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Consider the impact of US interest rate policy on the RMB exchange rate forecast research against the US dollar

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Abstract. Global economies are interconnected, with each country's monetary policy spilling over to affect others' goods and capital, especially under full capital mobility. The U.S., faced with the twin challenges of rising inflation and unemployment due to the pandemic, the Russia-Ukraine conflict, and trade tensions with China, has started raising interest rates. This has intensified fluctuations in the RMB exchange rate, highlighting the need for accurate prediction. To address this, a deep learning-based ARIMA-EEMD-IAWT-LSTM model is proposed, which enhances time series denoising by combining improved adaptive wavelet thresholding (IAWT) and ensemble empirical mode decomposition (EEMD). This model, integrated with LSTM, effectively predicts the nonlinear aspects of the time series, reducing risks associated with exchange rate volatility. The model's prediction accuracy reaches 98.4822%, underscoring its practical significance in exchange rate forecasting.

Keywords: U.S. monetary policy, RMB exchange rate, deep learning, ARIMA-EEMD-LSTM model, IAWT algorithm.

1. Introduction

As China's economy continues to grow, the Sino-US trade relationship has become seriously unbalanced, with the US frequently adjusting its interest rate policies, leading to sharp fluctuations in the global financial markets and the RMB-to-US dollar exchange rate. In 2019, after the US introduced new tariff laws, the RMB-to-US dollar exchange rate hit a nearly 10-year high, affecting China's import and export trade and financial markets. During the COVID-19 pandemic in 2020, the US implemented a large-scale loose interest rate policy, causing the RMB to appreciate rapidly. From April to December 2020, the RMB rose from "7.07" to "6.54". In November 2021, the US Federal Reserve began to slow the pace of asset purchases, and in March 2022, it raised interest rates for the first time and planned to reduce its balance sheet to address inflation risks. By January 2024, the Federal Reserve had paused rate hikes four times in a row, and its balance sheet was expected to be reduced by about 950 billion US dollars, aiming to gradually tighten monetary policy to combat inflation. This policy shift has led to frequent fluctuations in exchange rates, increased the spread between onshore and offshore markets, fueled speculative behavior, and increased the risk in China's foreign exchange market. In the context of globalization, a crisis in one country can quickly spread to others, potentially triggering regional or global financial crises, or even economic recessions and political turmoil. Therefore, analyzing the impact mechanism of US interest rate policy fluctuations on the RMB exchange rate becomes important. Using the fluctuation of US interest rate policy as a characteristic factor in the RMB exchange rate prediction model can improve prediction accuracy. This study is crucial for the Chinese government to respond to exchange rate risks.

This paper discusses the process of constructing an ARIMA-EEMD-IAWT-LSTM exchange rate prediction combination model using deep learning methods. Based on data from January 2008 to April 2024, the paper conducts backtesting of the model's predictive results from an empirical perspective and concludes that the constructed ARIMA-EEMD-IAWT-LSTM combination model has good predictive effects on the RMB-to-US dollar exchange rate, accurately capturing the trends, seasonality, and cyclical patterns of time series data, providing certain reference value for policymakers, businesses, and individual investors.

In the study of the spillover effects of U.S. interest rate policy, Miranda-Agrippino S, Rey H (2020) argue that with the continuous strengthening of the dollar’s monetary status, U.S. monetary policy has become a significant factor influencing global financial market changes, exerting significant financial spillover effects on the global economy [1]. Wang Sheng et al. (2022) believe that as the world’s largest economy, the U.S.'s monetary policy has become an important factor affecting the global financial market, exerting significant financial spillover effects on the global economy, and its impact on the Chinese financial market is also growing [2]. Zhang Tianding and Fang Zhiyuan (2022) starting from the financial spillover channel, using the SVAR model, found that fluctuations in U.S. monetary policy will have a negative spillover effect on the Chinese capital market [3]. Huang Yuzhe et al. (2022), Du Jie and Cao Weiyu (2020) argue that the implementation of U.S. monetary policy, in the short term, will exacerbate the volatility of the real economy and financial markets for China [4], but it has no effect on the long-term development trend of the economy [5].

