WEP Warwick Evans Publishing

Transactions on Computer Science and Intelligent Systems Research
ISSN: 2960-1800, eISSN: 2960-2238 | Volume 5
AIDML 2024

Prediction of USD/RMB Price Change Based on BP Neural Network

Xiaorui Li

Puyang Oil-field No.1 High School, Henan, China

lixiaorui6666@outlook.com

Abstract. The market position of the RMB has gradually increased, and the price change of the US dollar against the RMB has become increasingly important. Therefore, it is vital to use scientific means to forecast the exchange rate forecasting model. In this thesis, the BP neural network model is established by MATLAB, and the price change of the USD/RMB exchange rate is analyzed and processed according to the characteristics of the exchange rate prediction model. Part of the data is elected for the network training, the other part is used to verify the accuracy of neural network prediction. The results indicate that the fitting accuracy is 94.6%. Continuing to modify some arguments of the model including changing the number of training rounds to 100000, and changing the training target to 1e-15 with the learning rate remaining unchanged, The equal accuracy could be further increased to 96%. In the results, the model can precisely, mirror the trend of fluctuations, verify the effectiveness of this forecasting method, provide an important reference for financial institutions and personnel engaged in the financial industry, and have great significance for foreign exchange management to effectively avoid market risks and cope with the impact of exchange rate fluctuations.

Keywords: BP neural network; MATLAB; prediction of USD/RMB price change.

1. Introduction

The RMB and US dollar are important currencies in the world, and their price changes reflect the economic changes in China and America. With the gradual establishment of the market-oriented status of the RMB exchange rate formation mechanism, the inclusion of RMB in the Special Drawing Rights, and the emergence of various economic situations at home and abroad, the law of USD/RMB exchange rate fluctuations has gradually become more complicated [1]. The foreign exchange market is complex and changeable, and the exchange rate fluctuations are affected by various factors, which is difficult to predict accurately [2]. Exchange rate fluctuations are closely related to individual investment, enterprise import and export, national internal economy, and international economic linkage [3]. Therefore, the prediction of foreign exchange rates has become more and more crucial in the field of foreign exchange risk management and data mining. The forecast exchange rate can be an important reference for investors to make investment decisions and national economic policies. This prediction helps them to correctly judge market trends and make the right investments and decisions. Machine learning models can efficiently utilize large amounts of historical data for learning analysis, and improve the accuracy of predictions by training models and applying algorithms. Based on this, it is important to build a forecast model for the change in the USD/RMB exchange rate over time.

On the issue of exchange rate forecasts, domestic and foreign scholars have established models of exchange rate changes through different methods. Among them, Xu Shaoqiang used the Auto-Regressive and Moving Average Model (ARMA) to effectively forecast the medium and long-term trend of the RMB exchange rate after exchanging the rate reform [4]. Carriero used the Bayes Vector Autoregression Model (BVAR) to model the exchange rate between 33 currencies and the US dollar and used the linear model to forecast various exchange rate data [5]. Refine and Barac made use of neural network and smoothing methods to forecast exchange rates, and found that neural network prediction has a better effect [6]. Dai Xiaofeng found that EGARCH's prediction effect on the RMB exchange rate was better than the Autoregressive Integrated Moving Average Model (ARIMA) [7].

Subsequently, Ye used the BP neural network to forecast the central parity of the USD/RMB transform rate in the experimental work, which showed that the network showed obvious merits in terms of forecasting efficiency and accuracy [8]. In recent years, Wang Li used the Ensemble Empirical Mode Decomposition(EEMD) method in data preprocessing to decompose, screen, and reconstruct the original exchange rate data and then used BP neural network to model and forecast, which can further accurately describe the volatility of exchange rate changes [9].

Among the above research methods, the linearized economic variable analysis and prediction method has a large error in the prediction results. The artificial neural network has the characteristics of distributed parallel processing, nonlinear mapping, adaptive learning, etc., so that it can accurately describe the nonlinear dynamic process. The volatility of exchange rate changes can be further accurately described which provides a new way of thinking for the analysis and prediction of financial and economic systems. However, the BP neural network still has some problems, such as the training speed is low and the generalization ability is weak.

