ISSN: 2472-3703 DOI: 10.6911/WSRJ.202004_6(4).0024

RMB Exchange Rate Prediction Based on ARIMA and BP Neural Network Fusion Model

Mingzhu Liao[1]

[1]School of Economics, Jinan University, Guangzhou 510630, China.

Abstract

The data structure of the RMB exchange rate time series can be decomposed into linear and non-linear parts. This paper uses the ARIMA model to predict the linear subject of the series, and then uses the BP neural network model to estimate its nonlinear residuals and fuses together to form a combined model. For the prediction of RMB exchange rate, the research found that the combined model is better than the single model.

Keywords

RMB exchange rate, ARIMA, BP neural network.

1. INTRODUCTION

Because China's economic situation and the international economic environment are undergoing a dynamic adjustment process, especially China's economic situation has changed very rapidly since the reform and opening up, China's exchange rate system has also been continuously adjusted in recent years. From the beginning of the reform and opening up, China's exchange rate was officially announced. This exchange rate often differs greatly from the market. However, since 1994, the official RMB exchange rate has been combined with the exchange rate of the foreign exchange market. A single, managed floating exchange rate system based on market supply and demand was introduced. It was also in 1994 that China's exchange rate jumped from 5.8 in 1993 to 8.7, and the RMB depreciated greatly, but remained at a level of about 8 for a long time afterwards. Later in 1997, due to the impact of the East Asian financial crisis, China chose to keep the exchange rate intact for the sake of a stable currency, and gradually evolved into a de facto pegged exchange rate system. Subsequently, in 2005, the People's Bank of China announced the implementation of a managed floating exchange rate system based on market supply and demand, with reference to a "basket" of currencies, making the reform of the exchange rate system a key step towards marketization. In August 2008, in response to the financial crisis, China adopted a temporary exchange rate policy focusing on the US dollar, which appropriately reduced the fluctuation range of the RMB exchange rate. However, on June 19, 2010, the central bank restarted exchange rate reform and decided to further advance the reform of the RMB exchange rate formation mechanism and increase the flexibility of the RMB exchange rate. It is foreseeable that China's exchange rate adjustment will become more market-oriented in the future, and the fluctuation of the exchange rate will also increase.

Obviously, how to accurately estimate the exchange rate trend, provide the basis for the development of future monetary policy, in order to control inflation, against the interference of the external economy, to maintain stable economic growth target, will be an important issue in front of the central bank. In addition, exchange rate trends to determine future changes in the right or not, is also an important factor affecting business risk control capacity and international competitiveness; the same time, institutional investors and individuals want to assign the change by predicting the trend of the exchange rate is the proportion of their assets and Risk management provides useful decisions. Therefore, it is of great practical significance to

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202004_6(4).0024

correctly predict the trend of the RMB exchange rate by constructing a reasonable prediction model in combination with China's actual situation.

2. LITERATURE REVIEW

There are many research methods of exchange rate prediction in China, but the most commonly used is the exchange rate prediction based on the GARCH and ARIMA methods. The ARIMA model is widely used in exchange rate research because of its simplicity, feasibility, and flexibility. The exchange rate prediction was mainly studied by linear models at the beginning. The ARMA and A RIMA models were mainly used. For example, Dai (2005) used the ARIMA model to predict the exchange rate of the RMB against the US dollar [1]. Xu (2007) used the ARMA model to predict the exchange rate of the euro and the yen, and then based on the reference to the "basket" currency principle determined by the RMB exchange rate reform, combined with the weighted calculation of the US dollar exchange rate, predicted the medium and long-term trend of the RMB exchange rate [2]. However, many research literatures show that the time series data of exchange rates mostly contain non-linear relationships. So in order to improve this defect, the application of threshold autoregression (TAR) model, autoregressive conditional heteroscedasticity (ARCH) model, generalized autoregressive conditional heteroscedasticity (GARCH) model, etc. have also begun to attract attention. Hui (2003) based on GARCH model to predict the RMB exchange rate is relatively early to start using GARCH study of the RMB exchange rate forecasting model [3]. After that, Wei(2014) based on the GARCH model and the ARIMA model, respectively to study the exchange rate of RMB against the US dollar and predict the trend of RMB appreciation [4][5].

