RMB/USD Exchange Rate Forecasting and Analysis by SES and ARIMA Model

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Abstract. The RMB/USD exchange rate is important in the worldwide financial sector. Predicting the future RMB/USD exchange rate is critical in such circumstances. Forecasting the RMB/USD exchange rate effectively can assist people in analyzing the economic situation and avoiding financial dangers. This research proposes two statistical models, Simple Exponential Smoothing (SES) model and Autoregressive Integrated Moving (ARIMA) model, for forecasting the RMB/USD exchange rate, and then discovers a better model for forecasting exchange rates. To find a better model, forecast value with accuracy, and uncertainty and model limitation are compared. We find that although SES model shows a better accuracy, the residual check and uncertainty shows ARIMA is a better forecast. Moreover, ARIMA is more complex and has relatively less limitations for RMB/USD exchange rate. Thus, Autoregressive Integrated Moving model is a better forecast compared with Simple Exponential Smoothing model.

Keywords: Simple Exponential Smoothing, Autoregressive Integrated Moving, RMB/USD Exchange rate, time series model.

1. Introduction

The exchange rate is a significant component affecting the global economy that is becoming increasingly important in the international financial market. People can understand the economic environment and minimize financial risks with effective forecasting of the RMB/USD exchange rate. As a result, it is critical to research high-precision RMB/USD exchange rate forecasting [1]. Looking through current papers, most employ the Autoregressive Integrated Moving Average (ARIMA) model to forecast, which has strong scientific validity in the short term. In recent years, relevant articles have largely avoided using the Simple Exponential Smoothing (SES) model to forecast the exchange rate. Given that the SES model is also one of the most extensively used forecasting techniques with little computation, we utilize it to estimate the exchange rate between China and the United States and compare it to the ARIMA [2]. Therefore, this article collects data on the RMB/USD exchange rate from June 2003 to June 2023 from FRED Economic Data website and employs the SES model and the ARIMA model to predict the future two-year exchange rate. As a result, ARIMA model is a better forecast after comparing both results and model properties. The rest of paper is designed as follow: the second part will introduce the basic information of forecast models and accuracy evaluation; the third part will cover the results after applying the two forecast models; the fourth part mainly covers the comparison of models; and the last part is the conclusion of the paper.

2. Methodology

2.1. Introduction of Model Chosen

This part mainly introduces the two models used to forecast the future exchange rates: Simple Exponential Smoothing (SES) model and Autoregressive Integrated Moving Average (ARIMA) model.

2.1.1 SES Model

SES is a basic and widely used time series forecasting approach. It is a variant of the exponential smoothing method for producing short-term forecasts for time series data with a single source of underlying trend and no seasonality. SES excels in dealing with data that has random or chaotic oscillations and a steady or slowly changing level.

Forecasts for more periods ahead can be made for the SES model using the trend projection technique, and the forecast is deemed more accurate because it accounts for the gap between actual projections and what transpired in reality. Furthermore, the SES model prioritizes recent observations, which is critical for projecting exchange rates on time. The SES model requires the smoothing constant value, a weighting factor that reflects the weight given to the most recent data values, and the model is simple to apply [3].

2.1.2 ARIMA Model

ARIMA is a popular and effective time series forecasting approach. It is designed to handle non-stationary behavior through differencing while capturing both the autoregressive and moving average components of the data. ARIMA models are particularly beneficial for time series data with trend and seasonality in a range of forecasting applications [4].

For ARIMA model, the model can effectively capture the patterns, trends, and seasonality of data using a combination of past values, differences and errors. One of the main advantages of ARIMA model is that it is flexible and can handle a wide range of time series data as long as they are univariate. And the model can be used for various patterns, such as linear or non-linear trends, constant or varying volatility, and seasonal or non-seasonal fluctuations. Also, the model is easy to implement and interpret, as it only requires a few parameters and assumptions, which can provide reliable forecasts and confidence intervals [5].

2.2. Data Source and Processing

The data used is from FRED-Economic Data website (https://fred.stlouisfed.org/) and employed the data of exchange rates between CNY and USD. Considering the effectiveness and timeliness of the data for prediction, choosing the time period of 20 years ranging from 2003 to 2023 guarantees long enough period to provide sufficient samples and frequent enough data to offer better accuracy. Since exchange rates are not recorded in the weekend and the statistic model requires time series to analyze, it is better to use monthly- basis data instead of daily-basis data. To have more stabilized forecasting results, our model will predict the exchange rates in the following 2 years with more valid information.

