A Novel Combination Forecast Method on Non-Stationary Time Series and its Application to Exchange Rate Forecasting

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***Abstract* — Currency exchange rate is affected by many factors, which are often uncertain, thus exchange rate time series is a typical non-stationary time series. However, only stationary series forecasting methods are used on the research of exchange rate forecasting. Based on the non-stationarity that exchange rate possesses, a novel combinational forecasting model suitable for non-stationary time series is proposed in this paper. First, we adopt the NARX neural network as the original forecasting model. And then, we operate a novel prediction model combining empirical mode decomposition (EMD) with NARX neural network to improve the forecast precision. Finally, we proposed a combination model according to NARX model and EMD-NARX model and use two examples to demonstrate the prediction effect. To study the difference of prediction results in different time intervals, we use the 5 min exchange rates and daily exchange rates of US dollar against Japanese yen. The forecasting results indicate that the precision is likely to be higher when the time interval is shorter. Moreover, by forecasting the exchange rate of RMB before and after the exchange rate reform, we find that the exchange rate reform barely affects EMD-NARX model, showing the relatively high stability of the model.**

Keywords - Non-stationary time series, NARX neural network, empirical mode decomposition, exchange rate forecasting

I. INTRODUCTION

Today, in a highly global economy, exchange rate is playing an increasingly important role in the international market, especially in the terms of international trade and currency circulation. Therefore, grasping the changing rule and trend of exchange rate is extremely important. This paper aims to seek for a new and direct exchange rate forecasting method with a higher precision that helps to avoid the risks caused by the change of exchange rate. Some mainly adopted methods currently for exchange rate forecast include support vector machine (SVM) [1-3], BP artificial neural network [4-8], time series prediction model(e.g. ARIMA) [9,10], wavelet analysis[11] and so on. Moreover, Xie and Ouyang suggested that the combination model of neural networks has a higher forecasting precision [12]. Tseng's team (2002) combined the BP neural network with time series model-SARMIA (Seasonal Auto-regression Moving Integrate Average) model. They used the SARMIA model to do the linear prediction on exchange rate and adopted the neural networks to deal with the residuals of the SARMIA model forecasting [13]. Sharing the similar ideas, Zhang (2003) advocated the combination model of the ARMIA (Autoregressive Integrated Moving Average) model and ANN (Artificial Neural Networks) in the prediction of exchange rate between USD and GBP [14]. Yu, Wang and Lai (2000) utilized the Generalized Linear Regression Model and neural network to forecast foreign exchange rates [15]. The mean absolute percentage error of currently used prediction methods is approximately between 0.1% and 10%. As the exchange rate time series is usually non-stationary and nonlinear, the model with nonstationarity and nonlinear property should be more effective in forecasting. However, current research focuses on stationary series forecasting methods. Based on this and inspired by the combination prediction model, we creatively propose a combination model with high precision for the change in exchange rate based on NARX neural network [16-20] and EMD [21-25].

II. THEORETICAL MODEL

A. *Model Steps*

Because of the non-stationarity of the exchange rate time series, the NARX neural network model, which is perfectly suitable for the nonlinear system forecasting, is introduced in the research. And then a combination model is proposed based on Empirical Mode Decomposition (EMD). First of all, we apply the NARX neural network to the prediction of the exchange rate time series. To prove the applicability of the model, the error of the forecasting result would be analyzed. After that, the EMD model is applied to discompose the exchange rate time series into several stationary time series in different frequency band. Taking good use of the nonlinear forecasting ability of NARX neural network, we operate the prediction for each stationary time series. These forecasting results are summed up in equal weight to get the final forecasting value.

Specific modelling process is illustrated in Fig.1.

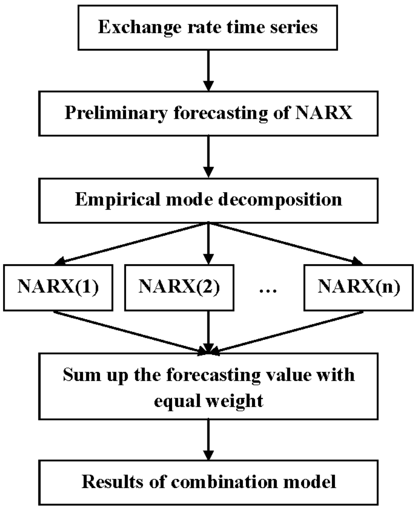

Fig. 1 Model steps.

