Forecast USD/RMB Exchange Rate and Fitting Comparison Based on Three Methods

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Abstract: In light of the current complex and volatile international landscape, continuously updated exchange rate forecasts are indispensable. Accurate exchange rate forecasts enable enterprises to mitigate trade risks and optimize investment decisions, assist financial institutions in risk management, and support policy formulation. Furthermore, they provide robust support for macroeconomic policymakers, helping to maintain exchange rate stability, balance international payments, and foster steady economic growth, which holds significant importance across all economic levels. In this paper, through Auto-Regressive Integrated Moving Average Model (ARIMA), Error-Trend-Seasonal (ETS) and Simple Moving Average (SMA) traditional time series models forecast the next 10 steps (one step every five consecutive working days) based on the USD/RMB exchange rate in 2022-2025. The result is compared with the actual value pair. In this study, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are employed for model selection when utilizing ARIMA, ETS, and SMA models. The model's performance was assessed using Root Mean Squared Error (RMSE) and residual P-values. Given the volatile international situation, updated exchange rate forecasts are needed. Accurate exchange rate forecasts enable enterprises to mitigate trade risks and optimize investment decisions, assist financial institutions in risk management, and support policy formulation.

1 INTRODUCTION

Over the past few decades, due directly to the factors mentioned above, there has been a significant acceleration in the expansion of forex exchange markets driven by increased cross-border capital flows (de Paula, Ferrari-Filho, & Gomes, 2013). A number of economic indices exist for this market but perhaps the most crucial is exchange rates (Baffour et al., 2019). Exchange rate forecast is a very important part of the foreign exchange market, and it plays a very important role in the external development of enterprises and social and economic development and provides an important evaluation index. Previously, many experts and scholars have used traditional time series models to fit together and accurately updated and adjusted the model to make it more suitable for today's global situation. Even though conventional models like the ARIMA are regarded as efficient methods, they demand both stationary time series and non - stationary time series that have been appropriately transformed to become stationary (Cappello et al., 2025). The ARIMA model was used to stabilize the difference of the data and then proved to reach the predictable stage by different test standards. The model parameters were adjusted and fitted, and the rationality of this model for short-term exchange rate prediction was obtained. Using the time series model to forecast the exchange rate over a short period is beneficial to the trade development of import and export enterprises and can provide investment basis for international investors (Jiang & Liu, 2022). The remaining two models underwent the best process via steps similar to the first one. In this study, the core objective is to identify the most premier prediction model for short - term time series. This is achieved by juxtaposing the three models against the actual values. Initially, the paper meticulously preprocesses the data and assesses its fitting potential. Subsequently, distinct parameters

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within different models are adjusted. Eventually, the goodness of each model is evaluated from two diverse dimensions, leading to a well - founded conclusion.

2 DATA AND METHOD

2.1 Data Collection and Description

This study acquires its data from China Money Network by visiting the website and downloading the data. This dataset includes 728 USD/RMB exchange rate data from January 1, 2022 to January 1, 2025. The data set is grouped by weekdays, that is, data points are grouped by every five consecutive working days. The specific sample information is shown in Table 1:

Table 1: Sample description.

Statistical Index	Numerical Value	Remark
Number of Data Points	728	Daily data, spanning two years
Exchange Rate Minimum	6.3014	44621
Exchange Rate Maximum	7.2258	45107
Average Exchange Rate	6.85	Based on the data
Data Frequency	Everyday	One data point per business day
Data Integrity	Integrity	No missing value

2.2 Data Pre-processing

Through data cleaning, the error value and missing value in the data are eliminated. In this paper, RStudio software was used to analyse the data, and the samples were drawn into a time series chart (Figure 1). It can be found that since the epidemic had just ended at this time, economic activities and market environment had not completely returned to the stable state, so there was a sharp rise in the first period and a sharp decline in the subsequent data, and the subsequent data also fluctuated. The differential data (Figure 2) are stable and eliminate long-term trends. This represents an expansion of the Autoregressive Moving Average Process applicable to time series processes lacking stationarity. In this approach, the data is subjected to a transformation so as to convert the process into a stationary one (Marcy, 2021).

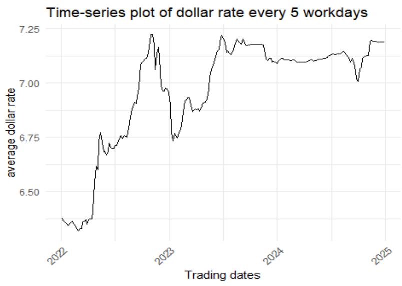

Figure 1: Timing diagram of original data (Picture credit: Original)

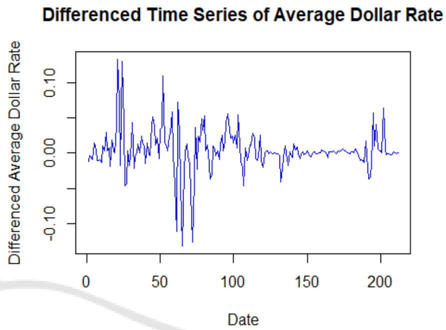

Figure 2: Stationary sequence diagram after difference (Picture credit: Original) .