2.3. Forecasting and Evaluation Metrics

Based on the accuracy calculation in R studio, model evaluation metrics mainly include Mean Error (ME), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Scaled Error (MASE), This section will give simple explanations to these metrics. ME also called the margin of error, is an indicator of the precision of an estimation and is defined as one-half the width of a confidence interval. RMSE indicates the square root of the mean squared error. The RMSE number is in the same unit as the projected value, and this makes it easier to comprehend in comparison to MAE. MAE is defined as the average of the absolute difference between forecast and true values. The MAE shows us how much inaccuracy should be expected from the forecast on average. The lower the MAE value, the better the model is. MPE is a relative measure that essentially scales ME to be in percentage units instead of variable's units, and the main advantage of MPE is that it allows the comparison of variances between differently scaled data. MAPE is the proportion of the average absolute difference between projected and true values divided by the true value. MASE stands for a measure for determining the effectiveness of forecasts generated through an algorithm by comparing the predictions with the output of a naive forecasting approach [6].

3. Results

3.1. Forecasting Results Using SES Model

3.1.1 Trend and Seasonality

First, to observe the trends and seasonality for last 2 decades, plotting the exchange rates graph and find the maximum value, minimum value and last recorded value [7]. And Table 1 shows several special values of exchange rates during past 2 decades: Maximum value, Minimum value, and Present value. Then the rest of this part mainly analyzes the trends and seasonality of historical values according to Figure 1 and Table 1.

Table 1. Maximum, Minimum and Present Value

Value Type	Value	Time
Maximum Value	8.2773	July 2003
Minimum Value	6.0509	January 2014
Present Value	7.1614	June 2023

Then, from the Figure 1, no overall trend of RMB/USD exchange rates can be observed. However, it shows a monotone decreasing trend for first 10 years, from maximum value 8.2773 in 2003 to minimum value 6.0509 in 2014, which are shown in Table 1. Chinese improvement of overall national strength and a better bilateral relation with United States may be the cause of decrease trend. In the last 10 years, there are an overall increase from minimum value 6.0509 to final value 7.1614 in table 1, which increase slower than decreasing trend. And there exist two obvious drops in the period of 2017-2018 and period of 2020-2021. This may be the result of Trump's administration, which announces sweeping tariffs on Chinese imports in 2018, and COVID-19 pandemic, which has severe impacts on bilateral relations.

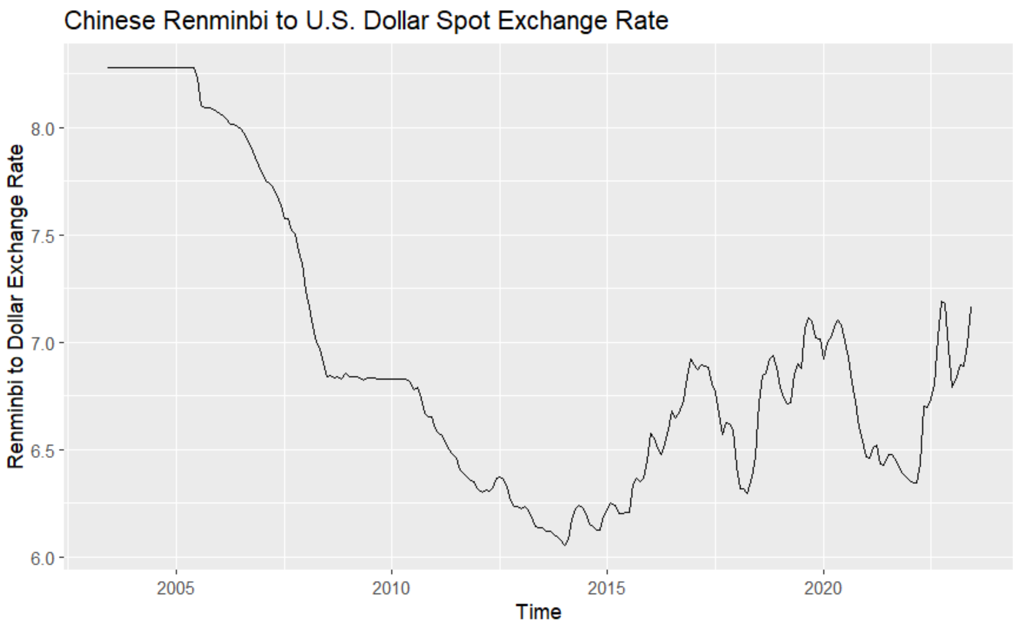


Fig. 1 Historical Exchange Rates from 2003 to 2023

Then, by figure 1, no seasonal pattern for the RMB/USD exchange rates can be observed [7]. One possible reason for this is that the exchange rate is not influenced by seasonal changes. Besides that, exchange rate change easily as geopolitical events change. More detaily, take drop at 2021 as an example, one possible reason for this may be the change of policies related to Covid pandemic.

