Advances in Economics, Business and Management Research, volume 215
Proceedings of the 2022 7th International Conference on Social Sciences and Economic Development (ICSSED 2022)

The Long Short-Term Memory of GBP/CNY Exchange Rate Forecasts

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ABSTRACT

The issue of exchange rate forecasting has always been a hot topic, and with the increasingly close relationship between the UK and Chinese import and export trade, the GBP/CNY exchange rate has received increasing attention. Forecasting the GBP/CNY can help trading companies on both sides to effectively control their risks and help foreign exchange investors find arbitrage opportunities from it. For forecasting methods of foreign exchange, the main methods include traditional time series methods and deep learning methods. This study mainly uses the LSTM model to forecast the exchange rate of GBP/CNY from 31 January 2020 to 30 September 2021 and compares the results with ARIMA and GRU models, using RMSE, MAE and MAPE as the evaluation index of the results. Based on the results of the LSTM, ARIMA, GRU models, the RMSE values were 0.04268, 0.043791, 0.051312 respectively, we found that that the LSTM model has the best short-term forecasting results for GBP/CNY. We argue that the main reason for the LSTM to be the best model is that ARIMA and GRU models are more susceptible to parameter effects due to the shortcomings of the models themselves.

Keywords: *LSTM, ARIMA, GRU, GBP/CNY, exchange rate, prediction*

1. INTRODUCTION

The question of exchange rates has long been a hot topic in international financial studies. The volatility of the exchange rate has a significant impact on the growth of international commerce and investment [1], the monetary stability and price level [2], and ultimately, the economy's long-term viability and health improvement. As China and the United Kingdom's import/export trade connection grow stronger, for many years, China has been the UK's greatest import partner. China stayed in 26th of the UK’s export market, but in 2020, it became sixth place, worth £30. 7bn. On the other hand, China is the fourth largest source of imports in UK, worth £49bn [3]. The huge volume of transactions makes exchange rate issues as an unavoidable problem. As the Bretton Woods system collapsed and an increasing number of currencies began to fluctuate freely, changes in exchange rates became a major risk for non-financial businesses around the world. For those transactions based on foreign exchange, such as some importing and exporting companies, the cash flow of the company and the value of the company can be seen as a function of the exchange rate, which makes exchange rate risk become a major part of the company's risk control works [4]. The demand for foreign currencies may increase with the frequent increase in international trade and the movement of currency exchange rates. For investors, foreign currencies are traded on financial markets, making them available for buying and selling and seeking arbitrage opportunities from them [5]. Interest rates and foreign exchange rates are key variables in determining equity returns [6]. In addition, Dwumfour et al. (2019) showed the interaction between exchange rate fluctuations and government fiscal spending. It is therefore essential to construct effective models to track exchange rate fluctuations and accurately forecast their future trends.

Different market forecasting approaches have been developed to anticipate the value of foreign exchange since the establishment of the foreign market in the 1970s, especially deep learning models which have proven effective in many forecasting problems [7-11]. To predict future movements, a variety of methodologies are utilized, including fundamental, technical, and hybrid analysis [12]. Among these methods LSTM has garnered considerable attention, and it is applied for time series and forecasting of foreign currency transactions [13]. At the same time deep learning models have started to appear in various fields of economics. In particular, the use of deep learning models for exchange rate forecasting is at the forefront of this trend when considering their volatility [14].

In this article, we constructed a time series based on GBP/CNY Forex data for the period from 31 January 2020 to 30 September 2021, studied the series using the ARIMA, LSTM, and GRU models, and conducted hyper-parameter tuning on two deep learning models, LSTM and GRU. Finally, by evaluating the performance of different models on indicators such as RMSE, MAE and MAPE, we found that the LSTM model performed the best in terms of forecasting results. Based on these results, we conclude that the LSTM and GRU models are more influenced by the superconducting parameters, while the ARIMA model performs relatively consistently.

2. LITERATURE REVIEW

As the study of exchange rates continues to gain traction, a variety of different methods have been applied to modeling and forecasting exchange rates. LSTM models are widely used in related studies, and were first proposed by Hochreiter and Schmidhuber (1997) [15]. Wang (2021) combined CNN models and LSTM models and proposed a new CNN-TLSTM model, which models data from January 2006 to October 2020 USD/CNY, and the results show the advantage of predicting the results for the next trading day [16]. Maneejuk (2021) argued that the predictive performance of autoregressive integrated moving average and deep learning methods in making forex forecasts ultimately finds a clear advantage for LSTM [12]. Jung (2021) proposed a hybrid model combining a LSTM and an autoencoder model and used the model for forecasting the FXVIX index from 2010 to 2019, and the autoencoder-LSTM model showed significant advantages over the traditional LSTM model [13]. Escudero (2021) used ARIMA, Elman, and LSTM models to calculate forecasts for 2 January 1998 to 31 December 2019 for ERU/USD data, and their results demonstrate the superiority of the Elman and LSTM models for short-term forecasting [17].

