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RMB Exchange Rate Prediction based on EMD-LSTM Model

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Abstract. With the promotion of internationalization and marketization of RMB, it is of great importance and urgency to improve the prediction performance of RMB exchange rate. On the basis of EMD-LSTM model, this paper focus on USD/CNY exchange rate prediction, systematically integrating short-term influencing factors including Crude Oil, Gold, Interest Spread, VIX and EPU. The results showed that Empirical Mode Decomposition (EMD) can greatly improve prediction accuracy. Besides, the integration of EPU and VIX can make the model perform better, indicating that policy uncertainty and market fear sentiment both have obvious influence on USD/CNY fluctuation. These findings can help enrich the researches of exchange rate prediction and have important referencing meaning for related policy-making in China.

Keywords: RMB exchange rate; prediction; EMD-LSTM

1 Introduction

Exchange rate is crucial in connecting international trade activities. The prediction of the RMB exchange rate return is conducive to monitoring and controlling the exchange rate risks, promoting the stable development of foreign trade and providing the direction for the implementation of foreign exchange policies. Compared to traditional statistical models and other machine learning methods, LSTM model can provide a more accurate prediction for exchange rate with nonlinear and complex characteristics. Besides, LSTM model is able to learn long-term dependencies by introducing a memory cell to lengthen the time of holding information (Abedin et al., 2021)[1]. Moreover, EMD is an effective way to analyze inherent characteristics of nonlinear time series (Lu et al., 2022)[2]. Therefore, on the basis of the data of USD/CNY exchange rate between 2015 and 2023, this article proposed EMD-LSTM model introduced different influencing factors of exchange rate. To better evaluate the forecasting ability, this article compared proposed model with single LSTM model and EMD-LSTM model without exogenous variables. At the same time, this paper examined exchange rate volatility features at different time scales, systematically incorporated short-term influencing factors of exchange rate, and analyzed the forecasting impacts of different influencing factors. The organization of the article is given as: Section 2 illustrates the literature review

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about the influencing factors and forecasting methods of exchange rate. In section 3, the methodology and methods are shown. In section 4, research data and indicators are analyzed. Section 5 provides the research results and discussion. Section 6 is conclusion.

2 Literature Review

2.1 Influencing Factors of Exchange Rate

Li et al. (2019)[3] pointed out that USD/CNY exchange rate had a negative correlation with the balance of payments differential and commodity prices, while it was positively correlated with inflation, GDP and foreign exchange reserves. Yang et al. (2023)[4] proposed that the influencing factors of RMB exchange rate include money supply (M2), economic growth, interest rate, investors' expectation (VIX) and economic policy uncertainty (EPU). Liao (2020)[5] found that RMB exchange rate was affected by amount of import and export trade, monetary policy (M2), consumer price index (CPI) and WTI CRUDE price (WTI). However, most of the existing studies only focus on the discussion of certain factors. In other words, they did not have a systematic study within a framework and a further discussion about the prediction performance of these factors on exchange rates. To conduct systematic classification based on the existing literature, the long-term fundamental factors include the GDP growth, the balance of payments, money supply and inflation. Short-term market factors are composed of interest rate spreads, commodity prices (e.g. crude oil prices, gold prices), market fear sentiment (VIX index), and economic policy uncertainty (EPU index). This paper will introduce short-term factors in empirical models to measure the prediction effect of these influencing factors.

2.2 Forecasting Methods of Exchange Rate

Time series models include traditional statistical models and advanced machine learning methods (Liang et al., 2022)[6]. Traditional statistical models include linear model (e.g. ARIMA, ARMA) and nonlinear model (e.g. GARCH). Traditional statistical methods require the financial data and model parameters to satisfy certain assumptions, so nonlinear and complex exchange rate patterns cannot be captured by statistical models (Abedin et al., 2021)[1]. For simple machine learning methods with shallow architectures (e.g. SVR), it is difficult for them to deal with influencing factors with interconnected relationships (Cao et al., 2020)[7]. However, deep learning methods (e.g. CNN, LSTM) overcame these issues listed above and outperformed other methods (Wang et al., 2021)[8]. Compared to other neural networks, LSTM model is proved to be a more effective approach in financial time-series analysis since it creates both a short-term and a long-term memory component (Abedin et al., 2021)[1]. However, the volatility of exchange rate is often influenced by many factors and has the characteristic of multiple time scales. Therefore, this paper firstly conducted empirical mode decomposition (EMD) based on the original sequence, and then made LSTM prediction for each component, and then the results of each component were integrated to get the final prediction outcome.

