

# Several Problems of Exchange Rate Forecasting Using Neural Network

Meng Li, and Sun Lin

School of Management, Xiamen University, PR China

Email: xxxsunlin@163.com

**Abstract**—In this paper, the authors discuss several controversial issues about exchange rate forecasting by using neural network, which include whether the type of data sample and the size of it will affect the prediction accuracy, whether time-series model or neural network model is more suitable for exchange rate forecasting, and whether neural network suitable for long-term prediction or short-term prediction. The techniques that the authors applied are BP-neural network model in Matlab and time-series model in Excel. Some beneficial results are indicated from this study, for example, the type of data sample has little effect on the prediction accuracy in exchange rate forecasting by neural network.

**Index Terms**—neural network, exchange rate, prediction accuracy

## I. INTRODUCTION

In recent years, artificial neural network technology in the financial derivatives market analysis is improved greatly. The promotion of this usage not only increased people's awareness of the exchange rate market, but also greatly expanded the research of neural network and its application scope. However, since neural network is used to analyze the exchange rate market, there have been large number of controversies like whether neural network can predicate exchange rate effectively or not, whether the nonlinear prediction model has advantages compared to time-series prediction model or not, whether the sample size affect the accuracy of prediction or not, and How to solve neural network of its own shortcomings (for example: it is easily be trapped in local minimum value, algorithm is slow convergence, and so on).

In 1994, Hutchinson proved that neural network is efficacious for financial market analysis through the study of options data collected from 1987 to 1991<sup>[1]</sup>. But Hann and Steurer's study (1996) showed the prediction accuracy of neural network is worse than the simplest linear regression model based on monthly data (USD/GM)<sup>[2]</sup>. Then Meade N.A (2002) concluded that there is no obvious advantage of non-linear model compared to linear model through the comparison of short-term exchange rate models<sup>[3]</sup>. But Lean Yu, Shouyang Wang and K.K. Lai's studies (2005, 2009) showed that neural network

technology in the exchange rate forecasting is efficient, and nonlinear prediction model is generally more effective than other models by experiment<sup>[4,9]</sup>. Yuehui Chen, Ajith Abraham and Bo Yang (2005, 2006) also proved that neural network model is more effective to predicate than an ordinary model. They built a flexible neural tree model and proved its predictive accuracy is higher than an ordinary model by experiment<sup>[5, 7]</sup>. Since then the controversy on the accuracy of two kinds of predicating model has always existed. The domestic studies incline to support the neural network predicating. Wei weixian and Jiang zhenghua built a short-term neural network prediction model for DM/USD (data used selected from May, 1987 to December, 1992, weekly, from London foreign exchange market and New York foreign exchange market), they compared the prediction result between the traditional linear time series model and neural networks'. Their study suggested neural network model is more precise than previous. Yang xi and Ma hongbo from Tsinghua University studied DM/USD exchange rate with neural network model and Random walk model, result of their experiment also provided that the neural network model is more effective. These achievements have advanced the study of neural network beyond all doubt. But at the same time it should be noted that the indicator used to measure the prediction accuracy of prediction model is 'mean absolute percentage error (MAPE)', which can be used to compare the prediction accuracy of different models with different data sample, but whether it is effective in practical application need to be further explored.

In order to improve the predication accuracy of neural network and solve the problem of local convergence, people used various methods to ameliorate neural networks such as Genetic Algorithm, Gray Theory, Fuzzy theory, rough set theory, ant colony algorithm and so on. For example, Hui xiaofeng, Hu yuanquan and Hu Wei have built a GA-BP model, the prediction accuracy of this model is 99.92%<sup>[6]</sup>. Someone intended to improve the prediction accuracy by adjusting the number of hidden units, while some others give the weight random initial value time after time<sup>[11]</sup>. The prediction accuracies of these ameliorated neural networks are better than ordinary ones. But there are always unexpected situations that a model only fits to one particular sample, once it is applied to another sample the prediction accuracy becomes poor, and there were even opposite conclusions in someone's studies. In such case, someone claimed that for the data in exchange rate market is rich and uncertainty and