In the research on prediction models based on their own sequence characteristics, Ci Bicong and Zhang Pinyi (2022) concluded that the newly constructed ARIMA-LSTM combined model had better prediction effects than the three control models [6]. Liu Shijin, Sun Lihua, and Guo Peng (2021) concluded that the prediction values obtained through the EEMD model decomposition process were more accurate than those without decomposition [7].

In the aspect of reducing the impact of noise on data prediction, Ren Haijun, Wei Chong, and Tan Zhiqiang (2023) applied complete ensemble empirical mode decomposition with adaptive white noise to decompose the signal, generating IMF components. And the IAWT algorithm was applied to remove the noise in the IMFs [8].

2. Empirical Analysis of US Dollar to Renminbi Exchange Rate Forecasting

2.1. Construction of the Exchange Rate Forecasting Model

The general model of the Exchange Rate Forecasting Model consists of five basic elements, which are:

(1) The original time series data y_t is decomposed into linear components l_t and nonlinear components h_t, as shown in Equation (1):

$$y_t = l_t + h_t \tag{1}$$

(2) To meet the requirements for using the ARIMA model, it is necessary to difference the time series data to ensure stationarity. Once stationarity is achieved, the ARIMA model is used to identify and extract the linear component l_t of the time series data y_t. The ARIMA model is a predictive model that treats time series data as a linear combination of its past values (autoregressive terms $l_{t-1}, l_{t-2}, \ldots, l_{t-p}$) and past prediction errors (moving average terms $n_{t-1}, n_{t-2}, \ldots, n_{t-q}$). Where p and q are the orders of the autoregressive and moving average terms of the model, respectively, and n_t is the prediction error at time t. [9]

The specific form of the ARIMA model can be expressed as in Equation (2):

$$\hat{l}_t = f\left(l_{t-1}, l_{t-2}, \ldots, l_{t-p}, n_t, n_{t-1}, \ldots, n_{t-q}\right) \tag{2}$$

Here, l_t is the model's predicted value of the linear component l_t at time t, and $\boldsymbol{f}$ is a linear function of the ARIMA model, representing how the current linear component is predicted through past values and prediction errors.

(3) In the combined forecasting model, after identifying the linear component of the time series data, the next step is to subtract the linear component predicted by the ARIMA model from the original time series data to obtain the nonlinear component. This process can be expressed as in Equation (3):

$$h_t = y_t - \hat{l}_t \tag{3}$$

The obtained nonlinear component h_t may contain complex patterns and noise within the time series.

(4) To better handle these nonlinear characteristics, this chapter employs the Ensemble Empirical Mode Decomposition (EEMD) method, which is a time series decomposition technique. It decomposes the nonlinear component into a set of Intrinsic Mode Functions (IMFs) and a residual term. The decomposition process can be expressed as in Equation (4):

$$h_t = \sum_{i=1}^{M} IMF_i + r \tag{4}$$

Where, IMF_i represents the i -th Intrinsic Mode Function, M is the total number of IMFs decomposed, and r is the residual term, representing the undecomposed remainder of the sequence. Each IMF represents fluctuations or trends of different scales in the data, and they are orthogonal, meaning they are independent of each other, which can help eliminate noise in non-stationary sequences, thereby improving the accuracy of predictions.

In time series analysis, the IMF components and residual r obtained from the EEMD model decomposition can be further processed to improve the accuracy of predictions. Perform correlation analysis between each IMF component decomposed by EEMD and the original signal to identify effective IMF components. This can be done by calculating the correlation coefficient between each IMF and the original signal. The closer the absolute value of the correlation coefficient is to 1, the stronger the correlation between the IMF and the original signal. Based on the size of the correlation coefficient, the IMFs can be divided into effective components and noise components. Typically, a threshold of 0.5 is set, and IMFs with a correlation coefficient greater than this threshold are considered effective components, while those less than this threshold are considered noise components. The identified noise components are removed from the model and not used for subsequent predictions. For effective IMFs with a high noise content, denoising can be performed using the Improved Adaptive Wavelet Transform (IAWT). [10] The IAWT is a signal processing technique that recombines the denoised effective IMFs and the residual rr to reconstruct the nonlinear part of the time series. This improves the accuracy of the prediction model by reducing the impact of noise on predictions, the formulas are shown in (5) and (6):

