RMB exchange rate forecasting algorithm and empirical analysis*

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Abstract . This paper studies the forecasting algorithm of RMB exchange rate. Firstly, the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise algorithm (CEEMDAN) is used to decompose the exchange rate data into several intrinsic mode functions (IMF). Then the correlation coefficients of each IMF are calculated, and the high-frequency components with low correlation are regarded as noisy signals for filtering. The low frequency IMF components are forecast by Autoregressive Integrated Moving Average Model (ARIMA) time series model, while the high frequency IMF components are predicted by BP neural network model and Long Short Term Memory (LSTM) neural network model. Finally, the predicted values of each component are added to construct a new forecasting algorithm for the RMB exchange rate. In the empirical analysis, we collected the exchange rate data of RMB against US dollar and RMB against EUR every working day(FOREX opening hours Beijing time. Monday to Friday) from January 2, 2019 to December 22, 2022, and carry out empirical analysis of the exchange rate from December 23, 2022 to January 20, 2023 by using the prediction algorithm constructed in this paper. By comparing with the true value (the true exchange rate value published by FOREX), the average forecast error is 0.1779 % (RMB/USD) and 0.2072 % (RMB/EUR) respectively. It should be emphasized that our forecasting method can more precisely predict the RMB exchange rate over four weeks, which provides sufficient buffer time for the foreign exchange management department to conduct supervision and formulate countermeasures.

Keywords:RMB Exchange Rate Forecast, CEEMDAN decomposition, ARIMA time series, BP neural network, LSTM neural network

1 INTRODUCTION

Exchange rate fluctuations have an important impact on national income, interest rates, etc. Therefore, the accurate analysis and forecast of exchange rate are essential[1]. The analysis and research on exchange rate forecast have attracted the attention of many scholars, and there have been a lot of research work.

* This research is supported by the Innovation and Entrepreneurship Program of Beijing University of Chemical Technology.

A. Rauf et al. (eds.), *Proceedings of the 3rd International Conference on Management Science and Software Engineering (ICMSSE 2023)*, Atlantis Highlights in Engineering 20,
https://doi.org/10.2991/978-94-6463-262-0_12

In the early stage, the prediction of foreign exchange rate was studied from the exchange rate theory[2], including purchasing power parity theory[2], interest rate parity theory[4] and asset balance theory under floating exchange rates[5] etc. A number of ARCH and associated extended econometric models have appeared according to the different volatility characteristics. Engle first proposed the ARCH model[6]; Hui et al. combined genetic algorithms with BP neural networks to build a forecasting model of the RMB/USD exchange rate[7]; Xiong established a forecasting model of ARIMA fusion neural networks[8]; Dai et al. combined ARIMA and GARCH model for forecasting[9]; Yao et al. established a two-component mixed volatility model for the RMB exchange rate[10].

All the above prediction algorithms have achieved relatively accurate prediction of the RMB exchange rate, but the prediction time is mostly short, which is not conducive to the regulatory authorities to put forward effective measures according to the exchange rate fluctuations. And this is one of the main motives of this paper. This paper constructs a multi-model prediction algorithm based on CEEMDAN decomposition, which provides more precise forecasts for the RMB exchange rate within one month. Our research has certain positive significance for foreign exchange management.

2 Construction of RMB exchange rate forecasting algorithm

2.1 CEEMDAN Decomposition

The common characteristics of financial time series are heteroscedasticity and high nonlinearity, so it is difficult to predict and measure financial time series by traditional economic models. In order to analyze nonlinear and nonsmooth

signal sequences with a high signal-to-noise ratio and strong time-frequency focus[11,] NE. Huang et al. introduced the Empirical Mode Decomposition (EMD) method. Although EMD decomposition has advantages like adaptability and multi-resolution, it also has some problems such as envelope fitting deviation, endpoint effect, and modal aliasing, so the improved CEEMDAN decomposition algorithm is adopted in this paper. CEEMDAN decomposition algorithm can perform adaptive analysis on nonlinear and non-stationary data, and decompose the data into several intrinsic mode functions IMFs[12]. We will perform CEEMDAN decomposition on RMB exchange rate data.

2.2 Correlation coefficient method for noise reduction

After the RMB exchange rate data is decomposed into several IMFs by CEEMDAN decomposition algorithm, the characteristics of each component are different, so it is necessary to select the IMF component that best represents the original data, and the correlation coefficient method is adopted for screening.

In order to reduce the noise in the original data, we calculate the Pearson correlation coefficients of each IMF component of the original sequence obtained by

CEEMDAN decomposition. By filtering out small components and noise with low correlation, we achieve noise reduction of the original data. The data after noise reduction constitute the basic signal of the subsequent model. In comparison to the original data, the denoised data are smoothed, and the interfering noise is essentially eliminated.