---

Financed by the Science Foundation of Department of Education (Grant No. 07JA790033) ; Natural Science Foundation of Province of Fujian (Grant No2009J1314);

Society Science Foundation of Province of Fujian; Post-Doctorate (Grant No. 20070411077)

characteristics of the model are weak, it is very hard to show the law of exchange rate fluctuations with one model. A model only can be applied to a particular sample within a specific time period [12, 14]. In addition, although most people consider neural network fits for short-term forecast, someone conducted long-term forecast research [12, 15]. This paper intends to discover the differences between short-term forecast and long-term forecast.

According to the review of previous studies forenamed, this paper conducted an empirical study on the following issues: a) Whether the prediction accuracy of neural network model is better than time-series model. b) Whether the type of data sample will affect the prediction accuracy. c) Whether neural network is suitable for long-term or short-term prediction. d) Whether the sample size will affect the prediction accuracy. e) Whether the indicator we used in this paper for the model is appropriate.

## II. MODEL AND DATA

### A. Model

The model we applied is BP-neural network in Matlab and time-series model in Excel; six BP-neural networks were built in our study. The transfer functions of all neural networks are {'logsig', 'logsig', 'purelin'}. The "logsig" is the Unipolar-shaped Sigmoid function. Its expression is:  $\text{logsig}(n) = 1/(1 + \exp(-n))$ . The "purelin" is the pure linear function. Training function is Conjugate gradient function "trainscg". "trainscg" combines the confidence interval approach of Levenberg-Marquardt algorithm and the Conjugate Gradient algorithm, and it needs more iteration compared to other Gradient algorithms. However, it need not do linear research in each iteration step, so computation is reduced. Structure of the network that used to deal with AUD/CAD (daily) data sample is as follow (the other networks' structures are similar to this one):

```
net=newff(minmax(p), [20 5 1], {'logsig', 'logsig', 'purelin'}, 'trainscg')
```

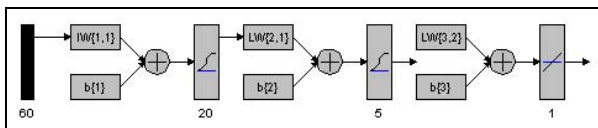


Figure 1. Structure of neural network

It can be easily understood with the scheme of Fig.1.

The learning rate of this model is 0.01, Objective function is "mse", and training target is 1e-5. Taking into account the over-training problem (Over-training problem generated from the infinite approximating to data sample when neural network training because the network always studies some individual properties of a sample. When over-training problem accorded, the prediction accuracy usually reduced, and the model should stop training [10], the maximum training step is set as 2000. To identify the number of hidden layer nodes, we consult GAO daqi's method [13]. The identification of transfer function and

training function in all levels is due to experiment time after time. Because of a training function is usually fit for a data sample with specific curvilinear trend, to determine the training function is the key to success. The relationship between the curvilinear trend of data sample and the training function is worthy of further exploration.

### B. Data

There are six data samples used in our study. AUD/CAD exchange rate is selected to be the main research data. In experiments with small samples, three sets of data is selected, they are AUD/CAD 100 daily Closing prices data from May 1, 2000 to September 15, 2000, AUD/CAD 100 weekly average Closing prices from May 1, 2000 to March 15, 2002 and AUD/CAD 100 monthly average Closing prices from May 1, 2000 to August 29, 2008. 90 pre-selected are set to be training data, the last 10 were the Test Set. The prediction data is generated from its former 60 data. In experiments with large samples, three set of data are AUD/CAD 1010 daily Closing prices data from May 1, 2000 to April 9, 2004, EUR/USD 1010 daily Closing prices from May 1, 2000 to March26, 2004 and USD/JPY 1010 daily Closing prices from May 1, 2000 to March 12, 2004. 1000 pre-selected are set to be training data, the last 10 were the Test Set. The prediction data is generated from its former 600 data. All data sample are acquired from China Merchants Bank foreign exchange market analysis V2.6. The closing price is pitched on because it is a kind of very useful data in commercial application. Part of the data is shown in Tab. I .