However, most of the ARIMA models are used to study the linear trend, and GARCH can study the non-linear part. However, the above two methods are parameter estimation, which has certain limitations. However, with the development of neural network research, neural network methods have been continuously applied to exchange rate prediction. As early as Hann (1996), neural network methods were used to predict currency exchange rates. Monthly and weekly data were used to study whether nonlinear methods are better than linear models. However, it was found that neural networks cannot explain the economic meaning of exchange rate prediction [5]. Later, Leung (2000) used the G RNN method to study the fluctuation of the pound-dollar exchange rate. He believed that the neural network method can indeed improve the accuracy of prediction. It lies in analyzing the economic problems of exchange rate prediction [6]. With the increase of foreign research, more and more neural network methods are continuously introduced into the field of exchange rate research. Xie (2008) compared several neural network methods to predict the RMB exchange rate, and considered that the components of the neural network method considered the exchange rate [7]. Linear and non-linear characteristics. However, for data with linear features, the effect of neural networks is often not as good as traditional processing methods such as ARIMA. In addition, Bayesian average classification regression model is also used in exchange rate prediction. In fact, each method has certain limitations, which is unavoidable.

Due to the limitations of the single model method, the combination model method has also begun to be applied to exchange rate prediction research. Hibon (2005) to 3003 sequences were different types of data based on a comparative study, the results showed that overall predicted effect of the combination was significantly better than the model prediction of the effect of a single model [8]. Tseng (2002) used the SARIMABP model composed of a seasonal ARIMA model and a neural network to predict seasonal time series [9]. Xiong (2011) also conducted a research on exchange rate prediction based on the fusion method of ARIMA and particle swarm neural network [10].

This paper synthesizes the previous research methods and selects the combined method of ARIMA and BP neural network to predict the RMB exchange rate.

3. THEORETICAL MODEL

3.1. ARIMA Model

ARIMA is an extension of the autoregressive moving average model (ARMA) to meet the requirements of time series stationarity. If the non-stationary sequence xt undergoes d times difference to form a stationary sequence, the ARMA (p, q) model can be used to model and predict the stationary sequence, and an ARIMA (p, d, q) model is actually formed. For the stationary sequence xt forming D after the d times difference, the corresponding ARMA (p, q) model can be written as follows:

$$x_t = \theta_t + \sum_{i=1}^{p} u_i x_{t-i} + \sum_{j=0}^{q} \theta_j \varepsilon_{t-j}$$

εt is a random error at time t. It is a normal white noise sequence with a normal distribution of 0 and a variance of σ2. The advantage of using the ARIMA model is that the stationary series formed after the d times difference can be directly used for prediction research using the ARMA (p, q) method.

ARIMA modeling and prediction include 4 steps: First, the sequence is smoothed. If the sequence is non-stationary, the difference can be made to meet the stationary condition. Second, the model is identified, mainly through the autocorrelation coefficient and partial autocorrelation. coefficient to determine a model order of p and Q; and then model parameter estimation and diagnosis, estimation of the model parameters, a significance test parameters and test the randomness of the residuals, and determines whether the model type if desirable; Finally, the model with appropriate parameters selected is used for prediction.

3.2. BP Neural Network Model

A BP neural network consists of an input layer, an output layer, and one or more intermediate layers, also known as a hidden layer. Hidden layers can capture non-linear relationships between variables. Each layer consists of multiple neurons that are connected to neurons in adjacent layers. Because these networks contain many interacting non-linear neurons in multiple layers, they can capture relatively complex phenomena. A neural network can be trained on historical data of a time series to capture the characteristics of the time series. Model parameters (connection weights and node biases) will be adjusted iteratively through a process that minimizes prediction errors. The process is shown in Figure 1:

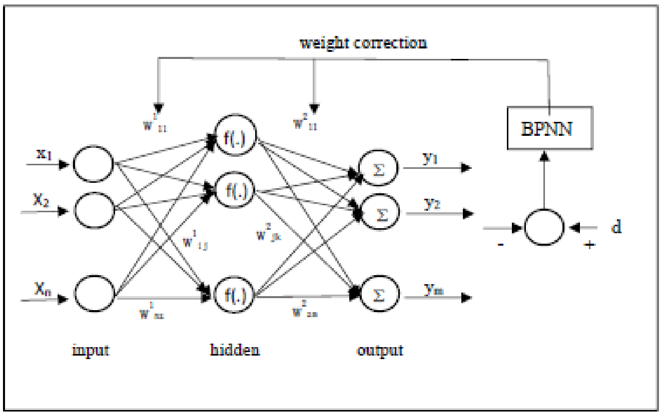


Figure 1. BP neural network

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202004_6(4).0024

For each training iteration, a randomly selected input vector from the training set is submitted to the input layer of the network being trained. Use the following equation to propagate the output of each processing unit (or neuron) forward through each layer of the network:

$$a^{(1)}{}_j = \sum_{i=1}^{D} w^{(1)}{}_{ji} \times x_i + w^{(1)}{}_{j0}$$

$$z^{(1)}{}_j = h(a^{(1)}{}_j)$$

$$a^{(2)}{}_j = \sum_{i=1}^{D} w^{(2)}{}_{ji} \times z_i + w^{(2)}{}_{j0}$$

$$y_k = f(a^{(2)}{}_k)$$

Is shown above the data from the input layer x through 1 hidden layer to the output layer y calculation process. The h () function in the hidden layer is the activation function. The tanh function is commonly used, and the final conversion function f () is to use the sigmoid function to convert the output value to a value between 0-1.

$$y_k = \frac{1}{1+\exp(-a_k^{(2)})}$$

In the hidden layer input initial coefficient matrix W, BP content is the core algorithm error by the true value of the output value of the hidden low-level stacked generations, in order to find the optimal model error is minimized. The formula for error progression is as follows:

$$\delta_k^{(2)} = (T_k - y_k) \times f'(a_k^{(2)}) = (T_k - y_k) y_k (1 - y_k)$$

$$\delta_j^{(1)} = \sum_{k=1}^{m} \delta_k^{(2)} \times w_{jk}^{(2)} \times f'(a_j^{(1)}) = \sum_{k=1}^{m} \delta_k^{(2)} \times w_{jk}^{(2)} \times z_j (1 - z_j)$$

For incremental changes in iterative weights, where c1 is the learning rate that controls the learning speed:

$$w_{ji}^{(2)} = w_{ji}^{(2)} - c_1 \delta_j^{i+1} \times z_{ij}$$

$$w_{ji}^{(1)} = w_{ji}^{(1)} - c_1 \delta_j^{(1)} x_{ij} = w_{ji}^{(1)} - c_1 \sum_{k=1}^{m} \delta_k^{(2)} \times w_{jk}^{(2)} \times z_j (1 - z_j) x_{ij}$$

BP neural network can be summarized as the following five steps: First, normalize the data set and prepare the input data. Second, determine the architecture and parameters. It includes setting the learning rate, momentum factor, and architecture. The architecture includes setting the number of hidden layers and the number of nodes in each hidden layer. The setting of these parameters and architectures has no established standard except for the method of trial and error. Third, training, iterative update coefficients, where the stopping criterion is that the number of iterations reaches a predetermined value or the sum of squared errors is lower than a predetermined value. Fourth, choose the network with the smallest error. Finally, predict future results.

3.3. The ARIMA and BP Neural Networks Fusion Model

As mentioned earlier, the actual time series data usually have linear and non-linear composite features, neither a single ARIMA model or BPNN model can describe the composite features well. However, although ARIMA and B P NN each have obvious defects, the shortcomings of this model are the advantages of another model. In other words, there is obvious complementarity between ARIMA and B P NN. Therefore, the fusion of the two may produce better prediction results than a single model.

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202004_6(4).0024

First we propose the hypothesis: the time series yt includes two parts, a linear autocorrelation subject Lt and a residual Et containing a nonlinear part, namely:

$$y_t = L_t + E_t$$

Based on the above assumptions, we can first use the ARIMA model to model and predict the linear part $\hat{L}$. There is a difference between the predicted value and the original sequence value, which is the residual e:

$$e_t = y_t - \hat{L}_t$$

A residue comprising non-linear relationship of the original sequence, we use on BPNN models to approximate this linear relationship, the on BPNN linear prediction part, on BPNN is the requirement for the data input layer, and ARIMA generated residues The difference sequence and prediction value are used as the input layer of the BP network. BPNN finds a suitable network based on the input layer samples provided by ARIMA and predicts the nonlinear part of the residual sequence, so the residual sequence can be divided into BPNN prediction. Non-linear part $\hat{N}_t$ and other errors ε_t:

$$e_t = f(e_{t-1}, e_{t-2}, \ldots, e_{t-n}) + \varepsilon_t = \hat{N}_t + \varepsilon_t$$

Where f is a non-linear function determined by BPNN, ε_t can be regarded as a random error. In this way, the prediction of the sequence y value can be composed of the linear prediction of ARIMA $\hat{L}$ and the nonlinear prediction of neural network prediction $\hat{N}_t$:

$$\hat{y}_t = \hat{L}_t + \hat{N}_t$$

In this way, through the comprehensive application of the two models, they can give full play to their respective advantages and complement each other at the same time.