2.3 Build prediction algorithms

Commonly used forecasting models include time series forecasting models, neural network forecasting models, gray models, etc., which have different forecasting effects for different series. After data processing and analysis, ARIMA time series model, BP neural network model and LSTM neural network model have better prediction effect and higher accuracy for IMF curve decomposed by exchange rate data. Therefore, based on the above three prediction models, we construct the RMB exchange rate prediction algorithm in this paper.

ARIMA time series model is suitable for homogeneous stationary long time series analysis, so it is used to forecast IMF curve with low frequency after CEEMDAN decomposition [1314].The BP neural network is a "automatic feedback training process," its principle is to analyze the error between the results after each training and the ideal results, and constantly modify to improve the prediction accuracy[15]. LSTM neural network, also known as long short-term memory network, is a special RNN model that effectively captures and processes long-term dependencies by introducing a gating mechanism[16]. So the above two prediction models are used for IMF components with high frequency.

The RMB exchange rate prediction algorithm developed in this paper can be represented by Figure 1 :

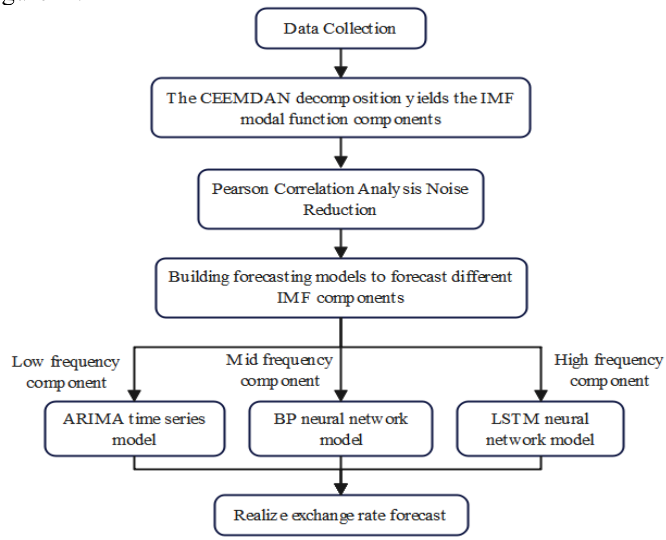

Fig. 1. Schematic diagram of the prediction algorithm established in this paper

3 Empirical Analysis

3.1 Data Collection

We collected the daily exchange rate data of RMB/USD and RMB/Euro from January 2, 2019 to January 20, 2023, and obtained a total of 986 sets of data samples. We chose the first 966 sets of samples as the training set, and the remaining 20 sets of samples as the test set. The data exchange rate time series charts are shown in Figure 2 and Figure 3 :

Fig. 2. RMB\USD exchange rate time series chart.

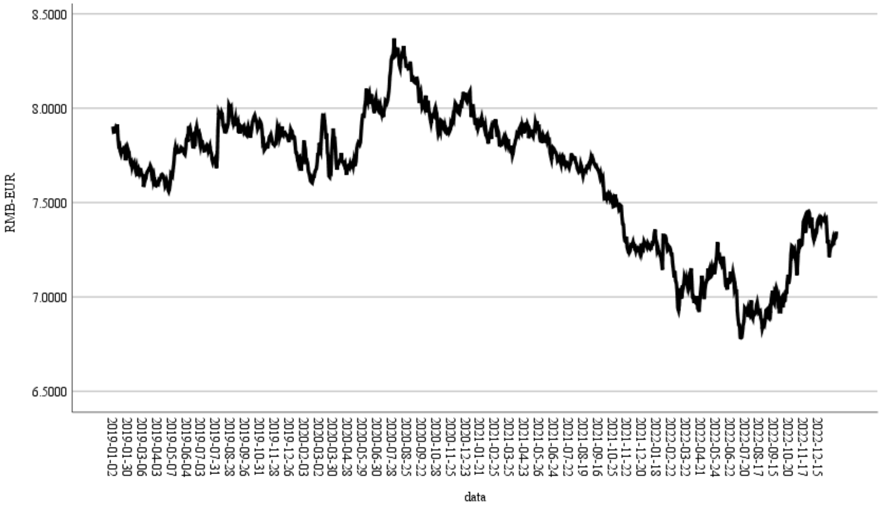

Fig. 3. RMB\EUR exchange rate time series chart.