TABLE I  
SIX SORTS OF CLOSING PRICE OF EXCHANGE RATE (CUT-OFF ELECTION)

	AUD / CAD 100daily	AUD / CAD 100weekly	AUD / CAD 100monthly	AUD / CAD 1010daily	EUR / USD 1010daily	USD / JPY 1010daily
1	0.8607	0.87682	0.8635	0.8607	0.9157	108.76
2	0.8685	0.86536	0.8774	0.8685	0.9098	108.48
3	0.8839	0.85424	0.8678	0.8839	0.8956	109.00
4	0.8825	0.85944	0.8607	0.8825	0.8907	108.02
5	0.8885	0.85746	0.8203	0.8885	0.8967	108.46
6	0.8656	0.86816	0.7987	0.8656	0.8973	109.00
7	0.8693	0.88048	0.8054	0.8693	0.9073	109.11
8	0.8672	0.88286	0.8340	0.8672	0.9064	109.51
9	0.864	0.88756	0.8342	0.864	0.9013	108.50
10	0.8607	0.88022	0.8126	0.8607	0.9197	108.48
...	...	...	...	...	...	...

Source: China Merchants Bank foreign exchange market analysis V2.6

The indicator we used to evaluate the prediction accuracy is MAPE; its formula is as follow:

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^N \frac{e_i}{y_i} \quad (1)$$

$e_i$  is the Absolute Error;  $y_i$  is the Exchange Rate;

This indicator is widely used in people's study. According to previous research, it can reflect the prediction accuracy objectively. So it is used to compare

the prediction accuracies between different models or the same model with different data samples in this paper.

### III. EXPERIMENT AND ANALYSIS

#### A. Comparison of prediction accuracy between neural network and time-series model

In order to discover the prediction accuracy of time-series model, we studied AUD/CAD 100 daily Closing prices data with several regression models and Moving Average Method in Excel. Results are shown in Tab. 2.

The regression model used here is Exponential Regression Model, its formula is:

$$y_n = 0.8718 * e^{-0.0001 * n} \quad (2)$$

The Linear Regression Model, Logarithmic Regression Model, Moving Average Method and Exponential Regression Model were compared to identify which prediction accuracy is the best. The most effective ones are Exponential Regression Model and Moving Average Model as shown in the Tab. II. The best MAPE is 4.52%.

TABLE .II  
PREDICTION VALUE WITH TIME-SERIES MODELS

Number	1	2	3	4	5	MAPE
Exchange rate	0.8464	0.8397	0.8336	0.8243	0.8195	
Linear regression	0.863903	0.863816	0.86373	0.863643	0.863557	
Error	2.07%	2.87%	3.61%	4.77%	5.38%	
Moving Average	0.86700	0.86678	0.86648	0.86613	0.86569	
Error	2.38%	3.12%	3.80%	4.83%	5.34%	
Number	6	7	8	9	10	
Exchange rate	0.8303	0.8251	0.8213	0.8158	0.807	
Linear regression	0.863471	0.863384	0.863298	0.863212	0.863125	
Error	4.00%	4.64%	5.11%	5.81%	6.95%	4.52%
Moving Average	0.86520	0.86484	0.86443	0.86399	0.86350	
Error	4.03%	4.59%	4.99%	5.58%	6.54%	4.52%

Then a three layered BP-network was built to analyze the same sample, the network is as follow:  
net=newff (minmax (p), [20 5 1], {'logsig', 'logsig', 'purelin'}, 'trainscg');  
Results are shown in Tab.III.

