

The Analysis of Global RMB Exchange Rate Forecasting and Risk Early Warning Using ARIMA and CNN Model

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ABSTRACT

The purpose of this study is to predict exchange rate fluctuations more accurately and enhance Chinese enterprises' ability to avoid exchange rate risks. Renminbi (RMB) exchange rate fluctuation's prediction methods are studied based on data mining technology. The Auto-Regressive Integrated Moving Average (ARIMA) model is introduced first using a modeling method that combines linear and nonlinear models. The linear prediction is obtained by the application of ARIMA model in the RMB exchange rate's dynamic fluctuation analysis. The nonlinear residual prediction is obtained by integrating the ARIMA model with the convolutional neural network (CNN) algorithm. The RMB exchange rate fluctuations' influencing mechanism on China's economic growth is explored by theoretical analysis and empirical research. The empirical research shows that the final fitting sequence obtained from the composite model has the same trend as the original USD exchange rate sequence. Import and export trades are essential factors affecting China's economic growth.

KEYWORDS

ARIMA Model, China's Economy, Convolutional Neural Network, Data Mining, Economic Globalization, Economic Growth, Exchange Rate Fluctuation Prediction, Nonlinear Residual Prediction, Renminbi

INTRODUCTION

Economic globalization is the inevitable result of contemporary social and economic development. Since China joined the World Trade Organization (WTO) in 2001, the connections between China's economy and the world economy have been increasingly strengthened. Lahmiri (2017) proposed that the global economy's integration, economic interdependence among countries, and monetary policies' closer cooperation increase exchange rate fluctuations' complexity. After the exchange rate reform in July 2005, the RMB exchange rate continued to appreciate, and the fluctuation amplitude increased significantly. Therefore, Du et al. (2020), Nayak et al. (2016), and Gbatu et al. (2017) suggested that various microeconomic entities in China must improve their exchange rate risk management as soon as possible. From the exchange rate system reform in July 2015 to 2013, the RMB exchange rate maintained a long-term trend of one-way appreciation against the US dollar. As the US dollar has appreciated against other major currencies such as Euro, RMB also appreciated against Euro. Afterward, Nour et al. (2019) put forward that the RMB exchange rate continued to

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fluctuate bilaterally and significantly, gradually leading to a market expectation of RMB exchange rate devaluation. In 2016, the RMB officially became a member of the basket of currencies of the International Monetary Fund. In such a complex and volatile foreign exchange market, any major international emergency may lead to great fluctuations in the RMB exchange rate, resulting in exchange rate risks and affecting China's economic stability. Moreover, Lagat et al. (2016) stated that the RMB is not yet fully convertible in the balance of payments in the capital account, and the RMB exchange rate is still determined by market supply and demand conditions and exchange rate policy choices.

In the open economy, the exchange rate is an essential factor affecting a country's economic development and a reliable basis for ensuring the international trade balance. As the relative price of two different countries' currencies, the exchange rate has become a recognized and significant link to maintain international economic exchanges. Alagidede et al. (2017) indicated that the exchange rate fluctuations' characteristics have always been scholars' concern in international finance. The exchange rate prediction methods include basic analysis and time-sequence analysis currently. The basic analysis method predicts the long-term exchange rate fluctuations based on variables such as international exchange interest rates, gross domestic product (GDP), and balance of payments. It is not suitable for short-term exchange rate fluctuation prediction. Tehranchian et al. (2018) and Ouma et al. (2018) showed that the time-sequence analysis method predicts exchange rate fluctuation based on the information generated by the sequence changes over time, so it can also realize good prediction when applied to short-term fluctuation prediction. The Auto-Regressive Integrated Moving Average Model (ARIMA) model is adopted in the linear model for exchange rate fluctuation prediction. As a traditional linear model for time-sequence fitting, the ARIMA model can convert non-stationary sequences into stationary sequences for more precise fitting predictions. However, the focus of ARIMA model's prediction lies in the sequence level, so linear expressions cannot accurately describe the complex exchange rate sequences increasing or declining nonlinearly, resulting in a limitation. Ehikioya et al. (2020) suggested that scholars in finance and economics had successively proposed the autoregressive conditional heteroscedasticity model and the generalized regression conditional heteroscedasticity model to solve the ARIMA model's autocorrelation problem in the residual sequence. On this basis, some scholars proposed the Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) model. Adelakun et al. (2020), Zhang et al. (2018), Hossin et al. (2020) and Nguyen et al. (2017) held that the GARCH model performed better than the ARIMA model in exchange rate prediction, so it had become a significant research direction in modern econometrics.

Each financial prediction model needs to ensure that the model parameters and financial data meet certain assumptions before sequence data study to accurately predict the exchange rate's dynamic fluctuation trend, bringing about heavy workload to practical operation. Tian et al. (2019) proposed that the neural network can train the network according to the mapping relationship between input and output under unknown parameters and data objects' dynamic characteristics, so it is widely used in exchange rate prediction. Aiming at the foreign exchange market with high volatility and noise, a modeling method that combines linear and nonlinear models is adopted herein, and the ARIMA model's theoretical basis and the neural network parameter settings are introduced. The ARIMA model and the convolutional neural network (CNN) algorithm are integrated herein. First, the ARIMA model predicts the linear data, and then the neural network model predicts the ARIMA model's residual. The final prediction result of exchange rate fluctuation is obtained by summing the linear prediction and the nonlinear prediction. Finally, the RMB exchange rate fluctuations' impacts on China's economic growth are analyzed by theoretical analysis and empirical research. The results have significant practical values for predicting RMB exchange rate fluctuations and helping Chinese enterprises avoid exchange rate risks.

RELATED WORK

Research Status of Exchange Rate Forecast

The time sequence analysis has developed from linear model to nonlinear model and from parametric model to nonparametric model (Chen, 2020; Zhang & Chen, 2020; Ma et al., 2021). Bakar et al. (2017) suggested that because of the ideal statistical characteristics and recognized modeling methods, the summation ARIMA model was widely used in linear models. ARIMA model is applied to many time sequences. Engel et al. (2019) pointed out that through the construction of the ARIMA model, China's monthly Consumer Price Index (CPI) can be forecasted, which can provide a quantitative basis for the effective implementation of price control policies at the macro-level. In the investigation of the average price of second-hand houses in Guangzhou and Shenzhen, the ARIMA model could make a rolling prediction of future house prices, with high prediction accuracy. ARIMA model could predict two exchange rate sequences with different lengths of time sequence. Wong et al. (2020) took the weekly average exchange rate of RMB against the US dollar as the research object, predicted it with the ARIMA model, and speculated that RMB had an appreciation trend, and the prediction effect was ideal. Hua et al. (2020) studied the intermediate price sequence of RMB's exchange rate against the US dollar, and predicted its short-term trend through the ARIMA model, and the forecast results could reflect the short-term fluctuation of the exchange rate. The fluctuation of the exchange rate was very complex, which makes it difficult to be measured accurately with a simple linear relationship (Qiao et al., 2021; Wu et al., 2022; Yu et al., 2021; Liu et al., 2021). The linear model could not model the nonlinear part in the time sequence. Hereupon, a nonlinear parameter model was proposed. The ARIMA model, GARCH model (including GARCH, TGARCH, and EGARCH model), and the related extended models of the GARCH model (GARCH-M model and AR-GARCH model) were constructed to forecast the fluctuation of the daily exchange rate. The comparison analysis showed that the TGARCH-M model had the best fitting effect and the highest prediction accuracy, and RMB exchange rate fluctuation had significant asymmetry. Iregui et al. (2021) stated that the variance equation performance of the GAECH and ECARCH model was not stable and could not analyze the RMB exchange rate volatility. Iregui et al. (2021) used the ARIMA model, ARIMA-GARCH model, and Threshold Autoregressive (TAR) model to forecast the RMB exchange rate. Jiang et al. (2021) indicated that the TAR model could greatly reduce the mean absolute error (MAE) and standard deviation (SD) of the forecast and improve the accuracy and stability of the forecast.