3.1.2 Forecasting exchange rates for next 2 years

Then applying the *ets()* function of SES model and *forecast()* function to forecasting exchange rate of next 2 years. Note that parameter h is equal to 24 in the forecasting function since the data has frequency 12. Considering the number of forecast values for next 2 years, the forecast values graphs is shown in the report, instead of forecast values table [7].

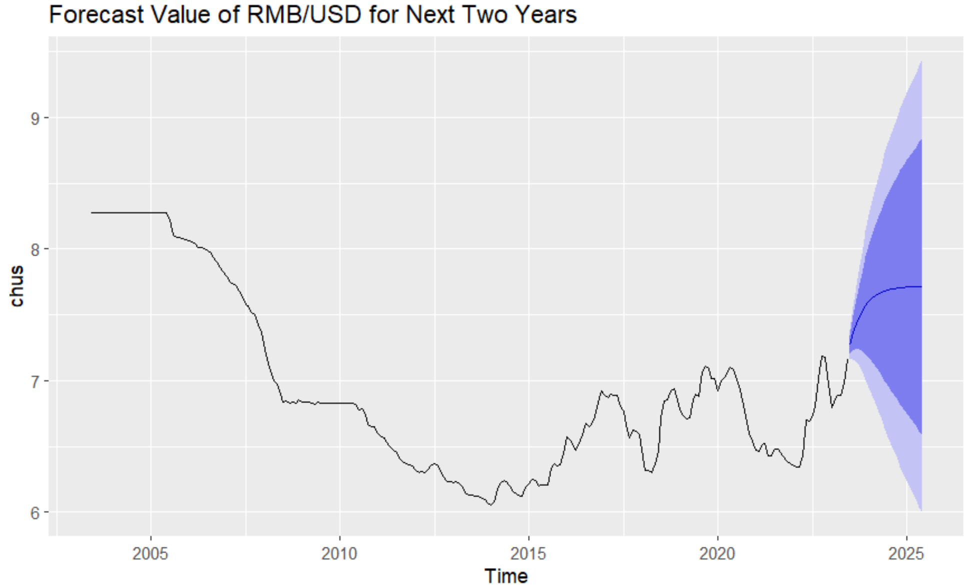


Fig. 2 Forecast Values Using SES Model

In the Figure 2, the forecast rates show a slow increase up to 7.72. Finally, the forecast value plot shows that forecast value will be stable on 7.71 in 2025. And the width of intervals increase as the forecast horizon increases. This reflects the increasing uncertainty in long-term forecasts. In the short future, the intervals show a small uncertainty which indicates the SES model is rationale in the short-term forecasting. While for the forecast of 2025, the width is significant, and even the 95% prediction interval has bounds exceeds historical maximum value. It shows the forecast in long period is highly uncertain [7].

3.1.3 Accuracy of Next 2-Year Forecast

Then, using *accuracy()* function to evaluate the accuracy of SES model analyze values of metrics, which is shown in Table 2.

Table 2. SES Model Evaluation Metrics

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Value	-0.0001365	0.0539553	0.0340217	0.0004097	0.5018525	0.1320766	0.0667858

In Table 2 notice that it has a negative Mean Error. It suggests that the model is tending to be conservative and underpredicting the actual values. However, since ME is slightly negative, the forecasts are centered around the actual values, and the model's bias is small. Then MAE and RMSE are 0.0340217 and 0.0539553 respectively. For the RMB/USD exchange rates, the value of MAE and RMSE are relatively small. These values generally indicate a good forecast accuracy. Then as for MPE and MAPE with values 0.0004097 and 0.5018525 respectively, it suggests that the model is a very accurate forecast. In conclusion, using SES model to RMB/USD exchange rates is accurate.

3.1.4 Check Error by Residuals

To ensure SES model is appropriate, it is necessary to check residuals of SES model and analyze the outcome.

Table 3. Ljung- Box Test

Data: Residuals from ETS (A, Ad, N) Function			
Q* value	*df value*	p value	Model *df* value
52.487	24	0.0067570	0
Total lag		24	

According to Table 3, Ljung-Box test shows there exists significant autocorrelation in the residuals, with p-value strictly smaller than 0.05. The result suggests that SES model does not fit the RMB/USD exchange rates.