TABLE .III  
SINGLE PREDICTIVE VALUE

Number	1	2	3	4	5	MAPE
Exchange rate	0.8464	0.8397	0.8336	0.8243	0.8195	
Predictive value	0.8579	0.807	0.8495	0.8322	0.8466	
Error	1.36%	3.89%	1.91%	0.96%	3.31%	
Number	6	7	8	9	10	
Exchange rate	0.8303	0.8251	0.8213	0.8158	0.807	
Predictive value	0.8248	0.8481	0.817	0.7753	0.8163	
Error	0.66%	2.79%	0.52%	4.96%	1.15%	2.15%

As is shown in Tab. 3, the prediction accuracy is not good — MAPE is 2.15%, which is too high (but it is better than time series model). Error of number 8 is only 0.52%, but the number 9 is 4.96%, that is too bad. Why the difference is so great? As we all know the network will be given a random weight when it is initialized, then training will not stop until the network meets the requirements through revising this weight. The revised weight is the solution of this neural network. The principle of the network learning is Gradient Descent algorithm. Because of Gradient Descent algorithm can not avoid the situation of falling into local optimal solution, so there is great relationship between the initialized network weights and the solution of neural network searched. If the location of the initialized solution is poor, the result is always not the optimal solution. The method we used to solve this problem is to give the network a number of random initialized weights.

The network is given 10 sets random initialized weights in our experiment. That means to each training process we make it 10 times repeat. The average of 10 times prediction is our predictive value. This value is definitely not the optimal solution, but the prediction accuracy will be improved greatly. Experiment results are shown in Tab. IV.

TABLE .IV  
REPETITIOUS PREDICTIVE VALUE (10TIMES)

Number	1	2	3	4	5	MAPE
Exchange rate	0.8464	0.8397	0.8336	0.8243	0.8195	
Predictive value	1	0.8579	0.807	0.8495	0.8322	0.8466
	2	0.8485	0.8607	0.8433	0.8251	0.8287
	3	0.8501	0.8381	0.8442	0.8354	0.8271
	4	0.8539	0.8483	0.8461	0.7984	0.8181
	5	0.8452	0.8548	0.8531	0.8435	0.8316
	6	0.8547	0.8654	0.8601	0.7462	0.8258
	7	0.8546	0.8468	0.8471	0.8432	0.8296
	8	0.8397	0.8499	0.8353	0.8463	0.7983
	9	0.8439	0.8492	0.833	0.8479	0.8019
	10	0.85	0.8516	0.8561	0.8236	0.8367
The average forecast	0.84985	0.84718	0.84678	0.82418	0.82444	
Absolute error	0.41%	0.89%	1.58%	0.01%	0.60%	
Number	6	7	8	9	10	
Exchange rate	0.8303	0.8251	0.8213	0.8158	0.807	
Predictive value	1	0.8248	0.8481	0.817	0.7753	0.8163
	2	0.8532	0.8348	0.8339	0.8523	0.8141
	3	0.8365	0.8279	0.8301	0.8325	0.8181
	4	0.8009	0.8289	0.8331	0.8211	0.8228
	5	0.8415	0.8507	0.8394	0.8215	0.8302
	6	0.8177	0.8156	0.828	0.7592	0.8184
	7	0.8247	0.8428	0.836	0.8237	0.8319
	8	0.8274	0.832	0.8342	0.8174	0.7816
	9	0.8292	0.8432	0.8586	0.8233	0.8342
	10	0.827	0.8468	0.8213	0.7804	0.8033
The average forecast	0.82829	0.83708	0.83316	0.81067	0.81709	
Absolute error	0.24%	1.45%	1.44%	0.63%	1.25%	0.85%

The MAPE is only 0.85%, which means the prediction accuracy is 99.15%.

As is shown in Tab.III and Tab.IV, the network given the initialized weight repetitiously (10 times) method improves the prediction accuracy significantly by contrast to an ordinary neural network model.

From the experiment above we can see there is an

obvious advantage by neural network model than time-series model in exchange rate forecasting through comparison of MAPE.

### B. The impact of data type to the prediction accuracy

In order to discover which kind of data types is more suitable for neural network model, we conducted experiments with weekly data and monthly data separately. At the same time we also explored whether the predictive ability of the network given multiple random initialized weights is stable.