Research Status of the Composite Model

Zhang et al. (2017) reflected that linear models and nonlinear models have had successful applications, respectively, but they are not universal models and have specific limitations. Given these limitations and for higher prediction accuracy, the combination of multiple models is widely used to predict the time sequence. According to the theory of the composite model and its empirical research, the combination of different models is an effective method to improve prediction accuracy. Song et al. (2018) stated that the accuracy of time sequence prediction can be improved through the combination of feedback neural network models. Qian et al. (2020) predicted that the stock market prediction based on the combination of Artificial Neural Network (ANN) and Genetic Algorithm (GA) can achieve a better effect. Under the combination of GA with the Backpropagation Neural Network (BPNN) model, the structure and initial weights of the neural network are optimized by GA, and a new composite model is established. The weekly and daily data are predicted by the model. Wang et al. (2020) revealed that the combined model overcomes the slow convergence speed of GA and poor global search ability of BPNN, and the weekly and daily data of exchange rate are reduced. Meanwhile, compared with the weekly data, the prediction effect of the model is better. Palmqvist et al. (2021) predicted exchange rates with ANN and random walk models and compared the results with that of a single model, and the composite model showed a better prediction effect.

Summary and Analysis of Related Literature

ARIMA can fully capture the linear part of the time sequence, and the ARIMA model has a simple structure and is easy to use. In many fields, ARIMA is used to build a linear prediction model. ARIMA model reflects the application value of the linear model in time sequence prediction. ANN performs well in nonlinear fitting and is widely used. A composite ANN model with a stronger fitting ability has been proposed, which further improves the prediction accuracy. However, Zhang et al. (2021) pointed out that although a single linear model or nonlinear model can achieve a good prediction effect in its own field, the prediction effect of the linear model in nonlinear time sequence or nonlinear model in linear time sequence is not ideal, which can be perfectly solved through the application of the composite model. Here, the significance of the research is as follows: after the new exchange rate reform, the uncertainty of the exchange rate trend is further enhanced, and the fluctuation range of the exchange rate is getting large. And the gradual deterioration of Sino-US relations has a significant impact on the exchange rate, exacerbating the downward trend of the RMB exchange rate. In this context, improving the accuracy of exchange rate volatility prediction has important theoretical research significance and practical application value for enterprises, individuals, and other micro-entities to avoid foreign exchange risk, as well as for the central bank and relevant management departments to strengthen financial supervision and formulate accurate and effective exchange rate policy. Thereupon, innovatively, the linear and nonlinear models are combined, and the traditional composite model is built here to study the volatility characteristics of the RMB/US dollar exchange rate's intermediate price series. First, the linear main part of the RMB exchange rate is predicted with the ARIMA model. Then, the nonlinear residual is fit through the Support Vector Machine (SVM) model. Finally, the two parts are combined to get the final forecast result of the RMB exchange rate sequence. Compared with the ARIMA model and CNN model, the results show that the composite model has a better prediction effect and better prediction accuracy.

MATERIALS AND METHODS

The construction process of the RMB exchange rate forecasting model based on the ARIMA and CNN model is as follows: first, Zhang's traditional composite model is chosen, and the model construction is divided into three steps. Step one, the linear components of the time sequence are modeled with ARIMA, and the residual between the original data and ARIMA prediction is obtained. Step two, the nonlinear residual obtained in the first step is modeled with the CNN. Step three, the prediction results obtained by the two methods are superimposed. Because the nonlinear components of the time sequence cannot be captured by the ARIMA model, the relevant information of nonlinear components is contained in the residual of the linear model. The prediction result of CNN can be used as the prediction of residual sequence obtained by the ARIMA model. When a single CNN model is used to forecast the exchange rate, its input dimension is 4, that is, the exchange rate data of the next day is forecasted using the exchange rate data of the previous four days. For consistency, the input dimension of the nonlinear residual prediction part is also set to 4, that is, the first four residual values are used to predict the next one. The details of algorithm construction are shown below.

Differential ARIMA Algorithm Model

The ARIMA model combines the differentiation operation and the autoregressive moving average (ARMA) model. First, the non-stationary time sequence is transformed into a stationary time sequence by a differentiation operation. Yao et al. (2020) implemented a time-sequence prediction model by regressing the dependent variable's lag value and the random error term's present value and lag value. In the ARIMA (p, d, q), *AR* represents "autoregressive," *I* represents differentiation, and *MA* represents "moving average;" p represents the autoregressive term number, d represents the

differentiation order, and q represents moving average term number. Equations (1) and (2) show the ARIMA (p, d, q)'s structure.

$$\begin{cases} \phi(B)\nabla^d y_t = \theta(B)\varepsilon_t \\ E(\varepsilon_t) = 0, Var(\varepsilon_t) = \sigma_\varepsilon^2, E(\varepsilon_t \varepsilon_s) = 0 \\ E(y_s \varepsilon_t) = 0, \forall s < t \end{cases} \quad (1)$$

$$\nabla^d = (1 - B)^d \quad (2)$$

(ε_t) is the white noise sequence with a mean of zero, $\phi(B)$ is the autoregressive coefficient polynomial, and $\theta(B)$ is the moving smoothing coefficient polynomial, which can be used to evaluate the model's stationarity. When the unit root is outside the unit circle, ARIMA (p, d, q) is stable, and when the unit root is outside the unit circle, ARIMA (p, d, q) is reversible.

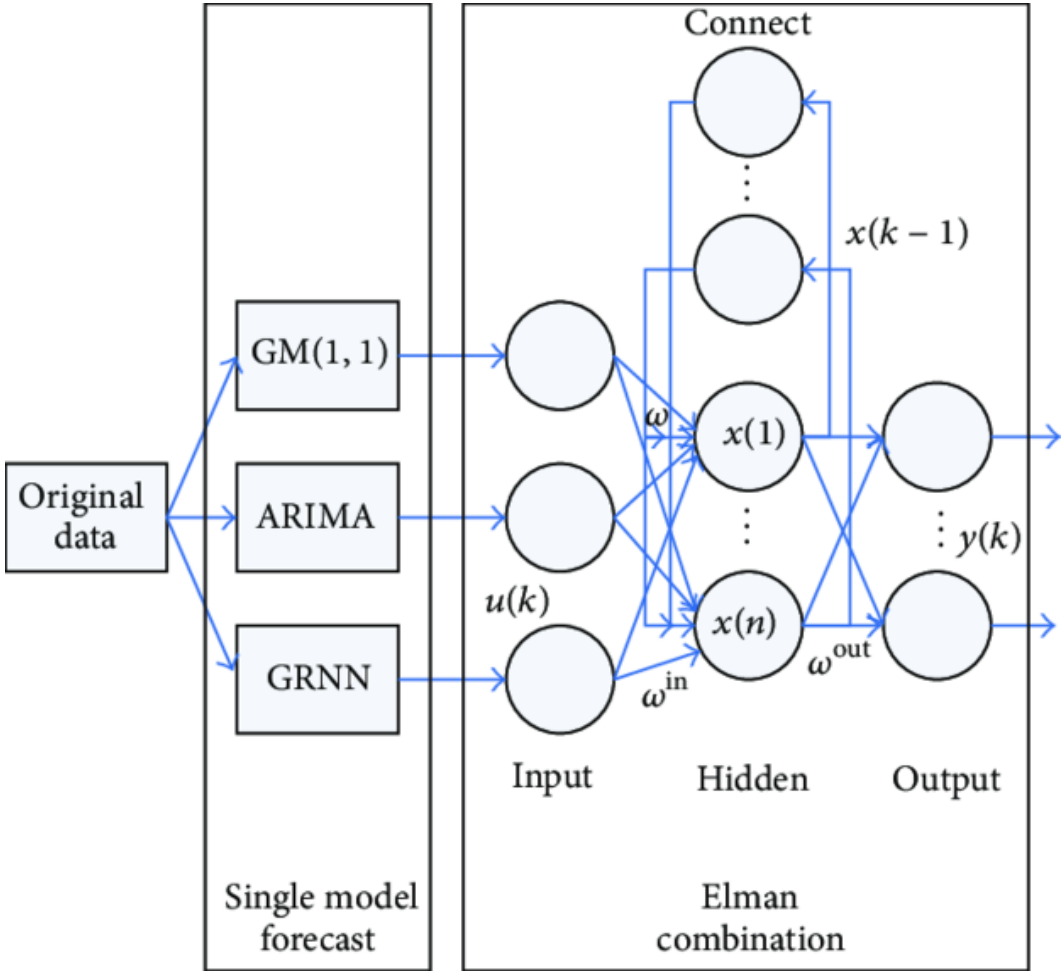
Before constructing the ARIMA model, whether the time-sequence is stationary should be judged. If the time-sequence is stationary and the data do not need to be differentiated, the ARIMA model is ARIMA ($p, 0, q$), equivalent to ARMA (p, q). However, most complex financial time-sequences have a particular trend or cycle and usually do not meet data stationarity requirements, so differentiation operations on the non-stationary sequence are necessary. The sequence is changed by d -order differentiation to become stationary. The logarithm is taken first and then differentiated for the exchange rate time-sequence, obtaining the logarithmic return sequence to extract deterministic information. If the sequence is stationary after the logarithmic differentiation, the stationary sequence is tested for white noise to determine whether it has an analytical value. If the sequence is non-white noise, it can be modeled by ARIMA. The specific structure is shown in Figure 1.