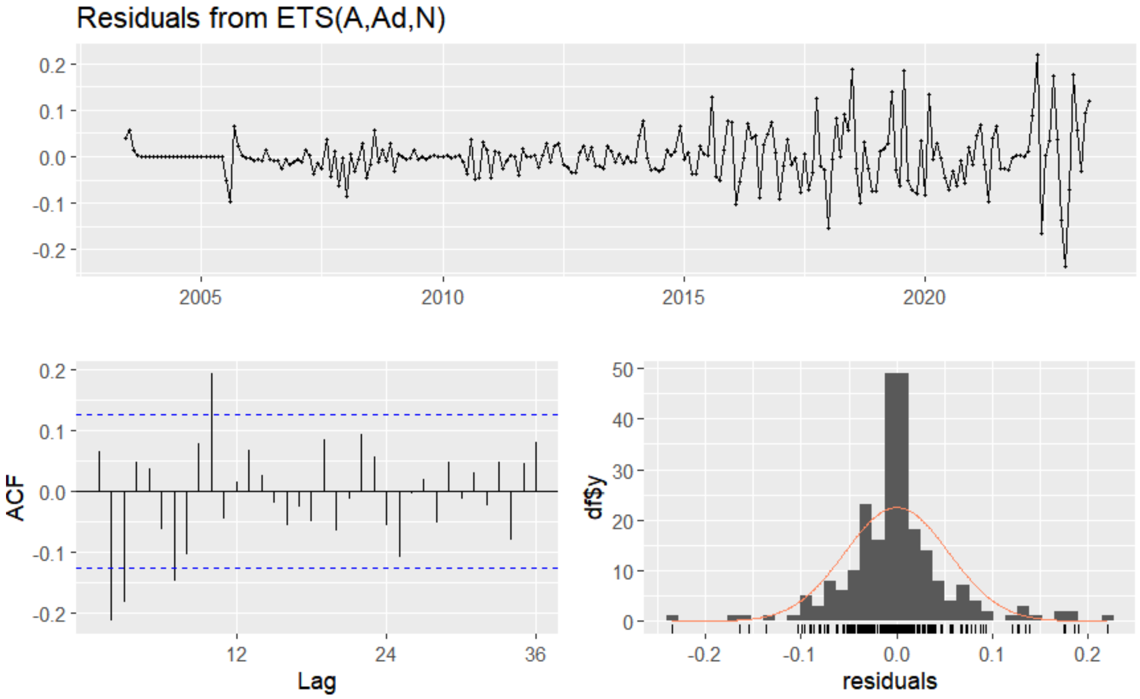


Fig. 3 Residual Check and Autocorrelation

For Figure 3, autocorrelation plot of residuals does not fit white noise, indicating there is some remaining pattern or autocorrelation in the residuals that the SES model has not adequately captured. Thus, SES model may not be a good forecast for RMB/USD exchange rates.

3.2. Forecasting Results Using ARIMA Model

3.2.1 Analysis of autocorrelation (ACF) plot and partial autocorrelation (PACF) plot

Before applying the ARIMA model, checking the time series is stationary is required. In this case, plotting ACF plot and PACF plot is a way to check stationarity. And plots are shown below in Figure 4 and Figure 5 separately.