The network is as follow: `net = newff (minmax (p'), [25 5 1], {'logsig','logsig','purelin'}, 'trainscg');`

Results are shown in Fig.2.

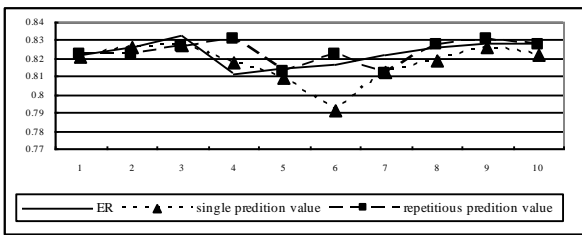


Figure 2. Average exchange rate (weekly) and the predictive value

The MAPE of single prediction is 0.84%; the MAPE of the network given the initialized weight repetitiously (10 times) method is 0.63%, which means the prediction accuracy of the network given the initialized weight

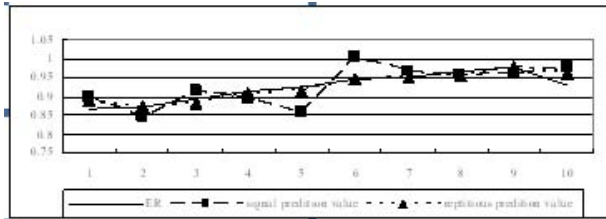


Figure 3. Average exchange rate (monthly) and the predictive value

repetitiously (10 times) model is higher than an ordinary neural network.

The network used for monthly data is the same as previous one. Results are shown in Fig.3.

The MAPE of single prediction is 3.48%; the MAPE of the network given the initialized weight repetitiously (10 times) method is 1.12%. According to the above experiment, the neural network given the initialized weight repetitiously model is more suitable for exchange rate forecasting compared to an ordinary neural network.

The problem of whether the type of data sample can impact the prediction accuracy also can be explored from the above experiments.

The MAPE of daily data is 0.85%; the MAPE of weekly data is 0.63%; the MAPE of monthly data is 1.12% (But at the same time we should note that the MAPE of first 9 predictive errors of monthly data is only 0.83%, which is very similar to the MAPE of daily data and weekly data. It is abnormal that the predictive error of last month was so large, the reason may be the last data

of month contained too much noise.). According to the experiment, their prediction accuracy is at the same level. Therefore, we can suggest that the type of data sample has little effect on the prediction accuracy in exchange rate forecasting using neural network.

### C. Problem of whether neural network suitable for long-term or short-term prediction

To explore whether neural network suitable for long-term or short-term prediction, we expanded sample size from 100 to 1010 in following experiments. Three kinds of exchange rate (AUD / CAD, EUR / USD, and USD / JPY) were adapted to this experiment. The model we used is an ordinary BP network but not the network given initialized weight repetitiously model for the latter running too slow with large sample. The network used for AUD / CAD data sample is as follow:

`net =newff (minmax (p'), [30 6 1], {'logsig', 'logsig', 'purelin'}, 'trainscg');`

Experiment results are shown in Tab.V. As is shown in Tab.V, the MAPE of long-term prediction is 4.07%, while the MAPE of short-term prediction is only 0.43%, which means the short-term prediction is more accurate.

The network used for EUR / USD data sample is the

TABLE V  
AUD / CAD LONG-TERM PREDICTION AND SHORT-TERM PREDICTION COMPARISON

Number	1	2	3	4	5	MAPE
Exchange rate	0.9787	0.9863	1.0044	1.0021	0.9952	
L-Prediction	0.966	0.9643	0.9599	0.9986	0.9646	
L-Error	1.30%	2.23%	4.43%	0.35%	3.07%	
S-Prediction	0.98440	0.99340	1.00440	1.00290	1.00220	
S-Error	0.58%	0.72%	0.00%	0.08%	0.70%	
Number	6	7	8	9	10	MAPE
Exchange rate	0.9905	0.9964	1.0065	1.0101	1.013	
L-Prediction	0.9311	0.9505	0.9546	0.9749	0.9107	
L-Error	6.00%	4.61%	5.16%	3.48%	10.10%	4.07%
S-Prediction	0.99650	1.00320	1.00490	1.00490	1.01520	
S-Error	0.61%	0.68%	0.16%	0.51%	0.22%	0.43%

same as previous one.

