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Thai Baht and Chinese Yuan Exchange Rate Forecasting Models: ARIMA and SMA-ARIMA Comparison

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ABSTRACT. This study evaluates the effectiveness of classical Autoregressive Integrated Moving Average (ARIMA) models and k^{th} Simple Moving Average - ARIMA (k^{th} SMA-ARIMA) models in forecasting the exchange rate between the Thai Baht (THB) and the Chinese Yuan (CNY). The analysis uses a dataset of historical monthly exchange rates from January 2011 to November 2022, covering 143 months. The dataset is divided into two segments: the initial 127 months are used as the training dataset for model development, while the subsequent 16 months serve as the testing dataset to evaluate forecast accuracy. The Akaike Information Criterion (AIC) is the decision criterion for model selection during the development phase. The forecasting models' effectiveness is subsequently assessed on the testing dataset using two statistical measures: the Mean Absolute Percentage Error (MAPE) and the Root Mean Square Error (RMSE). The findings indicate that the classical ARIMA (0,1,1) model outperforms the k^{th} SMA-ARIMA models in this study, exhibiting the lowest RMSE and MAPE of 0.1702 and 2.6644, respectively. Additionally, a focused comparison of the k^{th} SMA-ARIMA models for k = 2, 3, and 4 reveals that the 2^{nd} SMA-ARIMA (0,1,2) model demonstrates superior performance compared to the 3^{rd} and 4^{th} SMA-ARIMA models. This superiority is reflected in their respective RMSE values of 0.3202, 0.5146, and 0.6339, and corresponding MAPE values of 5.3533, 8.7531, and 10.4949. These results provide valuable insights for decision-makers in the financial sector, enhancing investment strategy formulation based on anticipated currency movements.

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1. Introduction

The exchange rate is a numerical representation of the proportion at which one currency may be traded for another ([1], [2]). Exchange rates impact the costs associated with international business. When the value of a nation's currency increases, foreign purchasers pay a higher price for exported goods and a lower price for imported goods. Trade imbalances and the ability to compete may be negatively impacted. A robust currency can impede the global competitiveness of local firms, whereas a depreciated currency might enhance export performance. Businesses are required to mitigate the risks associated with fluctuations in foreign currency exchange rates. Karakostas [3] forecasting exchange rates is a significant financial subject that is garnering attention, mostly due to its intricate nature and practical importance. In 2021, Thailand's top three trading partners are China, Japan, and the United States, respectively, with a total trade value of more than 7 trillion Baht. China has a proportion of trade value growth of more than 30%, whereas Thailand has a continuous trade deficit with China [4]. As a result, it will affect exchange rate changes and cause the Chinese Yuan to depreciate. In the past year, it was found that the Yuan exchange rate fluctuated within the range of 5.12 to 5.52 Baht per 1 Yuan [5]. Therefore, the basics of bilateral exchange rates change over time, so it is important to consider exchange rates. Before the 1980s, economists used financial or purchasing power parity (PPP) theory to forecast foreign exchange rates. However, the models produced from these theories will remain inconsistent with the changing times [6]. In [7] the authors found that a simple random walking model performed better in the foreign exchange model than the economic theory model. Subsequent analyses generally confirm the general conclusion of the above studies; in particular, it is difficult to identify a model that explains and predicts all currencies for all periods ([8], [9]).