Other types of models are also explored in the literature. Houssein (2021) used three deep learning models, BE, IM and SCG, to predict the specific closing price of the Egyptian Stock Exchange and found the superiority of the BE model by comparing MSE and other indicators [18]. Sadeghi (2021) combined ensemble multi-class SVM and fuzzy NSGA-II to forecast real EUR/USD data for the six-year period from 2014 to 2019 and obtained an extremely high level of forecast accuracy [19]. Wang (2021) proposed a reinforcement ensemble learning framework based on Adaboost and combined it with the deep learning model DRNN for multivariate exchange rate prediction and demonstrated the accuracy of the model for exchange rate prediction [20]. Maté (2021) analyzed the forecasting performance of the iMLP model for EUR/USD, GBP/USD and AUD/USD and obtained the desired results [21]. Amelot (2020) investigated the volatility and forecasting of foreign exchange rates by constructing time series models, artificial neural networks (ANNs) and statistical topologies. They use the Mauritian foreign exchange market from 2014 to 2018 as a case study, where EUR/MUR, GBP/MUR, CAD/MUR and AUD/MUR are applied for forecasting. Their results show that the NARX topology has better research [22]. Kamalov (2020) concluded that outlier detection methods greatly outperform traditional machine learning and proposed a new outlier detection method PKDE method that produced the best overall results for USD/EUR, USD/GBP, USD/YEN, and USD/AUD data over a 10-year period [23].

3. DATASET DESCRIPTION

Forex trading is almost never interrupted, and the prices traded are constantly fluctuating, so we can think of Forex prices as a continuous signal. In this paper, the GBP/CNY exchange rate is selected as the data set, and the daily closing price is used as the forecast target. All data on exchange rates are from Yahoo Finance (https://finance.yahoo.com).The time range for the selected data is 31 January 2020 to 30 September 2021.The training size is from 31 January 2020 to 1 June 2021; the test size is from 2 June 2021 to 30 September 2021. A trend chart of the exchange rate is shown in Figure 1.

