The Time Series Forecasting for CNY-USD Exchange Rate

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Abstract. China and the United States has worsened their foreign relationship after the trade war begin in 2018. Then the following policies and treaties also strongly affect the commercial activities of both sides. These also affect the exchange rate between Chinese YUAN and US dollar. First, this research is going to explain why two important time series forecasting models, neural network model and long short-term memory model, are used to predict the future exchange rate. Then the research would divide the exchange rate data into training set and testing set, then train the models with training set and forecast the exchange rate between Chinese Yuan and US dollar by using the R studio in programming. Finally compare the mean square error and mean absolute percentage error of the model's forecasting value and the testing set value to show which model would have the higher accuracy in predicting the currency exchange rate.

Keywords: CNY-USD exchange rate, neural network model, long short-term memory model.

1. Introduction

Nowadays, The U.S. consumer price index (CPI) has exceeded the government's 2% target since March 2021 in a large extent, and then it has risen every month since, soaring to 7.5% in January 2022, a 40-year high [1]. Then, the US federal reserve started its seventh round of interest rate hikes in March 2022. Besides, the foreign relation between China to US and Western Europe has remained deadlock since the Ukraine war and Chinese balloon incident. That significantly lead to the decoupling of foreign commercial trade and investment occurred between China and Western world (US and Western Europe countries), declining in Chinese exports and foreign investment for China. In this case, the exchange rate between Chinese Yuan (CNY or RMB) and the US dollar (USD) has depreciated significantly [2, 3]. Beginning on December 2022, the exchange rate has continued to depreciate, falling to 7.242CNY/USD in August 2023, which is the highest exchange rate since 2008 and which is higher than the highest point during 2018-2019 China-United States trade war [4]. So, whether the RMB will continue to depreciate in the future and how the RMB will fluctuate have become a hot topic of attention. Not only can the prediction of the RMB - US dollar exchange rate help people stop their losses in time in foreign trade and investment between China and the United States, but also help predict the future situation of the world.

The unstable of exchange rate could also affect the foreign student group. Approximately 300 thousand Chinese students only studied in colleges and universities in the United Stated in 2021 [5]. The average annual tuition for international students in US 4-year public college is more than 40,000 dollars and more than 50,000 dollars for private college [6]. These students have intensively contact with foreign currency exchange in their studying and living. The exchange rate could affect their school life in a large extent. Especially for students who cannot afford the expense on their own.

The purpose of this paper is using the appropriate forecasting model to forecast the future one-year trend for CNY-USD exchange rate. After consideration and optimization, this paper is going to use neural network model and Long Short-Term memory model to study and forecast the currency exchange rate. Compare to the former model that use only one layer of lagged input values to auto-calculate and fit the model like ARIMA model, neural network model could have a additional hidden layer to re-calculate the data that lagged value given, which means it calculate the original data twice by using the additional hidden layer. This way could make the final output effectively avoid the effect of some extreme values [7]. Also, neural network model has been proved by scholar authorities that could made a higher accuracy when forecasting the exchange rate and other economic data than the former ARIMA model. For Long Short-Term model (LSTM), three parts control the information of time step, the Forget gate, the Input gate and the Output gate. The forget gate could control whether the information from previous time step should be preserve or forget. The input gate quantifies the importance of the new information from the input. And the output gate could qualify the output, and finally use the gate to update the cell state and get the final output. LSTM model is a type of recurrent neural network (RNN) with additional memory cell. It has more complex cell structure than the neural network model with input, output and forget gates. And that makes the LSTM model perform better on long-term memory task [8]. Using LSTM model in time series forecasting may not efficient as the neural network model but it could make the exchange rate forecasting more precise and detailed.

2. Methods

2.1. Data Source

First of all is to set up the data set from FRED. The data set has been downloaded as the csv. Format with monthly CNY-USD exchange rate. Since China carry out the reform policy on their exchange rate, the data before 2006 is significantly different from before, hence the research will only use data from 2006 onward. The data split into training set and testing set. Training set is from January 2006 to September 2022, and it will be used for training the model and forecast the exchange rate. The testing set is used for testing the forecast model distribution and accuracy, and it will be the one year from September 2022 to August 2023.