Forecasting exchange rates using the time series method assumes the use of time series data in forecasting, that historical data will continue in its original form in the future. Many researchers use time series techniques to analyze data to play a role in forecasting future events. Exponential smoothing, Box–Jenkins methods, and neural networks are popular exchange rate forecasting techniques. In recent years, many authors have been studying exchange rates. In [1] the authors found that the exponential smoothing method is better than the Autoregressive Integrated Moving Average (ARIMA) model in some cases for the forecast of the Romanian Leu and the Euro, US Dollar, British Pound, Japanese Yen, Chinese Yuan, and Russian Ruble. In [10] the authors forecast the exchange rate for the Malaysian Ringgit (MYR) against the US dollar (USD) by using Artificial Neural Network (ANN) and ARIMA techniques. The results showed that the ANN model is better for forecasting USD/MYR Exchange Rate data than the ARIMA model. In [11], a Nonlinear Autoregressive with Exogenous Input (NARX) Neural Network approach was used to forecast the Euro exchange rate against the US dollar. It appears to be an effective approach to forecasting currency exchange rates. In [12], they researched daily Euro/Yuan exchange rates using artificial neural networks. The results indicated that incorporating additional variables such as year, month, day of the month, and day of the week into the analysis significantly improved the accuracy and organization of the time series equalization. In [13], they compared forecast models to assess their accuracy in the short-term using data on the EUR/USD exchange rate by using three methods: ARIMA, Recurrent Neural Network (RNN) of the Elman type, and Long Short-Term Memory (LSTM). Results show that LSTM provided the best forecast model. In [2], they showed that the future closing price of the AUD/JPY, NZD/USD, and GBP/JPY can be accurately predicted by utilizing a novel Convolutional Neural Network (CNN) model integrated with a random forest regression layer. The findings revealed that the CNN outperformed the ARIMA, Multi-Layer Perceptron (MLP), and Linear Regression (LR) models.

The above study revealed that no work has employed a SMA-ARIMA model for predicting currency exchange rates. Therefore, this paper aims to investigate the optimal forecasting model for predicting the exchange rate between the Thai Baht and the Chinese Yuan (THB/CNY) by comparing k^{th} SMA-ARIMA models to classical ARIMA models.

ARIMA is a comprehensive model utilized to analyze and forecast time series data. It is suitable for a wide range of time series data, provided that it can be made stationary and exhibits linear relationships. By ensuring the data satisfies these criteria and applying necessary transformations, ARIMA can effectively capture and forecast the underlying patterns and trends in the time series. To effectively employ ARIMA, the data should possess specific characteristics and meet certain criteria: univariate time series, stationarity (meaning its mean and variance remain constant over time), linear relationships, and the absence of seasonal patterns. ARIMA is designed to analyze univariate time series data, stationary time series, and linear relationships within the data. While it can capture various patterns through AR and MA components, it may need to be better suited for highly non-linear data. Additionally, ARIMA is not inherently designed to handle seasonal patterns.

The SMA-ARIMA model is a hybrid approach that combines SMA's smoothing capabilities with the ARIMA model's forecasting abilities. This integration leverages the strengths of both techniques to enhance the accuracy of time series forecasting. SMA is employed to smooth time series data by averaging data points over a specified period. It helps reduce short-term fluctuations and reveals the underlying trend in the data.

The remainder of this paper is structured as follows. Section 2 provides an overview of the study area and the methods used for data collection. Section 3 presents a detailed explanation of the ARIMA and the k^{th} SMA-ARIMA models. Section 4 presents the results obtained from the analysis. Finally, Section 5 concludes the paper.

2. Data

The historical daily THB/CNY exchange rates provided by the Bank of Thailand (https://www.bot.or.th) were collected from January 2011 to November 2022 and averaged into monthly data. The dataset, consisting of 143 observations, has been divided into training and testing datasets. The first 127-month exchange rates (until July 2021) were used as the training dataset for model building, while the testing dataset, comprising the remaining 16-month exchange rates, was used to compare the forecast accuracy of the forecasting methods.

This paper compares the forecasting potential of two models: the ARIMA and SMA-ARIMA models. Therefore, the study derives the forecasting performance from these two models to identify the most suitable forecasting procedure for each stock price, following the steps outlined below:

1. Fit the ARIMA model to the training dataset.
2. Fit the SMA-ARIMA model to the training dataset.
3. Compare the forecast accuracy measures for all models using the training dataset.
4. Compare the forecast accuracy measures for the models using the testing dataset.

3. Methods

This section details ARIMA and k^{th} SMA-ARIMA models, including model selection criteria and accuracy metrics.

3.1 Autoregressive Integrated Moving Average Model

The Autoregressive Integrated Moving Average (ARIMA) model, which was developed by Box et. al. [14], is widely recognized as one of the most commonly used forecasting techniques.