The ARIMA model has a good fitting effect in the analysis of linear series, so the ARIMA model is used to predict the exchange rate sequence under the comparison of four ML (Machine Learning) models. The ARIMA model performs better on linear data, while the ML model performs better on nonlinear series. The exchange rate sequence is decomposed into linear trend term and nonlinear periodic term using the HP filtering method, and then the trend term and periodic term are forecasted, by ARIMA model and ML model. Finally, the two prediction results are summed up, thereby improving the prediction effect of the model. The specific process is as follows.

Due to the exchange rate sequence's linear and nonlinear time-sequence characteristics, the ARIMA model is combined with the neural network model to construct the prediction model of the exchange rate sequence. Assuming that the RMB exchange rate sequence consists of two parts, namely the linear autocorrelation part L_t and the nonlinear residual part e_t , equation (3) shows the RMB sequence.

$$S_t = L_t + e_t \quad (3)$$

Figure 1. Model structure of differential ARIMA algorithm



First, the ARIMA model completes the fitting modeling of the exchange rate sequence S (fitting the logarithmic differentiation sequence of S), obtaining the prediction of the logarithmic differentiation sequence. The exchange rate sequence's linear autoregressive prediction can be obtained after de-differential, and antilog of S . Equation (4) shows the residual sequence.

$$e_t = S_t - \hat{L}_t \tag{4}$$

Afterward, the CNN completes e_t 's modeling, and the residual sequence's predicted value is obtained by fitting prediction. Finally, the prediction value of the exchange rate sequence S is obtained by summing the linear prediction and the residual prediction. Equation (5) shows its expression.

$$\hat{S} = \hat{L}_t + \hat{e}_t \tag{5}$$

CNN Structure

A neural network propagates information through large-scale interconnected neurons, describes the complex relationship between input and output, and analyzes the internal structure of data. The common neural network structure includes three layers: input layer, hidden layer, and output layer. The basic unit of each layer is called a neuron, which imitates the working principle of the human brain and processes its nodes only when the signal exceeds a particular threshold. The number of nodes in the input layer is determined by the sample size. The prediction effect of the model can be improved through the number of nodes in the hidden layer and the activation function of each node. Equation (6) shows the activation function for the output layer.

$$Z_k = f(u_k), k = 1, 2, \dots, N \quad (6)$$

Equation (7) shows this layer's network input.

$$u_k = \sum_{j=0}^m w_{jk} \cdot y_j \quad (7)$$

Equation (8) shows the hidden layer's activation function.

$$y_j = f(u_j), j = 1, 2, \dots, M \quad (8)$$

The Sigmoid function Equation (9) is selected as the activation function because it is continuous and differentiable.

$$f(x) = \frac{1}{1 + e^{-x}} \quad (9)$$

Equation (10) defines the output error.

$$E = \frac{1}{2}(d - O)^2 = \frac{1}{2} \sum_{k=1}^N (d_k - O_k)^2 \quad (10)$$

Equation (11) shows its substitution to the output layer.

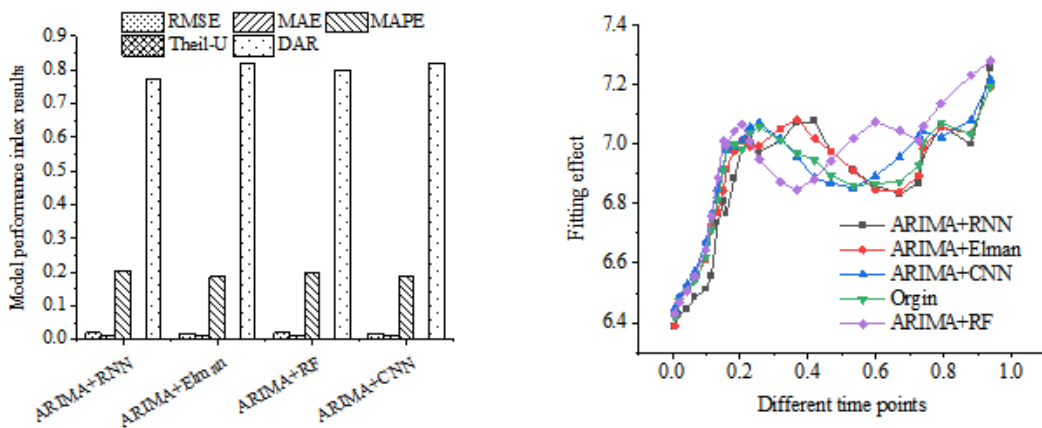
$$E = \frac{1}{2} \sum_{k=1}^N \left[d_k - f \left(\sum_{j=0}^M w_{jk} \cdot y_j \right) \right]^2 \quad (11)$$

Equation (12) shows the Expansion of the neural network's hidden layer.

$$E = \frac{1}{2} \sum_{k=1}^N \left\{ d_k - f \left(\sum_{j=0}^M w_{jk} \cdot f \left(\sum_{i=0}^N v_{ij} \cdot x_i \right) \right) \right\}^2 \quad (12)$$

The complex high-dimensional functions such as high-variable functions can be better represented by combining deep learning (DL)'s imitation of the human cerebral cortex's characteristics and neural networks. CNN is the most classic network structure in DL networks. The CNN is derived from the biological visual system structure, reasonably reducing the parameter number in the neural network and solving the model's overfitting. Figure 2 shows CNN's structure. The entire network's input is generally the picture's pixel matrix. The 3D matrix's length and width represent the image size, and the depth represents the image's color channel. The convolutional layer is CNN's most significant part, and each node input is only a small section of the neural network's upper layer. The pooling layer reduces the nodes' number in the final fully-connected layer, reducing the entire neural network's parameter. The final fully-connected layer is the classifier in the entire CNN. Zhang et al. (2020) proposed that the fully connected layer recognized and classified the results after deep networks such as convolution, softmax activation function, and pooling. The forward propagation process of the convolutional layer structure moves a filter from the upper left corner of the current layer in the neural network to the lower right corner and calculates each corresponding identity matrix during the movement. The only difference between a fully connected layer and a convolutional layer is that the convolutional layer's neurons are only connected to the local input area and many neurons in the convolutional layer share parameters. However, the neurons in the two layers still calculate the dot product, so they have the same functional form and can shuttle between the fully connected and convolutional layers. Neurons in CNN's every layer are locally connected to realize the input's feature extraction. Neurons with the same connection weight can be connected to different areas of the upper layer in the neural network, obtaining a neural network structure with translational invariant properties.