This paper will utilize the achievements of current research, starting from the BP neural network, and select the data of USD/RMB exchange rate in recent two years to establish a prediction model of USD/RMB exchange rate change over time, to realize the prediction of USD/RMB exchange rate and make a scientific prediction of the recent trend of RMB exchange rate. It provides an important reference for financial institutions and personnel engaged in the financial industry to help them avoid various investment risks in a timely and effective manner and reduce losses caused by exchange rate fluctuations.

2. Research Methods and Data

2.1. BP Neural Network Introduction

Artificial Neural Networks (ANN) are theoretical mathematical models based on the human brain and its activities. It is a large-scale nonlinear adaptive system composed of a large number of processing units interconnected properly. The neural network is a data classification method based on distance measurement. Amidst the practical applications of Neural networks, BP algorithm-based Back Propagation Neural Network (BP neural network), also known as a multilayer feedforward network, is the most widely used artificial neural network. It was developed and designed in 1986 by D.E. Rolelhart and J.L. McElland and their research group [10]. At present, in the practical application of artificial neural networks, 80% to 90% of neural network models are based on BP neural networks or their variations [10]. BP neural network is composed of the input layer, output layer, and several hidden layers in between, each layer has several nodes. First, the data of the prediction model is entered from the input layer, and processed by the hidden layer, then transmitted to the output layer. When the output value from the network differs greatly from the expected value of the network, the error will be allocated to each layer in the reverse direction. The network can constantly adjust the parameters according to the gap between the two values until the error reaches the required accuracy range to stop the cycle. The advantage of the neural network is that it can autonomously train, learn, and store the internal link between input and output data, and constantly adjust the connection weight between neurons at each layer so that the network's output is constantly close to the real price [11].

2.2. Data

The data selected for this study is from August 22, 2019, to March 11, 2024. The data is selected from the China Statistical Yearbook, the State Administration of Foreign Exchange, the People's Bank of China, and the US Bureau of Labor Statistics website. The data source is reliable. The data sample is large, the error in data is small and the data is more accurate. A total of 1081 sample points were used for neural network training from August 22, 2019, to October 19, 2023, and a total of 100 sample points were used for test verification from October 20, 2023, to March 11, 2024.

3. RMB Exchange Rate Analysis and Forecast

The analysis is based on the BP neural network. In this thesis, a 3-layer neural net is selected, consisting of one input layer, nine middle nodes, and one export layer. The number of training rounds is 1000, the training goal is le-8, and the learning rate is 0.01. The remaining 100 sets of data are used to test the BP network that has been trained. The horizontal coordinate in Fig. 1 is the prediction sample in units. The ordinate is the exchange rate in units of 100. R^2 represents the suitable accuracy. The R^2 value reaches 0.94264. The true value of the exchange rate is indicated by the dashed blue line, and the solid red line reveals the predicted value. In Fig. 2, the horizontal coordinate is the predicted sample in units. The red circle indicates that the relative error is small when the number of prediction samples is different, indicating that the accuracy of the prediction is higher.

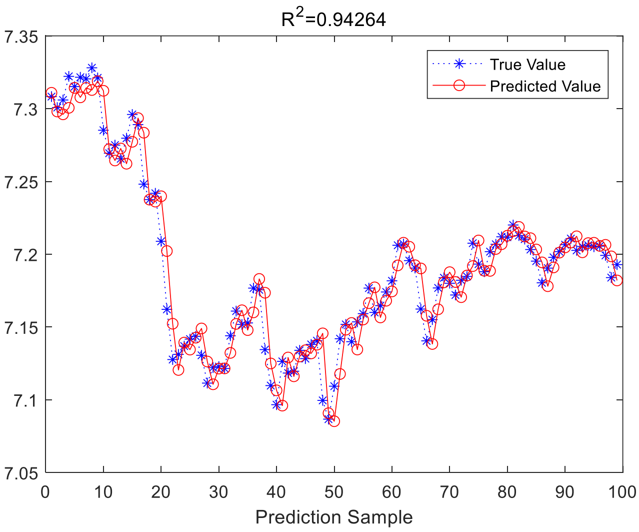

Fig. 1 Comparison and fitting accuracy between the predicted results and the actual results of the BP neural network (Photo/Picture credit: Original).