B. NARX Neural Network

In general, the performance of NARX neural network is above the completely connected recursive neural network and can mutual exchange with the latter. In the application of nonlinear dynamic system, NARX neural network has become the most widely used neural network. A typical NARX neural network is mainly composed by input layer, hidden layer, output layer and the delay of input and output. Normally, the delay order of input and output and the number of neurons in the hidden layer have to be determined before application.

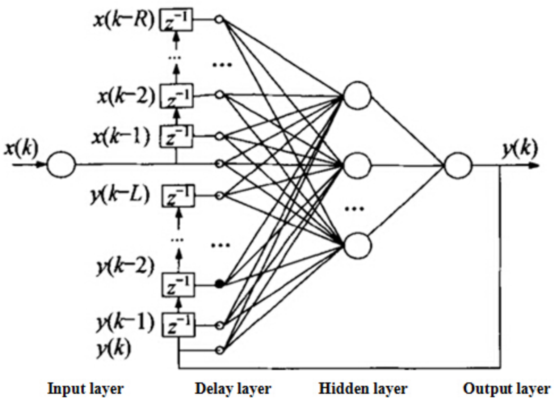

Fig.2 Structure of NARX neural network.

Inspired by the model in the reference[18], in the Fig.2, *x(t)* refers to external input of neural network, i.e. exchange rate; *m* refers to the delay order of external input; *n* is the delay order of output; *s* represents the number of neurons in the hidden layer. Therefore, the j-th unit in the hidden layer can be described as follows:

$$H_j = \tanh\left(\sum_{i=0}^{m} w_{ji}x(t-i) + \sum_{l=1}^{n} w_{jl}y(t-l) + b_j\right)$$

(1)

In formula (1), W_{ji} is the connected weight between i-th and j-th neurons in the hidden layer, b_j is the offset value of j-th neurons in the hidden layer, and the value of network output is *y(t+1)* as follows:

$$y(t+1) = f\begin{bmatrix} y(t), y(t-1), \cdots, y(t-n), \\ x(t), x(t-1), \cdots, x(t-m+1); W \end{bmatrix}$$

(2)

C. Principle of empirical mode decomposition (EMD)

The method of EMD is to decompose the signal into several intrinsic mode functions (IMF) and stable trend terms. Each intrinsic mode function is narrow-band signal, which indicates that the IMF should satisfy the following conditions: firstly, the difference of the number between extreme point and zero-crossing point should be no more than one; Secondly, in any time, the average of the upper enveloping curve defined by the maximal points and the lower enveloping curve defined by minimal points should remain zero, suggesting that the upper and lower enveloping curve of the signal should be symmetric along the time axis. The specific steps are as follows [21]:

Step1. Find out all the maximal points of the original signal $s(t)$ and introduce the cubic spline function to fit the upper enveloping curve of the original signal, and then similarly locate all the minimal points of the signal and fit the lower enveloping curve.

Step2. Calculate the average value of upper and lower enveloping curves denoted as $m_1(t)$,and the first IMF component of the original signal is acquired:

$$h_1(t) = s(t) - m_1(t)$$

(3)

Step3. $h_1(t)$ is theoretically an IMF but generally it cannot satisfy the conditions of IMF component. Therefore, the process mentioned above should be repeated for k times until $h_1(t)$ satisfy the conditions and the average results tend to be zero, and by which can we acquire the first IMF component $c_1(t)$ referring to the component with the highest frequency of the signal $s(t)$.

$$h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t)$$

(4)

$$c_1(t) = h_{1k}(t)$$

(5)

Step4. Separate $c_1(t)$ from $s(t)$ and then obtain a difference signal $r_1(t)$ without high frequency component:

$$r_1(t) = s(t) - c_1(t) \tag{6}$$

Now utilize $r_1(t)$ as the original signal and repeat the first three steps to get the second IMF component $c_2(t)$ for n times and then n IMF components will be gained:

$$r_1(t) - c_2(t) = r_2(t) \tag{7}$$

$$r_{n-1}(t) - c_n(t) = r_n(t) \tag{8}$$

$r_n(t)$ is a residual function representing the average trend of the signal. Moreover, each IMF component includes constituents with different characteristic time scale of the signal and the scale ranks in ascending orders. Thus, each component contains constituents of different frequency from up to low.