3 Methodology & Method

3.1 EMD-LSTM Model

Figure 1 showed the proposed EMD-LSTM. The methodology is made up of three steps: decomposition of the original sequence, fitting of the model and final prediction. On this basis, the proposed model also incorporated influencing factors of short-term exchange rate fluctuations, including Sino-US interest spread, Crude oil, Gold, VIX and EPU. The reason is that the short-term high frequency fluctuations of exchange rate is more easily influenced by extraneous factors.

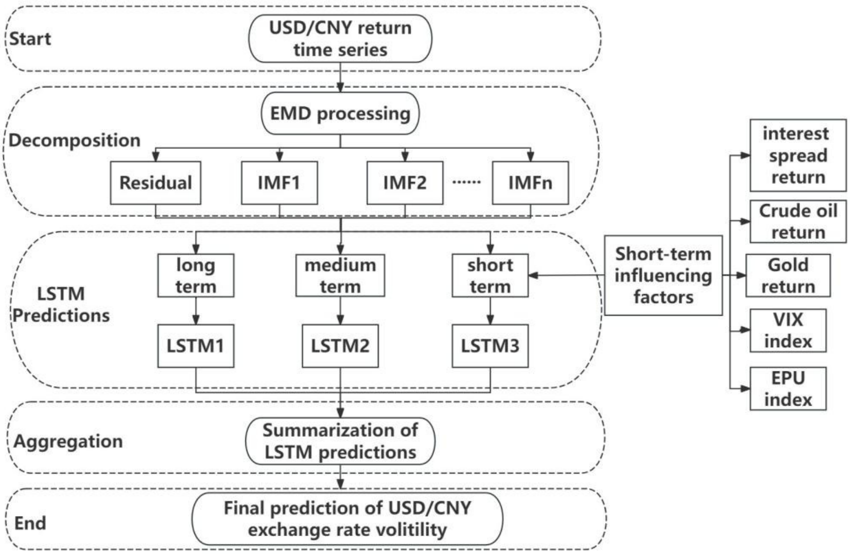

Fig. 1. Process of the EMD-LSTM model

In order to evaluate the prediction ability of the proposed model, a single LSTM model and an EMD-LSTM model without exogenous variables are used to conduct comparison. RMSE and MAE are chosen as the measure indicators of forecasting capability. RMSE and MAE are expressed as follows:

$$RMSE = \sqrt{N^{-1}\sum_{t=1}^{N}(Y_{(t)} - \widehat{Y_{(t)}})^2} \tag{1}$$

$$MAE = N^{-1}\sum_{t=1}^{N}\left|Y_{(t)} - \widehat{Y_{(t)}}\right| \tag{2}$$

Where $Y_{(t)}$ and $\widehat{Y_{(t)}}$ represent the predicted value and actual value at period t, respectively. N denotes the sample size. According to Liang et al. (2022)[6], a lower index value suggests better prediction performance.

3.2 Empirical Mode Decomposition (EMD)

Through EMD, complex signal can be decomposed into simple intrinsic mode functions (IMFs) according to formula (3):

$$x(t) = \sum_{i=1}^{n} IMF_i(t) + tx(t) \tag{3}$$

According to Qiu et al. (2017)[9], these IMFs need to meet two basic requirements: (1) The IMFs have only one extreme between zero crossings. In other words, the difference of extreme points is at most 1; (2) The average extreme value of the signal is 0. The process of EMD is illustrated in Fig. 2:

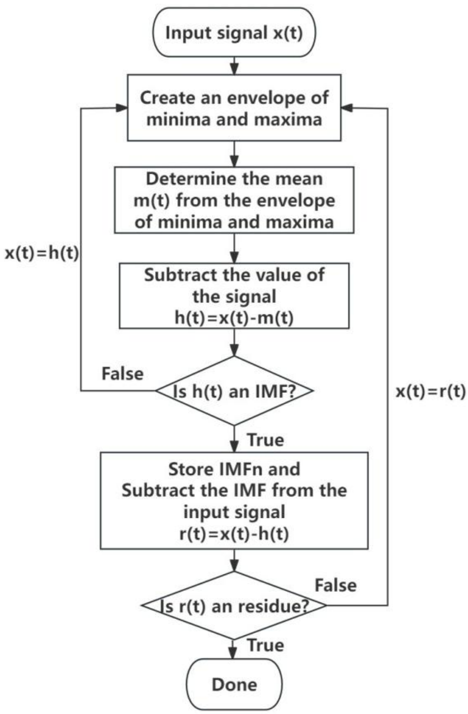

Fig. 2. Process of EMD

3.3 Long Short-Term Memory (LSTM)

LSTM model is an improved method to learn long-term dependency information (Biswas et al., 2023)[10]. LSTM model consists of input, forget and output gates. When these gates are relevant, a lagging association is built and a constant flow error is compelled to keep in circulation. As a result, when processing distant series, the phenomenon of gradient disappearance or explosion is reduced, and the memory capacity of LSTM model would be better. The structure of the forget, input and output gate is presented in expression (4) - (6):

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \tag{4}$$

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \tag{5}$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \tag{6}$$

The state of the LSTM cell can be defined as follows:

$$C_t = f_tC_{t-1} + i_t\widetilde{C_t} = f_tC_{t-1} + i_t\tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \tag{7}$$

The output of the LSTM cell can be obtained by the following equation:

$$h_t = o_t\tanh(C_t) \tag{8}$$

In the above formulas, x is the input layer variable, h is the hidden layer variable, W represents the weight matrix of the related structure, and b refers to the bias in the structure.

4 Data and Indicators

4.1 Data Source

This paper selects daily USD/CNY exchange rate data between 2015/01/05 and 2023/11/30, and 80% of the data is selected as the training set, while the remaining 20% is chosen as the validation set. The training set scale is enough to fit a good model and to avoid excessive fitting. According to the analysis in the previous literature review, Sino-US interest spread, crude oil, gold, VIX index and US EPU index would be selected as exogenous variables. The Sino-US interest spread is the difference between China's 10-year treasury yield and the US 10-year treasury yield. The EPU index came from policyuncertainty.com. The data of other influencing factors and USD/CNY exchange rate was provided by Investing.com.

4.2 Data Characteristics & Stability

The trend diagrams of different research data are shown in Fig. 3-6. In Fig. 3, USD/CNY exchange rate greatly decreased from 2017 to 2018 because of Federal Reserve's consecutive and significant interest rate hikes. Besides, USD/CNY exchange rate obviously dropped between 2020 and 2022 due to Covid19. Since 2016, USD/CNY and Interest Spread had similar trend in Fig. 4 for the reason that “811 exchange rate reform” promoted the marketization of RMB exchange rate and improved the correlation of exchange rate and interest rate. It can be seen in Fig. 5 that Oil and Gold changed similarly and both increased continuously, indicating that commodity prices are relatively stable. Fig. 6 showed that the trend of VIX was quite similar with EPU and both rose swiftly in the early days of the epidemic.