2.3 Auto-Regressive Integrated Moving Average Model（ARIMA）Model Principle

ARIMA is widely used in time series prediction analysis. Its essence aims to transform non-stationary time series into stationary ones through difference operation, and then build ARIMA model and perform prediction analysis. The ARIMA model, short for moving average with auto-regressive integration is usually represented as ARIMA. In this model, “p” represents the order of the autoregressive part, “d” indicates the level of differencing necessary, and “q” stands for the order of the moving average part (Chen et al., 2023). The basic structure of the model is shown in formula (1), formula (2) and formula (3):

$$\phi(B)\nabla^d X_t = \Theta(B)\varepsilon_t \quad (1)$$

$$E(\varepsilon_t) = 0, Var(\varepsilon_t) = \sigma^2, E(\varepsilon_t\varepsilon_s) = 0, s \neq t \quad (2)$$

$$E(X_s\varepsilon_t) = 0, s < t \quad (3)$$

Where $\Theta(B)$ is the polynomial of the moving smoothness coefficient, $\phi(B)$ is the polynomial of the autoregressive coefficient, and $\{\varepsilon_t\}$ is the zero-mean white noise sequence (Sun & Cheng, 2016). In the analysis of time series, autocorrelation and partial autocorrelation tests are carried out for the difference series, and the orders of autoregression (p) and moving average (q) within the ARIMA model are preliminarily inferred. Then, The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Root Mean Squared Error (RMSE) were comprehensively used to identify and determine the ARIMA model more accurately, and the most suitable ARIMA model was selected. After the model is selected, the fitting performance of the model is evaluated by its residual sequence and correlation coefficient. If the remainder sequence is similar to the white noise and the correlation coefficient is within a reasonable range, it indicates that the model has a good fitting effect on the data. If not, model flaws exist; optimize. ARIMA forecasts, and real - predicted value comparison gauges its practical reliability.

2.4 Error-Trend-Seasonal（ETS） Model Principle

Exponential smoothing method is to use the average based on weighted values of the actual observed amounts of the series to prognosticated the projected value, the latest data in the series is multiplied by a most substantial weight, and the data over the long haul is added with a lesser weight (Shao et al., 2021). TS model is a smoothing method, which is widely used in processing time series data with seasonality and trend (Li et al., 2025). Exponential smoothing uses error, trend, seasonal params. ETS auto - selects, adjusts, and evaluates to find best - performing model. In the process of model selection, the best-fit model is chosen relying on the minimum values of AIC, BIC and RMSE. The P-value of the residual is tested by Ljung-box Q to determine whether the residual is white noise.

2.5 Simple Moving Average（SMA） Model Principle

Moving average method is a method to calculate the average containing a certain number of items to reflect the changing trend of time series. The details are shown in formula (4):

$$M_t = \frac{y_t + y_{t+1} + \cdots y_{t-N+1}}{N}, \quad t \geq N \tag{4}$$

Where M_t is the moving average of the t period and N represents the quantity of moving average items.

The prediction method is shown in formula (5)：

$$\hat{y}_{t+1} = M_t \tag{5}$$

The period's moving average t is used as the predictive value of period $t+1$. By checking the P-value of the residual, the people can judge whether the residual is white noise. In general, the predicted values of subsequent periods can be calculated accordingly. Error accumulation causes larger errors later; SMA suits one - period - ahead forecasts.

3 RESULTS AND DISCUSSION

3.1 ARIMA Model

3.1.1 Model Fitting

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of data after first-order difference are shown in Figure 3. This article uses RStudio to try different parameter combinations, as shown in Table 2, and finally determines that ARIMA (2,1,2) is optimal. AIC, BIC and RMSE of ARIMA (2,1,2) are all the smallest. The residual P value exceeded 0.05. At this time, the data of logarithmic first-order difference have excellent performance in AIC, BIC and RMSE detection. If the residual is white noise, most of the information parts of the model have been extracted and can be fitted.

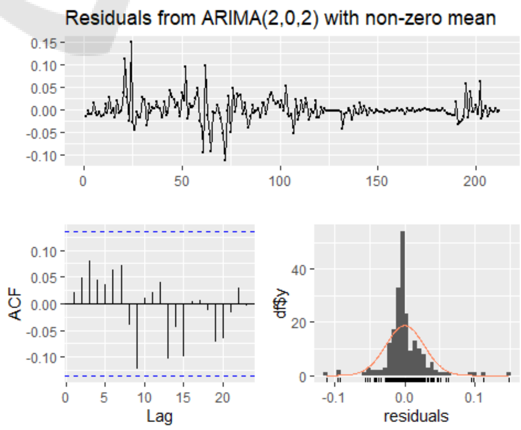

Figure 3: ARIMA (2,1,2) residual test (Picture credit: Original）.