3.2 CEEMDAN decomposition

It can be found from the above two RMB exchange rate charts that the RMB exchange rate data is highly volatile and has obvious nonlinear characteristics. Therefore, we performed CEEMDAN decomposition on the RMB exchange rate data, and then eliminated abnormal signals to make the curve stable and smooth, which is conducive to the accurate prediction of the prediction model. The decomposition charts are shown in Figure 4 and Figure 5 :

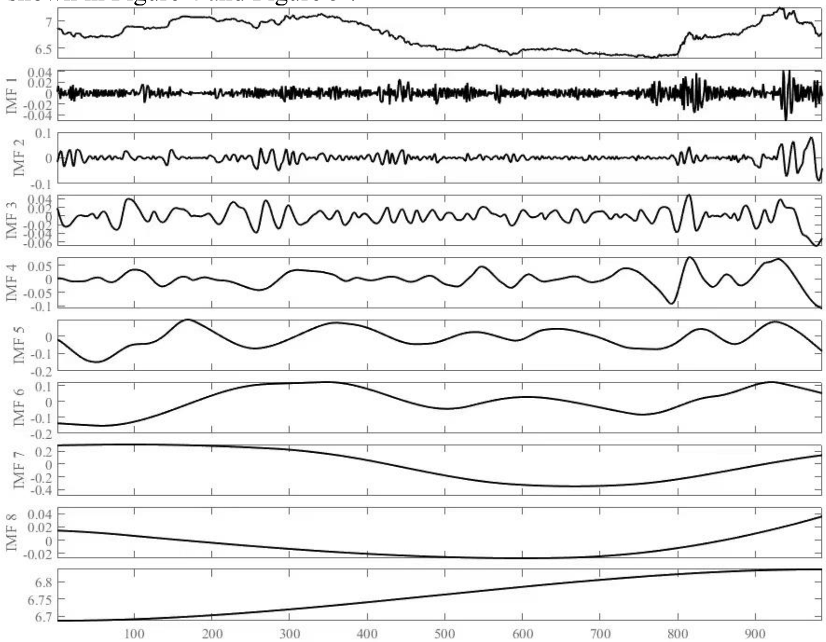

Fig. 4. RMB/USD Exchange Rate CEEMDAN decomposition

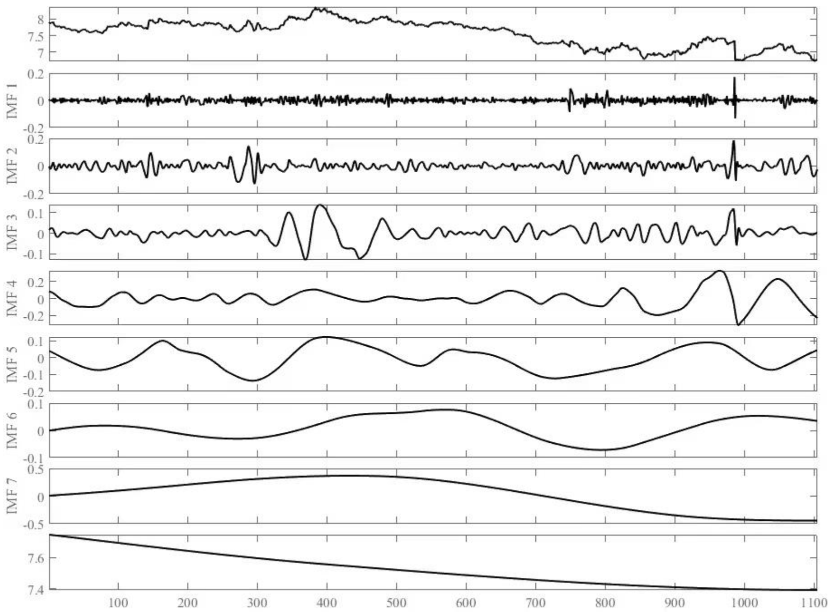

Fig. 5. RMB/Euro Exchange Rate CEEMDAN decomposition

As can be seen from the above figure, the RMB/USD exchange rate is decomposed into 8 IMF component curves, in which IMF2-IMF4 are high-frequency signals, IMF1 and IMF5-IMF6 are medium-frequency signals, and IMF7 and IMF8 are a low-frequency signals. Among the 7 IMF curves obtained from the decomposition of the Euro/RMB exchange rate, IMF1 and IMF2 are high-frequency signals with obvious volatility, IMF3 and IMF4 are medium-frequency signals, and IMF5-IMF7 are low-frequency signals.

3.3 Correlation coefficient method for noise reduction

After CEEMDAN decomposition of the original exchange rate data, several IMF components were obtained. We calculated the correlation between each IMF component and the original exchange rate data. The calculation results show that the correlation coefficients of IMF7 are the largest, which are 0.8 (RMB/USD exchange rate) and 0.918 (RMB/Euro exchange rate) respectively; the correlation coefficients of IMF3-IMF8 are all greater than 0.1; the correlation coefficients of other IMF and original data are all less than 0.1.

Therefore, the two components with the lowest correlation, IMF1 and IMF2, are regarded as the noise signal filtering of the original data, so as to realize the noise reduction of the original data. The data after noise reduction becomes the basic data for the subsequent prediction model establishment, and the data after noise reduction is smoother than the original data.

