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Forecasting Model for Foreign Currency Exchange Rates[†]

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Abstract

The objective of this research was to investigate the most suitable forecasting model for 3 currency exchange rates (eg. USD, EUR and CNY), which are time series from January 2022 to December 2022. The comparative study was used to find the most proper forecasting model from 6 forecasting models (eg. simple exponential smoothing, Additive Holt-Winters, Multiplicative Holt-Winters, ARIMA) based on 4 accuracy measures. The most suitable forecasting model plays a crucial role in international trade as well as effective import-export strategies of Thailand. The results indicate that the arima model outperformed the 5 statistical forecasting models, therefore 3 currency exchange rate patterns have followed a linear relation pattern. Therefore, the proposed model can be a promising tool to predict the currency exchange rates, and to support decision making on effective import-export strategies of Thailand.

Keywords: Linear forecasting model, Currency exchange rate, ARIMA, Statistical forecasting model

Introduction

Thailand's export sector is a part important role in the country's economy. Which can generate income into the country tens billions of US dollars per year (see **Figure 1** for details), but on the other side, Thailand still needs to import important products as well, resulting in international trade negotiations with trading partner countries (Office of Permanent Secretary Ministry of Commerce, 2023). According to mentioned above, the foreign currency exchange rates are important variables of government sector economy and private sector economy. Since risk foreign currency exchange rates, it will affect export revenues and production costs. especially if it is necessary to rely on large imports of product or raw materials from trading partner countries (Wilcoxson et al., 2020). The behavior of foreign currency exchange rate risk patterns continuously occurs all the time resulting that in forecasting the rate of change that will occur in the future (Markova, 2019). It is important information for the most effective export and import planning.

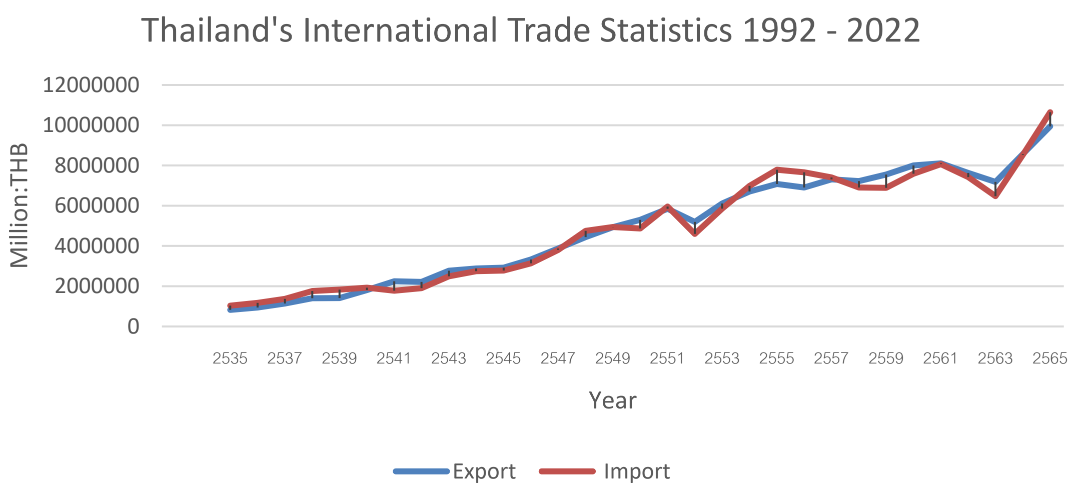

Figure 1 Thailand's International Trade Statistics 1992 - 2022.

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The pattern foreign exchange rate risk. Time-series models are widely used and accepted as effective tools for forecasting exchange rates. It uses historical and current data to create a model for predicting the value of future foreign exchange rates. The information obtained can decision support and management related to trade negotiations with the greatest efficiency. Therefore, the accuracy of forecasting results plays an important role and it is of interest to obtain the most useful information for decision making.

However, the methods for testing the correlation characteristics of time series data to be predicted are still unable to clearly identify the correlation characteristics in every situation. There is no forecasting model is effective in all situations. Therefore, it is necessary to apply various forecasting models to create a forecasting model from the historical and current data relations for predicting future values and choosing the most accurate forecasting model to take advantage of further forecasting.