Figure 2. The CNN structure



CNN's training is similar to that of the BP neural network (BPNN). After the prediction value is obtained by forward propagation, the backpropagation algorithm is used for the chain derivation. The loss function's partial derivative for each weight is calculated, and the gradient descent method is used to update the weight. CNN's training process. In forward propagation, a sample (X, Y_p) is randomly selected from the training set. X is the neural network input, and Y_p is the neural network's expected output. Equation (13) shows X 's actual output after its calculation from the input layer to the final output layer.

$$O_p = F_n \left(\dots \left(F_2 \left(F_1 \left(X W_1 \right) W_2 \right) \dots \right) W_n \right) \quad (13)$$

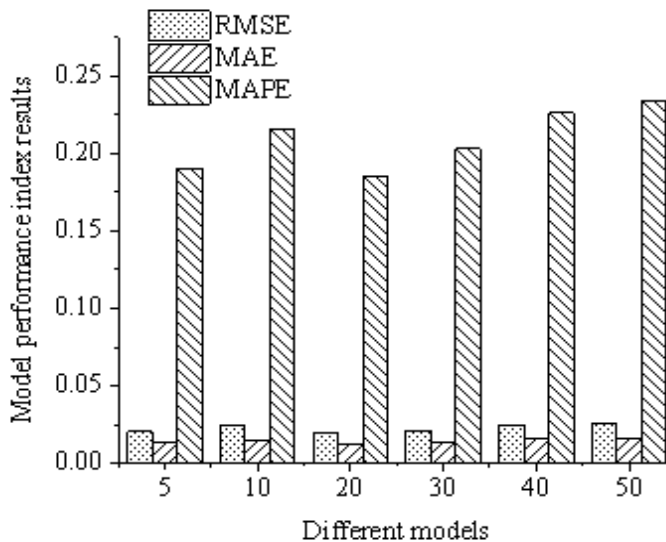
The BP calculates the error E_p between the actual output O_p and the expected output Y_p .

$$E_p = \frac{1}{2} \sum_j (y_{pj} - o_{pj})^2 \quad (14)$$

In information's forward propagation, the convolution kernel and its input are convolved effectively. If the current layer is a convolution layer in the BP process, its error is propagated from the down-sampling layer. CNN can be trained successfully by sharing the convolution kernel, which can process high-dimensional data. Besides, features do not need to be selected manually in the CNN. When the weights are trained, effective feature classification is obtained, which is very suitable for pattern recognition tasks. If all the CNN parameters are in a reasonable value range, the optimized algorithm is based on gradient results in the network's good training results.

The steps for CNN network exchange rate prediction are as follows: first, the RMB exchange rate data from December 1, 2015 to October 8, 2019 are processed, in which the data of the first four days are input variables and the fifth day is output variables, forming a variable matrix of 186 lines multiplied by five dimensions, that is, the model contains four input layers and one output layer. Second, according to the equations, the number of neurons is determined to be between three and thirteen, which is then judged one by one using the trial and error method based on the Minimum Mean Square Error (MMSE) of the model. Finally, the number of neurons in the hidden layer is determined to be four. In conclusion, the neural network structure is set as 4x4x1, in which the transfer function is Tansig, the training function is Train-lm, the learning algorithm of weight and threshold and the performance function are Learngdm and Mse, respectively. Additionally, the target error of the model is 1×10^{-5} , and the maximum number of iterations is 1,000. The details are shown in Figure 3.

Figure 3. CNN's training process



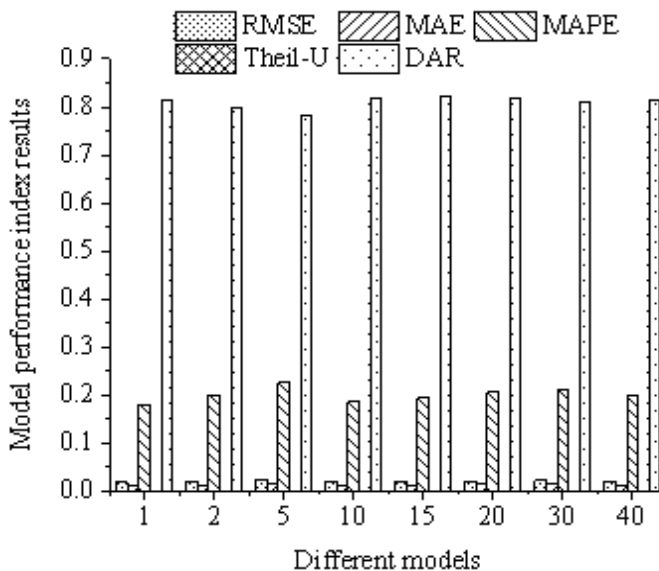
RMB Risk Measurement

Exchange rate fluctuation in a country will drive part of and even the entirety of international economic changes. The most intuitive effects of exchange rate fluctuation on the economy are the export price fluctuation. If the country’s currency devalues, the exported commodities’ price will fall, increasing the export trade volume significantly. Hoseyni et al. (2016) pointed out that, with the country’s commodity price unchanged, foreign currencies’ purchasing power will be relatively enhanced. If a country’s exchange rate falls, the imported traded commodities’ price will increase, restraining the country’s demand for imported commodities to a particular extent, reducing the imported trade volume, and increasing the total output ultimately. The exchange rate decrease attracts foreign tourists and promotes tourism and other non-trade incomes. Valueva et al. (2020) showed that, on the contrary, after the currency devaluation, foreign tourism and other labor expenditures become more expensive for the residents in the country, suppressing the country’s foreign labor expenditures. It should be noted that devaluation may have adverse effects on a country’s unilateral revenue and expenditure transfer. An increase or decrease in a reserve currency’s exchange rate directly affects reserve assets’ actual value. Elhoseny and Shankar (2019), El-Mousawi et al. (2018), and Atarodi et al. (2018) proposed that if a reserve currency’s exchange rate falls, the country with this currency as a reserve suffers losses, while the country that issues this reserve currency passes on the currency devaluation loss and reduces its debt burden. Besides, the exchange rate’s instability also affects the reserve currency’s status. In summary, the exchange rate does not directly impact economic growth. It acts on variables that affect economic growth first and affects economic growth ultimately.

The RMB exchange rate fluctuations’ impact mechanism for economic growth is analyzed empirically herein. Figure 4 shows that China’s trade volume soared from US\$20.64 billion in 1978 to US\$304,217 billion in 2019. The turning point is China’s joining the WTO in 2001. China has participated in the economic globalization process actively and seized the significant opportunity of international industrial transferring. However, this also brings more trade frictions simultaneously.

First, Equations (15) and (16) show the construct demand functions of China’s export and import trades, respectively.