III. APPLICATION TO EXCHANGE RATE FORECASTING

A. Data Procurement

We select a series of exchange rate data from August 27th, 2013 to May 23th, 2014 recorded in the NFL Meta-Trader system. The sample contains more than 20000 data. By comparing the forecasting results of the exchange rate data in time intervals of 5 minutes and 1 day, we get the effects of different time intervals on the NARX neural network and EMD-NARX model.

B. Prediction of NARX Neural Network

In order to compare the forecasting effects under different time intervals, the node number in hidden layer as well as the lag phase number is set as 10. Moreover, the initial data in the time intervals of 5 minutes and 1 day are selected to operate the exchange rate forecasting respectively. In addition, the first 70% of the data is the training set while the rest is the test set. The prediction results are shown below:

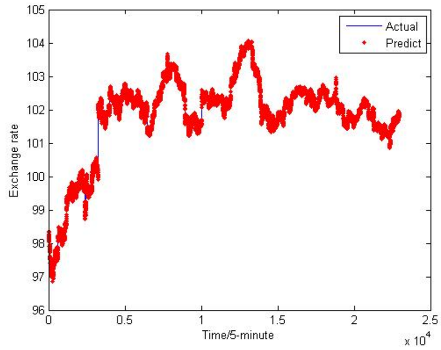

Fig.3 Prediction of 5 minutes data using NARX model.

Fig.3 shows the forecasting effect of NARX neural network, using the data in 5 minutes time interval. The coefficient of determination R^2 is 0.9974 and the mean square error（MSE）is about 0.000738. Likewise, Fig.4 illustrates the prediction result of NARX neural network with daily data. The coefficient of determination R^2 is 0.9769 and the mean square error is 0.0059. From the experiment results, a conclusion can be drawn that NARX neural network performs well in forecasting the exchange rate, owing good prediction and generality ability and high precision. But compared to the model of daily data, the model using 5 minutes time interval data performs relatively better.

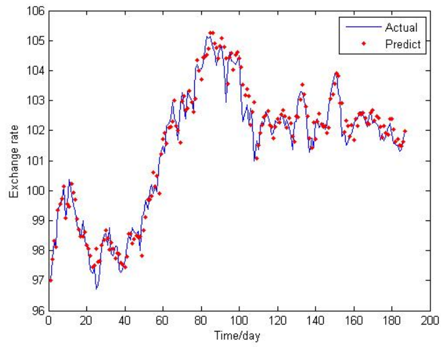

Fig.4 Prediction of daily data using NARX model.

C. Combination Model Forecasting

Stp1. The EMD of exchange rate time series.

According to EMD decomposition algorithm, we used software MATLAB (2011 version) to decompose 5 minutes and one-day time interval exchange rate signal respectively. The original signal is decomposed into several IMF components and the data of each IMF component are recorded for the next step to operate the exchange rate forecasting.

Step2. Forecasting model of EMD & NARX neural network.

Owing to the great non-stability of exchange rate time series, some errors still exist, even when the NARX neural network model is used to forecast. To improve the precision of the model, EMD model is applied to weaken the nonstationarity of time series. And then NARX neural network is used to predict each frequency band. Finally, the forecasting results of each component are summed up in equal weight and the mean square error is calculated.

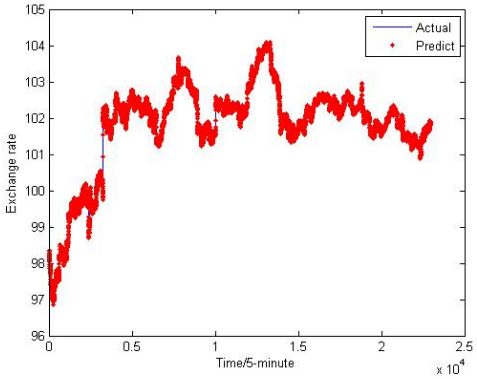

Fig.5 Prediction of 5 minutes data using EMD & NARX model.