The simple exponential smoothing model is one of the simple forecasting models which is easy to use because of its simple correlation function (Maria & Eva, 2011). It is popular and applied in various forecasting. The equation of simple exponential smoothing was used to describe the change in time series data. However, forecasting model based on this principle cannot explain time series data with trend and season characteristics. This makes to the development of more complex exponential smoothing models in order to better describe the change patterns. The exponential smoothing Holt-Winter method developed with a complex structure to describe trend and seasonal data based on 3 smoothing equations to describe such data (Bolarinwa & Bolarinwa, 2021).

The Autoregressive Integrated Moving Average model (ARIMA) is a statistical forecasting model developed from the principle of built-in correlation under stationary state conditions that recognized for its predictive performance with a linear relation. It is popular used to forecast foreign currency exchange rate (Tripathi et al., 2020). The disadvantage of ARIMA models can not to describe non-linear time series data (Escudero et al., 2021).

This research applied to forecast 3 foreign currency exchange rates and compared the performance of forecasting accuracy with 6 statistical forecasting models and 4 measurements of accuracy as follows: Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Mean Squared Error (MSE), root mean square error (RMSE) to find the most suitable forecasting model and can use the information obtained from the forecasting model to make decisions and formulate strategies for international trade negotiations effectively.

Literature review

Moving average method

Moving average method comes in various forms, but their underlying purpose remains the same, that is to track the trend determination of the given time series data

Simple moving average (SMA)

A Simple moving average (SMA) is a common average of the previous n data points in time series data. Each point in the time series data is equally weighted, so there are no weighting factors applied to any of the data points (Hansun, 2013).

$$SMA = \frac{P_m + P_{m-1} + \cdots + P_{M-(n-1)}}{n}$$

In the formula above, P_M time M and η stands for the numbers of data points used in the calculation. When calculating successive values, a new value comes into the formula's sum and the oldest data will be dropped out (Hansun, 2013).

$$SMA_{today} = \frac{P_m}{n} + SMA_{yesterday} - \frac{P_{m-n}}{n}$$

Exponential smoothing method

Exponential smoothing is a procedure for continually revising a forecast in the light of more recent experience. Exponential Smoothing assigns exponentially decreasing weights as the observation get older. In other words, recent observations are given relatively more weight in forecasting than the older observations (Kalekar, 2004).

Simple Exponential Smoothing (SES)

This is also known as simple exponential smoothing. Simple smoothing is used for short-range forecasting, usually just 1 month into the future. The model assumes that the data fluctuates around a reasonably stable mean (no trend or consistent pattern of growth). The specific formula for simple exponential smoothing is (Kalekar, 2004):

$$S_{t+1} = \alpha Y_t + (1 - \alpha) S_t$$

where y_t is the actual, known series value at the time t;
S_t is the forecast value of the variable Y at the time t;
S_{t+1} is the forecast value at the time t + 1;
α is the smoothing constant.

The forecast S_{t+1} is based on weighting the most recent observation Y_t with a weight α and weighting the most recent forecast F_t with a weight of $1-\alpha$.

Double exponential smoothing (DES)

This method is used when the data shows a trend. Exponential smoothing with a trend works much like simple smoothing except that 2 components must be updated each period - level and trend. The level is a smoothed estimate of the value of the data at the end of each period. The trend is a smoothed estimate of average growth at the end of each period. The specific formula for simple exponential smoothing is (Kalekar, 2004):

$$S_t = \alpha Y_t + (1 - \alpha)(S_{t-1} + b_{t-1})$$

$$b_t = \gamma(S_{t-1} + b_{t-1}) + (1 - \gamma) b_{t-1}$$

Note that the current value of the series is used to calculate its smoothed value replacement in double exponential smoothing.

Holt-Winters exponential smoothing (HW)

The Holt-Winters (HW) method was originally developed by Winters and involves estimating 3 smoothing parameters associated with the level, trend and seasonal factors. Relatively to the seasonal type it can be additive or multiplicative, depending on the oscillatory movement along the time period. In both versions, forecasts will depend on the following 3 components of a seasonal time series: its level, its trend and its seasonal coefficient (Maulana & Mulyantika, 2020).