Figure 4. China’s import and export trade from 1978 to 2019



$$EX = EX(Y^*, REER) \quad (15)$$

$$IM = IM(Y^*, REER) \quad (16)$$

Equations (17) and (18) show the constructed equations for China's export and import trades.

$$\ln EX = \alpha_1 + \beta_1 \ln Y^* + \lambda_1 \ln REER + \varepsilon_1 \quad (17)$$

$$\ln IM = \alpha_2 + \beta_2 \ln Y + \lambda_2 \ln REER + \varepsilon_2 \quad (18)$$

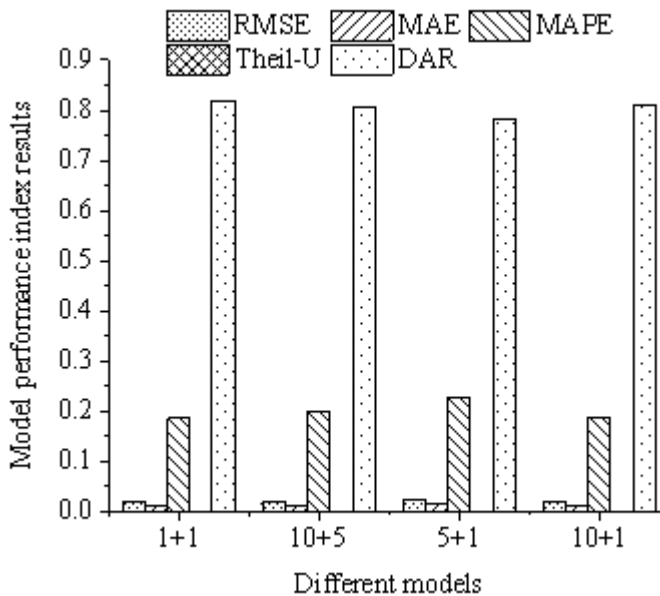
The *REER* represents RMB's actual effective exchange rate index, *Y* represents China's GDP, and *Y** represents foreign countries' GDP. The trade cooperation countries and regions selected include the United States, Japan, South Korea, and Hong Kong. First, the proportion, the weight $w_{i,i}$ of the trade volume between each country or region and China in China's total import and export trade needs to be calculated.

$$w_{i,i} = trade_{t,i} / \sum_i trade_{t,i} \quad (19)$$

In equation (19), $trade_{t,i}$ represents the trade volume between trade partner *i* and China in the *t*-th year, and $\sum_i trade_{t,i}$ represents China's total import and export trade volume of in the *t*-th year.

A vector autoregressive model is constructed by equations (17) and (18), and the optimal lag order is determined. The optimal lag order of the export trade and the import trade equations is determined as 2 to ensure robustness. Figure 5 shows the stability test of the VAR (Value at Risk) model of the export trade equation and the import trade equation, respectively. All the import and export trade models' characteristic roots are in the circle, indicating the VAR model is stable.

Figure 5. Stability test of VAR models of import and export trades



Data Source and Performance Test

- (1) Data source: here, the central parity data of the RMB/US dollar exchange rate from January 2, 2015 to October 2, 2019 are selected as the sample interval, and a total of 203 pieces of original data after holidays are excluded. 183 pieces of data from January 2, 2015 to September 28, 2019 are used as training samples to estimate the model parameters. From October 8, 2015 to November 2, 2019, after holidays are excluded, 20 pieces of data are used as test samples for the model prediction.
- (2) Data preprocessing: the features are analyzed according to the trend diagram of time sequence, namely, the sequence diagram and sequence autocorrelation diagram. If the time sequence shows no significant trend change or periodic change but fluctuates around a constant value, then it can be judged as a stable time sequence. By comparison, if the sequence diagram is monotonic or periodic, it can be roughly determined as a non-stationary time sequence. Difference operation is a common method for processing non-stationary time sequences, which can eliminate the non-stationarity of the series and extract the relevant information. However, the differential operation cannot be performed as many times as needed. Otherwise, Mehnatfar et al. (2016) suggested that an over-difference will occur because every differential operation will cause some information loss in the time sequence. Over-difference is the excessive loss of time sequence information caused by multiple difference operations, which causes unreliable prediction of model parameters and reduces the prediction accuracy. Given the phenomenon of over difference, the low order difference operation and the high order difference operation are used as far as possible in the processing of non-stationary time sequence. Besides, several effective fitting models can be generated for the same time sequence, from which the one with the best fitting effect can be chosen for prediction and research. Azcona (2017), Pierdzioch et al. (2016) and Balcilar et al. (2017) proposed that the AIC criterion and the SBC criterion are commonly used to judge relatively better models. AIC criterion judges the model by likelihood function and the number

of parameters. The larger the likelihood function is, the higher the fitting degree of the model is. The number of parameters reflects the flexibility of the model, and the model with more parameters is easier to fit. The expression of AIC reads:

$$AIC = -2\ln(L) + 2N \quad (20)$$

In Equation (20), L represents the maximum likelihood function; N denotes the number of unknown parameters. Because of overfitting, the model with the minimum AIC value is considered the optimal model.

(3) Performance evaluation: five indexes RMSE (Root Mean Square Error), MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), Theil-U, and DAR (Direction Accuracy Rate) are selected to measure the prediction effect of ML, ARIMA, and their fusion model. Of these, RMSE, MAE, MAPE, and Theil-U can measure the tracking error, and their calculations are shown in Equations (21) to (24), where y' and y represent the predicted value and real value, respectively. Sulaiman et al. (2017) held that the smaller the index value is, the better the prediction effect is. DAR represents the ratio of predicted positive and negative values to true positive and negative values, and the calculation is shown in Eq. (25). The larger the DAR is, the better the prediction effect is. With these five indexes, the advantages and disadvantages of each model can be more accurately judged.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y' - y)^2} \quad (21)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y' - y| \quad (22)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|y' - y|}{|y|} \quad (23)$$

$$\text{Theil-U} = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (y' - y)^2}}{\sqrt{\frac{1}{n} \sum_{i=1}^n y'^2 + \frac{1}{n} \sum_{i=1}^n y^2}} \quad (24)$$

$$DA = \frac{1}{n} \sum_{i=1}^n \alpha \quad (25)$$

RESULTS AND DISCUSSION

Prediction Effect Analysis of Single Model

Figure 6 shows the out-of-sample prediction error of the exchange rate sequence predicted with a single-model. Obviously, among all ML models, the ARIMA model performs well, and its RMSE, MAE, MAPE, and Theil-U are lower than the other four, while its DAR is higher than other ML models. Among the other four ML models, the best one is the simple CNN network, and its prediction error is only higher than ARIMA, while the RF (Random Forest) and RNN (Recurrent Neural Network) perform generally. Worst, the Elman recurrent network has an RMSE of 0.2843, which is much higher than that of other models with a DAR of 0.5638, which indicates that the accuracy of its prediction of exchange rate fluctuation is only more than 50%.

Figure 6. Prediction effect analysis of single model

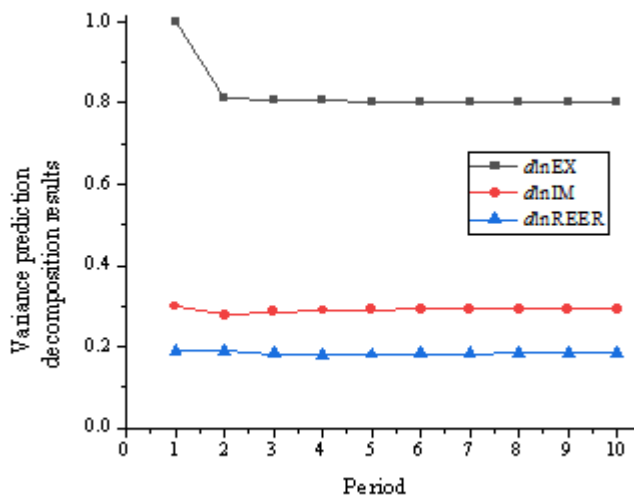


Figure 7 draws the prediction curves of five single models, in which the real line origin is the original sequence of exchange rates. Apparently, the ARIMA model prediction curve is very close to the exchange rate curve, and the CNN model prediction curve also performs better, which is only slightly worse in the later stage, while the RF model prediction curve also performs better in the early stage, but worse in the later stage. By comparison, the RNN and Elman model prediction curves always perform worse. Overall, the effect of exchange rate sequence prediction of ML-based model is not good, because the ML model analyzes the sequence data mainly through the nonlinear modeling method, while the original exchange rate sequence contains many linear factors. Thus, the fitting effect of the ML model is not as good as the classical linear model.