4. AN EMPIRICAL STUDY OF RMB EXCHANGE RATE PREDICTION BASED ON A HYBRID MODEL

4.1. Data Processing and Descriptive Analysis

As mentioned earlier, China’s exchange rate of RMB against the US dollar has taken into account the actual market level after the reform of the exchange rate system in 1994, and the data is relatively reliable. The exchange rate in 1994 was officially determined, and there may be a relatively large deviation from the market situation, so the data before 1994 are not suitable for research with the following data. Therefore, this article mainly selects the RMB exchange rate data of the average RMB exchange rate during the monthly period from 1994 to June 2018. There are a total of 294 data. The data comes from the BIS website. The data from 1994 to 2016 are used as training samples for modeling, and the data after 2017 are used as prediction samples.

At the same time, the log rate is used to deal with exchange rate prices to reflect exchange rate fluctuations. Pt is the exchange rate price and Rt is the log rate of return:

$$R_t = \ln P_t - \ln P_{t-1}$$

According to the analysis of the original serial data of the exchange rate of RMB against the US dollar and the data of the calculated logarithmic return rate, it can be roughly seen that China's RMB exchange rate has shown a significant downward trend since 1994, that is, the trend of China's RMB appreciation. At the same time, look at the logarithmic rate of return of the monthly data, reflecting the fluctuation of the exchange rate from 2005. The fluctuation of the exchange rate is relatively obvious. Prior to this, the fluctuation of the exchange rate was relatively small, which also reflected that China implemented managed floating in 2005. Prior

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202004_6(4).0024

to the exchange rate system, China's exchange rate remained basically unchanged, but also because the strategy of pegging the US dollar was actually adopted. Since then, the exchange rate system has gone one step further towards liberalization and marketization, so exchange rate fluctuations have become more apparent.

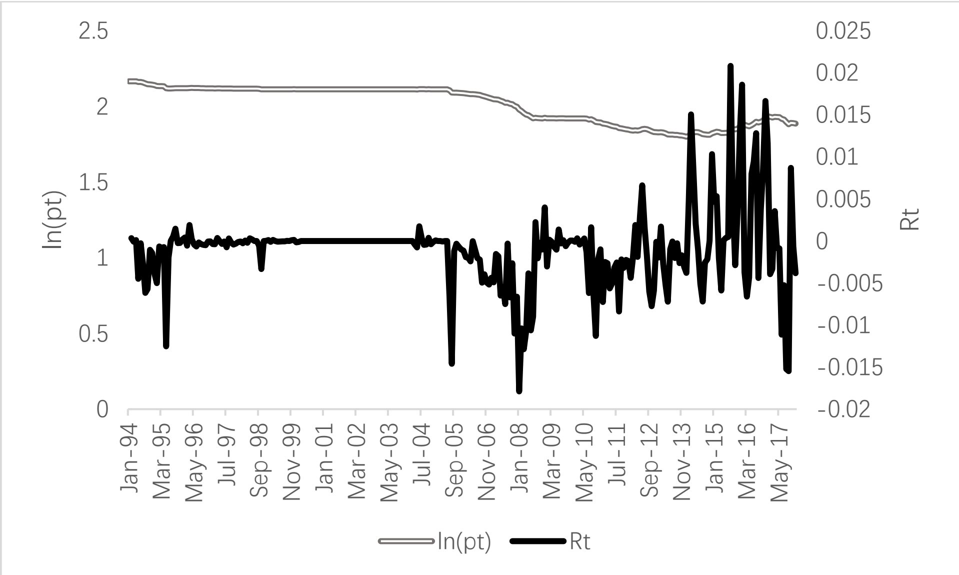


Figure 2. RMB exchange rate trends and fluctuations

4.2. Model Construction and Empirical Analysis

With reference to other research literatures, the exchange rate is generally processed on a logarithmic basis. The first is to reduce the trend of exchange rate data, and also to make the entire series more stable, which is convenient for subsequent estimation. So in the data processing part, the exchange rate prices have been processed logarithmically into a series of logarithmic returns. This article studies the prediction of exchange rates, not the value of direct exchange rates. There have been many studies in previous studies, and such direct value predictions often have large deviations. Therefore, logarithmic processing is required. Reflect changes in exchange rates. Therefore, this article studies the exchange rate fluctuations to estimate and predict the exchange rate, and uses the hybrid model of ARIMA and BP neural network to assume that the fluctuation of the exchange rate includes a linear part and a non-linear part. The rest are unestimated random residuals. It is under this premise that our next mixed model estimation can be unfolded. So the next step is to analyze the logarithmic rate of return.