2.2. Method introduction

The research is going to use the R studio to forecast the neural network model and long short-term memory model. The whole forecasting process has three stages. At first, both models are going to train and fit from the training set data between January 2006 to September 2022. The variables in the models are still undefined. This stage is to identify the variables of different models that could well fit the training data. Next, forecast the one-year data based on the fitted models. The length of the time series should be equal to the length of testing set in previous part. Then compare the forecasting value with the actual testing set value. The comparison will use the mean square error and the mean absolute percentage error to define the error of the model for forecasting the currency exchange rate. These two comparison ways are widely used in statistics and machine learning to compute the error of the estimated values and the observed values. The model with smaller errors would have better accuracy and that suggests higher reliability on CNY-USD exchange forecasting.

3. Results and Discussion

3.1. Neural Network Model Results

Since the training data set has already been given. The first step is to set the seed and then fit the neural network model in the training set. Use the “nnetar” code to automatically fit the model. Then use “forecast” to forecast the expected one-year value. Because the neural network model cannot automatically create the predicted interval, hence we should use “forecast (fit.RNN, PI=TRUE, h=12)” and create the plot of fitted and forecast value.

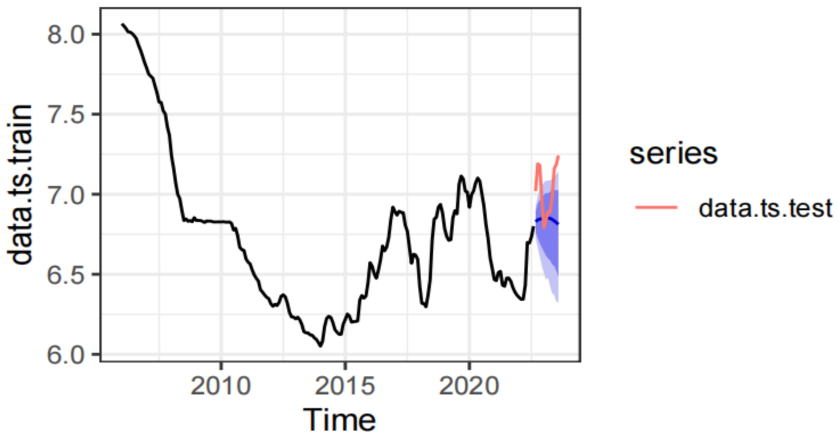

Fig. 1 Forecasts from NNAR (2,1,2)[12]

The variables of the fitted neural network model is NNAR(2,1,2)[12]. That means this model has inputs yt-1, yt-2, and yt-12, and 2 neurons in the hidden layers. From Fig. 1, the blue line is the forecasting value for one-year exchange and the red line is the value of testing set. The shade with blue color is the 95 percent predicted interval for this forecasting model.

Then check the residual to verify the validity of the model. We could use the Ljung-Box text to show that forecasting from NNAR(2,1,2)[12] would have Q*=21.766, df=24 and p-value = 0.59032. Ljung-Box test shows the p-value is a very large value, which means that we failed to reject the hypothesis that the data is independently distributed.