The ARIMA model was selected in light of the observed trend in the monthly data and by the recommendations of Box and Jenkins. For a nonstationary time series of data y_t $(t = 1, \dots, n)$, the ARIMA model, denoted as ARIMA(p, d, q), can be expressed by:

$$\phi_p(B)(1-B)^d y_t = c + \theta_q(B)\varepsilon_t, \quad (2.1)$$

where $\phi_p(B) = \left(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p\right)$ is the autoregressive operator of order p: AR(p), $\theta_q(B) = \left(1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q\right)$ is the moving average operator of order q: MA(q), c is a constant term, $(1-B)^d$ is the differencing operator, and d is the number of times needed to differentiate y_t to make the data stationary, B is the backward shift operator defined as $B^k y_t = y_{t-k}$, and ε_t is an error term, usually a white noise process with variance σ^2. If d is nonzero, a basic differencing transformation can be employed to eliminate the trend [15] . In all instances, if there is a trend, the model does not incorporate a constant term c [16].

The Box and Jenkins' ARIMA modeling is best performed by following a protocol consisting of a four-step iterative process [17].

Step 1: Data Preparation. In this step, we apply transformations and differencing to the time series to assess its stationarity. The first part of this process involves using the augmented Dickey-Fuller (ADF) unit root test ([15], [18]) to check for data stationarity.

Step 2: Model Identification and Parameter Estimation. First, we estimate the general form or order of the model. Then, we use maximum likelihood estimation [19] to estimate the model parameters. Finally, we use the t-test to check the statistical significance of each parameter in the model.

Step 3: Diagnostic Checking. To assess the appropriateness of the model, the Ljung-Box test is conducted to ensure that the residuals exhibit characteristics of white noise [20]. The Kolmogorov-Smirnov (K-S) test is also performed to check for normality. If the forecast model fails these suitability checks, the researcher must redefine the forecast model. If the model is inadequate, the first three stages are repeated until a satisfactory ARIMA model is obtained. This protocol is repeated until a suitable ARIMA model is selected for the analyzed time series. The AIC is computed for each model, and the smallest AIC is chosen.

Step 4: Forecasting. Use the identified optimal forecasting model from Step 3 to predict future outcomes.

3.2 The k^{th} Simple Moving Average –ARIMA Model

The k^{th} Simple Moving Average – ARIMA (k^{th} SMA – ARIMA) model was proposed by [21] and [22]. It is based on modifying a given time series x_t into a new k-time moving average time series and then predicting the new time series $\widehat{x_t}$ by using the ARIMA model from the Box and Jenkins method. Once the new time series $\widehat{x_t}$ is predicted, a back-shift operator is then applied to obtain the forecasted values $\widehat{y_t}$ of the original time series y_t. The k^{th} SMA-ARIMA process x_t of a time series y_t and the corresponding back-shift operator of the forecasted values $\widehat{y_t}$ are defined by

$$x_t = \frac{1}{k}\sum_{j=0}^{k-1} y_{t-k+1+j};\ t = k, k+1, \ldots, n, \quad (2.2)$$

and

$$\widehat{y_t} = k\widehat{x_t} - y_{t-1} - y_{t-2} - \ldots - y_{t-k+1}, \quad (2.3)$$

respectively.

We can summarize the process of developing the subject model as follows:

Step 1: Transform the original time series into the k^{th} SMA-ARIMA process using Eq. (2.2).

Step 2: Prepare the data by checking for stationarity. Conduct the ADF test to determine the order of differencing, denoted as d. Iterate d = 0, 1, 2, ... until stationarity is achieved.

Step 3: Identify and estimate the parameters for the model. Decide the order of the process, denoted as r. In our case, we set r = 6, where $p + q = 6$. Once (d, r) is selected, generate all possible sets of (p, q) for $p + q \leq r$. For each set of (p, q), estimate the parameters in the model.

Step 4: Perform diagnostic checking to confirm the model's suitability. Use the Ljung-Box test to verify that the residuals behave like white noise. Additionally, the K-S test will be conducted to assess normality. The AIC is calculated for each model, and the model with the lowest AIC is selected.

Step 5: Forecasting. Utilize the optimal forecasting model identified in Step 4 to predict future outcomes and determine the estimates for the original time series using Equation (2.3).

3.3 Model Selection Criterion

The best-fit model could be determined by using the Akaike Information Criterion (AIC) which is a widely used model selection criterion due to its computational simplicity and effective performance [23]. The AIC [24], is given as

$$AIC = -2\log L + 2m \quad (2.4)$$

where L is the likelihood of the model and m is the total number of estimated parameters in the model. The optimal model is selected from the models that adequately fit the data. The AIC value is computed for each candidate model, and the model with the lowest AIC value is identified as the most appropriate.