The additive version ought to be considered whenever the seasonal pattern of a series has a constant amplitude over time. In the additive case, the series can be written by:

$$Y_t = T_t + S_t + \varepsilon_t$$

where T_t represents the trend (The sum of the level and slope of the series at time t);
S_t is the seasonal component;
ε_t are error terms with mean zero and constant variance.

In the multiplicative case, the series can be represented by:

$Y_t = T_t \times S_t + \varepsilon_t$

The recursive equations of the multiplicative and additive HW methods, for level, trend, seasonal factors and forecast with $h^+_s = [(h-1) \bmod s] + 1$, are presented in **Table 1**, where Y_t is the observed data at time t, s is the length of seasonality (number of months in a season), h is the number of forecast ahead, and $\theta = (\alpha,\beta,\gamma)^T$ is the vector of smoothing parameters (Lima et al., 2019).

Table 1 Holt-Winters method recursive equations.

Additive HW method	**Multiplicative HW method**
Level: $l_t = \alpha(Y_t - s_{t-s}) + (1-\alpha)(l_{t-1} + b_{t-1})$, $0 \le \alpha \le 1$	Level: $l_t = \alpha\frac{Y_t}{S_{t-s}} + (1-\alpha)(l_{t-1} + b_{t-1})$, $0 \le \alpha \le 1$
Trend: $b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1}$, $0 \le \beta \le 1$	Tren: $b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1}$, $0 \le \beta \le 1$
Seasonal: $s_t = \gamma(Y_t - l_t) + (1-\gamma)s_{t-s}$, $0 \le \gamma \le 1$	Seasonal: $s_t = \gamma\left(\frac{Y_t}{l_t}\right) + (1-\gamma)s_{t-s}$, $0 \le \gamma \le 1$
Forecast: $\hat{Y}_{t+h} = l_t + hb_t + S_{t-s+h_s^+}$ $h = 1, 2, \ldots$	Forecast: $\hat{Y}_{t+h} = (l_t + hb_t)S_{t-s+h_s^+}$ $h = 1, 2, \ldots$
Where Initial level = $l_0 = \beta_0$ = intercept Initial growth rate $b_0 = \beta_1$ = Slope $S_t = y_t - \hat{y}_t$ and $\overline{S_{[l]}} = \frac{1}{L}\sum_{k=i-1}^{\le n} S_{2k+1}$ L = No. of seasons in a year Initial seasonal factors = $sn_{i-L} = \overline{S_{[l]}}$, i =1, 2, ..., L	Where Initial level = $l_0 = \beta_0$ = intercept Initial growth rate $b_0 = \beta_1$ = Slope $S_t = y_t/\hat{y}_t$ and $\overline{S_{[l]}} = \frac{1}{L}\sum_{k=i-1}^{\le n} S_{2k+1}$ L = No. of seasons in a year Normalized Constant = CF = $L/\sum_{i=1}^{L}\overline{S_{[l]}}$ Initial seasonal factors = $sn_{i-L} = \overline{S_{[l]}}[CF]$, i = 1, 2, ..., L

Autoregressive integrated moving average (ARIMA)

An ARIMA model is a univariate model that seeks to depict a single variable as an Autoregressive Integrated Moving Average process. The ARIMA model can be described as atheoretical, as it ignores all potential underlying theories, except those that hypothesize repeating patterns in the variable under study. Herein, the series is fully described by *p*, the order of the AR component, *q*, the order of the MA component and *d*, the order of integration. The AR component is built on the assumption that future realizations can be approximated and predicted by the behavior of current and past values. The MA component, on the other hand, seeks to depict the processes where the effects of past environment innovations continue to reverberate for a number of periods. If y_t is an ARIMA *p,d,q* process, then the series evolves according to the following (Islam & Raza, 2020):

$$y_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \theta_0 + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q}$$

θ_0 is a constant, ε is the error term, q is the number of lagged terms of ε and p is the number of lagged terms of y_t. It is required that the series used in the estimation process is stationary. The formulating of ARIMA model is a complicate process, but in summarization it includes 4 steps (Escudero et al., 2021):

1) Identification of the ARIMA (p, d, q) structure.
2) Estimating the coefficients of the formulation.

3) Fitting tests on the estimated residuals.

4) Forecasting the future outcomes based on the historical data.