Likewise, the experiments of USD-JPY exchange rate are performed in the time intervals of 5 -minute and 1 day respectively to figure out the effects of time intervals on the forecasting result. In NARX model, the node number in hidden layer as well as the lag phase number is 10. The first 70% of the data used is the training set while the rest is the test set. The results are showing in Fig.5 and Fig.6.

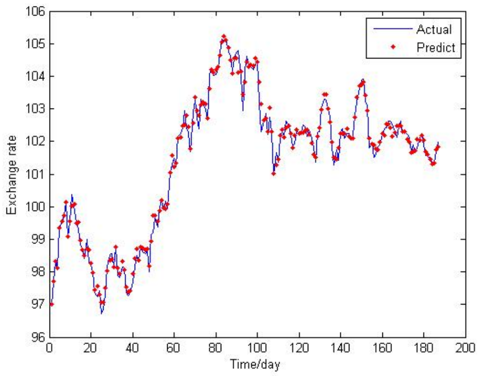

Fig.6 Prediction of daily data using EMD & NARX model.

Step3. Combination model forecasting.

Let the forecasting results of NARX neural network and EMD neural network be variable X_1 and X_2, and the practical data be dependent variable *Y*. And then we set up a linear regression model to obtain the final prediction results.

D. Error Analysis

It is of great importance to choose error indexes scientifically when evaluating the effect of forecast result. The coefficient of determination R^2 and mean square error are chosen as the error indexes to indicate the functions of the models. The specific mathematical formulas are expressed as (9) and (10):

Forecasting Model	R2	MSE
NARX(5 minutes)	0.9974	7.38E-04
EMD-NARX(5 minutes)	**0.9998**	**3.12956E-05**
SVM(5 minutes)	0.9964	9.8654E-04
Wavelet neural network(5 minutes)	0.9986	1.3584E-04
ARIMA(5 minutes)	0.8430	0.0105
NARX(days)	0.9769	5.9E-03
EMD-NARX(days)	**0.9988**	**3.7210E-04**
SVM(days)	0.9837	4.9038E-04
Wavelet neural network(days)	0.9743	9.3720E-04
ARIMA(days)	0.6928	0.0517

$$R^2 = \left[\frac{\sum (x-\bar{x})(y-\bar{y})}{\sqrt{\sum (x-\bar{x})^2 \sum (y-\bar{y})^2}} \right]^2 \tag{9}$$

In the formula: x --initial data, $\bar{x}$ --average of initial data, y --prediction value, $\bar{y}$ --average of prediction value.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}[x(k) - p(k)]^2 \tag{10}$$

In the formula: $x(k)$ --initial data, $p(k)$ --forecasting result, N --sample number of prediction value.

After collecting the forecasting results from NARX neural network model, EMD-NARX model and common algorithms (SVM [3], Wavelet neural network [11], ARIMA [10]) in other references, the error analysis is processed. In each model, the first 70% of the data is training set and the rest is test set. The result of error analysis is showed in the Table **1**.

TABLE I. ANALYSIS OF FORECASTING ERROR

According to Table **1**, the forecasting results given by the models in 5 minutes time interval are more precise than that in one-day time interval. Besides, the experiment effects of function approximation based on neural networks are generally better than that of traditional time series forecasting methods (e.g. ARIMA).To be more specific, in the case of 5 minutes time interval, the proposed EMD-NARX model obtains the best experiment effect having small MSE, only 3.12956E-05. And the coefficient of determination R^2 reaches 0.9998, which comes to the lead of the list. The result indicates that the combination of NARX neural network and EMD can eliminate noisy data and help us to discover the nonlinear relationship behind time series data sufficiently. The combination of these two models has theoretical significance and actual value in discovering the changing rule and trend of exchange rate.