3.4 Accuracy Metrics

Two common metrics, Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), have been applied to evaluate the forecasting methods.

The most common forecasting measure is RMSE calculated by Eq. (2.5):

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \tag{2.5}$$

where y_t is the actual value at time t, $\hat{y}_t$ is the forecasted value at time t, and n is the sample size. MAPE is a relative forecasting accuracy measure and it is a scale-independent measure that is defined as:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100 \tag{2.6}$$

The model demonstrating the lowest values of RMSE and MAPE was designated as the most suitable for future exchange rate predictions.

The criteria for evaluating forecasting accuracy based on the MAPE have been established as follows ([25], [26]):

a. Forecasting accuracy is considered excellent when the MAPE is below 10%.
b. Forecasting accuracy is considered satisfactory when the MAPE falls between 10% and 20%.
c. Forecasting accuracy is deemed acceptable when the MAPE ranges from 20% to 50%.
d. Forecasting accuracy is evaluated as poor when the MAPE exceeds 50%.

4. Results

This section presents descriptive statistics for the exchange rates and reports the results obtained from applying the ARIMA and k^{th} SMA-ARIMA models. All computations involved in this task were performed using the R programming language version 4.4.1.

4.1 Descriptive Statistics

Before fitting the model, descriptive statistics were conducted on the 127-month currency exchange rates and presented in Table 1. Table 1 summarizes the dataset, revealing that the average exchange rate was 4.958 Thai Baht per Yuan, with a standard deviation of 0.324 Baht. The coefficient of variation was 6.535%, indicating that the dataset exhibited low dispersion around its mean.

Table 1: Descriptive statistics of the 127-month exchange rate

Variable	Exchange Rate
Mean	4.958
Median	4.960
Minimum	4.278
Maximum	5.648
Standard deviation	0.324
Coefficient of variation	6.535

4.2 ARIMA Model Results

To determine the stationarity of the monthly exchange rate, time series plots were created to visualize the movement of the exchange rate for the training dataset, as depicted in Figure 1. Based on the analysis of Figure 1, the data exhibits a fluctuating pattern; the average value changes over time, indicating that the exchange rate series is non-stationary. As the Box-Jenkins model does not apply to non-stationary data, it was necessary to transform the training dataset into a stationary series. To achieve this, a first differencing transformation (d=1) was applied, and the resulting plot is shown in Figure 2. From Figure 2, it can be inferred that the differenced series appears stationary. The ADF test was conducted to confirm the stationarity, and the results are presented in Table 2. The ADF test yielded a t-test statistic of -4.3399 and a p-value of less than 0.001 for the first differenced exchange rate, indicating significance below the 0.01 level. Therefore, it can be concluded that the first differenced exchange rate is stationary, thus making it suitable for ARIMA model identification.

