# Asian Currencies Forecasting and Modelling Using a Time Series Analysis

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*Abstract* - **The objectives of this study are to forecast and model the Asian foreign exchange rate by using the extension of time series analysis technique proposed by Box-Jenkins (1970), which it is universally known as an Autoregressive Integrated Moving Average with Explanatory Variable or "ARIMAX". This empirical study selectively gathers the foreign exchange rate of the Asian countries since September 2015 to March 2017. The sample consists of 4 major Asian currencies that are actively traded in the foreign exchange market including Japanese Yen (JPY), Chinese Yuan (CNH), Singapore Dollar (SGD), and Malaysia Ringgit (MYR). These currencies are specifically denominated in Thai Baht (THB). In order to overcome a misspecification problem, Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) are used as a criterion to select the forecasting model. The forecasting performance of each model has been competed together with a classical ARIMA and a random walk model. The finding shows that MSE of the forecasting errors calculated by a random walk model is the smallest comparing to other two models. In contrast, MAPE of the forecasting errors calculated from each model is slightly different in determining the forecasting performance since the ARIMAX performed the best in forecasting Malaysia Ringgit (MYR). Moreover, the ARIMAX also performed better than the classical ARIMA in forecasting Singapore dollar (SGD). Considering graphical illustration of a 30-day ahead forecasting performance, we found that the random walk model performed the best in forecasting the movement of a foreign exchange rate that exhibit low volatility characteristic. On the other hands, the ARIMA and its extension, "ARIMAX" performed the best in forecasting the movement of a foreign exchange rate that exhibit high volatility characteristic.**

*Keywords* - **Asian Currency, Time Series Analysis, ARIMAX Model, Forecasting, Modelling**

## I. INTRODUCTION

The Foreign Exchange Market is considered as the largest financial market in the world that their weekly trading volume is larger than the US's GDP. There are plenty of players in the foreign exchange market. Some investors may trade for their profit maximization. Some of them may trade for their risk management. But the others may trade for their own payment of products and services. According to the higher volatility and the need of a large amount of money investments, the foreign exchange market provides an attractive return on investment which positively allures the investors to enter the foreign exchange market searching for an opportunities.

However, the Thailand law allows only government entities and some financial institutions trade in the foreign exchange market. However, the retail investors in Thailand can individually trade the foreign exchange rate via the offshore brokerage services as their alternative choices. The ability to accurately forecast the foreign exchange rate can largely create the wealth distributed to the investors and also perfectly reduce the foreign exchange rate risk concealed with the export business or even assist the policy makers to manage the key economic indicators in order to stimulate growth.

## II. LITERATURE REVIEWS

We have seen for many years that the time series analysis technique proposed by Box-Jenkins (1970) have extensively used to construct a forecasting model in order to estimate the prospective results. Yin-Wong Cheung (1993) applied the generalized method of which is the Fractionally Integrated Autoregressive Moving Average (*FARIMA*) to examine the long-term memorable characteristics of the foreign currencies including Pond Sterling (GBP), German Mark (DEM), Swiss Franc (CHF), France Franc (FRF), and Japanese Yen (JPY). His result proved that the long-term memory in the foreign exchange market existed.

In Thailand, the model has also been used to estimate variety of products such as broiler chickens, gold, rice, foreign currencies, common stock, and etc. For example, the study of Benjaporn (2004) who applied and to estimate the price of broiler chickens. The results found that these two models were the most suitable structures for estimating the price of the broiler chickens as considered from the Root Mean Square Error (RMSE) and the Thiel's Inequality Coefficient. The estimated results were positively in line with the actual observed value.

Moreover, Pongsiri (2007) applied the combination of and the Artificial Neural Network in estimating the price of PTT's and BBL's stocks. The results found that the combination of and the Artificial Neural Network performed the best in estimating the price of PTT's stock comparing to the standalone or Artificial Neural Network. In contract, the Artificial Neural Network performed the best in estimating the price of BBL's stock.