Prediction Effect Analysis of Fusion Model

Figure 8 suggests that the effect of the ARIMA model in predicting trend sequence is particularly prominent, with RMSE of only 0.0004, Theil-U close to 0, and DAR of 0.9867. Compared with the original exchange rate sequence prediction in Table 1, the accuracy of the model has been greatly improved. The RMSE of the RNN model is reduced from 0.0952 to 0.0207, and the RMSE of the Elman model is reduced from

0.2843 to 0.0197. The prediction effect of the CNN and RF model is also greatly improved. However, because the ML model predicts a highly volatile periodic sequence, the direction of the sequence is not clear from Figure 7, so the DAR of other models is not significantly improved except for the Elman model. Overall, the HP filtering method can be used to divide the exchange rate sequence into trend sequence and periodic sequence, and both the ARIMA and ML model can achieve better results than the original sequence.

Figure 7. Single model prediction curve

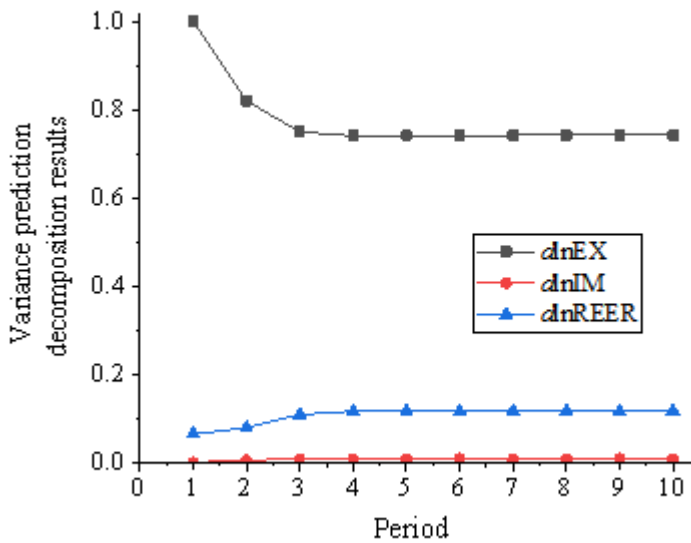


Table 1 Comparison of model prediction performance results

Models	RMSE	MAE	MAPE	Theil-U	DAR
ARIMA	0.0004	0.0003	0.0043	0	0.9867
RNN	0.0207	0.014	0.2699	0.0017	0.492
Elman	0.0197	0.0129	0.2289	0.0015	0.6649
ANN	0.0204	0.0136	0.2571	0.0015	0.6569
RF	0.0195	0.0128	0.1968	0.0017	0.6729

Figure 9 illustrates that to further verify the prediction effect of the ARIMA model on the linear sequence and ML model on nonlinear series, the reverse prediction effect of the model is reported in Table 3. In other words, the ARIMA model is used to fit nonlinear periodic sequences, while ML models are used to fit linear trend sequences. Obviously, the fitting result of the ARIMA model for the periodic sequence is very poor, and its RMSE is as high as 0.3545, which is much higher than 0.0288 for the original series and 0.0004 for the trend sequence. The results of other error terms also show that the prediction efficiency of the ARIMA model is low. The fitting result of the ML models

Figure 8. Prediction error and curve of trend sequence (ARIMA) and periodic sequence (ML)

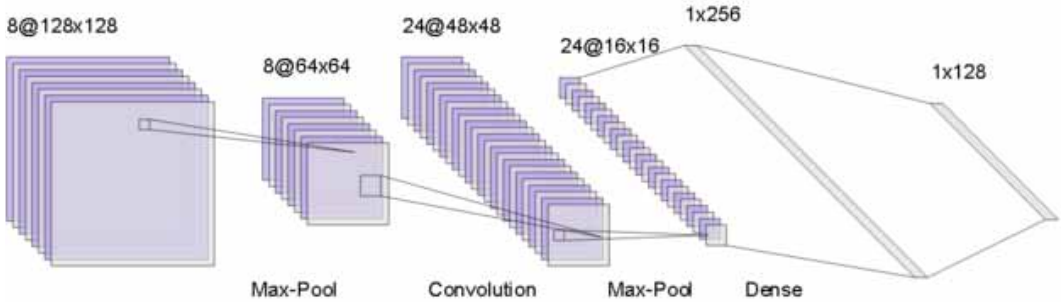
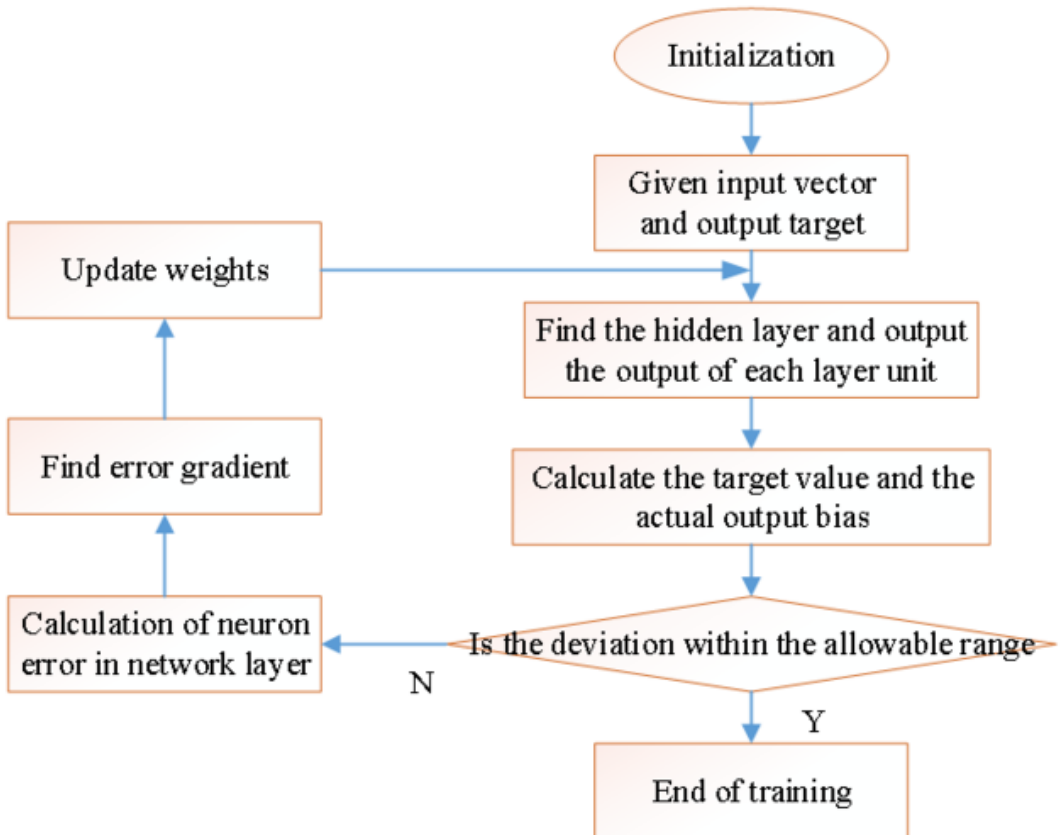


Table 2 Performance comparison of reverse prediction model

Models	RMSE	MAE	MAPE	Theil-U	DAR
ARIMA	0.3545	0.4486	5.2269	0.3852	0.4973
RNN	0.0941	0.0716	1.0377	0.007	0.7181
Elman	0.3006	0.2696	3.91	0.0225	0.6702
CNN	0.0198	0.0091	0.1295	0.0015	0.9309
RF	0.0597	0.0279	0.3996	0.0044	0.8118

Figure 9. Reverse prediction error of trend sequence (ML) and periodic sequence (ARIMA)



for trend sequence is slightly better than that of the original sequence (except for Elman), but it is significantly worse than the original sequence in terms of the periodic sequence (except for CNN). The comparison results of Figure 8 and Figure 9 verify the effectiveness of the ARIMA model in predicting linear sequence and the effectiveness of the ML model in predicting nonlinear sequence.