3.4 Different IMF component forecasts

The time series model is suitable for predicting curves with relatively flat volatility. We use the ARIMA time series model to predict the IMF4-IMF7 components obtained by decomposing the EUR-RMB exchange rate data and compare the prediction results with the true value. The prediction error is between 0.09% and 0.49%, which is small and effective.

The neural network model is suitable for predicting curve data with large volatility. Therefore, we employed BP neural network to predict the IMF5-IMF8 component of the USD/RMB exchange rate data, and compared the predicted result with the true value, and found that the prediction error was between 0.01% and 0.54%.

By adding a gating mechanism to efficiently collect and handle long-term dependencies, the long short-term memory network (LSTM) neural network has developed into a very effective sequence modeling technique. This model is used to forecast the IMF3 and IMF4 components of the USD/RMB exchange rate data and the IMF3 components of the EUR/RMB exchange rate data. Comparing the predicted result with the true value, the prediction error is between 0.04% and 0.54%.

3.5 Analysis of prediction results

The predicted value of each IMF component is added together to obtain the predicted value of the USD/RMB and the EUR/RMB exchange rate data for each working day. Compared with the true value, the average error of USD/RMB exchange rate forecast is 0.1779%, and the average error of EUR/RMB exchange rate forecast is 0.2072%. The results of empirical analysis show that the average error of our prediction algorithm is small and the feasibility is high. Forecast data and errors of each working day are shown in Table 1 :

Table 1. 20 working days empirical analysis results (5 working days per week, forecast time is 4 weeks)

Data	RMB/USD			RMB/Euro		
	Predicted value	True value	error	Predicted value	True value	error
2022-12-23	6.9872	6.981	0.0883%	7.4146	7.4115	0.0425%
2022-12-26	6.9854	6.9825	0.0412%	7.4188	7.4115	0.0983%
2022-12-27	6.9821	6.9546	0.3950%	7.4190	7.4064	0.1706%
2022-12-28	6.9758	6.9681	0.1098%	7.4120	7.4194	0.0991%
2022-12-29	6.9660	6.9793	0.1911%	7.3982	7.4059	0.1034%
2022-12-30	6.9539	6.9646	0.1543%	7.3759	7.4114	0.4795%
2023-1-3	6.9359	6.9475	0.1663%	7.3471	7.339	0.1110%
2023-1-4	6.9129	6.9131	0.0026%	7.3159	7.2841	0.4370%
2023-1-5	6.8874	6.8926	0.0758%	7.2865	7.3014	0.2036%
2023-1-6	6.8573	6.8912	0.4920%	7.2642	7.2115	0.7314%
2023-1-9	6.8265	6.8265	0.0004%	7.2508	7.2424	0.1153%

2023-1-10	6.7976	6.7611	0.5391%	7.2493	7.2619	0.1733%
2023-1-11	6.7702	6.7756	0.0802%	7.2551	7.2702	0.2083%
2023-1-12	6.7500	6.768	0.2656%	7.2665	7.2739	0.1012%
2023-1-13	6.7356	6.7292	0.0954%	7.2802	7.2946	0.1977%
2023-1-16	6.7305	6.7135	0.2526%	7.2949	7.2745	0.2802%
2023-1-17	6.7336	6.7222	0.1689%	7.3078	7.3172	0.1282%
2023-1-18	6.7449	6.7602	0.2265%	7.3184	7.3087	0.1327%
2023-1-19	6.7591	6.7674	0.1221%	7.3275	7.3133	0.1946%
2023-1-20	6.7764	6.7702	0.0922%	7.3365	7.3465	0.1367%

4 Conclusions

In this paper, the CEEMDAN method is used to decompose the exchange rate data into several IMF components, and then the correlation coefficient method is used to filter out the high-frequency components with low correlation. According to the characteristics of different IMF components, different forecasting algorithms are used to forecast the components, and the RMB exchange rate forecasting algorithm is constructed. Finally, we collected the exchange rate data of RMB/USD and RMB/Euro from December 23, 2022 to January 20, 2023, and conducted empirical analysis with our prediction algorithm. The average prediction error was 0.1779% (RMB/USD) and 0.2072% (RMB/Euro). The results of empirical analysis show that the prediction algorithm constructed in this paper has higher prediction accuracy and stronger feasibility.

In particular, it should be emphasized that compared with previous RMB exchange rate prediction algorithms, the RMB exchange rate prediction algorithm constructed in this paper can realize exchange rate prediction for up to 20 days. It is noted that there are 5 working days in a week, so our prediction model gives a relatively accurate forecast of RMB exchange rate within a 4-week time, which provides a certain basis and sufficient buffer time for the supervision and decision-making of the national foreign exchange regulatory authorities.

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