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Study on Forecasting Method of CNY Exchange Rate Fluctuations

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Abstract: The issue of Chinese Yuan (CNY) rate has been focusing extensively home and aboard in recent years and it has affected many fields, such as politics, finance, trade and so on. So, how to scientifically predict the trend of the CNY and as a reference to take corresponding measures to avoid risk has become a focus and difficult problem in China. This study first introduces the basic principles of exchange rate forecasting with neural network. Secondly, with the ability of numeric approaching and memory, it makes use of the neural network to forecast the CNY exchange rate according to the historic data. The practical methods indicate that it is feasible and effective to forecast CNY Exchange rate based on neural network.

Key words: Neural network, exchange rate, forecast, time series

INTRODUCTION

Foreign exchange rates as an important indicator of the international financial markets, as an important means to regulate internal and external balance in the national economy, its intrinsic nature and projected research is extremely important theoretical significance and application value. So, research on influence of CNY exchange rate fluctuation on China's economic development, not only has theoretical value, more practical.

Research on the method of exchange rate forecasting can be divided into three categories: The first category is prediction based on time series analysis. Time Series are data of study object gathered sequentially in time. Such as Engle (1982) proposed auto-regressive conditional heteroskedasticity model analysis fluctuations of exchange rate in the United Kingdom. Nelson (1991) proposed the exponential Generalized Auto Regressive Conditional Heteroskedasticity model (GARCH) model. Ding and Yu (2003) researched on the CNY exchange rate volatility by Auto Regressive Conditional Heteroskedasticity (ARCH) model.

The second category is based on the existing theory of exchange rate determination to build mathematical models between the exchange rate and the impact of the factors and then test correction. Such as Kuan and Liu (1995) proved that there is a certain relationship between the exchange rate and purchasing power parity by using the method of unit root, the maximum likelihood method to research some country's exchange rate fluctuation for many years. Zhu (2011) analyzed the correlation between macroeconomic factors, transformation of system factors, policy factors and exchange rate fluctuation by using purchasing power parity and behavioral equilibrium exchange rate model.

The third category is combination forecasting method. The combination forecasting is to use two or more different single forecasting methods to do weight average to get a combination forecasting model. The combined model can be divided into a linear combination and non-linear combination, whose aim is combine the single research model to get better prediction. Such as Zhang (2003) decomposed exchange rate sequence into a linear sequence and non-linear sequence and the Auto-Regressive Moving Average Model (ARMA) and Back-Propagation (BP) neural network modeling and finally combined to predict then get ideal short-term prediction. Jiang and Song (2010) forecast the exchange rate of the U.S. dollar against the Japanese yen by NARX-ARIMA mixed prediction model.

It can be concluded from the above study, Linear model of exchange rate determination in the short-term exchange rate forecast did not predict, the ability to forecast exchange rate in the long-term needs to be further studied (Andersen and Bollerslev, 1998). Non-linear characteristics of the exchange rate data so far still has not been excavated. The use of neural networks in theory has unlimited function approximation with memory function, according to the value of the exchange rate historical observations, identify the internal mode of exchange rate sequence, analysis and improved the test results (Hui *et al*., 2005).

This study based on analysis of the neural networks models and applied it to the nonlinear residuals prediction of the CNY exchange rate time series. Aiming at the drawback of BP neural network when founded in study, improved the model.

Theory and method: In this study, BP neural network model is used on the CNY exchange rate of the time series prediction. The theory of BP neural network model is artificial neural network. The following first introduced the artificial neural network.

Principle of artificial neural network: Artificial neural network is established by the artificial to the picture shows the topological structure of the dynamic system, through the continuous or intermittent input for state corresponding information processing.

According to the topological structure of the connection, the neural network model can be divided into:

- **Forward network:** In this network each neuron accept the input of the preceding stage and outputs it to the next level, there is no feedback in network, you can use a non-loop diagram means it. This network transform signal from the input space to the output space, the information processing capabilities is from simple non-linear function of many complexes, the structure is simple and easy to implement. The back-propagation network is a typical forward network (West and Cho, 1995)
- **Feedback network:** A feedback between the neurons in this network and it can be represented by a complete graph undirected. Information processing of this neural network is the transformation of the state; it can be handled with the theory of dynamical systems. The stability of the system is closely related with the associative memory function. Hopfield networks, Boltzmann machines are of this type (Dai and Xiao, 2005).