$$Correlation\ Coefficient(IMF_i, y_i) = \frac{\sum_{t=1}^{N}(IMF_i - \overline{IMF}_i)(y_t - \overline{y_t})}{\sqrt{\sum_{t=1}^{N}(IMF_i - \overline{IMF}_i)^2}\sqrt{\sum_{t=1}^{N}(y_t - \overline{y_t})^2}} \tag{5}$$

$$h_t^{'} = \sum_{i=1}^{M^{'}} IMF_i^{'} + r^{'} \tag{6}$$

Where, IMF_i is the original IMF component, $IMF^{'}$ is the denoised IMF component, $M^{'}$ is the number of remaining effective IMF components, $h_t^{'}$ is the reconstructed nonlinear component, and $r^{'}$ is the possible processed residual term.

(5) The Long Short-Term Memory network model (LSTM) is used to predict the processed IMFs. LSTM is a special type of recurrent neural network that is very suitable for processing and predicting time series data. The denoised and reconstructed IMFs are used as input to train the LSTM model to

predict the future values of each IMF. The LSTM model is capable of learning long-term dependencies in time series data. Using the trained LSTM model to predict each IMF results in the predicted IMF components. By adding up the predictions of all IMF components and the residual, the predicted value of the nonlinear component of the time series data is obtained. The predicted value of the linear component is added to the predicted value of the nonlinear component to obtain the final prediction. [11] The formulas are shown in (7), (8), and (9):

$$\widehat{IMF_i} = LSTM(IMF_i') \tag{7}$$

$$\widehat{h_t'} = \sum_{i=1}^{M'} \widehat{IMF_i'} + \widehat{r'} \tag{8}$$

$$\widehat{y_t} = \hat{l_t} + \widehat{h_t} \tag{9}$$

Where, IMF_i is the prediction for the i-th IMF component, r' is the prediction for the residual r' (if the residual is also predicted), h_t' is the predicted value of the nonlinear component, and y_t is the final predicted value.

2.2. Dataset and Evaluation Metrics

Data obtained from the Wind database, covering the period from January 2008 to April 2024, includes the effective federal funds rate (monthly) in the United States to reflect the monetary policy situation there. The average exchange rate (monthly) of RMB to USD is used to reflect the exchange rate condition of the RMB. According to research literature, the data from January 2008 to December 2023 is allocated to the training and validation sets at an 8:2 ratio; the data from January 2024 to April 2024 is allocated to the test set.

2.3. Empirical Backtesting and Verification

2.3.1. Data Preprocessing and Description

The data is preprocessed, which includes loading, viewing the data structure and content, ensuring data quality, and performing necessary cleaning. According to the data description shown in Table 1, we can see that the data description after logarithmic normalization of US monetary policy and RMB exchange rate includes mean, median, maximum, minimum, standard deviation, kurtosis, skewness, JB statistic, and P-value. Among these two variables, the US monetary policy data has the largest standard deviation, while the RMB exchange rate data has the smallest standard deviation. This reflects the more significant fluctuations in US monetary policy and the greater uncertainty in the US political and economic environment. The P-values of the JB statistics for all indicators are 0, indicating that at a significance level of 1%, all sequences exhibit normal distribution characteristics.

Table 1. Data Description.

	US Interest Rate Policy	RMB Exchange Rate
Mean	-0.627760	1.888850
Median	-1.020000	1.895166
Maximum	1.000000	1.980698
Minimum	-1.790000	1.808993
Standard Deviation	0.855123	0.047303
Skewness	0.534280	-0.093945
Kurtosis	1.756773	1.838868
JB Statistic	21.49947	11.06824
P-value	0.000021	0.003950

2.3.2. ADF Stationarity Test

As shown in Table 2, in order to effectively prevent spurious regression issues, a stationarity test is conducted on the data. The ADF root test is used to assess the stability of the two time series, with the null hypothesis being that if there is a unit root, the initial data belongs to a non-stationary series. From the data in Table 2, it can be observed that the initial state of the US monetary policy and RMB exchange rate data does not exhibit stability. After first-order differencing, both sequences have tended towards stationarity at a significance level of one percent.