Forecasting Model	R^2	SSE	SAE
NARX(5 minutes)	0.9974	21.538	413.201
EMD-NARX(5 minutes)	0.9998	6.289	217.505
Combination Model (5 minutes)	**0.99999997**	**6.273**	**216.618**
NARX(days)	0.9769	39.783	62.749
EMD-NARX(days)	0.9988	7.110	26.517
Combination Model (days)	**0.999996**	**6.992**	**26.475**

According to the forecasting results of NARX neural network and EMD neural network, we obtain the following regression function:

$$\hat{Y}_{5\,minutes} = 1.0225X_2 - 0.0225X_1$$
(11)

$$\hat{Y}_{days} = 1.0264X_2 - 0.0266X_1$$
(12)

$$SSE = \sum_{i=1}^{N}[\hat{Y}_i - Y_i]^2$$
(13)

$$SAE = \sum_{i=1}^{N}|\hat{Y}_i - Y_i|$$
(14)

In the formula: Y_i --initial data, $\hat{Y}_i$ --forecasting result, N --sample number of prediction value.

According to Equation (11-14), we obtain Table **2**. From Table **2** above, we conclude that the forecasting effect of Combination Model with NARX and EMD-NARX is better than that of EMD-NARX method, which is not significant. However, both of them are better than NARX method, SVM model, Wavelet neural network and ARIMA method.

TABLE II. ANALYSIS OF COMBINATION MODEL FORECASTING ERROR

IV. RMB EXCHANGE RATE FORECASTING

Author names and affiliations are to be centered beneath the title and printed in Times New Roman 12-point, non-boldface type. Multiple authors may be shown in a two or three-column format, with their affiliations below their respective names. Affiliations are centered below each author name, italicized, not bold. Include e-mail addresses if possible. Follow the author information by two blank lines before main text.

Apart from exploring the adaptability of NARX neural network and EMD-NARX combination prediction model, the stability of both models is investigated by observing the effect of RMB exchange rate reform on various models.

On 19th June, 2010, when answering the reporters' questions, the spokesman of people's Bank of China announced that China would strengthen the flexibility of RMB so as to promote the reform of exchange rate system which is called the second exchange rate reform. After years of exploration and trial, influenced by the global financial crisis in 2008 and the rapid development of Chinese economy, the financial environment of internal economy in China has changed a lot. These internal and external elements may affect the experiment results of forecasting models.

In order to explore whether the second exchange rate reform affects the forecasting results of NARX and EMD-NARX models, the historical data of USD-RMB exchange rate are selected in the experiment. The data range from 1st January 2005 to 31st December 2010, and the sample interval is 1 day. The data from 1st January 2005 to 31st December 2008 are adopted as the training set, and the data from 1st January 2009 to 31st December 2010 are adopted as test set. All the data come from State Administration of Exchange Control http://www.safe.gov.cn/. Prediction results given by both models are showed as Fig.7 and Fig.8.

Fig.7 and Fig.8 indicate that both NARX neural network and EMD-NARX model are suitable to the RMB exchange rate prediction and both have satisfying precision. In the early stage of network test, the precision of NARX neural network is similar to that of EMD-NARX model. But in the middle and later stage of the network test, the period of the second exchange rate reform, the error of forecasting result in the Fig.7 is obviously greater than that in the Fig.8.

In the further study of the stability of the exchange rate reform model, R^2 and MSE are adopted as the indicators of error analysis.

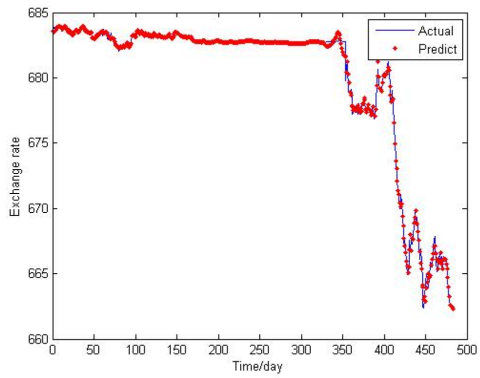

Fig.7 Prediction of NARX model to RMB.