Table 2: Comparison of different parameters.

Metric	ARIMA (2,1,2)	ARIMA (3,1,4)	ARIMA (2.1.3)	ARIMA (3,1,3)
AIC	- 915.21	- 904.32	- 905.11	- 904.37
BIC	- 895.07	-	-	-
RMSE	0.0271	0.0270	0.0272	0.0271
Residual p-value	0.2045	0.1378	0.1435	0.1562

3.2 ETS Model

3.2.1 Model Fitting

In this paper, RStudio was used to try to predict ETS. Different parameter combinations were shown in Table 3, and it was found that ETS (A, N, N) was the best. The residual P value of ETS (A, N, N) is 0.0506 and greater than 0.05, and the residual is white noise. The test result of the residual is presented in Figure 4, then the model has extracted most of the information. Model AIC, BIC are small. After the model's convergence is judged, it is found to fit well.

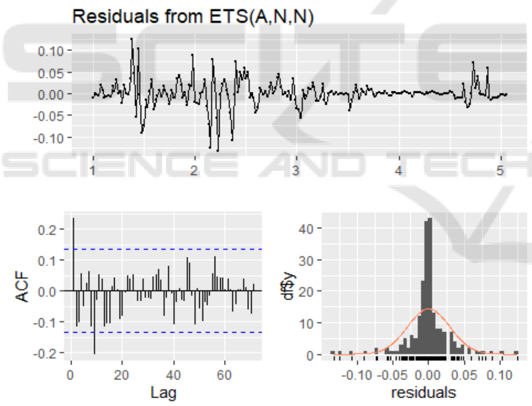

Figure 4: ETS (A, N, N) residuals test (Picture credit: Original）.

Table 3: ETS (A, N, N) Each detection index.

	ETS (A, N, N)
AIC	-350.5486
BIC	-340.4789
RMSE	0.0176
Residuals p-value	0.05063

3.3 SMA Model

3.3.1 Model Fitting

In this paper, RStudio was used to attempt SMA prediction, and it was found that the residual error of the SMA model after extracting information was 0.1787, greater than 0.05, and the residual error was white noise, so the model had extracted most of the information parts. When R^2 test is carried out, it reaches 1, which proves that the model has a good fitting effect. By judging the convergence and divergence of the model, it is found that it is convergent, so it can be fitted.

3.4 Experimental Result

3.4.1 Comparison Model Parameter

In the fitting of ARIMA model and ETS model, AIC, BIC and RMSE indictors were applied to assess the feasibility of the model. In the comparison of model goodness, the above indexes are first used for selection.

Table 4: Comparison of ARIMA and ETS model goodness.

	ARIMA (2,1,2)	ETS (A, N, N)
AIC	-915.21	-350.5486
BIC	895.07	-340.4789
RMSE	0.0271	0.0176
Residuals p-value	0.2045	0.05063

It is obvious that from Table 4 that the AIC, BIC and RMSE of ARIMA (2,1,2) are smaller, so the fitting influence of ARIMA (2,1,2) is better.

3.4.2 Contrast Error Value

In the ARIMA (2,1,2) forecast:

Table5: ARIMA (2,1,2) Model Error.

Date	Forecast	TRUE	Error
2025,1	7.1897	7.1878	0.0019
2025,2	7.1933	7.1886	0.0047
2025,3	7.1923	7.1882	0.0041
2025,4	7.1917	7.1826	0.0091
2025,5	7.1925	7.1703	0.0222
2025,6	7.1922	7.1698	0.0224
2025,7	7.1921	7.1693	0.0228
2025,8	7.1923	7.1699	0.0224
2025,9	7.1922	7.1713	0.0209
2025,10	7.1922	7.1704	0.0218

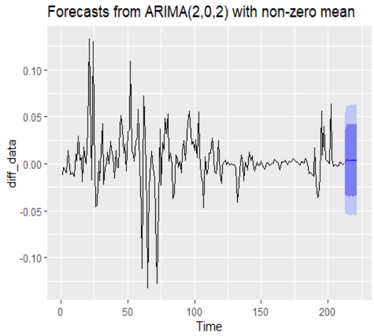

Figure 5: ARIMA (2,1,2) Forecast Graph (Picture credit: Original）.