Table 2. ADF Stationarity Test.

Variable	Original Data t-Statistic	P Value	Stationarity	First-Difference t-Statistic	P Value	Stationarity
US Monetary Policy	-2.602558	0.2798	Non-Stationary	-9.057553	0.0000	Stationary
RMB Exchange Rate	-2.320273	0.1667	Non-Stationary	-8.310106	0.0000	Stationary

Note: A P-value less than 0.1 indicates stationarity at the 10% significance level; a P-value less than 0.05 indicates stationarity at the 5% significance level; a P-value less than 0.01 indicates stationarity at the 1% significance level.

2.3.3. Model Forecasting Application

Subsequent to this, preliminary exploratory data analysis is conducted, which includes plotting time series graphs, calculating statistical summaries, checking for missing values, and performing necessary differencing treatments. Then, the ARIMA model is used for preliminary fitting and forecasting of the time series data. Following this, the EEMD model is used to decompose the nonlinear part of the time series data, and the IAWT algorithm is applied for further denoising. After this, the LSTM model is used for further prediction of the nonlinear part.

3. Results

After preprocessing and exploratory data analysis of the effective federal funds rate in the United States and the average exchange rate of USD to CNY, Figures 1 and 2 show the time series plots of the effective federal funds rate and the average exchange rate of USD to CNY, illustrating the trends and fluctuations of the two datasets.

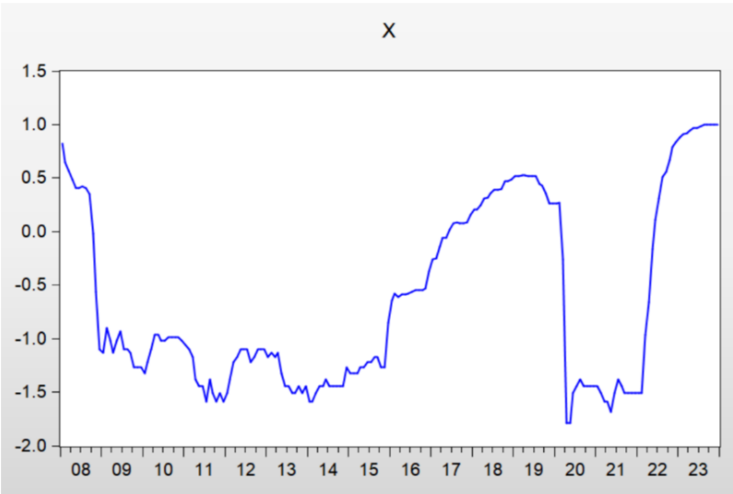


Figure 1. Time Series Plot of the Preprocessed Effective Federal Funds Rate in the United States (X).