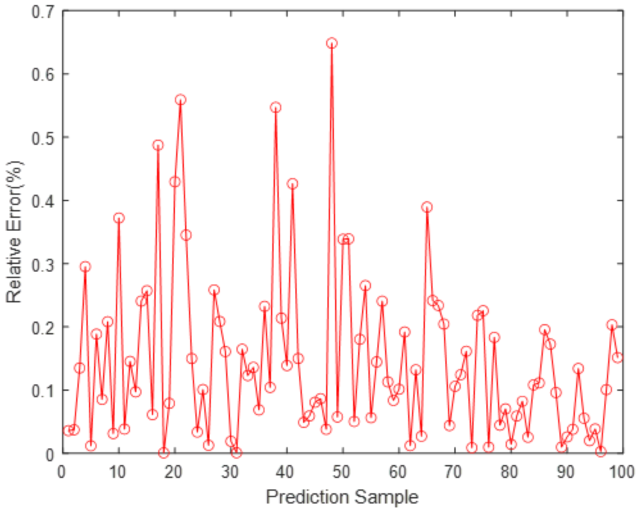

Fig. 2 The proportional error between the true value and the predicted value (Photo/Picture credit: Original).

4. Discussion

4.1. Analysis of Training Results

In Figure 1, R^2 represents the appropriate accuracy. The R ^ 2 value reaches 0.94264. The dashed blue line represents the real value of the exchange rate, and the solid red line shows the predicted value. The trend of the two lines is similar and there are a lot of overlapping parts, which indicates that the network model can forecast the exchange rate change more accurately. Figure 2 shows the relative error while increasing predicted samples. The relative error of some nodes reaches 0, which displays that the prediction is very accurate. Gradually increase hidden layer node number from 5 to 20, and the maximum relative error fluctuates around 0.6. With the increasing number of layer nodes that are hidden, the neural network's learning ability is enhanced, which makes the effective information in the prediction model disappear, the error of the training set and the test set increase, the generalization ability of the neural network deteriorates, and the problem of overfitting occurs.

4.2. Model Performance Evaluation

The applicable accuracy can reach about 94.2%, indicating that the results are according to the actual data and the relative error is small. The model can predict exchange rate changes accurately, and it has good stability and forecasting ability, especially in short-term forecasting. However, in the long-term exchange rate forecast, the accuracy and stability of this model are significantly decreased compared with the short-term forecast, which may be because various interfering factors in the long-term forecast are more than that in the short-term forecast, and the influence is more obvious.

4.3. Analysis of Parameter Adjustment Effect

Modify the training parameters, change the number of training rounds to 100000, change the training target to le-15, and keep the rate and the number of hidden layer nodes unchanged. In Fig. 3, the horizontal coordinate is the forecast sample, and the vertical coordinate is the exchange rate. R^2 represents the accuracy of the BP neural network. The R^2 value reaches 0.96389. The true value can be shown by the dashed blue line, and the solid red line manifests the predicted value. The two lines are similar. The coincidence degree is high. It shows that the prediction effect of the model is better.

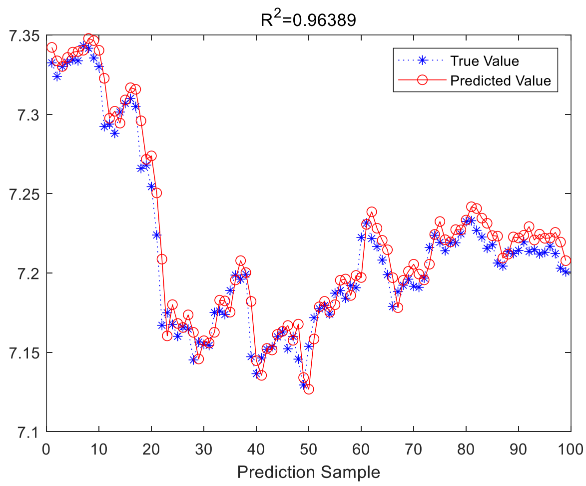

Fig. 3 Comparison and fitting accuracy between the predicted results and the actual results of the BP neural network (Photo/Picture credit: Original).

In Fig. 3, R^2 represents the fitting accuracy of the BP neural network. After modifying parameters, the fitting accuracy has been boosted to 96.3%, while the maximum relative error has also decreased. This indicates that the neural net model after training has relatively high accuracy and small error, the network generalization ability is good, and it can better predict the change of the exchange rate between the US dollar and RMB. The comparison between Figure 1 and Figure 3 shows that the fitting precision of the model is improved, the prediction ability is further improved, and the accuracy and stability of the prediction are improved when the parameters of the neural network. The number of hidden layer nodes is gradually increased from 5 to 20, and the maximum relative error fluctuates around 0.45. Compared with the relative error of the first result, the training set's error and the test set's error are reduced, and the probability of an overfitting problem is reduced.