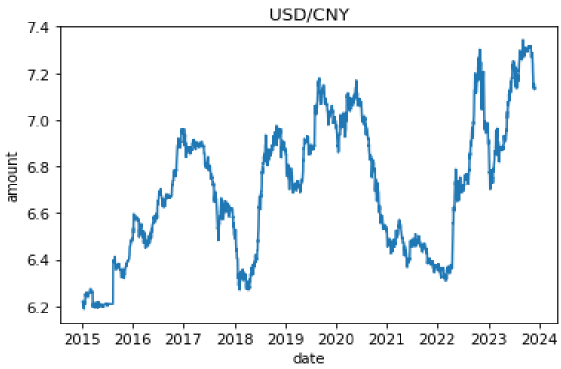

Fig. 3. USD/CNY trend diagram

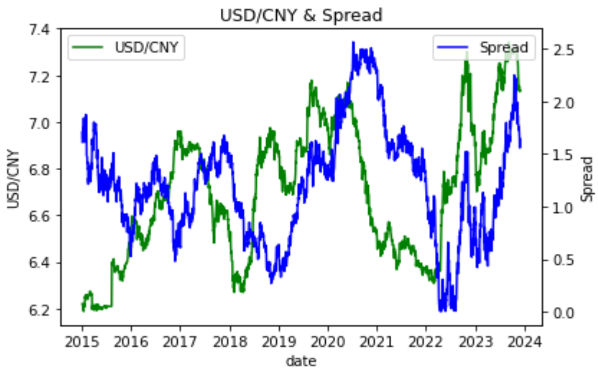

Fig. 4. USD/CNY & Spread trend diagram

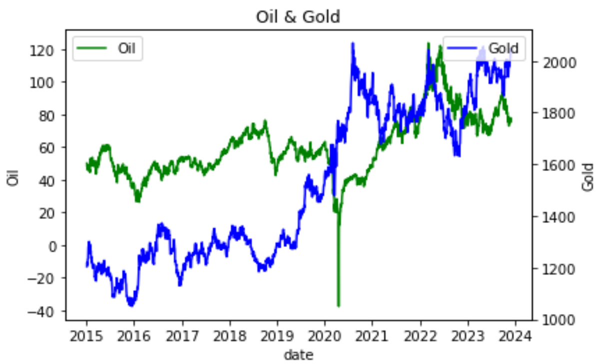

Fig. 5. Oil & Gold trend diagram

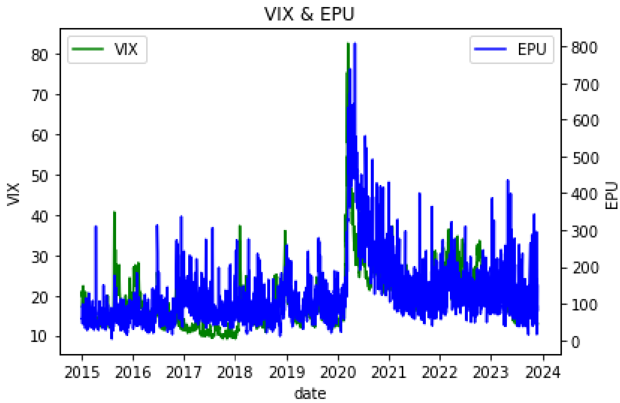

Fig. 6. VIX & EPU trend diagram

Table 1. Augmented Dickey Fuller Test

Variable	level		Natural logarithmic rates of return	
	C	C&T	C	C&T
USD/CNY	-1.560359	-1.708091	-46.09096***	-46.08135***
Oil	-2.058730	-2.784054	-29.40173***	-29.39543***
Gold	-0.747865	-3.000428	-47.80087***	-47.79264***
Interest Spread	-2.291121	-2.315718	-8.909344***	-8.936668***
VIX	-5.013896***	-5.314292***	—	—
EPU	-4.265135***	-4.536760***	—	—

Notes: C, T separately indicate that the ADF test equation has a constant term and a time trend term. *** refer to 1% levels of significance.

The stability is analyzed according to the ADF test in Table 1. The time series of USD/CNY exchange rate, the Sino-US interest spread, crude oil prices and gold prices are all non-stable at level, while their natural logarithmic rates of return are stable, thereby the latter ones would be used in the empirical test in order to eliminate the non-stability. However, time series of VIX index and EPU index are both stable and would be directly used in the experiment.

4.3 Descriptive Statistics

Table 2. Descriptive statistics

	USD/CNY	Oil	Gold	Interest Spread	VIX	EPU
Mean	6.54e-05	0.000543	0.000223	0.000922	18.61783	122.8459
Median	6.44e-05	0.002188	0.000315	0.000624	16.79000	96.07000
Maximum	0.018382	0.319634	0.057754	3.555348	82.69000	738.0200
Minimum	-0.016213	-0.282206	-0.051140	-2.542726	9.140000	10.92000
Std. Dev.	0.002681	0.030068	0.009214	0.206955	7.594354	91.70374

Table 2 shows the statistical characteristics of variables. The volatility of USD/CNY Return was the lowest with Std. Dev. of 0.002681. Compared to Gold, the volatility of Oil was higher with Std. Dev. of 0.030068. The interval of Interest Spread varied greatly from -2.542726 to 3.555348. The VIX and EPU have maximum of 82.69000 and 738.0200 separately in March in 2020. At that time of early epidemic, the plunge in crude oil prices greatly increase market fear sentiment, and the policy uncertainty rose since US Federal Reserve implemented an expansionary monetary policy.