It is evident that Table 5 that the error is inside the range of [0.0019,0.0228]. After calculation, the average relative error is 0.01523, which is within the normal range and the predicted value is too large. It shows that it is feasible to use ARIMA model to predicting RMB exchange rate, and the overall prediction effect is good, which is capable of effectively predict the future currency rate trend. In addition, as the forecast time elapses, the deviation among the forecast value and the factual value has a tendency to expand, so this simulation is better adapted to short-term exchange rate prediction (Zhu & Hu, 2019). The forecast trend is shown in Figure 5.

In ETS(A,N,N) forecast：

Table 6: ETS (A, N, N) Model Error.

Date	Forecast	TRUE	Error
2025,1	7.1906	7.1878	0.0028
2025,2	7.1928	7.1886	0.0042
2025,3	7.195	7.1882	0.0068
2025,4	7.1971	7.1826	0.0145
2025,5	7.1993	7.1703	0.0290
2025,6	7.2015	7.1698	0.0317
2025,7	7.2037	7.1693	0.0344
2025,8	7.2059	7.1699	0.0360
2025,9	7.2081	7.1713	0.0368
2025,10	7.2102	7.1704	0.0398

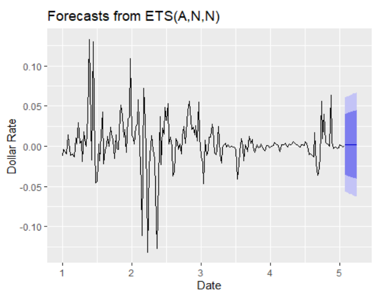

Figure 6: ETS (A, N, N) Forecast Graph (Picture credit: Original）.

As is evident from Table 6 that the error falls within the scope of [0.0028,0.0398]. After calculation, the average relative error is 0.0236, which is within the normal range and the predicted value is too large. The specific forecast trend is shown in Figure 6.

In the SMA forecast：

Table 7: SMA Model Error.

Date	Forecast	TRUE	Error
2025,1	6.7919	7.1878	-0.3959
2025,2	6.9383	7.1886	-0.2503
2025,3	6.7388	7.1882	-0.4494
2025,4	7.0478	7.1826	-0.1348
2025,5	7.0204	7.1703	-0.1499
2025,6	6.9553	7.1698	-0.2145
2025,7	6.8683	7.1693	-0.3010
2025,8	6.7866	7.1699	-0.3833
2025,9	6.9466	7.1713	-0.2247
2025,10	6.9984	7.1704	-0.1720

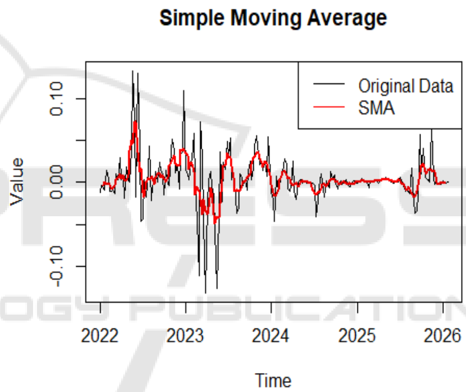

Figure 7: SMA Comparison of model prediction and original data (Picture credit: Original).

Table 7 reveals that the error is in the bounds of [0.1348,0.4494]. Avg. rel. error (0.26758) exceeds norm; predictions low. The comparison between the specific predicted value and model fitting is shown in Figure 7.

Among simple time - series models for USD/RMB rate, ARIMA shows top - notch fit. It's effective for stationary data, assuming linear future value determination. However, many real-world time series data exhibit complex nonlinear patterns that ARIMA cannot model effectively (Zhang, 2023). Simple moving average and exponential moving average are two standard technical analysis techniques (Billah et al., 2024). Predictions lose accuracy as lead time increases (Tian, 2017).

4 CONCLUSIONS

By comparing the estimated value and the value observed in practice and drawing the time series graph, this paper find that the ARIMA model has the best fitting effect on the USD/RMB exchange rate. In this paper, three traditional time series models of ARIMA, ETS and SMA were used to predict the USD/RMB exchange rate in the next 10 steps, and then the goodness of fit of the three models was evaluated through two dimensions. The first dimension is that the results of ARIMA (2,1,2) model are better by comparing AIC, BIC, RMSE and residual P-value. The second dimension shows that ARIMA (2,1,2) has the smallest error by comparing the predicted value with the actual value, followed by ETS (A, N, N), and finally SMA, and all three models are within the normal error range. The limitation of this paper is that the traditional time series model used in this paper will lead to fitting errors when predicting exchange rates with large fluctuations and randomness. The traditional statistical model has the disadvantage of being rigid, and the results obtained will not have good fitting effect when the original data does not meet some assumptions. Using the traditional time series model to forecast the exchange rate can make the innovation foundation more solid, the thinking clearer, and the innovation more accurate exchange rate prediction model. It can also be concluded from the above methods that traditional time series models like ARIMA model are suitable for short-term forecasting and have higher accuracy than long-term forecasting.

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