During the 4 steps, the first is the most important. Usually, the autocorrelation (ACF) and partial autocorrelation (PACF) functions are taken to identify the models because they show different features of the functions. For AR (p), the ACF tails off at the order of p but PACF cutoff; for MA (q), the ACF cutoff but PACF tails off at the order of q; for ARMA (p, q), none of the ACF and PACF tail off.

The ARIMA model could provide forecasting results with upper limits, lower limits and forecasted values. The upper and lower limits provide a confidence interval of 1 - α. The α is the given confidence, which means that any realization within the interval will be accepted.

Measuring forecast accuracy

After the model specified, its performance characteristics should be verified or validated by comparison of its forecast with historical data for the process it was designed to forecast. This is not opinion among researchers as to which measure is best for determining the most appropriate forecasting method. Accuracy is the criterion that determines the best forecasting method; thus, accuracy is the most important concern in evaluating the quality of a forecast. The goal of the forecast is to minimize error (Ostertagova & Ostertag, 2012).

Some of the common indicators used to evaluate accuracy are *MAE* (Mean absolute error), *MSE* (Mean squared error), *RMSE* (Root mean squared error) or *MAPE* (Mean absolute percentage error):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t|, MSE = \frac{1}{n}\sum_{t=1}^{n}|e_t^2|, RMSE = \sqrt{MSE}, MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|e_t|}{y_t}.100\,\%$$

where y_t is the actual value at the time *t*; e_t is residual at the time *t*; *n* is the total number of the time periods.

MAE is a measure of overall accuracy that gives an indication of the degree of spread, where all errors are assigned equal weights. If a method fits the past time series data very good, *MAE* is near 0, whereas if a method fits the past time series data poorly, *MAE* is large. Thus, when 2 or more forecasting methods are compared, the one with the minimum *MAE* can be selected as most accurate.

MSE is also a measure of overall accuracy that gives an indication of the degree of spread, but here large errors are given additional weight. It is a generally accepted technique for evaluating exponential smoothing and other methods.

Often the square root of *MSE*, *RMSE*, is considered, since the seriousness of the forecast error is then denoted in the same dimensions as the actual and forecast values themselves.

MAPE is a relative measure that corresponds to *MAE*. It is the most useful measure to compare the accuracy of forecasts between different items or products since it measures relative performance. It is one measure of accuracy commonly used in quantitative methods of forecasting. If *MAPE* calculated value is less than 10 %, it is interpreted as excellent accurate forecasting, between 10 - 20 % good forecasting, between 20 - 50 % acceptable forecasting and over 50 % inaccurate forecasting.

Selection of an error measure has an important effect on the conclusions about which of a set of forecasting methods is most accurate.

Methodology

This research uses the MINITAB software (Vinayakamoorthi et al., 2022) to forecast foreign currency exchange rates. There are 3 steps in this research follows: (See more **Figure 2**)

Step 1: We obtain the daily foreign currency exchange rate using the average value daily.

Step 2: Compute the currency exchange rate for forecasting through all 5 models (SMA, SES, HW-Additive, HW-Multiplicative, ARIMA).

Step 3 The results obtained from Step 2 come to evaluate the accuracy performance.