4.2.1. ARIMA model estimation

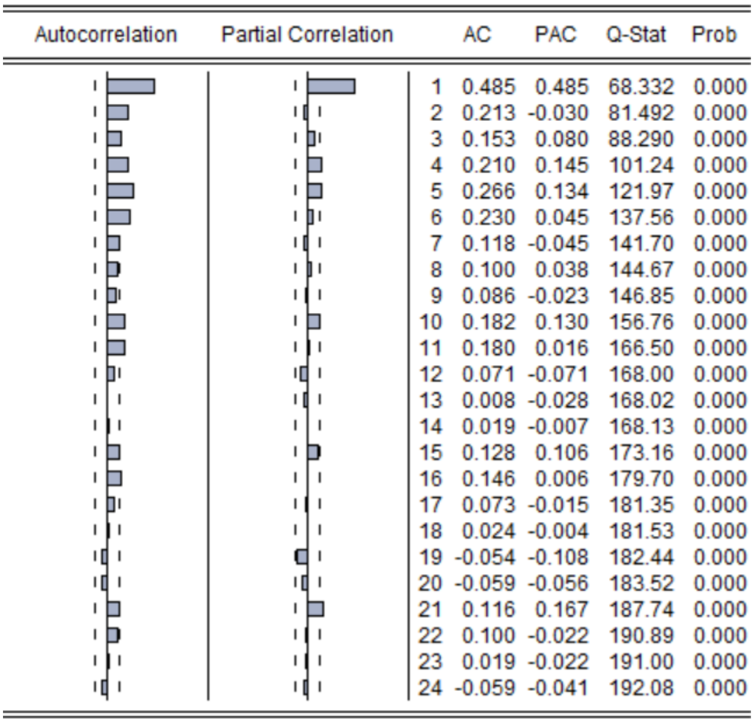
This article uses Eviews7 software to construct the ARIMA model. The logarithmic return sequence Rt has taken the logarithm of the exchange rate price and made a first order difference. This process can eliminate the trend of the original sequence and reduce the fluctuation of the sequence. If the sequence has reached a steady state, the ARIMA of the log rate the conduct of a difference. First, the unit Rt test was performed on the sequence Rt, and the significance test passed the significance level of 10%, 5%, and 1%. It shows that the logarithmic return series is a stable time series. In fact, both the constant term and the constant term and the trend term pass the test. However, according to the AIC minimum criterion, the test type of the ADF is the best result if the constant term is included.

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202004_6(4).0024

Table 1. ADF inspection situation

Inspection type	Significance level	ADF test value	Critical value	Conclusion
Contains constant terms	10%	-8.665385	-3.993471	smooth
	5%	-8.665385	-3.42707	smooth
	1%	-8.665385	-3.136819	smooth

After confirming that the Rt sequence is a stationary sequence, because the Rt sequence has been differentiated when it is generated, which is equivalent to a first-order difference of the log-processed exchange rate, d=1. The autocorrelation and bias of the sequence are further observed later Correlation graph to confirm the p, q order of ARIMA. As shown in Figure 3:



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.485	0.485	68.332	0.000
		2	0.213	-0.030	81.492	0.000
		3	0.153	0.080	88.290	0.000
		4	0.210	0.145	101.24	0.000
		5	0.266	0.134	121.97	0.000
		6	0.230	0.045	137.56	0.000
		7	0.118	-0.045	141.70	0.000
		8	0.100	0.038	144.67	0.000
		9	0.086	-0.023	146.85	0.000
		10	0.182	0.130	156.76	0.000
		11	0.180	0.016	166.50	0.000
		12	0.071	-0.071	168.00	0.000
		13	0.008	-0.028	168.02	0.000
		14	0.019	-0.007	168.13	0.000
		15	0.128	0.106	173.16	0.000
		16	0.146	0.006	179.70	0.000
		17	0.073	-0.015	181.35	0.000
		18	0.024	-0.004	181.53	0.000
		19	-0.054	-0.108	182.44	0.000
		20	-0.059	-0.056	183.52	0.000
		21	0.116	0.167	187.74	0.000
		22	0.100	-0.022	190.89	0.000
		23	0.019	-0.022	191.00	0.000
		24	-0.059	-0.041	192.08	0.000

Figure 3. Autocorrelation and partial correlation of the logarithmic return sequence Rt

According to the correlation diagram, it can be roughly determined that p is between 0 and 1 and q is between 1 and 3. A comparative analysis is performed according to the AIC minimum criterion. The results are shown in Table 2 below. Finally, the model can be determined to be ARIMA (1,1,2).