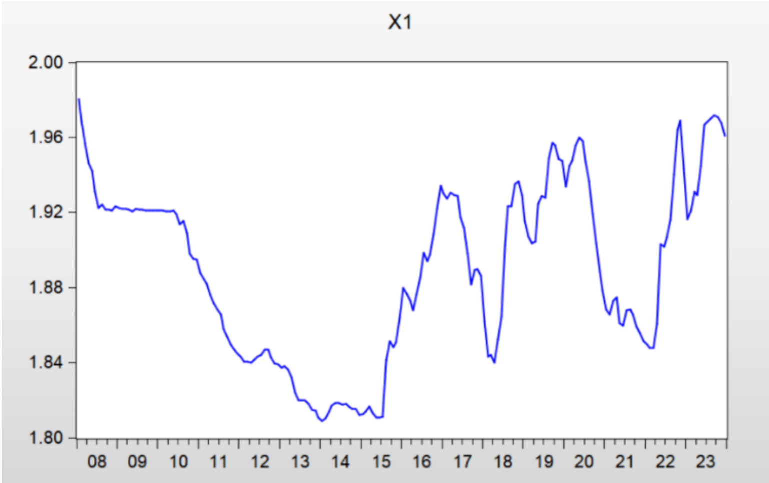
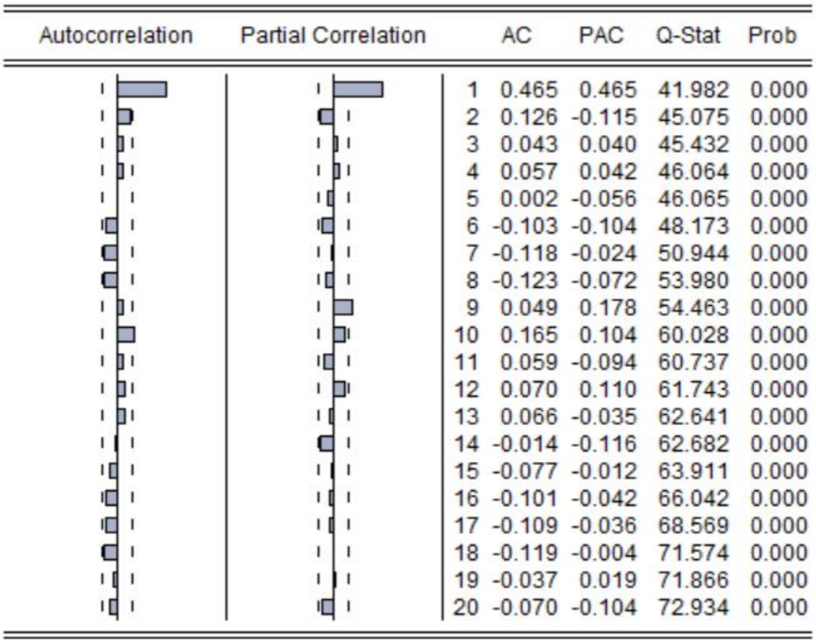


Figure 2. Time Series Plot of the Preprocessed Average Exchange Rate of USD to CNY (X1).

3.1. ARIMA Model Forecasting Results

Typically, the AIC (Akaike Information Criterion) is used to evaluate the parameters of the ARIMA model, where a smaller AIC value indicates better model performance. After training, the model achieved the minimum AIC value of -6.749476, with the best parameters being (1,1,2), as shown in Figure 3 and Table 3.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.465	0.465	41.982	0.000
		2	0.126	-0.115	45.075	0.000
		3	0.043	0.040	45.432	0.000
		4	0.057	0.042	46.064	0.000
		5	0.002	-0.056	46.065	0.000
		6	-0.103	-0.104	48.173	0.000
		7	-0.118	-0.024	50.944	0.000
		8	-0.123	-0.072	53.980	0.000
		9	0.049	0.178	54.463	0.000
		10	0.165	0.104	60.028	0.000
		11	0.059	-0.094	60.737	0.000
		12	0.070	0.110	61.743	0.000
		13	0.066	-0.035	62.641	0.000
		14	-0.014	-0.116	62.682	0.000
		15	-0.077	-0.012	63.911	0.000
		16	-0.101	-0.042	66.042	0.000
		17	-0.109	-0.036	68.569	0.000
		18	-0.119	-0.004	71.574	0.000
		19	-0.037	0.019	71.866	0.000
		20	-0.070	-0.104	72.934	0.000

Figure 3. Autocorrelation and Partial Autocorrelation Plots of USD-to-CNY Middle Rate (First-Order Difference).

Table 3. AIC Value Estimated by ARIMA Model Equation.

(p,d,q)	(1,1,0)	(1,1,1)	(1,1,2)	(2,1,0)	(2,1,1)	(2,1,2)
AIC Value	-6.745535	-6.747261	-6.749476	-6.509632	-6.743218	-6.513082

We have decided to fit the ARIMA(1,1,2) model to these two datasets and use it to predict future exchange rates. Based on the model's predictive results, we can forecast the values for the next 4 months, with the specific data presented in Table 4.