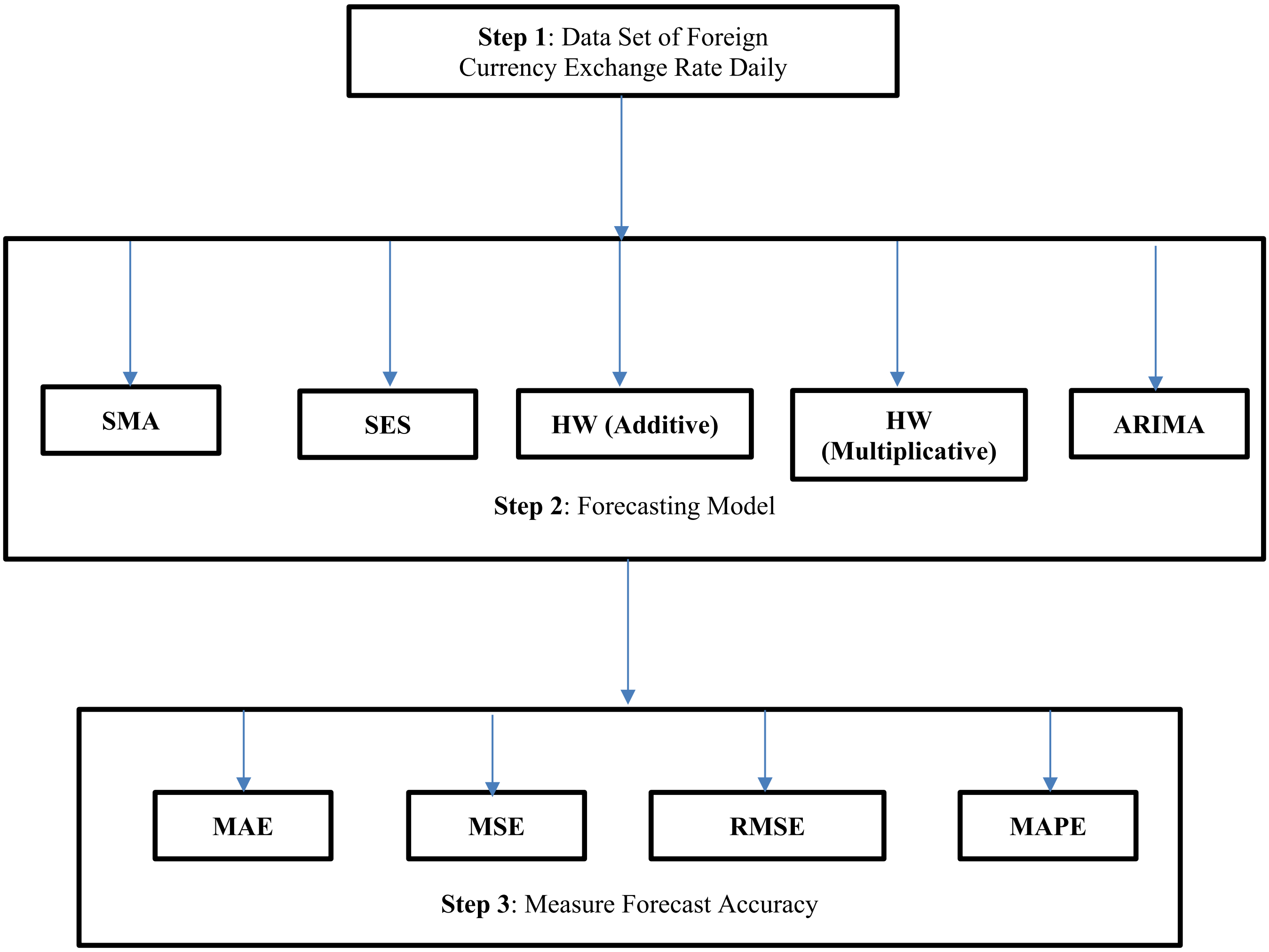

Figure 2 Conceptual model.

Results and discussion

Dataset

This study uses daily value for 3 major exchange rates, including the US dollar (USD/THB), EURO ZONE (EUR/THB), and YUAN renminbi (CNY/THB). The data were obtained from the record on BANK OF THAILAND (BOT) from 4 January 2022 to 31 December 2022, with a total of 360 observations. Each record represents the daily price of the USD/THB, EUR/THB and CNY/THB exchange rate from Monday to Friday. The dataset is shown in **Figure 3**.