In addition, the research's objective of Apicha (2012) was to study the methodology of Box-Jenkins in forecasting the world gold price which gathered the gold price from Kitco Gold Index since December 2002 to June 2012. She found that the model of forecasted closely to the actual gold price. In the meantime, Chamaiporn (2012) also estimated the euro rate by applying the method of Box-Jenkin. She found that the time series of currencies were not maintained the property of a stationary time series. Therefore, she performed by taking the first difference transformation to the time series in order to convert the time series become stationary. Unfortunately, the model hold the property of random walk so that she employed a trial and error method to construct a suitable order of in forecasting the euro rate. Considered from the Akaike Information Criterion (AIC), she finally got the model of to perform a prediction of euro rate which the forecasting performance was undesirable.

We usually observed from many works that the ARIMA model cannot capture some point of the data supported by Peter & Silvia (2012). Chaleampong and Tapanee (2013) suggested to include the explanatory variable into the ARIMA model in order to improve the forecasting performance. This model is known as the Autoregressive Intregrated Moving Average with Explanatory variable or ARIMAX model. They found that attaching the explanatory variable, trade partner's leading indicator, into the classical ARIMA model will improve the forecast performance of the Thailand exports to major trade partners.

In the study of Pareshkumar et al. (2014), they identified the possible factors that affect the Indian currency value using various forecasting models. They found that one of the most important factors was the rate of interest which it largely affected the flow of money in India. Higher the rate of interest, it will attract the investors to invest money. Therefore, the appreciation for India Rupee will be seen as the demand for Rupee will rise. As a results, we decided to incorporate the rate of interest, interbank borrowing rate, in this paper in the hope that the accuracy of forecasting would increase.

## III. RESEARCH OBJECTIVES

The aims of this study are to construct a forecasting model and prescience the Asian foreign exchange rate applying the extension of time series analysis technique proposed by Box-Jenkins (1970).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2$$

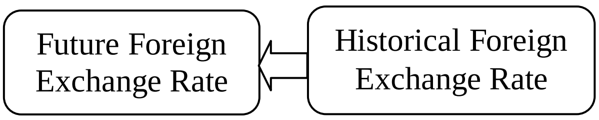
and

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{Y}_i - Y_i}{Y_i}\right| \times 100$$

In addition, we apply the Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) as the principal criterions used to select the forecasting model. These methods have been used to obstruct a misspecification problem in the model selection process.

## IV. CONCEPTUAL FRAMEWORK

A time series is a gathering of observations made consecutively and equally period in time which are examined in hope of encountering a historical pattern.




- **Dependent Variable:** The daily closed bidding price of a foreign exchange rate for the next forecasting period.

- **Independent Variable:** The time series of daily historical foreign exchange rates which they were ideally assumed to capture its behaviour of total volatility.

## V. DATA

The exchange rates used in this paper are the Asian currencies that are actively traded in the Asian foreign exchange market. We selectively chosen Japanese Yen (JPY), Chinese Yuan (CNH), Singapore Dollar (SGD), and Malaysia Ringgit (MYR) which they are all denominated in relation to Thai Baht (THB). These currencies are daily collected from the closed bidding price since 28 September 2015 to 31 March 2017 via the database of Bloomberg and the central bank of each country.

We assume the data from 28 September 2015 to 17 February 2017 (365 observations) to construct the forecasting model which it is considered as a sample fit model. The remaining period, 20 February 2017 to 31 March 2017 (30 observations), were used to examine the forecasting performance which it is considered as the out of sample model.

## VI. RESEARCH METHODOLOGY

The time series analysis technique proposed by Box-Jenkins (1970) mainly relies on the relationship of past information to construct the forecasting model that extracts the behaviour of information and applies this approach to forecast the prospective reaction of information. This technique is considered as the most efficient model in making a short term forecasting horizon. Moreover, this model has been broadly used in many literatures as because of its simplicity. This model has been widely known as the $ARIMA(p,d,q)$, which it stands for Autoregressive Integrated Moving Average. The model assumes that the current observation value is a linear function of the observed values and the value of past random errors which are generally illustrated as following equation:

$$Y_t = \delta - \varphi_1 u_{t-1} \ldots - \varphi_p u_{t-p} + \theta_1 Y_{t-1} \ldots + \theta_p Y_{t-p} + u_t$$

If the time series is difference-stationary, the time series can be mathematically illustrated as:

$$\theta(L)(1-L)^d Y_t = \varphi(L)u_t$$

where;

$Y_t$ is the observation value of the time series at time $t$.