The basic model of artificial neurons: Neural network is the information processing network structure of a parallel and distributed, generally made of multiple neurons, each neuron has only one output and can be connected to many other neurons, each neuron input a plurality of connecting channels and each connection channel corresponding to the weighting coefficient of a connection. Artificial neural network has the characteristics of distribution of information storage and processing and then through the learning experience to have a strong capacity for data processing and analysis.

The neuron unit consists of a plurality of input (i = 1,2, ..., n) and an output y composition. Intermediate state represented by the right of the input signal and the output is:

$$y_j(t) = f\left(\sum_{i=1}^{n} w_{ji} x_i - \theta_j\right)$$

where, θ_j is The offset value of the neuron unit, w_{ij} is the coefficient of the connection weights (For the excited state, take positive values, for the state of suppression, negative), n is The number of input signal, y_j is neuron output, t is time, f is output transform function can also be called excitation or excitation function. The following three activation functions are common types:

- **Sigmoid function:**

$$f(x) = \frac{1}{1+\exp(-ax)} \tag{1}$$

This function Eq. 1 is called S function and is the increasing function of strict, it shows a good balance between linear and nonlinear behavior and is more commonly used to construct artificial neural network activation function.

- **Threshold function:**

$$f(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{2}$$

The output of this function Eq. 2 only 0 and 1, neuron output of function with the weighted sum of the size of the input. When neurons of the input-weighted and exceeds a certain value (net value) of the neuron is activated, the output is 1, otherwise 0.

- **Hyperbolic tangent function:**

$$f(x) = \frac{1-e^{-ax}}{1+e^{-ax}}, -1 < f(x) < 1 \tag{3}$$

Equation 3 is available in the practical application instead of the S-function.

Theory of BP (Back Propagation) neural network: BP neural network is currently the most widely used, the basic idea most intuitive and easy to understand multi-class neural network and error back propagation algorithm.

BP (Back Propagation) neural network is a process of learning error back propagation includes forward propagation and error back-propagation. Each input layer neurons for receiving the external input information and this information is passed to the hidden layer neural unidirectional. Intermediate layer is responsible for processing internal information, according to the need of the information changes, the middle layer can be designed for a single hidden layer or hidden layer structure. The last hidden layer to output layer neurons, after processing the output layer, made a forward propagation learning process. From the output layer to the external output results of information processing, if the actual output is less than expected, then into the back-propagation of error learning process. Errors according to the error gradient descent method modify the weights, through the output layer to the input layer and middle layer, layer-by-layer to back-propagation. Process of again and again repeated adjustment each layer weights is forward propagation and error back propagation, also known as the process neural network training ,until the output is at or near the desired results or reached previously set number of repetitions is stopped.

Mathematical expression patterns of BP neural network propagation

Forward propagation process: Forward propagation from the beginning of the input layer, each of the input layers corresponding to the input data is:

$$A^k = (a_1^k, a_2^k, a_3^k, \ldots, a_m^k),\ k = 1, 2, 3, \ldots, n$$

where, n is a number of learning, m is one layer corresponding to the number of neurons for the input layer, the expected output data corresponding to is:

$$Y^k = (y_1^k, y_2^k, y_3^k, \ldots, y_j^k),\ k = 1, 2, 3, \ldots, n$$

where, j is the number of neurons of input layer, Usually in the S function as activation function:

$$f(x) = \frac{1}{1+\exp(-ax)}$$

The intermediate input data corresponding to the calculation function is:

$$s_j^k = \sum_{i=1}^{n} w_{ij} a_{ij}^k - \theta_j,\ j = 1, 2, 3 \ldots p$$

where, p is the number of neurons in intermediate layer. The results for the output layer is:

$$b_j^k = \frac{1}{1+e^{-\sum_{i=1}^{n} w_{ij} a_{ij}^k - \theta_j}} \quad j = 1, 2, 3 \ldots p$$

The input and output of the output layer neurons results were:

$$L_t^k = \sum_{j=1}^{n} v_{jt} b_j^k - \sigma_t,\ t = 1, 2, 3 \ldots q$$

$$c_t^k = f(L_t^k),\ t = 1, 2, 3 \ldots q$$

where, v_{jt} is connection weights of the intermediate layer to the output layer, σ_t is threshold for the output layer, Activation function is the S function, then a sequential propagation process ends.