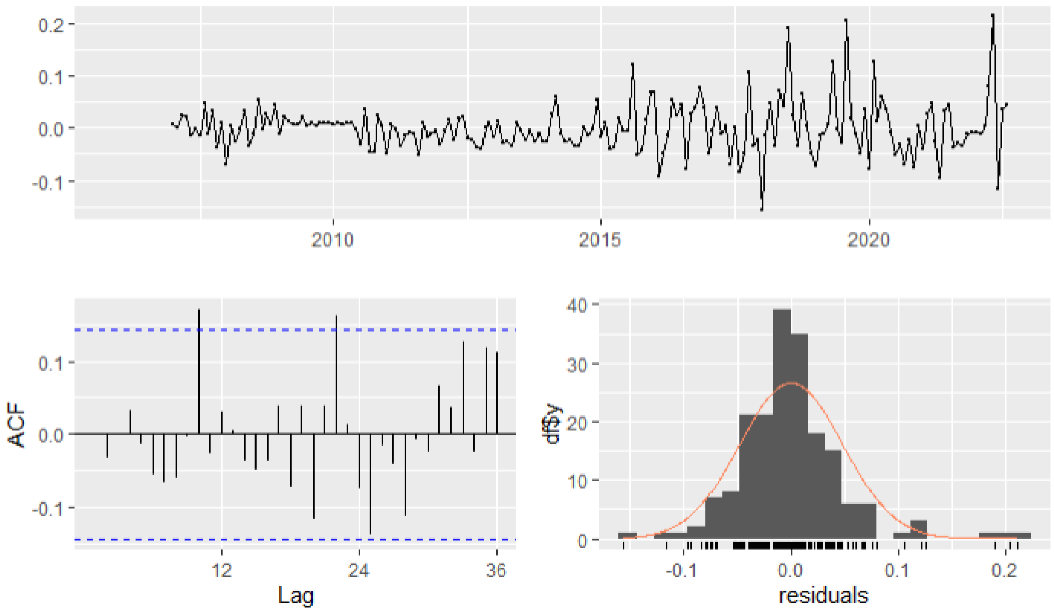

Fig. 2 Residual from NNAR (2,1,2)[12]

From ACF plot in Fig. 2, most of the autocorrelations are in the range of prediction interval, which suggests the correlation of model is weak and residual looks like white noise.

3.2. LSTM Model Results

The package that has been used is the "Long Short-term memory model for time series forecasting (TSLSTM)". The code ts.lstm could automatically fit the model and also forecast the value.

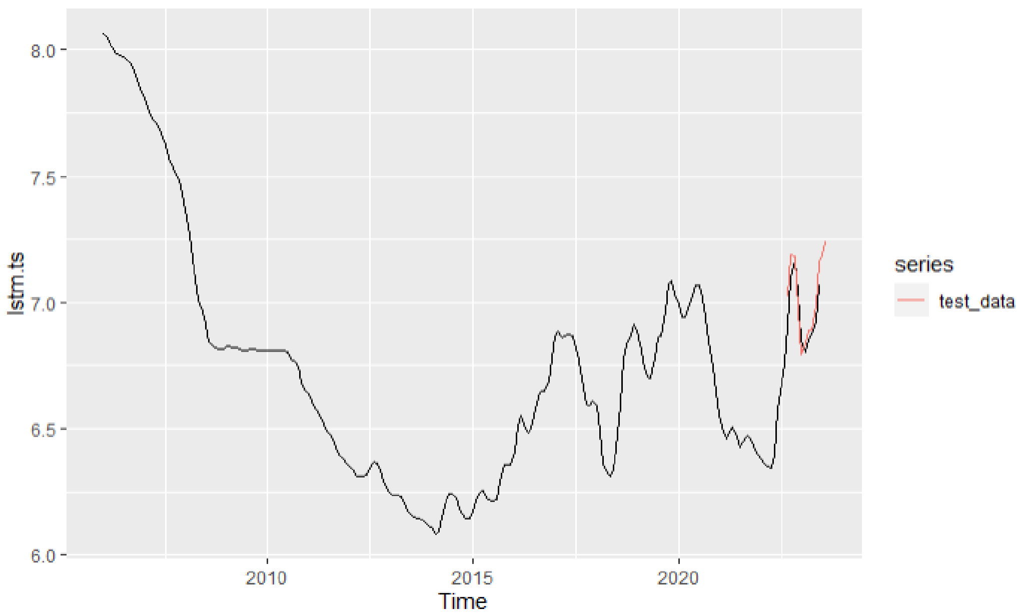

Fig. 3 Forecast plot for LSTM model (black line is the fitted and forecasting line for model and red line is the test data)

The lag of the time series data is set to 2, and the number of units in LSTM layer is set to 32. The number of epochs is set to default, 10 times. The split ratio is the training and testing split data. In general, the split ratio is 0.8, which means 80 percent of training data and 20 percent of testing data. In this research the ratio changes to 200/212 (200 training data and 12 testing data), so the ratio will be same as the neural network model.

The forecast plot shown above (Fig. 3), the black line is the bind line for the train fitted value and the test predicted value for the long short-term model, and the red line is the original test data from FRED. The forecast value for this model well fitted to the test data set.