Table 2. Selection based on model AIC

Model	AIC	p- value	Whether to include constant terms (is it significant)
ARIMA (1,1,1)	-8.5979	0.000	Yes
ARIMA (1,1,2)	-8.6233	0.000	No
ARIMA (1,1,3)	-8.6117	0.000	No

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202004_6(4).0024

Model estimation results:

$$R_t = 0.9424R_{t-1} - 0.4818\varepsilon_{t-1} - 0.2920\varepsilon_{t-2} + \varepsilon_t \quad (1)$$

t-value (24.0074) (-6.675) (-4.442)

p-value (0.0000) (0.0000) (0.0000)

The model parameters have been tested, and according to the autocorrelation analysis chart of the model's error sequence, it can be known that its autocorrelation coefficient and partial correlation coefficient are small, and both fall into the execution interval of 95% confidence level. The ADF test is performed on the residuals. The P value is close to 0, which indicates that the residual sequence is stable. It also shows that the established ARIMA model is suitable. The prediction of the exchange rate can be written as follows:

$$\ln P_t = 1.9424 \ln P_{t-1} - 0.9424 \ln P_{t-2} - 0.4818\varepsilon_{t-1} - 0.2920\varepsilon_{t-2} + \varepsilon_t \quad (2)$$

4.2.2. BP neural network to identify non-linear parts

After performing the model analysis using ARIMA, the residual sequence, that is, the non-linear part et can be obtained, and then the neural network method is used to perform model estimation and prediction on the non-linear part of et. This article uses python software to write code to implement BP neural network. Because the setting of the number of nodes in the hidden layer has a great impact on the actual prediction results, there is currently no method to determine the number of nodes in the hidden layer except trial and error.

And because we are using the residual data from previous periods, there is no clear way to predict how much parameter data should be used in the current period. In the end, according to the forecast situation, this paper continuously trial and error adjusts to determine the number of input layer nodes and hidden layers. Number of nodes. However, the number of hidden nodes has a broad range: $n\_hidden = \sqrt{n\_input \times n\_output} + \alpha$ .where n_hidden is the number of nodes in the hidden layer, n_input is the number of nodes in the input layer, n_output is the number of nodes in the output layer, and α is a value of 1-10. Because there are many times of repeated attempts, the following is a neural network model with better learning effect. Due to different settings, the learning results of the neural network are different. Therefore, the error is calculated by comparing the calculation result of the network learning with the real value. Models with better learning results. Combining the error of the training set from 1994 to 2016 with the error of the data test set from 2017 to the latest issue, the paper finally determined that the network model uses a 4x4x1 structure, that is, the input layer: et-1, et-2, et-3, et-4, the four lags of the residuals are the input layer, the learning rate is 0.01, and the momentum factor is 0.01.

Table 3. Neural Network Results

	Network 1	Network 2	Network 3
Number of input nodes	4	4	3
Hidden neurons	5	4	4
Learning rate	0.01	0.01	0.01
Momentum factor	0.01	0.01	0.01
Number of iterations	1000	1000	1000
Training set error	0.0126	0.0006966	0.0013272
Test set error	0.0005937	0.0002939	0.0005066

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202004_6(4).0024

This paper chooses network 2 to predict the residuals. Figure 4 shows the variation of the training set error during the iteration of the neural network. It can be seen that as the number of iterations increases, the error can be continuously reduced to 0.0007, but the number of basic iterations reaches 100, the error of the training set can hardly be reduced. And this error is basically close to 0, which also shows that the neural network has a better prediction effect. Then based on this learning network to make predictions on the following data.