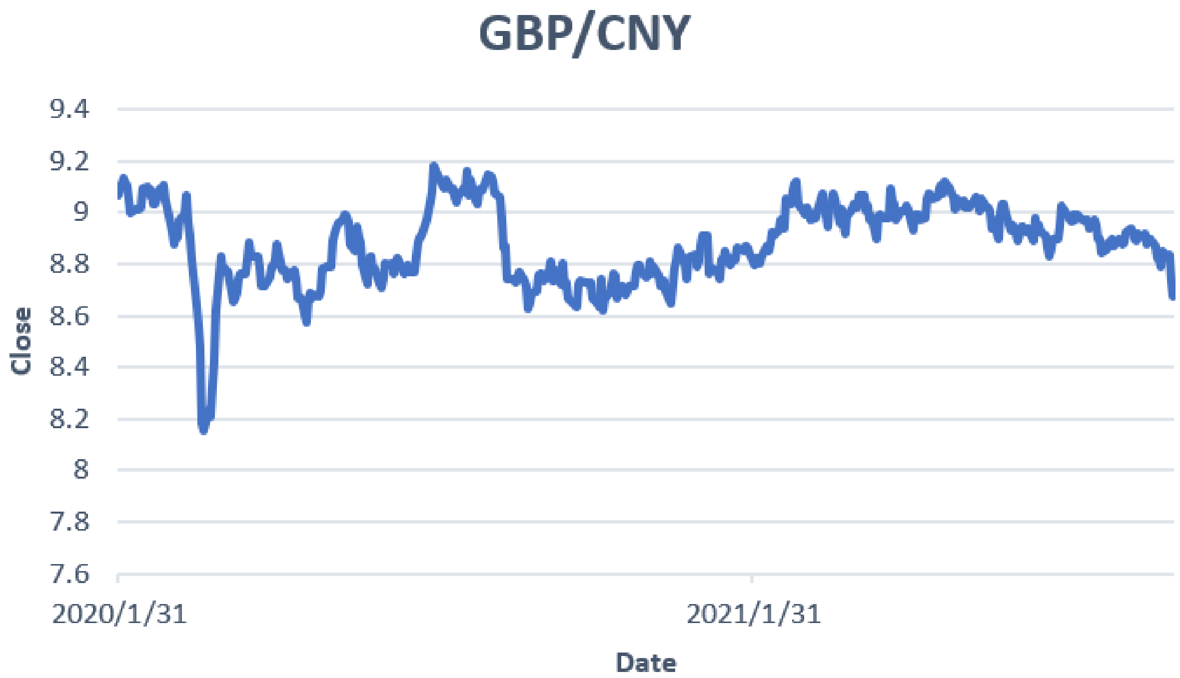

Figure 1. Raw data graph

4. MODEL DESCRIPTION

4.1. LSTM

The most representative neural network is the RNN, which has a recursive hidden layer and uses the results of previously hidden nodes as input data to learn continuous forms of data.

LSTM is designed to overcome the gradient vanishing problem of RNNs. As the network became deeper, earlier layers could not be trained correctly. The structure of LSTM consists of memory blocks, which is the main advantage of LSTM compared to the hidden units of RNN. The LSTM model has three steps (layers): the forgetting layer, the input layer, and the output layer. Figure 2 illustrates the LSTM process, in which t is the time of the slot index, c_t is defined as the cell state, the mean of h_t is the output value and x_t is the input value.

We define the forget gate as

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f) \tag{1}$$

where σ is the sigmoid activation function, and W and b are the parameters. The function of the forget gate is that decides to throw away some information from the cell state.

The input gate is defined as

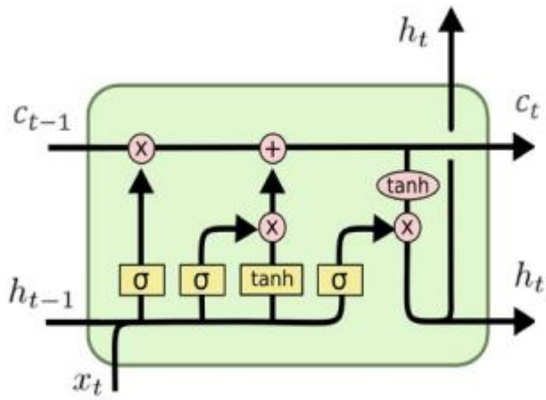

Figure 2. Structure of the LSTM

$$\begin{aligned} i_t &= \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_i) \\ \tilde{c_t} &= \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \\ c_t &= f_t * c_{t-1} + i_t * \tilde{c_t} \end{aligned} \tag{2}$$

where *tanh* is the tanh activation function, and $\tilde{c_t}$ is a matrix with a new candidate value that can add to the cell state. The input gate can decide to store some information in the cell state.

Finally, we define the output gate as

$$\begin{aligned} o_t &= \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \\ h_t &= o_t * tanh(c_t) \end{aligned} \tag{3}$$

where we can know the information to the output from cell state by the output gate.

4.2. Evaluation of Prediction Accuracy

To assess the performance of the proposed framework, we used the three most widely used metrics, root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). The specific formulae are as follows:

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

$$MAE = \frac{1}{k}\sum_{i=1}^{k}|y_i - \hat{y}_i| \quad (4)$$

$$MAPE = \frac{1}{k}\sum_{i=1}^{k}\left|\frac{\hat{y}_i - y_i}{y_i}\right| * 100\%$$

where k is the testing size, $\hat{y}_i$ denotes the result, and y is the true value.

5. EXPERIMENT

To demonstrate the superiority of LSTM, we also compared it with ARIMA and GRU. In addition, we divided the original data into a training machine and a test set based on a division ratio of 80% and 20%, respectively, i.e., 348 data points in the training set and 87 data points in the test set. In the next experiments, we applied the data from the training set to train the model and tested it with the data from the test set. The deep learning model was then combined with hyperparameters. In addition, we divided another 20% of the training set data as validation and based on the results the best deep learning model corresponding to the parameters was selected and applied to the test set.

Finally, we used metrics, root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE), and obtained the results for the different models on the testing set. The results are shown in Table 1.

Table 1. Test results of ARIMA, LSTM, GRU

	ARIMA	LSTM	GRU
RMSE	0.043791	0.042680	0.051312
MAE	0.034434	0.031907	0.042106
MAPE (%)	38.5699	35.7488	47.0603

From Table 1, we find that the LSTM models all perform optimally with RMSE, MAE and MAPE parameters of 0.042680, 0.031907, and 35.7488% respectively. In addition, the ARIMA model also outperformed GRU in the test results.