Experiment results are shown in Tab.VI

As is shown in Tab.VII, the MAPE of long-term

TABLE VI  
EUR / USD LONG-TERM PREDICTION AND SHORT-TERM PREDICTION COMPARISON

Number	1	2	3	4	5	MAPE
Exchange rate	1.2261	1.2252	1.2224	1.2385	1.2281	
L-Prediction	1.216	1.2901	1.2636	1.2495	1.2124	
L-Error	0.82%	5.30%	3.37%	0.89%	1.28%	
S-Prediction	1.23070	1.22460	1.22740	1.23580	1.22970	
S-Error	0.38%	0.05%	0.41%	0.22%	0.13%	
Number	6	7	8	9	10	MAPE
Exchange rate	1.2341	1.2339	1.2134	1.2133	1.2119	
L-Prediction	1.2415	1.1874	1.1867	1.192	1.2214	
L-Error	0.60%	3.77%	2.20%	1.76%	0.78%	2.08%
S-Prediction	1.22280	1.22420	1.23380	1.22380	1.22300	
S-Error	0.92%	0.79%	1.68%	0.87%	0.92%	0.63%

prediction is 0.65%, while the MAPE of short-term

TABLE .VII  
USD / JPY LONG-TERM PREDICTION AND SHORT-TERM  
PREDICTION COMPARISON

Number	1	2	3	4	5	MAPE
Exchange rate	108.97	110.07	110.02	111.1	112.05	
L-Prediction	109.42	109.67	108.87	110.4	110.77	
L-Error	0.41%	0.36%	1.05%	0.63%	1.14%	
S-Prediction	109.88	110.24	111.12	111.42	111.09	
S-Error	0.84%	0.15%	1.00%	0.29%	0.86%	
Number	6	7	8	9	10	
Exchange rate	112.09	111.29	110.88	110.74	110.82	
L-Prediction	110.9	110.18	110.81	111.1	110.36	
L-Error	1.06%	1.00%	0.06%	0.33%	0.42%	0.65%
S-Prediction	111.80	110.95	110.10	110.71	110.03	
S-Error	0.26%	0.31%	0.70%	0.03%	0.71%	0.51%

prediction is 0.51%. In general, as we can see from the above experiments the accuracy of short-term prediction is higher than long-term prediction.

The problem of whether sample size can impact the prediction accuracy can be explored from the above experiments too. Data collected are as shown in Tab. VIII.

*D. The suitability of indicator we used in this paper for the model*

Although prediction accuracies can achieve 99.57%, 99.37% and 99.49% in our experiment, the indicator of MAPE may not be able to fully reflect the model's prediction ability. There is another important factor to be considered: The volatility of data sample. The volatility of data sample used in the above experiments and prediction accuracy are shown in Tab. IX.

As is shown in the Tab. 9 we can see that the predictive error is too large compared to the volatility.

TABLE .IX  
DATA VOLATILITY AND FORECASTING ACCURACY COMPARISON

	The average volatility	MAPE
AUD/CAD 100 daily	1.29%	0.85%
AUD/CAD 100 weekly	1.30%	0.63%
AUD/CAD 100 monthly	1.07%	1.12%
AUD/CAD 1010 daily	1.15%	0.43%
EUR/USD 1010 daily	1.10%	0.63%
USD/JPY 1010 daily	0.90%	0.51%

While the MAPE of AUD / CAD 100 monthly is 1.12%, the average volatility is only 1.07%, which means the prediction on this data sample is worthless. So we can not determine the merits of a model only by MAPE. There should be a new indicator which combines volatility of data and predictive error to evaluate the merits of a model. The new indicator must reflect the mastery to the volatility of a data set. Volatility shows the fluctuation of a data set. The mean absolute percentage error (MAPE) reflects the scope of prediction error.

