structure of ANN, results are showed in table 1 (Hidden_num is the number of hidden layers)

Table 1. Parameters of ANN

For EUR	Delay of each scale						Hidden_ num
	d1	d2	d3	d4	d5	c5	
1 day	9	6	8	8	5	4	30
7 days	10	8	7	7	5	5	27
30 days	10	8	8	8	6	4	28

4.3 Prediction

Table 2 shows precision of 1 day、7 days、30 days prediction models.

Table 2. Forecasting error

For EUR	1 day	7 days	30 days
Training error	6. 2%	7%	6. 1%
Testing error	10. 2	9. 8%	9. 5%

The Conclusion

Table 2 shows that the proposed model can predict not only the short-term but also long-term exchange rate with the scale of one day, one week and thirty days, Compared with other time series models, such as AR, MA, or ARMA, the precision of prediction is not the decline trend when the forecasting scale is extended.

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