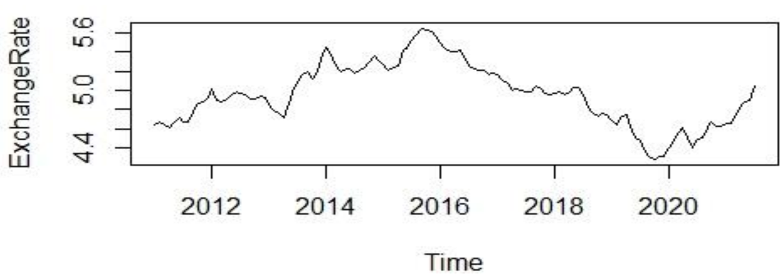

Figure 1: Time series plot of the training dataset

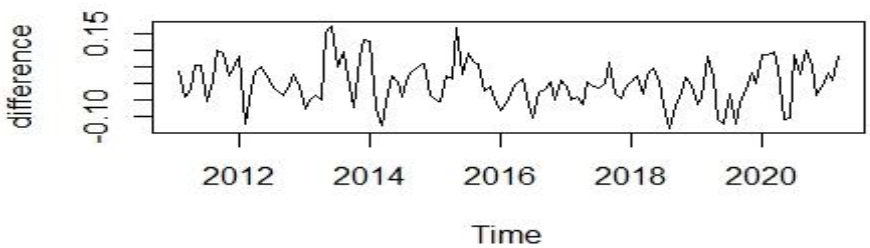

Figure 2: Differenced exchange rate plot

Table 2: ADF unit root test for time series

Time Series	Difference Order (d)	t-statistic	p-value
Exchange Rate	0	-1.7913	0.6633
	1	-4.3399*	< 0.001
2nd SMA	0	-1.7598	0.6764
	1	-4.1146*	< 0.001
3rd SMA	0	-2.3315	0.4388
	1	-4.0559*	< 0.001
4th SMA	0	-1.9414	0.6009
	1	-5.5941*	< 0.001

*Significant at the 0.01 level of significance

Our next step is determining the suitable p and q values for ARIMA models by analyzing the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots derived from the differenced time series, as depicted in Figure 3. Upon examining these plots, the ARIMA(0,1,1) model may be appropriate for the exchange rate. This is supported by the fact that the ACF plot only displays a significant spike at lag 1, while the PACF plot does not exhibit any significant lags. Nonetheless, we explored various models with different p and q parameters, assessing their performance using the AIC to determine the most optimal forecasting model. The findings presented in Table 3 reveal that the ARIMA(0,1,1) model, with an AIC value of -359.20, is the best choice.

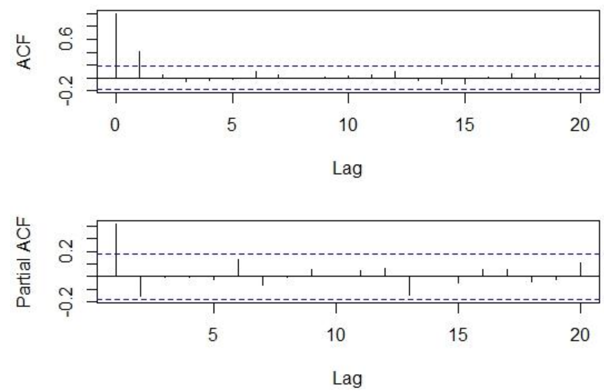

Figure 3: ACF and PACF plots of the differenced exchange rate series

Table 3: AIC for the ARIMA and k^{th} SMA-ARIMA models

(p,d,q)	Classical ARIMA	2^{nd} SMA-ARIMA	3^{rd} SMA-ARIMA	4^{th} SMA-ARIMA
(0,1,0)	-334.17	-375.90	-409.73	-437.81
(0,1,1)	**-359.20**	-498.83	-500.02	-574.75
(0,1,2)	-358.57	**-528.84**	-594.38	-608.06
(0,1,3)	-357.42	-527.35	-612.73	-660.70
(1,1,0)	-356.55	-443.89	-521.33	-586.40
(2,1,0)	-358.63	-476.41	-567.37	-633.48
(3,1,0)	-356.71	-490.22	-567.36	-632.43
(1,1,1)	-358.23	-522.84	-550.07	-635.81
(1,1,2)	-358.34	-527.28	-612.80	-635.08
(1,1,3)	-356.35	-525.01	-612.53	-678.76
(2,1,1)	-356.69	-526.70	-566.25	-636.40
(2,1,2)	-356.35	-525.47	**-613.30**	-638.34
(2,1,3)	-354.34	-523.63	-611.41	**-679.67**
(3,1,1)	-355.24	-525.37	-571.05	-647.57
(3,1,2)	-357.00	-523.21	-611.52	-645.90
(3,1,3)	-355.24	-521.27	-609.39	-678.77

After identifying the model, residual diagnostics were conducted to assess the adequacy of the ARIMA(0,1,1) model. The ACF and PACF patterns shown in Figure 4 were examined to ensure that the residuals resemble white noise. Additionally, both the Ljung-Box and K-S tests were performed, and the results are presented in Table 4. Based on the ACF and PACF plots in Figure 4, all values fell within the 95% confidence interval, indicating no autocorrelation in the residuals. The Ljung-Box test, conducted at a lag of 10, yielded a Q statistic of 4.5474 with a p-value of 0.9193, greater than 0.01. This confirms that there is no autocorrelation in the residuals, therefore, the null hypothesis that the residuals are white noise was not rejected. Furthermore, the K-S test resulted in a value of 0.0716 with a p-value larger than 0.01, confirming the normality of the residuals. Consequently, the ARIMA(0,1,1) model is deemed appropriate for analyzing the exchange rates.