Error back-propagation process: The process is during propagation of the error in the output layer d_t^k to the error in intermediate layer e_j^k. Error correction of the output layer is d_t, error correction of the middle layer is e_j. Then get:

$$\begin{aligned} & d_t^k = (y_t^k - c_t^k) f'(L_t^k), \\ & t = 1, 2, 3 \ldots q; \\ & k = 1, 2, 3 \ldots n \end{aligned}$$

where, $y_t^k - c_t^k$ is absolute error of expected output and actual output, $f'(L_t^k)$ is deviation of actual adjust about neuron:

$$\begin{aligned} & e_j^k = \left[\sum_{t=1}^{q} v_{jt} d_t^k\right] f'(s_j^k), \\ & j = 1, 2, 3 \ldots p; \\ & k = 1, 2, 3 \ldots m \end{aligned}$$

Then get two error corrections and then adjust from output layer to the middle layer:

$$Vv_{jt} = a d_t^k b_j^k \ v\sigma_x = -a d_t^k$$

where, j = 1, 2,…, p; k = 1, 2,…, n, t = 1, 2,… q, 0<a<1 (a is learning coefficient).

$$Vw_{ji} = \beta e_j^k a_j^k \ V\theta_j = -\beta e_j^k$$

where, j = 1, 2, p; k = 1, 2…n; i = 1, 2…m, 0<β<1 (β is learning coefficient).

And then repeat training so that the output value approximation or reach the expected satisfaction value.

Time series prediction based on neural network: Time series model is forecasting model based on the historical data of the exchange rate. This method is reached the predict purpose through the study of historical data to understand the object next step.

The time series model is used for one of the short-term statistical forecasting methods. If being enough data, time series model can get satisfactory results in the case of predetermined length.

Any time series can be seen as a non-linear mechanism to determine the input and output systems, can guarantee the feasibility of the time series prediction, nonlinear time series prediction using BP network can better reveal the non-linear characteristics of delay state so as to achieve the desired purpose.

Sample data: China's exchange rate system reform began in 2005; the paper selected the relevant data from 2009 to 2011 and data from the Caixin net (Liu, 2009).At the same time with the statistical software to make the following inspection first stability testing of selected data.

As can be seen from Table 1, the exchange rate time series ADF test statistics are less than the degree of confidence, respectively 1 and 5%, the absolute value of 10% critical values, the exchange rate is non-stationary time series. Then do correlation detection of selected data, the autocorrelation and partial correlation data as shown below.

From Table 2, it can be seen that even if the time duration longer autocorrelation coefficient remains high and the exchange rate time series autocorrelation coefficient decline slowly, after data detection shows correlation and non-stationary of this data set are very good and can be predicted.

Table 1: Stationary test results on sample data of CNY exchange rate

	Critical value (%)		
ADF test statistic	1	5	10
1.872250	-3.4438	-2.8667	-2.5695

Modeling: This prediction model uses the basic three layer BP neural network model to forecast the exchange rate time series. In the construction of BP network model, then elect the input neurons is 20, output neuron is 5, the number of neurons in the middle layer is 10, 20, 40 in the above mentioned BP network designed experience formula and then through tabular data to compare their prediction accuracy. Based on the BP neural network to forecast the exchange rate, is mainly forecast the exchange rate, analysis shows that BP neural network based on the selected variables and exchange rate data of actual exchange rate values are very high accuracy prediction. Forecast according to the selected data and divided into several groups in order to achieve the desired data rate for the purpose of prediction.

The data below shows prediction data samples of established several neural network and corresponding data in Table 3.