Figure 10 shows the prediction result of the fusion model. The results indicate that compared with the result in Figure 5, the prediction effect of all the fusion models has been greatly improved. The best model is ARIMA + CNN, with an RMSE of 0.0193, a Theil-U of 0.0014, and a DAR of 0.8218. The RMSE, Theil-U, and DAR of the ARIMA+Elman model are 0.0196, 0.0014, and 0.8191 respectively. The results of ARIMA+RNN and ARIMA+ANN are also good. Compared with the model in Figure 5, the prediction effect has been improved. Figure 10 suggests that the prediction curves of the four fusion models fit closely with the exchange rate curve. Except for a few data points, the curves are very similar, indicating that the models have achieved excellent prediction results.

Figure 10. Prediction effect analysis of fusion model

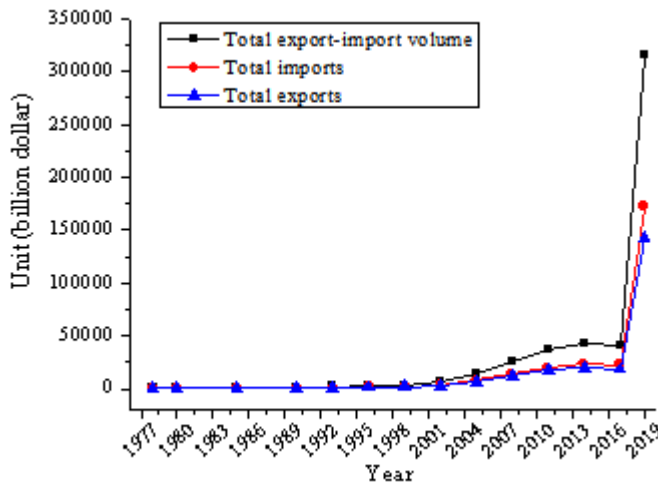
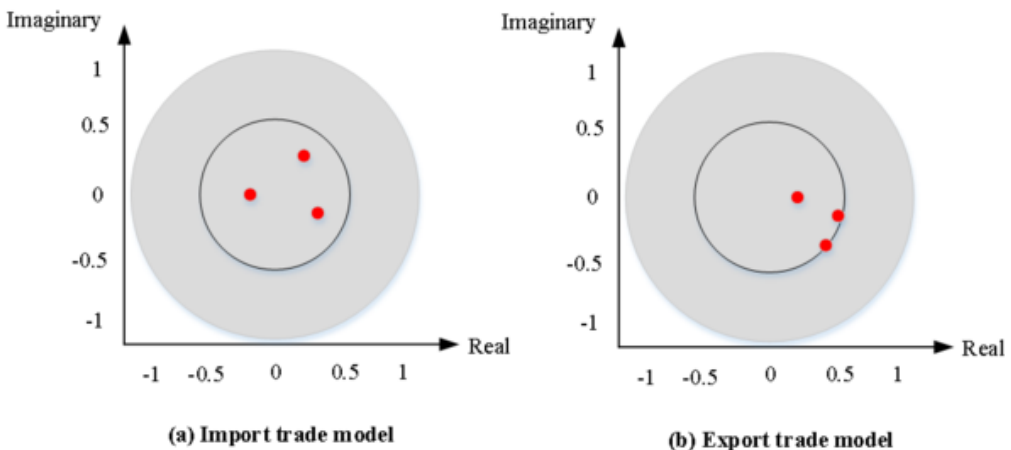


Figure 11. Robustness test results of input layer unit number model



On the whole, the HP filtering method is used to separate the trend term and periodic term of the exchange rate sequence, while the ARIMA and ML models are used to fit them respectively, which can accurately predict the offshore RMB exchange rate level.

Model Robustness Test

Figure 11 indicates that there are many parameters in the neural network model, and the effect of the model is greatly affected by the parameters. Therefore, the robustness is tested for neural network parameters, including the number of input layer units, the number of hidden layer neurons, and the number of hidden layer layers. The first five, 10, 20, 30, 40, and 50 exchange rate pieces of data are used as the independent variables of the model to test the impact of the number of input layer units on the prediction results of the model. Figure 11 reports the prediction results of the ARIMA+CNN fusion model. The results show that the increase in the number of input layer units does not improve the prediction effect of the model but worsens it. In comparison, when the number of input layer cells is 20, the prediction effect of the model is the best. But overall, no matter which input layer cell number is used, the prediction effect of the model is still excellent. It can be shown in Figure 11.

In Figure 12, the effect of the number of neurons in the hidden layer on the prediction effect of the model is tested. Here, the number of neurons of 1, 2, 5, 10, 15, 20, 30, and 40 are selected for analysis, and the out-of-sample prediction effect of the different number of neurons are reported in Table 3. The results imply that the increase in the number of neurons will not improve the prediction effect of the neural network. In all the eight models, only one hidden layer neural network performs best, and the network with five hidden layer neurons performs the worst. Overall, no matter how many hidden layer neurons are selected, the model can predict the exchange rate sequence very well. Compared with the single prediction model in Table 1, all the models in Table 3 fit better, indicating that the number of hidden layer neurons has a particular impact on the performance of the neural network but does not affect the research conclusion.

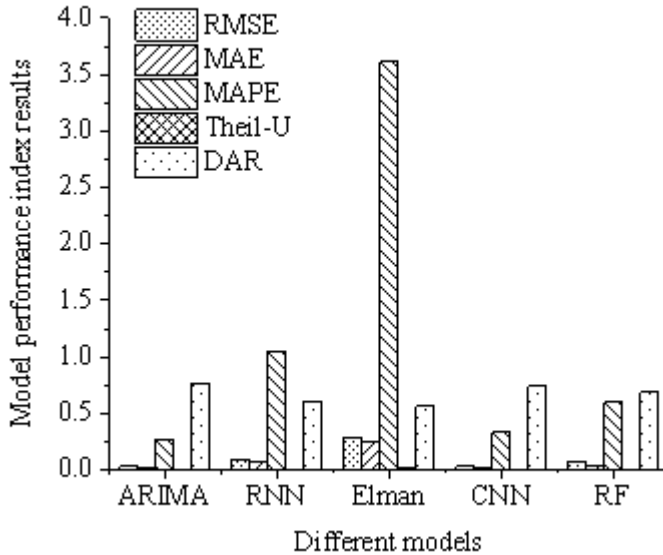
Table 3 Comparison of sample prediction results of different numbers of neurons

Number of neurons	RMSE	MAE	MAPE	Theil-U	DAR
1	0.0192	0.0123	0.1806	0.0014	0.8138
2	0.0213	0.0137	0.2012	0.0016	0.7979
5	0.0258	0.0155	0.2265	0.0019	0.7819
10	0.0196	0.0127	0.1858	0.0014	0.8191
15	0.0202	0.0133	0.1945	0.0015	0.8218
20	0.0217	0.0141	0.2066	0.0016	0.8165
30	0.0226	0.0144	0.2117	0.0017	0.8112
40	0.0208	0.0135	0.1984	0.0015	0.8138

Figure 13 illustrates the constructed three double hidden layers neural network, which are “10+5”, “5+1”, and “10+1”. “10+5” means that the first hidden layer contains 10 neurons, while the second hidden layer contains five neurons. Similarly, “5+1” and “10+1” can be defined. By comparison, the results of the original single hidden layer CNN network with 10 neurons are also listed. The analysis results show that the two-tier network cannot improve the prediction effect of the model compared with the single-layer network, but the prediction effect of the single model is greatly improved compared to Table 1. Overall, because of the small amount of data in the exchange rate prediction sequence, the simple single-layer

network is better, and even if the more complex network structure is selected, the better prediction effect can be obtained, which shows that the research conclusion here is robust.