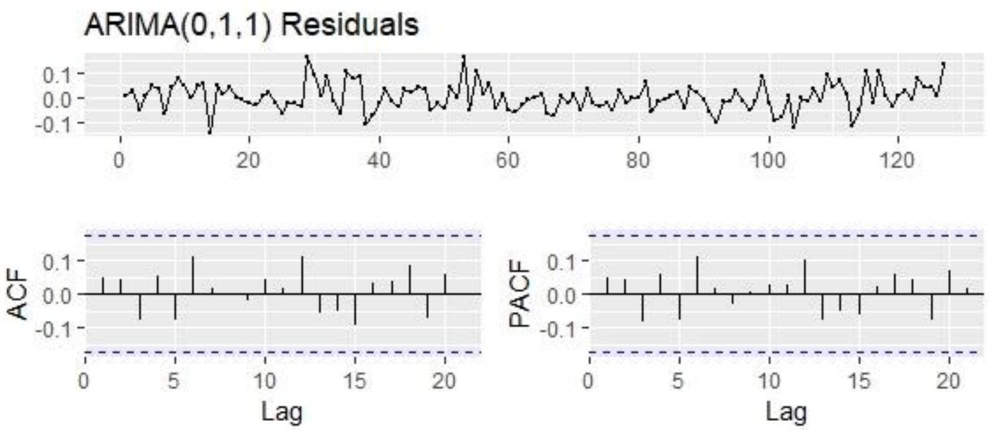

Figure 4: Residuals, ACF, and PACF of the residuals from the ARIMA(0,1,1) model

Table 4: Ljung-Box and K-S tests for the residuals of the candidate models

Candidate Model	Ljung-Box Test		K-S Test	
	Q	p-value	K-S	p-value
Classical ARIMA(0,1,1)	4.5474	0.9193	0.0716	0.5333
2^{nd} SMA-ARIMA(0,1,2)	2.6300	0.9888	0.0669	0.6256
3^{rd} SMA-ARIMA(2,1,2)	2.8227	0.9853	0.1022	0.1464
4^{th} SMA-ARIMA(2,1,3)	3.7834	0.9566	0.0610	0.7474

4.2 The k^{th} SMA-ARIMA Model Results

After exploring different values of *k* ranging from 2 to 6 months, it was found that the SMA-ARIMA model performed poorly with *k* = 5 and 6, so those models will not be discussed further. However, the SMA models with *k* = 2, 3, and 4 showed promising results, which will be reported next. Stationarity of the time series for k = 2, 3, and 4-month SMA was investigated using the ADF test, and the results are presented in Table 2. It can be observed from Table 2 that all SMA time series became stationary after the first differencing (d=1) with a significance level of 0.01. Therefore, the ARIMA model with p and q parameters, where $p + q \leq 6$, will be applied to the differenced time series of k = 2, 3, and 4-month SMA. The AIC values for different ARIMA models are presented in Table 3. From Table 3, it can be seen that the ARIMA(0,1,2), ARIMA(2,1,2), and ARIMA(2,1,3) models obtained the lowest AIC values for the k = 2, 3, and 4-month SMA time series, with AIC values of -528.84, -613.30, and -679.67, respectively. Next, the Ljung-Box test was performed with a total lag of 10, and the results are displayed in Table 4. Table 4 shows that all p-values obtained from the previous three models were greater than 0.01, indicating that the residuals obtained from the 2nd SMA-ARIMA(0,1,2), 3rd SMA-ARIMA(2,1,2), and 4th SMA-ARIMA(2,1,3) models were white noise. Additionally, the K-S test was conducted to assess the normality of the residuals, as presented in Table 4. The results of the K-S test indicate that the residuals from the 2nd SMA-ARIMA(0,1,2), 3rd SMA-ARIMA(2,1,2), and 4th SMA-ARIMA(2,1,3) models followed a normal distribution, as evidenced by p-values exceeding 0.01 for each model.