We have also plotted Figure 3 to compare the results.

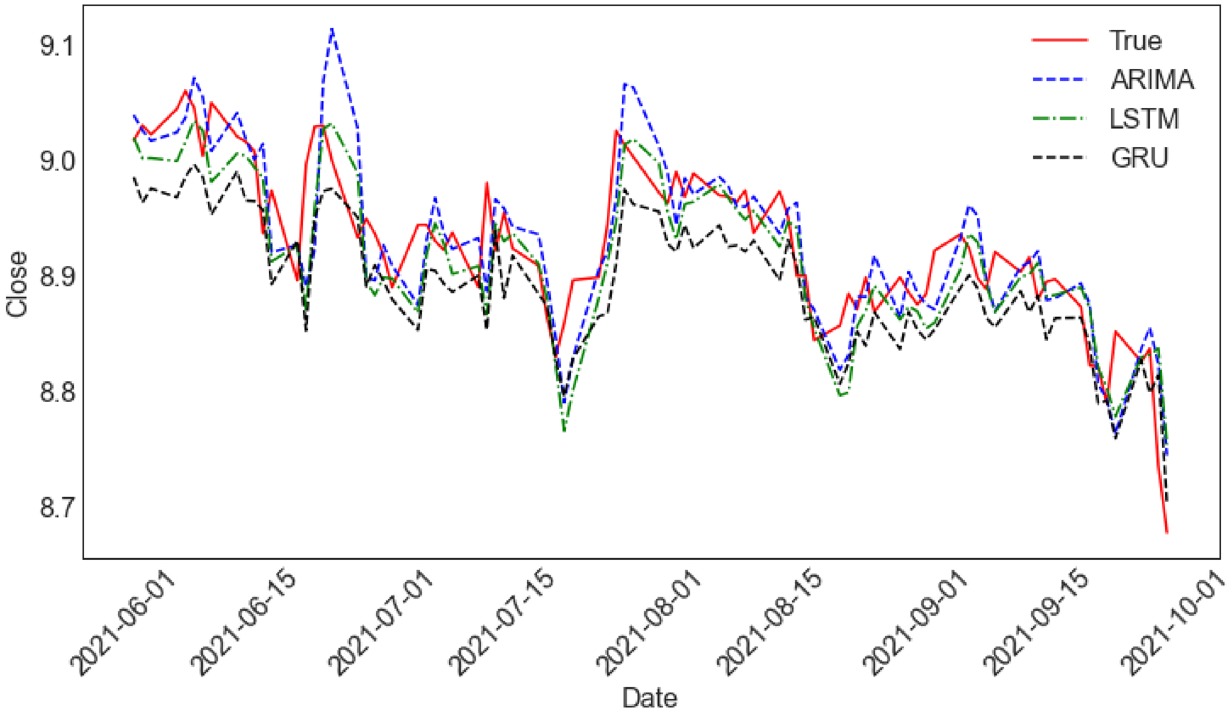

Figure 3. ARIMA, LSTM, GRU models predictions. (The Y-axis is the price of 1GBP to exchange CNY and the X-axis is the date in days)

From Figure 3 we clearly see that the ARIMA model deviates from the true value of the data approximately 2021-6-16 and 2021-7-25 and shows significantly larger results; however, it showed the significantly smaller forecasts indicated at these times. The LSTM forecasts are closest to the trend of the true value.

6. CONCLUSION

In this paper, by comparing the forecasting performance of the ARIMA, LSTM and GRU models for GBP/CNY, it is finally found that the LSTM model gives the best forecasting results, which provides a more effective solution to the exchange rate forecasting problem. The reasons for this result have been further discussed. We believe that the LSTM is the best model because the ARIMA model requires smooth data, whereas the exchange rate data is not smooth and is integrated into smooth data through differential processing, resulting in a reduction in the model's accuracy due to the model's limitations[17]; and the GRU model, as a simplified version of the LSTM, has one less gate to control the flow of information than the LSTM, its prediction results are more susceptible to the influence of the parameters[24]. For future research, the model can be applied to more types of exchange rate forecasting, such as USD/CNY, and on the other hand, other deep learning models or compound deep learning models, such as CNN-TLSTM, can also be used to find a model with better fit and thus improve the accuracy of forecasting.

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