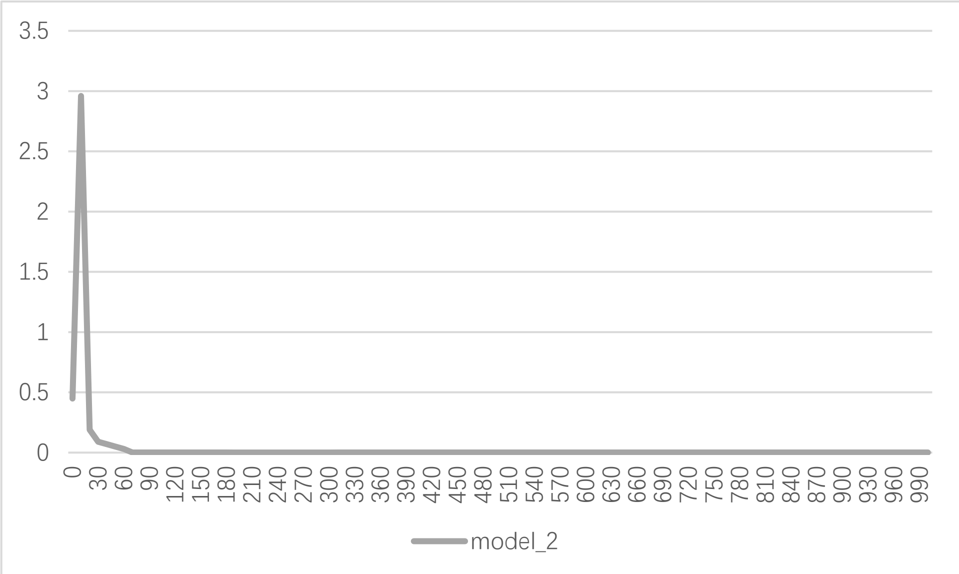


Figure 4. Errors of the neural network model

4.2.3. Combined prediction results

Linear part was predicted by the BP neural network, and the two were added together as the predicted value of the exchange rate $\hat{y} = \hat{L} + \hat{N}$. From the results of the exchange rate prediction sequence, comparing the single model ARIMA or neural network to predict the fluctuation of the exchange rate, it is found that the deviation from the actual value is relatively large. This article predicts the data from 2017 to 2018, which is just compared with the actual value. It is found that the combined forecast can well fit the fluctuation of the actual exchange rate, indicating that this combined model can better predict the exchange rate.

In order to more fully describe the forecasting effect of the combined model on the exchange rate, this article uses the root-mean-square error RMSE, the average absolute error MAE, and the inequality coefficient T. Three indicators are used to measure the model's prediction effect. At the same time the accuracy of the prediction join direction DA index, a measure of the accuracy of prediction of exchange rate changes direction, because the direction of exchange rate fluctuations is a very important market speculators decision -making basis.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

$$MAE = \frac{\sum_{i=1}^{N}|y_i - \hat{y}_i|}{N}$$

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202004_6(4).0024

$$T = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i)^2} + \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i)^2}}$$

$$DA = \frac{\sum_{i=1}^{N-1} a_i}{N-1}, \quad a_i = \begin{cases} 1 & if (y_{i+1} - y_i)(\hat{y}_{i+1} - y_i) > 0 \\ 0 & \text{other} \end{cases}$$

The results are shown in Table 4 below. The RMSE and MAE values are small, indicating that the deviation between the predicted value and the actual value is relatively small. The T metric indicates the prediction effect. The closer T is to 0, the better the prediction effect of the model. DA at 0. 87 about the level of accuracy of the prediction direction is not too high, the reason is selected paper data monthly data, the direction of greater exchange rate volatility is more difficult to predict. However, it can be seen from Figure 5 that the curve predicted by the combination model can better reflect the actual fluctuation of the RMB exchange rate. Judging from the overall and forecast results, this combination model has a better forecast effect on exchange rates. Comparing the effects of a single model, we can see that the combined model is far better than the single model.

Table 4. Result

index	RMSE	MAE	T	DA
Combination model	0.0100	0.0076	0.0027	0.87
ARIMA model	0.0693	0.0652	0.0318	0.69
Neural network model	0.0486	0.0591	0.0236	0.62