From Table 3, when the same error number trained, the more the number of neurons in the middle layer and the less training times, Table 4 shows that the more diverse in the three sample interval division, the intermediate layer neurons of the test of the smallest average error. Can thereby know that a sufficient number of neurons in the intermediate layer as long as the sample data are large enough, then the prediction error is smaller, so that the predicted value closer to the actual value. Observation from the time that the neural network model

Table 2: The results of auto-correlation and partial correlation from correlation test on the sample data

Autocorrelation	Partial correlation		AC	PAC	Q-statistic	Probability
.|********	.|********	1	0.994	0.994	593.26	0.000
.|********	.||	2	0.989	0.015	1181.00	0.000
.|********	.||	3	0.983	-0.010	1763.20	0.000
.|********	.||	4	0.978	0.003	2339.90	0.000
.|*******|	.||	5	0.972	0.000	2911.20	0.000
.|*******|	.||	6	0.967	-0.001	3477.10	0.000
.|*******|	.||	7	0.962	0.001	4037.60	0.000
.|*******|	.||	8	0.956	0.010	4593.00	0.000
.|*******|	.||	9	0.951	-0.013	5143.30	0.000
.|*******|	.||	10	0.946	-0.010	5687.90	0.000
.|*******|	.||	11	0.941	0.025	6227.70	0.000
.|*******|	.||	12	0.935	-0.015	6762.40	0.000
.|*******|	.||	13	0.930	-0.007	7292.00	0.000
.|*******|	.||	14	0.925	-0.004	7816.40	0.000
.|*******|	.||	15	0.919	-0.030	8335.30	0.000
.|*******|	.||	16	0.914	0.021	8849.10	0.000
.|*******|	.||	17	0.908	0.000	9357.80	0.000
.|*******|	.||	18	0.903	-0.020	9861.20	0.000
.|*******|	.||	19	0.898	0.015	10360.00	0.000
.|*******|	.||	20	0.892	-0.006	10853.00	0.000
.|*******|	.||	21	0.887	-0.004	11341.00	0.000
.|*******|	.||	22	0.881	-0.013	11824.00	0.000
.|*******|	.||	23	0.876	-0.022	12302.00	0.000
.|*******|	.||	24	0.870	0.013	12774.00	0.000
.|*******|	.||	25	0.865	0.004	13242.00	0.000
.|*******|	.||	26	0.859	-0.023	13704.00	0.000
.|*******|	.||	27	0.853	0.000	14161.00	0.000
.|*******|	.||	28	0.848	-0.010	14613.00	0.000

AC: Autocorrelation value, PAC: Partial autocorrelation value, .|*......*|: Correlation degree

Table 3: Divided sample data of neural network prediction and the corresponding data

Network name	Training samples interval/No.	Test sample interval/No.	Hidden layer nodes	Training steps	Training error
Net 1	09.07.22-11.03.17(572PC)	11.03.18-11.03.22(1PC)	10	500	0.0001
Net 2	09.07.22-11.03.17(572PC)	11.03.18-11.03.22(1PC)	20	142	0.0001
Net 3	09.07.22-11.03.17(572PC)	11.03.18-11.03.22(1PC)	40	40	0.0001
Net 4	09.07.22-11.03.12(571PC)	11.03.13-11.03.22(2PC)	10	600	0.0001
Net 5	09.07.22-11.03.12(571PC)	11.03.13-11.03.22(2PC)	20	69	0.0001
Net 6	09.07.22-11.03.12(571PC)	11.03.13-11.03.22(2PC)	40	38	0.0001
Net 7	09.07.22-11.03.02(569PC)	11.03.03-11.03.22(4PC)	10	1000	0.0001
Net 8	09.07.22-11.03.02(569PC)	11.03.03-11.03.22(4PC)	20	126	0.0001

The packet data through training and testing the neural network is shown below in table 4 forecast error

Table 4: Prediction errors of exchange rate got by training and testing packet data on neural network