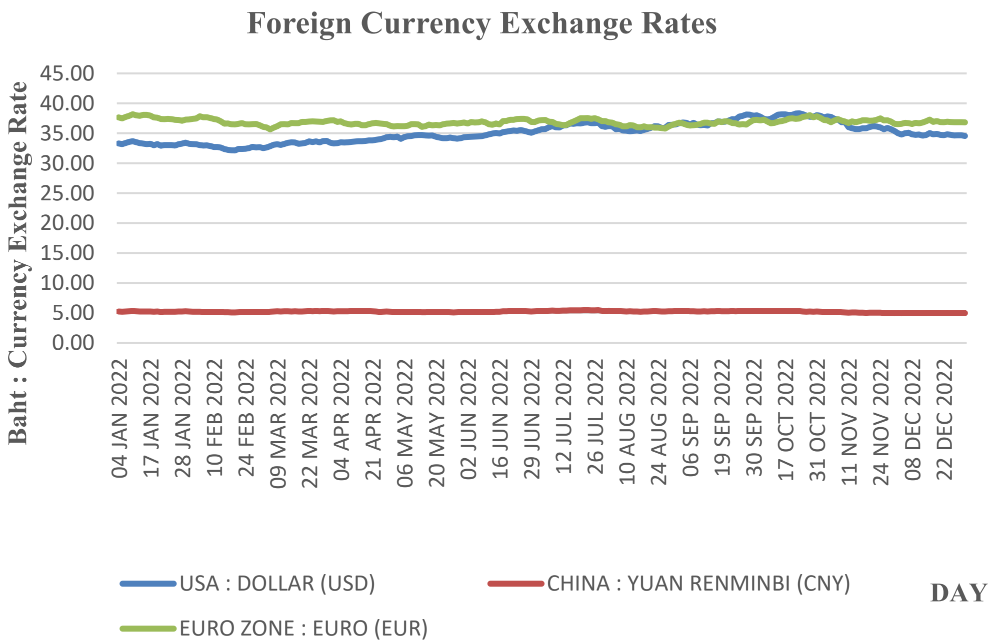

Figure 3 Dataset of currency exchange rates.

Comparison of forecasting model

Forecasting the US dollar exchange rate with various forecasting models, the forecasting results are shown in **Figure 4**, and the efficiency of the forecasting models is shown in **Table 1**.

The forecasting results in **Figure 4** show that the trend of forecasting by 6 models is consistent with the actual US dollar exchange rate time series data. but for the model HW-multiplicative, Simple exponential smoothing model (SES), Double exponential smoothing model (DES) and Simple Moving Average (SMA), the results are different from the actual data for some period time.

Table 2 is shown, The ARIMA model uses historical data time series to predict future currency exchange rates. It found that the average of the smallest error when measuring the statistical error of all 4 methods. It can be said that the US dollar exchange rate time series data has a linear relation. The ARIMA model demonstrates that using integer differences can characterize changes in the US dollar exchange rate.

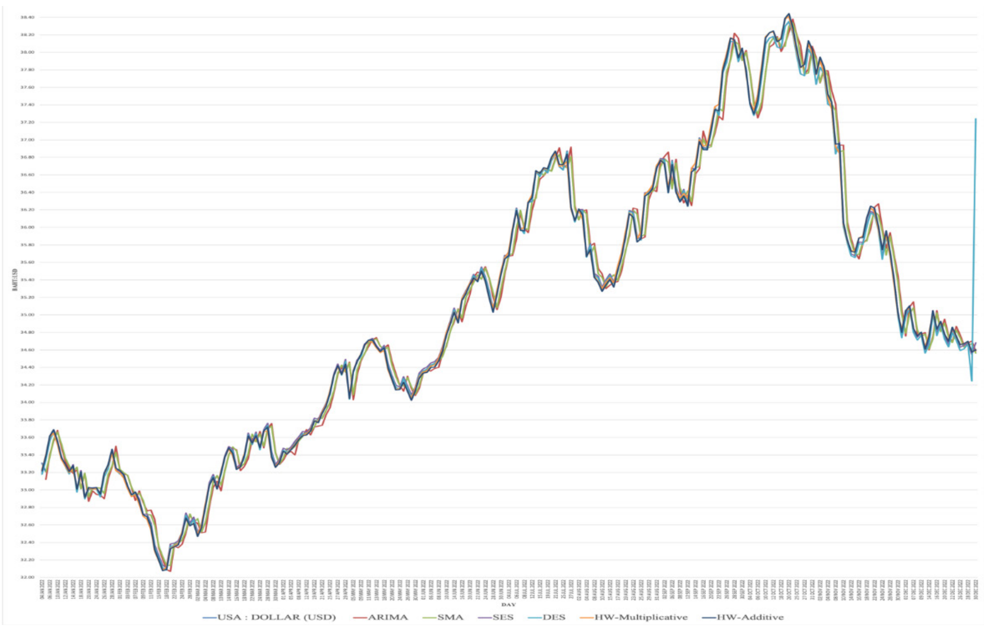

Figure 4 Forecast data of exchange rate for US Dollar.

Table 2 The summary of all forecasting model based on USD.