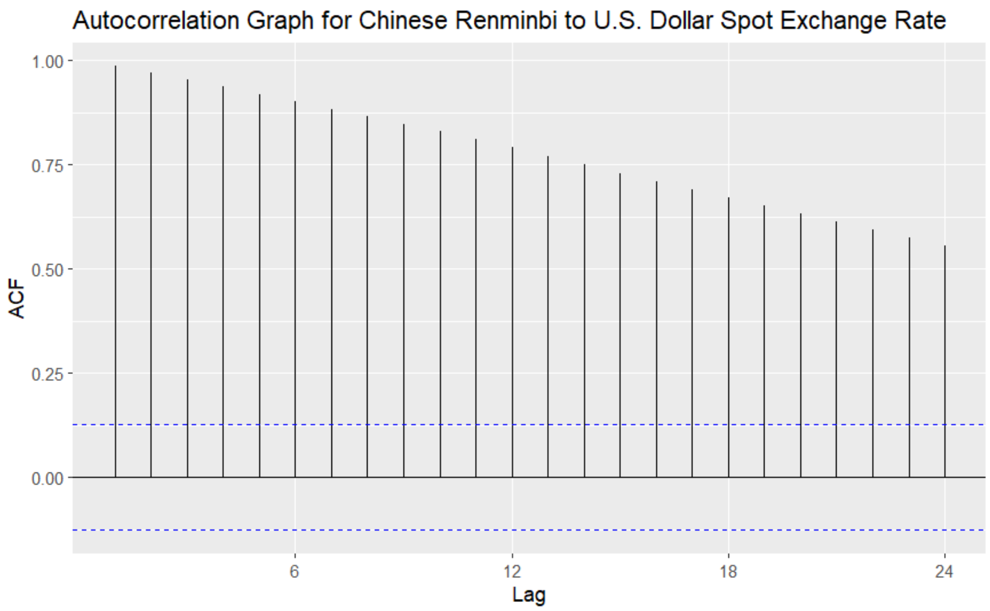


Fig. 4 ACF Plot for RMB/USD Exchange Rate RMB/USD

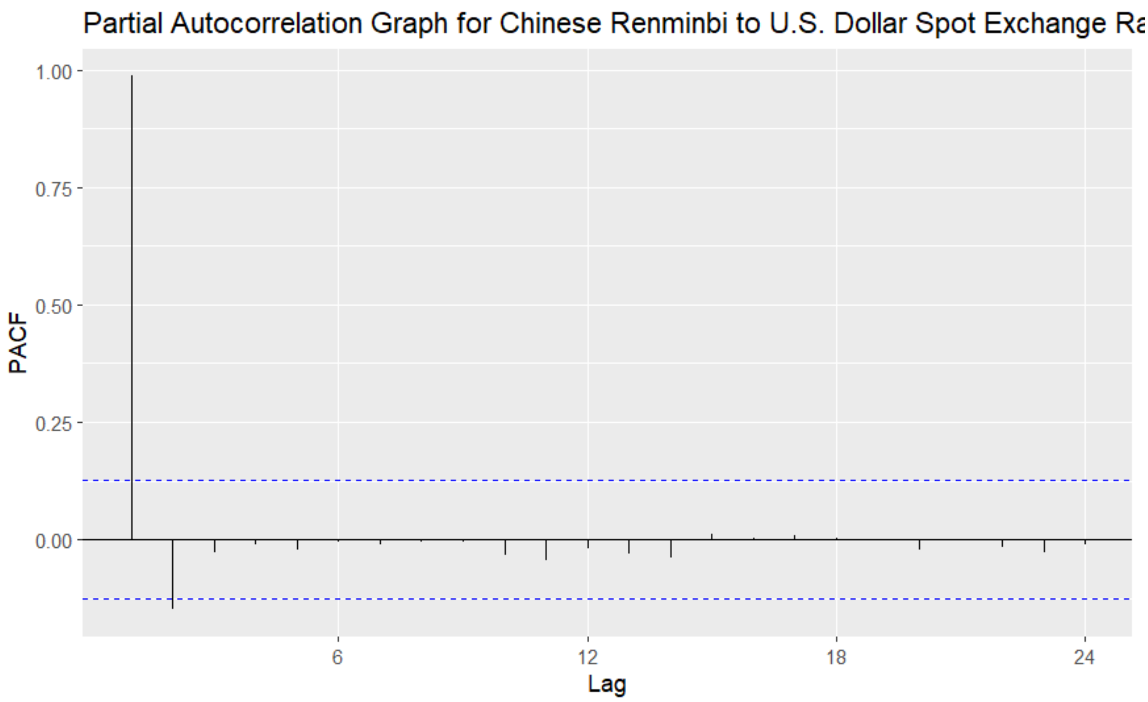


Fig. 5 PACF Plot for RMB/USD Exchange Rate

In Figures 4 and 5, ACF decays slowly in the first graph, and PACF plot does not show a slow decay or remain significant for multiple lags. Therefore, the time series, the RMB/USD exchange rates, is stationary. Then the order of differencing d is zero [7].

For above two plots, the lag at which the PACF plot cuts off and becomes non-significant is lag 1. Thus, AR (1) model, which is ARIMA model with parameter (1,0,0), is used when applying *arima()* function.

3.2.2 Apply ARIMA and Check Residuals

Then apply *arima()* function with parameter (1,0,0) to time series of RMB/USD exchange rate. In order to make sure no remaining patterns and systematic error remains, *checkresiduals()* function is applied to examine the residuals of the ARIMA model. Therefore, the Ljung-Box test table (table 4) and the second figure are generated.