Figure 12. Robustness test results of hidden layer neuron number model



Analysis of RMB Exchange Rate Risk

Figure 14 and Figure 15 show the variance decomposition results of the import and export trade equations based on the VAR model constructed by the variables of $\ln EX$, $\ln IM$, $\ln Y^*$, $\ln Y$, and $\ln REER$. The research period is divided into ten periods. In the first period, export trade is completely affected by its shocks. The impacts of foreign economic growth and the RMB exchange rate were weak, especially the former. Afterward, the export trade's impact gradually weakened, and the impacts of foreign economic growth and the RMB exchange rate on export trade gradually increased. By the tenth period, foreign economic growth's impacts on export trade were still very weak, and the RMB exchange rate's impact on export trade was 11.7%. In the long run, the export trade's impacts are the dominant factor, which can be regarded as the inertial factor. The import trade was completely affected by its shocks in the first period, and the impacts of China's economic growth and the RMB exchange rate are not significant. After the fifth period, import trade's impacts gradually stabilized at around 80%, and China's economic growth and RMB exchange rate maintained around 29% and 18.4%, respectively.

Figure 13. Robustness test results of hidden layer number model

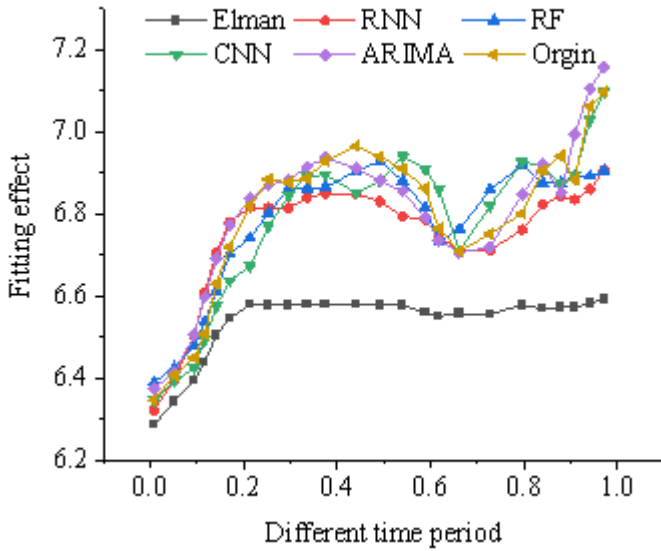


Figure 14. Variance decomposition result of the import trade equation

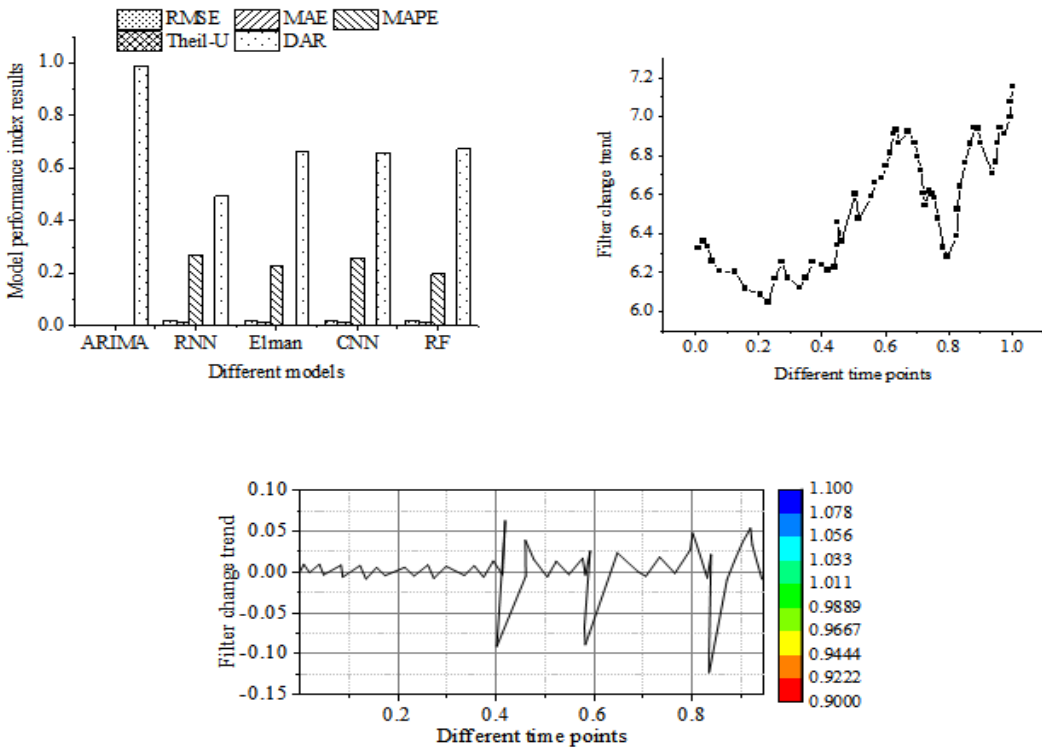
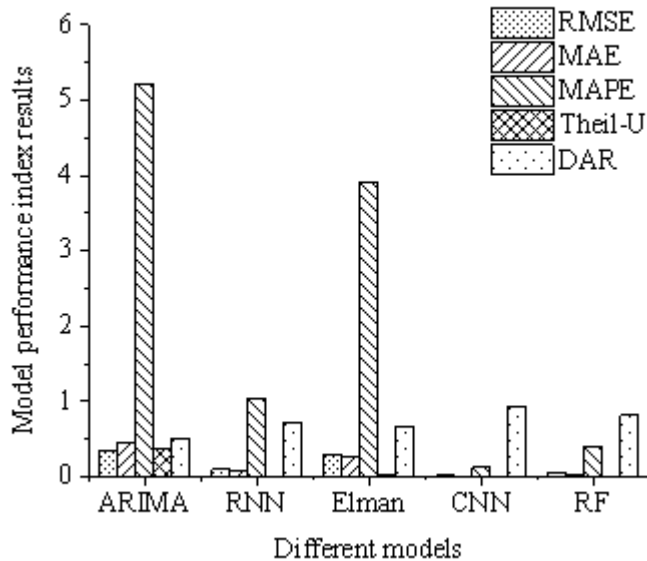


Figure 15. Variance decomposition result of the export trade equation



CONCLUSION

Here, through four kinds of ML models (CNN, RNN, Elman neural network, RF) and ARIMA time sequence prediction model, the RMB exchange rate is predicted, and five indexes (RMSE, MAE, MAPE, Theil-U, and DAR) are selected to measure the prediction effect of the model. Under the prediction of a single model, the ARIMA model performs the best, followed by a simple CNN model, while RNN, Elman, and RF perform moderately. The prediction of trend sequence and periodic sequence using ARIMA and ML model shows that under every single ML model, the prediction performance of the model has been significantly improved. The robustness test of multiple parameters of the neural network shows that the effect of a simple network is better, while the more complex RNN network or more hidden layer neurons and hidden layer layers cannot improve the prediction performance of the network. Accurate prediction of exchange rate can help enterprises avoid foreign exchange risk, but also has important reference value for enriching the theory of financial time sequence prediction.

Still, there are some deficiencies. Firstly, the financial time sequence usually contains more noise. If a single model is used directly, the prediction result is not optimal. Thus, HP filtering and other noise reduction methods can decompose the financial sequence into trend and periodic items. The combination of the linear model and nonlinear model can achieve a better prediction effect. Secondly, the prediction effect of CNN is relatively robust, which is mainly due to the attributes of its fusion learning method, which reduces the tendency of overfitting. Because the different selection of neural networks will lead to great changes in the prediction results, the selection appropriate ML model is critical for different problems to improve the prediction effect. Compared with thousands of input units in speech processing and image recognition, the input variables of the financial time sequence are less. In the financial field, a simple neural network or ML model can achieve better results. Deep learning can fit the data in the sample very well, but the characteristics of financial time sequence, such as excessive noise, the overfitting in the sample will reduce the performance outside the sample. In the future, deep learning and big data methods can be combined to predict and analyze financial data.

ETHICS STATEMENT

All Authors declare that they have no conflict of interest. This article does not contain any studies with human participants or animals performed by any of the authors. Informed consent was obtained from all individual participants included in the study.

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