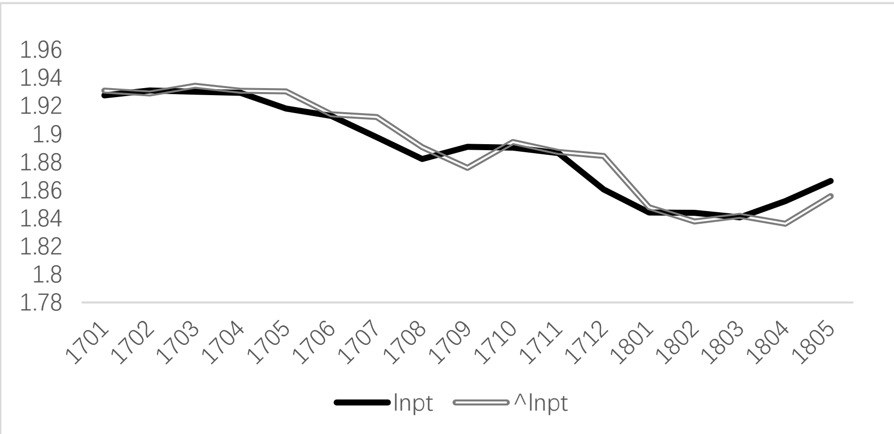


Figure 5. Real RMB exchange rate and forecast

5. CONCLUSION

Whether it is a single ARIMA model or a neural network model that directly predicts exchange rates, there are advantages compared with each other, but there are also unavoidable disadvantages. However, through the fusion of the two, they can complement each other and achieve better results in forecasting exchange rates.

This article predicts China's exchange rate by establishing a joint model of ARIMA and BP neural networks. The first is to use ARIMA to predict the linear part of the exchange rate, and the second is to use ARIMA's linear prediction to compare the result L with the real value Y to

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202004_6(4).0024

obtain a residual sequence. This residual sequence contains the nonlinear part of the exchange rate. Prediction of the non-linear part of the residual to get N, combining ARIMA prediction L and neural network non-linear residual prediction N, sum up to get the predicted value of the exchange rate. This predicted value can be more compared with the predicted value of a single model. Close to true. According to the prediction results of the combination model, we can see that the prediction effect of the combination model can well fit the fluctuation of the actual exchange rate. However, this article does not consider the impact of other factors on the exchange rate, and in fact the exchange rate will be affected by many factors of economic fundamentals, so based on historical time series data to make predictions, only short-term predictions can be made. The longer the time, the worse the prediction effect, and generally such predictions cannot see the future fluctuations, and can only judge the approximate trend. Although this paper uses the combination model method to make use of the nonlinear part of the neural network to make predictions, it still does not reflect the obvious fluctuations of the exchange rate in the future. This may also be related to the insufficient amount of data, resulting in the network's learning effect has not been good. Close to the actual situation. Because even though it can complementarity between the two models, but because learning neural network data is ARIMA based on, so ARIMA forecasting results are not affect the outcome of the neural network. But it will bring some deviations. But in general, the hybrid model can still make better predictions for future data than a single model.

REFERENCES

[1] X.F. Dai and Q.X. Xiao (2005). Time series analysis applied in prediction of RMB’s exchange rate. Journal of University of Shanghai For Science and Technology, vol.27, no.4, P.341-344.

[2] S.Q. Xu and Y.M. Li (2007). Refer to the prediction of RMB exchange rate of "a basket of currencies" --- an empirical method based on ARMA model. World Economic Papers, no.3, P.30-840.

[3] X.F. Hui and H.S. Liu and W. Hu etc. (2003). RMB exchange rate prediction based on time series GARCH model. Journal of Finance, no.5, P.99-105.

[4] H.Y. Wei and C.J. Meng (2014). Research on exchange rate prediction based on ARIMA model. Times Finance, no.3, P.13-15.

[5] H.Y. Wei and C.J. Meng (2014). Short-term exchange rate prediction based on GARCH model. Journal of Quantitative Economics, vol.31, no.1, P.81-84.

[6] TH. Hann and E. Steurer (1996).Much ado about nothing? Exchange rate forecasting: Neural networks vs. linear models using monthly and weekly data. Neurocomputing, no.10, P.323-339.

[7] MT. Leung, AS. Chen and H. Daouk (2000).Forecasting exchange rates using general regression neural networks. Computers & Operations Research, vol.27, no.11, P.1093-1110.

[8] C. Xie, O.Y. Liang (2008). Neural network methods for exchange rate prediction and comparison. Finance & Economics, no.5, P.47-53.

[9] M. Hibon and T. Evgeniou (2005).To combine or not to combine: selecting among forecasts and their combinations. International Journal of Forecasting, vol.21, no.1, P.15-24.

[10] F.M. Tseng, H.C. Yu and G.H. Tzeng (2002). Combining neural network model with seasonal time series ARIMA model. Technological Forecasting and Social Change, vol.69, no.1, P.71-87.

[11] Z.B. Xiong (2011). Research on RMB Exchange Rate Forecasting Model Based on Combining ARIMA with Neural Networks. The Journal of Quantitative & Technical Economics, no.6, p.64-76.