Table 4. Ljung- Box Test

Data: Residuals from ARIMA(1,0,0) Function			
Q* value	*df value*	p value	Model *df* value
89.539	23	8.494e-10	1
Total lag		24	

For the table 4, the model has p-value smaller than chosen significance level and the model is considered adequate. One thing should be noticed that is the prediction intervals may not be accurate due to the correlated residuals.

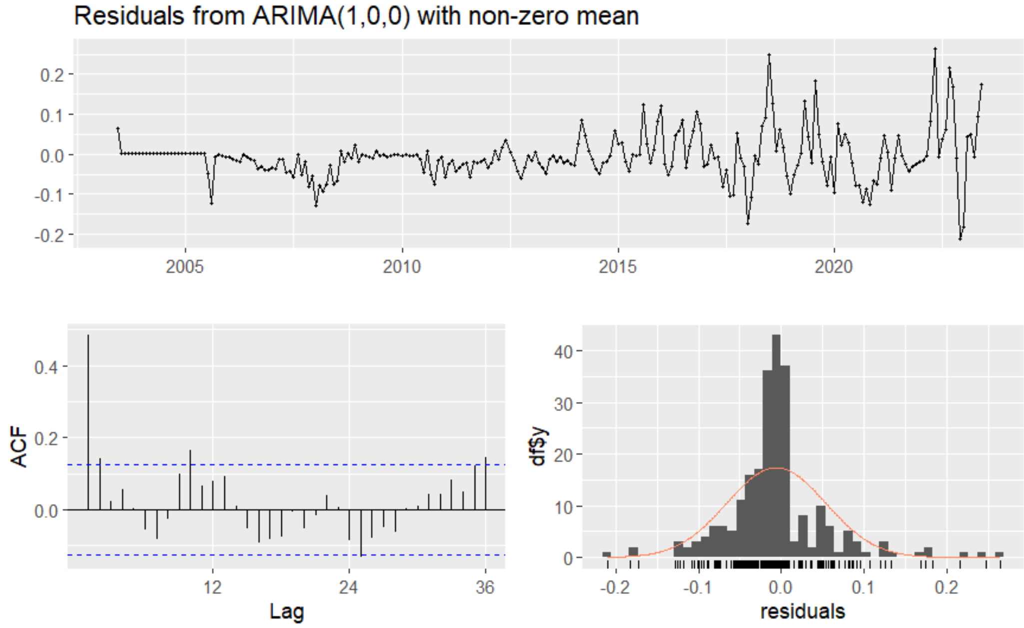


Fig. 6 Residual Check and ACF

Then the top graph of Figure 6, time series plot for residuals, shows that the model has no remaining trends and seasonality over time. Then, ACF plot, the left-bottom graph of Figure 6, has a significant peak, suggesting that the model is not capturing some temporal patterns in the data. And most autocorrelations do not exceed the critical bounds. Indicating the residuals is a White Noise, and therefore no systematic error. Finally, histogram and density plot, the right-bottom plots, visualize the distribution of the residuals and check for normality [7].

3.2.3 Forecasting exchange rates for next 2 years

After ensuring that no remaining pattern and systematic error, the forecast value for next 2 years are found by applying *forecast()* function with parameter h = 24. This is because the data chose is monthly basis, in this case the frequency of time series is 12. Then when h is 24, the next 2-year forecasted data and its plot are shown below [7].