Model	MAPE (%)	MAE	MSE	RMSE
MA	0.39388	0.139046	0.032129	0.179246
SES	0.392105	0.138391	0.031707	0.178065
DES	0.42581	0.150107	0.062652	0.250304
HW (Multiplicative)	0.395323	0.139654	0.032815	0.181149
HW (Additive)	0.388995	0.137398	0.031955	0.178760
ARIMA	0.386	0.136	0.032041	0.179000

The forecasting results in Figure 5 show that the trend of forecasting by 6 models is consistent with the actual EUR exchange rate time series data. but for the model HW-multiplicative, Simple exponential smoothing model (SES), Double exponential smoothing model (DES) and Simple Moving Average (SMA), the results are different from the actual data for some period time.

Table 3 is shown, The ARIMA model uses historical data time series to predict future currency exchange rates. It found that the average of the smallest error when measuring the statistical error of all 4 methods. It can be said that the EUR exchange rate time series data has a linear relation. The ARIMA model demonstrates that using integer differences can characterize changes in the US dollar exchange rate.

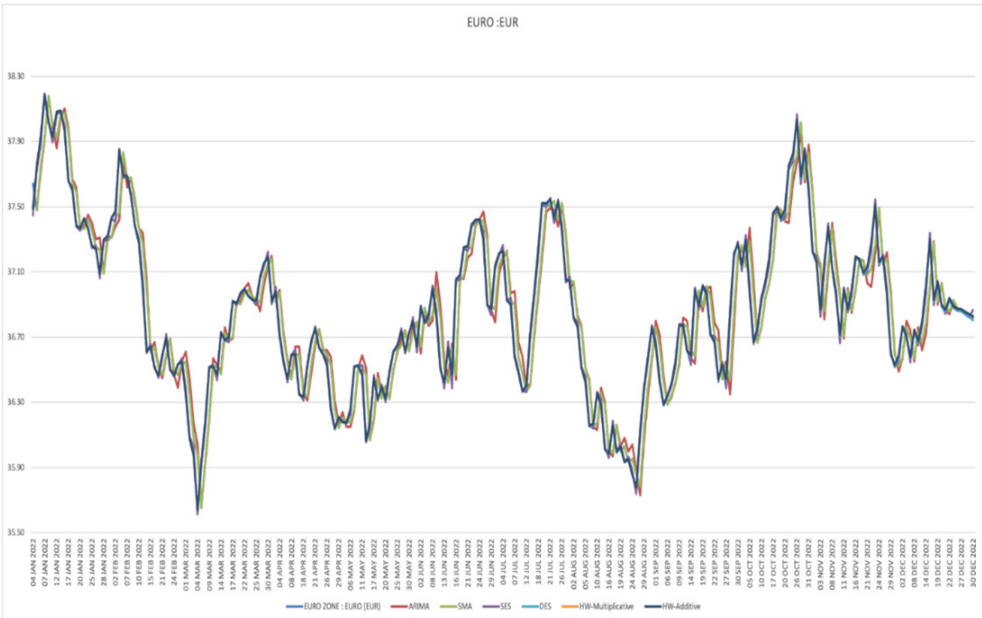

Figure 5 Forecast data of exchange rate for EUR.

Table 3 The summary of all forecasting model based on EURO.

Model	MAPE (%)	MAE	MSE	RMSE
MA	0.389487	0.1436	0.032395	0.378946
SES	0.384181	0.141644	0.031923	0.376356
DES	0.390431	0.143947	0.032544	0.379403
HW (Multiplicative)	0.390101	0.143821	0.032561	0.379237
HW (Additive)	0.388995	0.137398	0.031955	0.370672
ARIMA	0.383000	0.141000	0.032041	0.179000

The forecasting results in **Figure 6** show that the trend of forecasting by 6 models is consistent with the actual YUAN exchange rate time series data. but for the model HW-multiplicative, Simple exponential smoothing model (SES), Double exponential smoothing model (DES) and Simple Moving Average (SMA), the results are different from the actual data for some period time.

Table 4 is shown, The ARIMA model uses historical data time series to predict future currency exchange rates. It found that the average of the smallest error when measuring the statistical error of all 4 methods. It can be said that the YUAN exchange rate time series data has a linear relation. The ARIMA model demonstrates that using integer differences can characterize changes in the US dollar exchange rate.