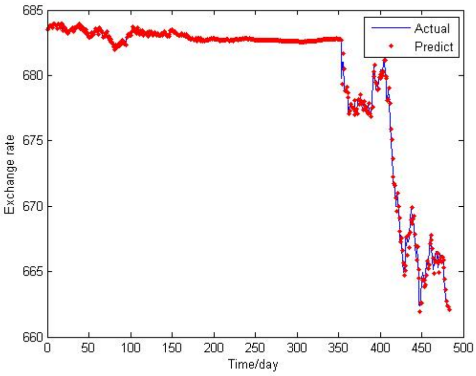

Fig.8 Prediction of EMD-NARX model to RMB.

TABLE III. ANALYSIS OF FORECASTING ERROR ON RMB

Forecasting Model	R^2	SSE	SAE
NARX(No Reform)	0.9996	614.949	430.850
EMD-NARX(No Reform)	0.9998	378.646	331.773
Combination Model(No Reform)	**0.99999945**	**321.188**	**328.303**
NARX(Reform)	0.9944	220.0702	234.8872
EMD-NARX(Reform)	0.9972	35.0097	72.3901
Combination Model(Reform)	**0.99999986**	**30.6424**	**64.4985**

The forecast result given by NARX neural network, EMD-NARX model and other common algorithms applied in domestic and overseas research literatures are collected for comparative analysis. In terms of "No Reform", the data from 1st January 2005 to 31st December 2008 are applied to each model using the first 70% of data as the training set. As to "Reform", the data from 1st January 2005 to 31st December 2008 are adopted as the training set, and the data from 1st January 2009 to 31st December 2010 are used as test set. The comparison of the forecasting results in various models is illustrated in Table **3**.

Let X_1 and X_2 be the results of NARX model and EMD-NARX model respectively, then we have:

$$\hat{Y}_{No\,Re\,form} = 0.693X_2 + 0.307X_1 \tag{15}$$

$$\hat{Y}_{Re\,form} = 0.848X_2 + 0.152X_1 \tag{16}$$

According to Equation (13-16), we get Table **4.**

Table **3** shows that the exchange rate reform can lead to more errors in the prediction experiments of most models. In the neural network models, the networks should be retrained when exchange rate reform occurs. However, in the experiment, noise resistance ability and robustness of EMD-NARX model is greatly improved due to the addition of EMD process. Under the context that the network is not retrained, EMD-NARX model still owes the highest precision for prediction and the MSE is only 1.5225E-04. Besides, the mean square error and determination coefficient R^2 of EMD-NARX model with exchange rate reform data is even better than that of SVM, Wavelet neural network and ARMA models. On the other hand, the change law of exchange rate is slightly different after the exchange rate reform, but it would not significantly reduce the prediction effect of the model.

TABLE IV. ANALYSIS OF COMBINATION MODEL FORECASTING ON RMB

Forecasting Model	R^2	MSE
NARX(No Reform)	0.9996	3.6951E-05
EMD-NARX(No Reform)	**0.9998**	**1.7623E-05**
SVM(No Reform)	0.9903	2.6640E-04
Wavelet neural network(No Reform)	0.9881	4.8202E-04
ARIMA(No Reform)	0.9614	1.6360E-03
NARX(Reform)	0.9944	9.3986E-04
EMD-NARX(Reform)	**0.9972**	**1.5225E-04**
SVM(Reform)	0.9862	5.5738E-04
Wavelet neural network(Reform)	0.9864	6.8320E-04
ARIMA(Reform)	0.9237	5.0148E-03

Table **4** shows that the combination model of NARX and EMD-NARX is better than all the methods above, including NARX model, EMD-NARX model, SVM model, Wavelet neural network and ARIMA method. And the prediction is also very good to the data after the reform of RMB exchange rate.

V. CONCLUSIONS

Owing to the effects of various elements, exchange rate time series exhibits great nonstationarity. The nonlinear dynamic neural network--NARX neural network is proposed to forecast exchange rate directly. And a new combination prediction model EMD-NARX based on NARX neural network and EMD is built to improve the forecasting accuracy. The experiments shows that EMD-NARX model has a higher precision than NARX neural network and the forecasting effects of these two models are better than that of other models. In addition, the model using the data of 5 minutes time interval is better in the prediction. Compared with other models, the EMD-NARX model proposed is relatively more stable, which is significant to the practical fields such as prediction of exchange rate and investment decision.

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