5 Experiment and Results

5.1 EMD

In Fig. 7, USD/CNY return was decomposed into seven IMFs and a residual sequence. Original signal showed that the the volatility of USD/CNY exchange rate is high. In Fig. 8, to better analyze the volatility characteristics at different time scales, the IMFs were further rebuilt according to the frequency similarity. The low-frequency IMF is equal to the sum of IMF6 and IMF7, showing periodic volatility characteristics. By summing IMF4 to IMF5, the medium-frequency IMF is obtained. The high-frequency IMF is gain from merging IMF1 to IMF3, showing obvious fluctuation aggregation.

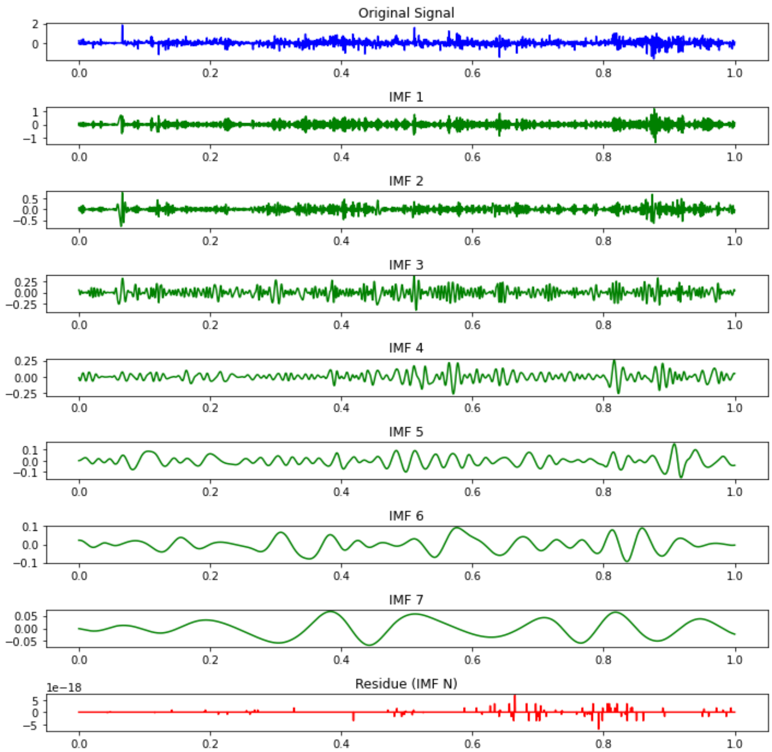

Fig. 7. EMD of USD/CNY exchange rate return

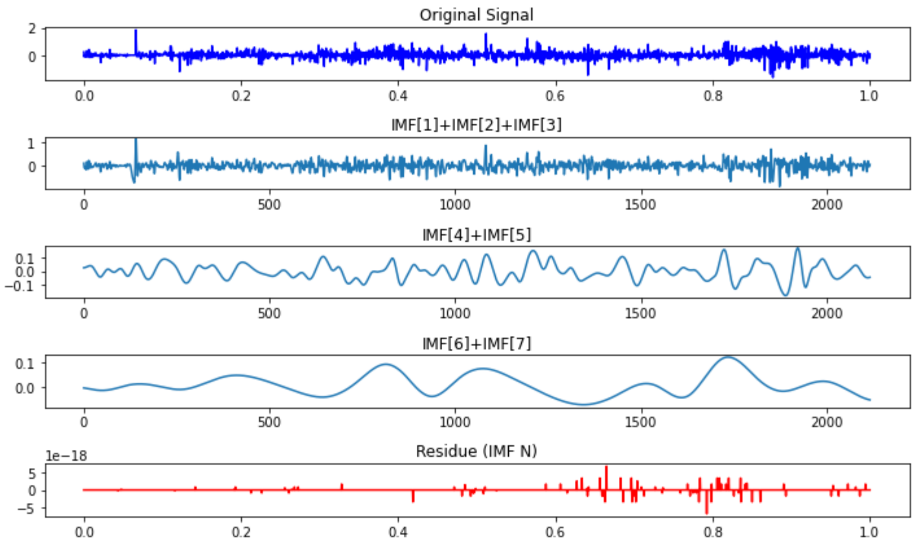

Fig. 8. High-frequency, medium-frequency and low-frequency IMFs

5.2 Comparison of Prediction Models

Table 3 showed the in-sample and out-of-sample model prediction outcome. Model 1 integrated Oil, Gold, Spread, VIX and EPU. Model 2 integrated Oil and Gold. Model 3 integrated Spread. Model 4 integrated VIX and EPU. Compared with single LSTM, both EMD-LSTM with and without exogenous variables have much smaller MAE and RMSE in and outside the sample, indicating that EMD decomposition has an optimization effect on exchange rate prediction. Compared with EMD-LSTM without exogenous variables, model 1 has slightly larger MAE and RMSE within and outside sample, indicating that the forecasting accuracy has reduced because of the over-fitting phenomenon when all influencing factors are introduced. However, compared with EMD-LSTM without exogenous variables, model 2,3,4 has slightly smaller MAE and RMSE in sample, indicating that the classified introduction of exogenous variables will improve the prediction effect. In model 2, 3, 4, MAE and RMSE of