4.3 Effectiveness Evaluation Results

The monthly currency exchange rate forecasting performances were evaluated using RMSE and MAPE (Eq. 2.5 and Eq. 2.6) on the testing dataset presented in Table 5. The classical ARIMA(0,1,1) model outperformed the k^{th} SMA-ARIMA models, achieving the lowest RMSE and MAPE values of 0.1702 and 2.6644, respectively. These results are considered excellent, as the MAPE is below 10%. When considering only the k^{th} SMA-ARIMA models, the results suggest that a smaller k value (k=2) leads to better performance for this dataset, with RMSE and MAPE values of 0.3202 and 5.3533, respectively. However, the 3rd SMA-ARIMA(2,1,2) model still demonstrates high forecasting accuracy, with a MAPE of 8.7531, falling below the 10% threshold. On the other hand, the 4th SMA-ARIMA(2,1,3) model exhibits satisfactory accuracy, as evidenced by its MAPE of 10.4949, which falls within the acceptable range of 10-20%. Based on these results, the optimal value of k differs from the findings of [21] and [22] due to the utilization of different time series data.

Table 5: RMSE and MAPE of the residuals obtained from the candidate models

Model	RMSE	MAPE
Classical ARIMA(0,1,1)	0.1702	**2.6644**
2nd SMA-ARIMA(0,1,2)	0.3202	**5.3533**
3rd SMA-ARIMA(2,1,2)	0.5146	8.7531
4th SMA-ARIMA(2,1,3)	0.6339	10.4949

In addition, the parameter estimate of the best fit ARIMA (0,1,1) model is given in Table 6, that is, the first-order moving average process with the first differencing. The forecast of ARIMA (0,1,1) is generated by the following equation for the next month (t)

$$(1-B)y_t = (1-0.4317B)\varepsilon_t. \tag{3.1}$$

From Eq. (3.1), expanding the first differencing and the moving operator, it becomes

$$\hat{y}_t = y_{t-1} + \varepsilon_t - 0.4317\varepsilon_{t-1}. \tag{3.2}$$

Neglecting the unknown value of ε_t in Eq. (3.2), the forecasting model can be written as

$$\hat{y}_t = y_{t-1} - 0.4317\varepsilon_{t-1}. \tag{3.3}$$

Table 6: Parameter estimate of the ARIMA (0,1,1) model

Parameter	MA(1): θ_1
Coefficient	0.4317
Standard error	0.0844
t-statistic	5.1149
p-value	< 0.001

5. Conclusion and suggestion

The main challenges financial traders and stock market investors face include reducing risk, maximizing returns, and implementing monetary policies. It is important to use appropriate forecasting methods to optimize processes and make strategic decisions. This study focuses on implementing classical Box-Jenkins ARIMA and SMA-ARIMA models, specifically ranging from the 2nd to the 4th order in the SMA component. The monthly THB/CNY exchange rate datasets are used for this analysis. The accuracy of the forecasting models is measured using RMSE and MAPE metrics. The findings of this study reveal that the ARIMA(0,1,1) model is the most suitable choice for forecasting the exchange rate. It demonstrates the smallest RMSE and MAPE metrics of 0.1702 and 2.6644, respectively. These results indicate a high level of forecasting precision, given that the MAPE is significantly below the 10% threshold. Furthermore, a comparison of the k^{th} SMA-ARIMA models (k = 2, 3, and 4) shows that the 2^{nd} SMA-ARIMA(0,1,2) model performs better than the 3^{rd} and 4^{th} SMA-ARIMA models. This is evidenced by their respective RMSE values of 0.3202, 0.5146, and 0.6339, as well as the corresponding MAPE values of 5.3533, 8.7531, and 10.4949. The effectiveness of SMA-ARIMA models is influenced by the choice of k in the SMA component. The second SMA-ARIMA model, with a k value of 2, balances smoothing the data and preserving important trends and fluctuations, ultimately improving forecasting precision. However, higher-order SMA-ARIMA models (k = 3 and k = 4) may excessively smooth the data, resulting in less accurate predictions when reverting to the original time series. These findings deviate from the optimal value of k as determined in previous studies conducted by [21] and [22], highlighting the significant influence of utilizing different time series datasets. Therefore, future research in this field should further investigate the effects of diverse datasets on model selection and forecasting precision.

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