4.4. Model Application Prospect

The fluctuation of USD/RMB price will not only directly affect import and export trade, but also have a profound impact on cross-border investment, international capital flow, and other aspects. This model can accurately predict the change in the exchange rate between the US dollar and RMB, and provide an important reference for financial institutions and personnel engaged in the financial industry, to help them avoid various investment risks in a timely and effective manner and reduce losses caused by exchange rate changes. At the same time, it is of great significance for foreign exchange management to effectively avoid market risks.

4.5. Research Limitations and Prospects

There are limitations to this study. The number of sample data selected is relatively small, and the prediction accuracy can be further augmented by increasing the amount of data. As far as neural network parameters are concerned, the ability to generalize is weak, the relative error between the training set and test set is large while the number of hidden layer nodes is large, and the problems of overfitting occur. It can be solved by modifying the parameters of the model, setting a reasonable number of hidden layer nodes, adding a genetic algorithm, or adding regular terms. The accuracy of exchange rate prediction can be limited simply by relying on the BP neural network. In future research, other mathematical methods should be incorporated or the structural code and parameters of the neural network should be further modified and optimized to improve the prediction accuracy and generalization ability.

5. Conclusion

The befitting accuracy of the BP neural network is as high as 96%. The result shows that the constructed network can fit the trend of USD/RMB exchange rate well.

It can be seen from the test results that the BP network after training has relatively high prediction accuracy, and the error of judging the trend of the USD/RMB exchange rate is small, and the network is good at generalizing. Therefore, through the BP network, the exchange rate trend can be judged to a certain extent under certain conditions.

Through the above analysis, it can be seen that the BP neural network better fits the trend of USD versus RMB, and the prediction effect is good. However, because the exchange rate market is a complicated system with erratic changes, and the variables that affect the exchange rate cannot be completely ascertained, the BP neural network model in this paper is only a prediction based on historical data and does not take other factors affecting the exchange rates changes such as balance of payments and interest rates into account.

Therefore, the accuracy of exchange rate prediction simply depends on the BP neural network is astricted. In future research, other methods should be incorporated or the structural code and parameters of the neural network should be further modified and optimized to enhance the prediction accuracy and the ability to extend.

References

[1] LuYuanYuan. Based on the GARCH - ELMAN model of RMB exchange rate prediction. Journal of Modern Business, 2022, (13): 56-60.

[2] Deng Jingwei. Research on Foreign exchange rate prediction based on neural network. Jinan University, 2017.

[3] Yan Haifeng, Xie Lili. RMB exchange rate prediction based on GARCH-M model. Journal of Chongqing Technology and Business University (Social Science Edition), 2009, 26 (04): 41-44.

[4] Xu Shaoqiang, Li Yamin. RMB Exchange rate forecast with reference to "Basket" currencies: An empirical method based on ARMA model. International Economic Review, 2007, (03): 30-40.

[5] Carriero A, Kapetanios G, Marcellino M. Forecasting exchange rates with a large Bayesian VARIJ. International Journal of Forecasting, 2009, 25(2): 400-417.

[6] Refens A N, Barac M A, Chen L, et al. Constructive learning and its application to currency exchange rate forecasting. Neural Computing & Application, 1993, 1 (1): 465-493.

[7] Dai Xiaofeng, Xiao Qingxian. Research on Time Series Analysis Method and Application of RMB Exchange rate Forecast. Journal of University of Shanghai for Science and Technology, 2005, 27 (4): 341-344.

[8] Xu Panpan. RMB Exchange rate forecast based on ARMIA-LSTM combination model. Northeast university of finance and economics, 2022.

[9] Wang Li, Yuan Peidong. The RMB exchange rate based on signal analysis and neural network forecasting model research. Journal of Gilu Industrial University, 2020, 34 (5): 61-67.

[10] Feng Wenfang. Analysis of RMB/USD exchange rate trend based on BP neural network. Hebei Enterprise, 2014(1): 46-47.

[11] Yu Dan. Research on Exchange rate prediction based on a synthetic artificial neural network model. Lanzhou Jiaotong University, 2019.