Table 4. Future 4-Month Predicted Values of
USD-to-CNY Middle Rate (Based on ARIMA Model).

Date	Middle Rate of USD-to-CNY Exchange Rate
2024-1-31	6.757254
2024-2-29	6.730571
2024-3-31	6.718395
2024-4-30	6.712838

3.2. EEMD-IAWT-LSTM Model Forecasting Results

After the ARIMA model is validated, the non-linear part of the data is calculated and input into the EEMD model for decomposition, yielding six decomposed sequences, including five IMF component sequences and one residual sequence. The IAWT algorithm is then used to filter out noise from the IMFs, and the processed IMFs are reconstructed into a signal. The reconstructed IMFs are then input into the LSTM model, and the prediction values of the IMF components are combined to obtain the non-linear part of the data sequence. The linear part and the non-linear part prediction results are added together to obtain the predicted values for the next four months, as shown in Table 5.

Table 5. Future 4-Month Predicted Values of USD-to-CNY
Middle Rate (Based on ARIMA-EEMD-IAWT-LSTM Model).

Date	Middle Rate of USD-to-CNY Exchange Rate	Actual Value
2024-1-31	7.0005	7.1060
2024-2-29	6.9949	7.1051
2024-3-31	6.9951	7.0978
2024-4-30	6.9951	7.1007

Through backtesting, we found that the prediction values are close to the actual values, indicating good prediction accuracy. To validate the effectiveness of the model, we compared the prediction results for the next 4 months with the ARIMA model, LSTM model, and ARIMA-EEMD-LSTM model, as shown in Tables 6 and 7.

Table 6. Comparison of the Prediction Results and Actual Values
between the ARIMA-EEMD-IAWT-LSTM Model and Three Control Models.

	ARIMA	LSTM	ARIMA-LSTM	ARIMA-EEMD-IAWT-LSTM	Actual Value
2024.1	6.7572	6.8430	6.9056	7.0005	7.1060
2024.2	6.7305	6.8389	6.9043	6.9949	7.1051
2024.3	6.7183	6.8399	7.0003	6.9951	7.0978
2024.4	6.7128	6.8307	6.8998	6.9951	7.1007

Table 7. Comparison of Accuracy between the Prediction Results
of the ARIMA-EEMD-IAWT-LSTM Model and Three Control Models.

	ARIMA	LSTM	ARIMA-LSTM	ARIMA-EEMD-IAWT-LSTM
2024.1	95.0915%	96.2989%	97.1798%	98.5153%
2024.2	94.8252%	96.2534%	97.1739%	98.4490%
2024.3	94.5560%	96.2675%	98.5250%	98.4518%
2024.4	94.5372%	96.1976%	97.1707%	98.5128%
Average Accuracy	94.7525%	96.2543%	97.5124%	98.4822%

4. Conclusions

By using the combined forecasting model for exchange rate prediction, the main conclusions are as follows:

(1) The ARIMA-EEMD-IAWT-LSTM combined model demonstrates excellent prediction results, with a small difference between the predicted and actual values.

(2) When comparing the prediction results of the ARIMA model, LSTM model, and ARIMA-LSTM model, it is shown that the prediction results of the ARIMA-EEMD-IAWT-LSTM combined model have a higher accuracy, reaching 98.4822%. This indicates that the constructed exchange rate combination model is meaningful in practical applications, as it can more accurately capture the trends, seasonality, and cyclical patterns of time series data, providing important reference value for policymakers and investors.

(3) When dealing with the complexity and randomness of exchange rate time series, directly performing signal denoising can filter out the high-frequency components of useful signals, thus making the denoised signal lose the high-frequency features of the exchange rate time series signal. Therefore, in order to obtain a denoised signal as close to the original as possible, it is necessary to decompose the signal first, separate out the useful signals, which is the reason for adopting the EEMD method.

(4) In response to the limitations of traditional forecasting models, which cannot adaptively select wavelet bases and decomposition levels, and the shortcomings of the threshold function, the IAWT denoising algorithm is introduced. This improved algorithm filters noise from the effective components, and experiments have proven that the introduction of this algorithm is effective.

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