Net 1	Net 2	Net 3	Net 4	Net 5	Net 6	Net 7	Net 8
-0.007702	0.0070419	-0.000950	0.0029009	0.0216680	0.0140620	-0.0247540	0.0019690
0.002217	-0.0039000	0.006458	-0.0105910	0.0124140	0.0061317	-0.0360340	0.0015357
-0.02082	0.0052220	0.006918	0.0020249	0.0043651	-0.0042020	0.0117370	0.0309660
-0.010411	-0.0095400	0.000852	0.0148580	0.0206810	0.0154780	0.0047934	0.0334710
-0.009209	-0.0048500	-0.011470	-0.0448970	-0.0057740	-0.0056650	-0.0058620	0.0482320
			0.0042030	-0.0062760	-0.0072520	-0.0148680	0.0497140
			-0.0032230	0.0108820	0.0062257	-0.0281560	0.0318640
			-0.0263890	0.0018914	0.0018029	-0.0093440	0.0305230
			-0.0060450	0.0099283	-0.0026140	0.0004892	0.0124910
			-0.0096160	0.0016372	-0.0080710	-0.0228660	0.0046049
						0.0043253	0.0275390
						0.0002698	0.0220540
						-0.0098680	0.0109480
						0.0089220	0.0145150
						-0.0259880	0.0025743
						-0.0201750	0.0062150
						-0.0024790	0.0064134
						-0.0180270	0.0096796
						-0.0157610	0.0119110
						-0.0043000	0.0073181
0.010072	0.0061115	0.0053304	0.0124748	0.0095516	0.0071503	0.0162979	0.0182269

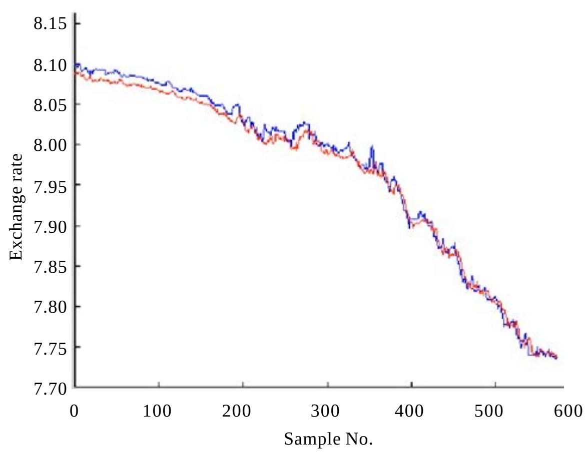

Fig. 1: Line graph of forecast CNY exchange rate value and the actual value (Jul 22, 2009-Mar 17, 2011)

to forecast the exchange rate, test time close to the sample of time, the error of predictive value and the actual value will be smaller. Treatment with MATLAB7.0, the processing results as shown below in Fig. 1 (blue line for the real exchange rate, the red line for the predictive value).

As illustrated above, the neural network model based on time series can make better prediction, the actual and predicted values are very close.

The evaluation of the model: There are many factors impact of changes in exchange rates and the impact of the factors are inextricably linked, if you want put all these factors into consideration and make an accurate exchange rate forecasting very difficult. Time series model can just ignore other influencing factors; simply use the available data relevant variables to forecast. Nonlinear time series model is the modeling and prediction of sequence changes for a certain period of time, it can more accurately grasp the behavioral characteristics of the time series data to achieve the desired goal, so now it caused a lot of its attention. However, the prediction of nonlinear time series model is more difficult compared to the linear time series model, it is also an important cause of nonlinear time series prediction is difficult to develop and widely used.

Improvement of the model: Through the observation and study of the model, two improvements can be put forward:

- Due to the time series model and the time period of data samples are closely connected, so update data sample time to achieve relatively accurate forecast, at the same time update the model
- The more recent data of the prediction data to predict the samples, the more accurate the prediction value obtained. For example, prediction the exchange rate of t+1 moments, the input from the t+1 moment closer, it will be higher accuracy. Therefore, the input data is processed as follows: Original t+1-n input time data is changed in the average of time t and time t+1-n, a more accurate prediction data will be obtained:

```
L is time, X [t] is the input value
i = 1;
while i<=L
for (j= 1; j<= n; j++)
Modify X [t+i-j] for the average exchange rate of time t+i-j and time t;
X [t+i- (n+1)]...X [t+i-1] as input to calculate exchange rate forecasting value
of time t+i X [t+i]
i = i+1;
End Of While
```

CONCLUSION

This study reached the current CNY exchange rate by time series modeling. Due to my limited, the accuracy of the predicted value may be not so high. While each individual prediction methods have different advantages and disadvantages, it gets better and more satisfied with the predicted results using a different prediction method in different times under different environments. The disadvantage of the various forecasting methods is inevitable, so how to avoid these shortcomings to build a better model is the focus and difficulty of future development. Of course, taking advantages of combination method combined with some single prediction methods to predict the effect will be better.

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