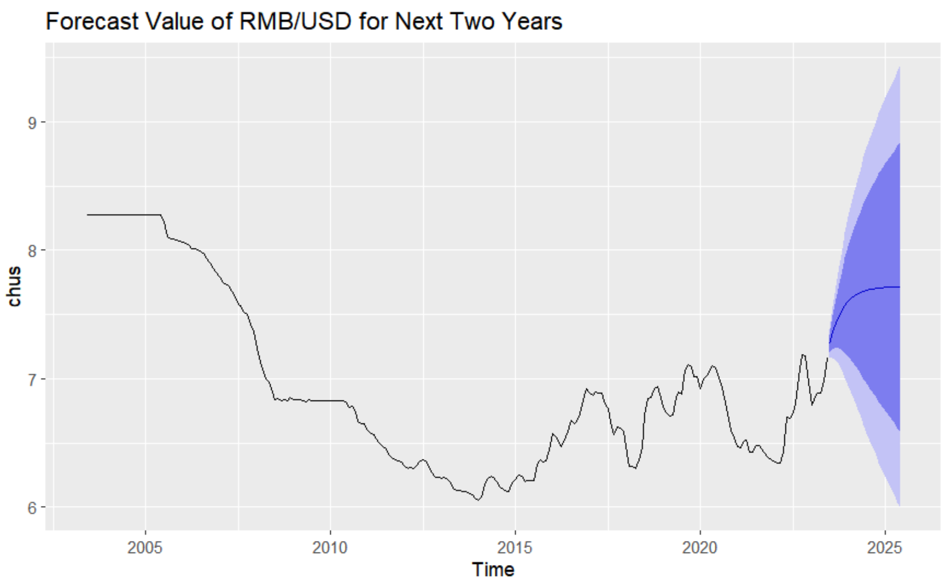


Fig. 3 Forecast Value of RMB/USD Exchange Rates for Next Two Years by ARIMA Model

Then analyzing Figure 7, the forecast values grow linearly with a small increment as the forecast horizon increases. This indicates that the ARIMA model's fitted values do not show any trend, seasonality, or variation, which is consistent with the graphs for historical data. Then for the uncertainty bounds, the light blue indicates 80% prediction interval and dark blues indicates 95% prediction interval. The uncertainty bounds have small width for both intervals, so the uncertainty for the forecast in long term is relatively low.

3.2.4 Accuracy of Next 2-Year Forecasting

Similarly, model evaluation metrics analyzes is generated to analyze the forecast value accuracy.

Table 5. ARIMA Model Evaluation Metrics

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Value	-0.006209	0.0599593	0.0388434	-0.0905225	0.5722796	0.150795	0.48455

After generating table 5, a slight positive ME indicates that forecast values are centered around the actual values and are accurate. Then (MAE and RMSE have value 0.0388434 and 0.0599593 respectively. When analyzing the exchange rates, these values are small and indicating a good forecast accuracy. For MPE and MAPE, they have values -0.0905225 and 0.5722796 separately. Then these values suggest that the model is accurate. In conclusion, using ARIMA model to forecast RMB/USD exchange rates are accurate [6].

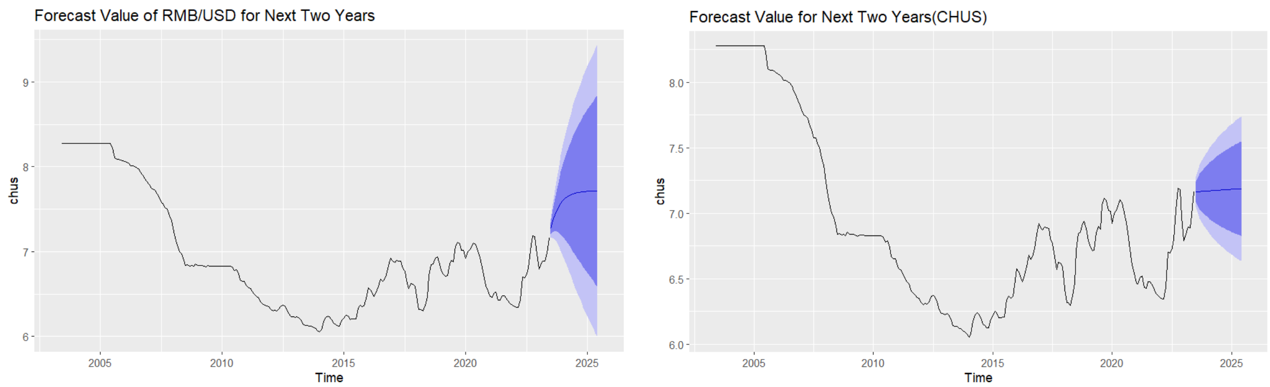
4. Discussion

4.1. Comparison Between Forecasting Results

This part aims to compare for different exchange rate, the strength and limitation of 2 different methods: SES model and ARIMA model.

4.1.1 Prediction Intervals and Uncertainty

Then, comparison of the uncertainty of forecast value by comparing the width of uncertainty bounds of prediction intervals using different model is made. First, for RMB/USD exchange rates, comparing the forecast value plots of 2 models:



(1) Forecast Using SES Model (2) Forecast Using ARIMA Model

Fig. 8 Forecast results

In Figure 8, the left plot is the forecast values plot using SES model, and the right plot is the forecast values plot using ARIMA model. It is clear that ARIMA model has smaller width of prediction intervals compare to SES model, especially as the forecast horizon increase. This comparison indicates that ARIMA model has lower uncertainty and is a better forecast when forecasting the exchange rate [6]. In the figures for forecasting exchange rates, SES model has wider prediction intervals than ARIMA model. Then, several possible reasons for this result are listed below: First, SES model use the exponential smoothing approach, giving more weight to recent data points. While this approach can provide effective short-term forecasts for stable time series, it may not be as robust in capturing complex patterns over longer forecast horizons, resulting in wider intervals. Second, ARIMA models is a more complex model that capture various patterns in the data, including long-term trends, seasonality, and more irregular patterns. As a result, ARIMA can produce narrower prediction intervals, providing a more precise forecast. Third, ARIMA model can handle non-stationary data and transform it into a stationary series, which can stabilize the forecast and narrow the width of prediction.