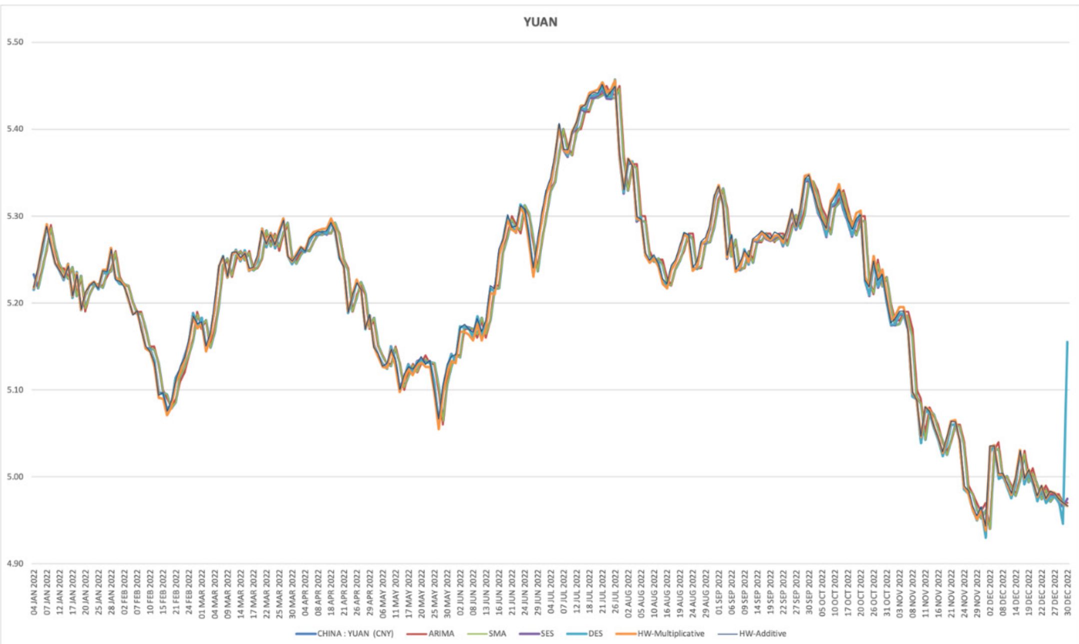

Figure 6 Forecast data of exchange rate for YUAN.

Table 4 The summary of all forecasting model based on YUAN.

Model	MAPE (%)	MAE	MSE	RMSE
MA	0.332753	0.017328	0.000505	0.022472
SES	0.331988	0.017286	0.000503	0.022428
DES	0.352062	0.018293	0.000658	0.025652
HW (Multiplicative)	0.340071	0.017718	0.000512	0.022627
HW (Additive)	0.388995	0.137398	0.031955	0.178760
ARIMA	0.331	0.017	0.000484	0.022000

Conclusions

The result of the study was divided into 3 parts: Forecast currency exchange Rate of US dollar, forecast currency exchange rate of EUR and forecast currency exchange rate of YUAN using SMA, SES, HW(Additive), HW(Multiplicative) and ARIMA. The criteria were used to measure accuracy include MAE, MSE, RMSE and MAPE. It was found that forecast currency exchange rate of US dollar using the ARIMA model was the most accurate model. Because it has a minimal value MAPE = 0.386 %, MAE = 0.136, MSE = 0.032041 and RMSE = 0. 179. Forecast currency exchange rate of EUR using the ARIMA model was the most accurate model. Because it has a minimal value MAPE = 0.383 %, MAE = 0.141, MSE = 0.032041 and RMSE = 0.179. Forecast currency exchange rate of YUAN using the ARIMA model was the most accurate model. Because it has a minimal value MAPE = 0.331 %, MAE = 0.017, MSE = 0.000484 and RMSE = 0.0220.

The ARIMA model is a linear relation forecasting model that has good predictive performance in all situations. The foreign currency exchange rates of all 3 currencies have a linear relation. Including the structure of the ARIMA model can describe the nature of time series data well, that is, the ARIMA model can be used as a tool for forecasting the exchange rates of the 3 currencies to support decision-making and planning international trade strategies.

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