model 2 are largest, while that of model 4 are smallest. It means that the introduction of Oil and Gold has least improved effect on USD/CNY prediction, while the introduction of VIX and EPU has the best prediction effect. In Fig.9, it is obvious that the predicted value of model 4 is quite close to the true value.

Table 3. Comparison of model prediction results

Model	Single LSTM	EMD-LSTM without exogenous variables	EMD-LSTM with exogenous variables			
			Model 1	Model 2	Model 3	Model 4
In-sample						

RMSE	0.240742	0.064745	0.066956	0.063971	0.064217	0.062067
MAE	0.163629	0.047056	0.050724	0.047539	0.046637	0.045166
			Out-of-sample			
RMSE	0.357125	0.104911	0.112428	0.105346	0.112295	0.102597
MAE	0.257325	0.071012	0.081341	0.074985	0.078994	0.071023

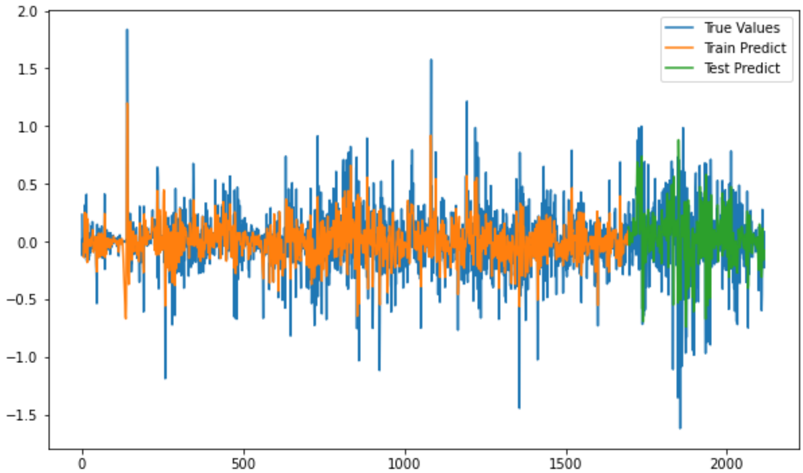

Fig. 9. In-sample and out-of-sample prediction of model 4

6 Conclusion

In order to predict USD/CNY exchange rate, this paper used a single LSTM model, an EMD-LSTM model without exogenous variables and four EMD-LSTM models with different exogenous variables. The results show that EMD can greatly improve the prediction effect due to tight internal correlation of each IMF. The research of EMD is also important for understanding the characteristics of USD/CNY return at different time scales. Besides, compared with interest rate spreads and commodity prices, the introduction of EPU and VIX make the EMD-LSTM model perform better. Obviously, uncertainty of the Fed's interest rate policy and market fear sentiment caused by the outbreak of the epidemic both have great impact on USD/CNY fluctuation. The proposal EMD-LSTM model considering the influencing factors is beneficial to increase the prediction accuracy and manage exchange rate risk.

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