4.1.2 Model Evaluation Metrics

First, two model evaluation metrics for RMB/USD exchange rates are shown in the table 6 and then compare the values for two models.

Table 6. Evaluation Metrics for 2 Models

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
SES Model	-0.0001365	0.0539553	0.0340217	0.0004097	0.5018525	0.1320766	0.0667858
ARIMA Model	-0.0062090	0.0599593	0.0388434	-0.0905225	0.5722796	0.1507950	0.4845497

In table 6, the first line represents the model evaluation metrics of SES model and the second line represents the model evaluation metrics of ARIMA model. It shows that the metrics for SES model have values closer to 0, indicating that SES model has more accurate forecast values compare with ARIMA model for RMB/USD exchange rates. But considering the outcome of *checkresiduals()* function for exchange rate, SES model may not appropriate . To conclude, for RMB/USD exchange rates, using ARIMA model to forecast this exchange rates may be a better choice [4].

4.2. Comparison Between Two Models

For two models, SES model is a simple time series forecasting method based on the weighted average of past observations, while ARIMA model is a more complex model that considers autoregressive, differencing, and moving average components. Then this part discusses the difference of two models from model complexity and their limitations.

4.2.1 Model Complexity

First, while SES model is a simple model with few parameters, ARIMA models are more complex [5]. SES assumes that the data follow a simple exponential growth or decay pattern. However, many real-world time series exhibit more complex and dynamic patterns, which SES cannot adequately capture. The ARIMA model's complexity is determined by its orders: the autoregressive order (p), the differencing order (d), and the moving average order (q) [7].

4.2.2 Model Limitation

Besides the difference of 2 models, the limitations also make influence when choosing models in the real time.

For SES model, First, SES model is unable to capture the trend and seasonality of the historical data [9]. Secondly, SES model has increasing uncertainty as forecast horizon increase [4]. Then, SES assumes that the error variance remains constant over time. In real-world data, the variance may change over time, leading to suboptimal forecasts [8,9]. As for ARIMA model, it cannot capture the nonlinear patterns effectively. Since ARIMA assumes that the underlying relationship between the time series and its past values is linear. In real-world data, the relationship might be more complex [5]. Besides that, ARIMA assumes a linear relationship between the time series and its lagged values. If the data exhibits strong nonlinear patterns, ARIMA might not be the best choice [7]. Then, ARIMA is typically not well-suited for real-time forecasting where new data is available frequently. Model updates and retraining might be computationally expensive [10]. When researching contemporary commemorative literature, it is discovered that using ARIMA to predict and analyze the RMB/USD exchange rate is rather frequent. In contrast, nearly no publications on utilizing the SES model to anticipate and analyze the exchange rate have been published. SES and ARIMA are two commonly used and accurate predictive statistical models; comparing and analyzing the two models at the same time can result in a more appropriate analysis method.

5. Conclusion

The exchange rate is a crucial component impacting the global economy that is becoming increasingly essential in the worldwide financial market. With accurate forecasting of the RMB/USD exchange rate, financial risks may be reduced. This study compares the features and outcomes of two statistical models used to estimate the RMB/USD exchange rate at the same time. Using the ARIMA model to predict the rather complicated exchange rate connection is proven to be a better choice when various elements are compared. But research still exists limitations in reality forecast. Many geopolitical events, such as the 2008 US economic crisis and the 2019 Covid-19 pandemic, cannot be considered by ARIMA when analyzing and forecasting. Simultaneously, being a component of the global economy, the exchange rate between China and the United States will unavoidably be influenced by other economies. These elements cannot be covered solely by statistical model analysis, and more and more extensive study is required to effectively assess and anticipate the RMB/USD exchange rate. Besides that, both SES and ARIMA model show accurate forecast values only in vary close future. In this situation, more complex models like GARCH, VAR et al. should be considered. For future research, a more precise and trustworthy exchange rate forecast can be generated by quantifying and reducing the impact of geopolitical events and utilizing more complicated models.

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