3.3. Model Discussion

The result will be shown by comparing the mean square error (MSE) and mean absolute percentage error (MAPE) for neural network model and long-short term memory model to explain which model has the more accurate forecasting [9]. MSE is a way to measure the average square difference between the test value and predicted forecasting value. The model with higher accuracy would have lower MSE difference and hence less MSE value. The formula of MSE is shown below. Where n is the data size, y_i is the observed value and $\hat{y}_i$ is the estimated value.

$$MSE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n} \tag{1}$$

For neural model, MSE is calculated by using the MSE formula with given sample size, forecasting value and testing value and the value is 0.061548, the MSE for LSTM model could be automatically calculated by ts.lstm. The result is shown in Table 1. The images have shown that the mean square error for LSTM model (0.03356) is lower than the neural network model (0.0615). which means the LSTM model has lower mean square error difference which means LSTM model has higher accuracy on forecasting the CNY-USD exchange rate than neural model.

Table 1. RMSE and MAPE of Model

	RMSE	MAPE
Train	0.0709	0.0073
Test	0.1832	0.0231

The result could also be shown by comparing their MAPE (table 1). MAPE is the mean absolute percentage error which is a more direct measure of prediction accuracy of forecasting method in statistics. It calculates the absolute number of forecasting errors in percentage by using the formula shown below. Where A_t is the observed value, F_t is the forecasting value and n is the data size.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{2}$$

The mean absolute percentage error in neural network model is calculated by the formula and the value is 0.19392, and the MAPE for LSTM model could also automatically calculated by package ts.lstm. The model with smaller MAPE value would have more accurate forecasting model, because data size is equal, the difference between two models is their forecasting error $A_t - F_t$, and lower error represent higher accuracy.

Based on the calculation, the MAPE for neural network model in Fig 6 is 0.1939, and the MAPE for test part of LSTM model is 0.0231. Hence the calculation shows that long short-term memory model has higher accuracy on forecasting the CNY-USD exchange rate compared with neural network model.

For MAPE, the average deviation percentage between the forecasting value and observed value is 19 percent for neural network model and only 2.3 percent for LSTM model. For MSE, the average squared difference for forecasting value and observed value is 0.0615 for neural model and 0.03356 for LSTM model. We could see the value of squared average difference between neural and LSTM model are not so different, they both in a pretty low difference. But for MAPE, the deviation is large. MSE is a scale-dependent measurement hence it cannot obviously show the difference in error between two models. So, the research mainly focuses on the MAPE value and concludes that the LSTM model has a very high forecasting accuracy compared with the neural model.

4. Conclusion

The research mainly focuses on the trend for exchange rate between Chinese Yuan and US dollar. After the exchange reformation in 2005, Chinese RMB has loosen its currency control and became more open to the foreign exchange market. This research mainly using two different forecasting method, neural network model and long short-term memory model (LSTM), to fit the Chinese Yuan Renminbi to US dollar exchange rate data between Jan 2006 to Aug 2022. And then forecast the one-year rate between Sep 2022 to Aug 2023. From the result part could see that the forecasting accuracy for LSTM model is very high. There is only 2 percent error compare with the 19 percent error for neural network model. Hence using LSTM model could possibly make a higher accuracy in forecasting the 1-year foreign exchange rate.

Based on the research, two model forecasting the exchange rate show the different result. The neural network model shows that CNY-USD rate was going to reach the top point at the middle of 2022, and then decreasing. While the actual data show the situation is still stable in a short term. In contrast, the LSTM model make a good fitting on its forecasting model. Based on the result, what we could see is that the time series for forecasting exchange shows that the CNY-USD exchange rate was going to remain stable even currently the diplomatic relation of two countries is still worse.

However, it is undeniable that the model forecasting on exchange rate may have some errors. The foreign exchange rate largely depends on the real global events and government policies, it makes the research tough to forecast in extremely high accuracy. Especially nowadays the trade war has severely affected the financial market and real economy, which also led to the depreciation of the CNY exchange rate. Next step the research will going to focus on using more advanced forecasting methods and models and adding realistic factors, like adding the factor's proportion on import and export or the foreign investment, in the research.

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