The indicator MAPE/ The average volatility may reflect the predictive level of a model to some extent. That needs to be further explored.

IV. CONCLUSION

This paper conducted an empirical study on exchange rate forecasting by constructing several neural networks. Some controversies about exchange rate forecasting using neural network were discussed once more by these experiments. The conclusions are as follow:

I There is obvious advantage with neural network model compare to time-series model in exchange rate forecasting;

II The type of data sample has little effect on the prediction accuracy in exchange rate forecasting using neural network;

III The accuracy of short-term prediction is higher than long-term prediction in exchange rate forecasting using neural network;

IV The accuracy of prediction with a large sample size is higher than with small sample size in exchange rate forecasting using neural network;

V Evaluation to predictive level of a model by the indicator of MAPE is unconsummated, the volatility of sample data should be considered.

Because of the lack of study about the indicator to evaluate predictive level of a model, there is not a convincing standard in application. So it is worthy to explore how to evaluate the validity of a model in application on exchange rate forecasting.

REFERENCES

- [1] Hutchinson et al. A nonparametric approach to pricing and hedging derivative securities via learning networks [J]. Journal of corporate finance, 1994, 49(3): 851-889.
- [2] Hann, T.H. and Steurer, E. Much ado about nothing? Exchange rates forecasting: neural networks vs. linear model using monthly and weekly data. Neurocomputing, 1996, 10:323-339.
- [3] Meade N.A Comparison of the Accuracy of Short Term Foreign Exchange Forecasting Methods [J].International Journal of Forecasting, 2002, 18(1):67-83.
- [4] Lean Yu, Shouyang Wang, K.K. Lai, A novel nonlinear ensemble forecasting model incorporating GLAR and ANN for foreign exchange rates [J]. Computers & Operations Research, 2005, 32(10): 2523-2541.
- [5] Yuehui Chen, Bo Yang, Jiwen Dong, Ajith Abraham. Time-series forecasting using flexible neural tree model [J].Information Sciences, 2005, 174(3-4): 219-235.
- [6] Hui xiaofeng, Hu yunquan, Hu wei. Based on genetic algorithm BP neural network prediction in the exchange rate of the Applied Research [J] Quantity economic and Techno-economic study, 2002, 2: 80-83.
- [7] Yuehui Chen, Ajith Abraham, Bo Yang.Feature selection and classification using flexible neural tree [J].Neurocomputing, 2006, 70(1-3): 305-313.
- [8] Zhang, G.P. Neural networks in business forecasting [J]. International Journal of Forecasting, 2005, 21(2): 394-395.
- [9] Yu Lean, Shouyang Wang, Kin Keung Lai, An intelligent-agent-based fuzzy group decision making model for financial multicriteria decision support: The case of credit scoring [J]. European Journal of Operational Research, 2009, 195(3):942-959.
- [10] Mao na, Liu qianjin, Neural network method to invest in the stock application [J]. Statistics and information forums, 2008, 23(1):63-67.
- [11] Zhang jian, Chen yong, Xia gang, He yongbao. Artificial neural network prediction of stock [J] Computer Engineering, 1997, 23(2): 52-55.

- [12] Xia jingming, Xiao dongrong, Xia jinghong, Jia Jia. Gray neural network model was applied to the securities of short-term prediction research [J]. Industrial techno-economic, 2004, 23(6): 109~111.
- [13] Gao daqi. Reaches on three layers back propagation network with learning target and Linear basic function [J]. Chinese Journal of Computers, 1998, 21(1): 80-86.
- [14] Shazly M R E, El Shazly H E. Comparing the Forecasting Performance of Neural Networks and Forward Exchange Rates[J]. Journal of Multinational Financial Management, 1997, 7(4): 345-356.
- Qi, M. and Wu, Y. Nonlinear prediction of exchange rates with monetary fundamental. Journal of Empirical Finance, 2003, 10:623~640.