$\delta$ is the constant in the model.

$u_t$ is the random error at time $t$ which it is assumed $\sim IN(0,\sigma^2)$.

$\theta_p$, $(p = 1, 2, \ldots, p)$ and $\varphi_q$, $(q = 1,\ 2, \ldots,\ q)$ are the parameters in the model which $p$ and $q$ are the order of the forecasting model.

$d$ is the $d^{th}$ degree of difference operator.

$L$ is a lag operator applied by:

$\theta L = 1 - \theta_1 L - \theta_2 L^2 - \ldots - \theta_p L^p$, which is a autoregressive polynomial and

$\varphi L = (1 + \varphi_1 L + \varphi_2 L^2 + \ldots + \varphi_q L^q)$, which is a moving average polynomial.

In the study of Stock and Watson (1999), they found that including leading indicators into the model to forecast a macroeconomic variable would improve the accuracy of forecasting performance. Therefore, we applied an extension of the ARIMA model which is included the explanatory variable:

$X_t$, called $ARIMAX(p,d,q)$. It can be typically represented by:

$$\theta(L)(1-L)^d Y_t = \psi(L)X_t + \varphi(L)u_t$$

where;

$X_t$ is the explanatory variable.

$\psi L = (1 + \psi_1 L + \psi_2 L^2 + \ldots + \psi_p L^p)$ is a polynomial of an explanatory variable.

In order to construct the ARIMAX model, the time series ($Y_t$) must exist the property of stationary which can be considered from the Theoretical Autocorrelation Function ($\rho_k$) or "ACF" and the Partial Autocorrelation Function ($\rho_{kk}$) or "PACF" as follow:

$$\rho_k = \frac{\sum_{t=1}^{n-k}(Y_t - \bar{Y})(Y_{t+k} - \bar{Y})}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2}\ ; k = 1, 2, \ldots$$

where;

$$\bar{Y} = \sum_{t=1}^{n}\frac{Y_t}{n}$$

The ACF of time series that shows the stationary property will quickly die down to zero when the distance of the time series increases or cut off at any specific time period. However, if the time series is non-stationary, these time series must be transfigured by either differentiation or power transformation before entering to the model construction processes. This is the standard procedure to determine the degree of differencing ($d$) in both ARIMA and ARIMAX modelling process.

On the other hand, the PACF is unlike ACF in the case that the PACF eliminates the effect of variables which are stand in between the considered variables $Y_t$ and $Y_{t+k}$. It is elaborated as follow:

$$\rho_{kk} = \begin{cases} \rho_1 & k = 1 \\ \dfrac{\rho_k - \sum_{j=1}^{k-1}\rho_{k-1,j}\,\rho_{k-j}}{1 - \sum_{j=1}^{k-1}\rho_{k-1,j}\,\rho_j} & k = 2, 3, \ldots \end{cases}$$

where;

$$\rho_{kj} = \rho_{k-1,j} - \rho_{kk}\rho_{k-1,k-j} \qquad j = 1, 2, \ldots$$

Alternatively, we also assign the Augmented Dickey-Fuller test to examine the stationary hypothesis on each time series variable. Three procedures of stationary testing under Dickey and Fuller (1979 and 1981)'s method are considered by Eview version 9.0 as follow:

$$1^{\text{st}}: \quad \Delta Y_t = \beta Y_{t-1} + \sum_{i=1}^{P}\Theta\Delta Y_{t-i} + u_t$$

2nd : $\Delta Y_t = \alpha + \beta Y_{t-1} + \sum_{i=1}^{P} \Theta \Delta Y_{t-i} + u_t$

3rd : $\Delta Y_t = \alpha + \gamma t + \beta Y_{t-1} + \sum_{i=1}^{P} \Theta \Delta Y_{t-i} + u_t$

In order to determine the order of the forecasting model "$ARIMAX(p,d,q)$", we consider altogether the characteristics of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the observed value. To determine the order $p$ in the Autoregresssive model "$AR(p)$", the figure of ACF will quickly die down to zero and the PACF that differs more than $p$ period will rapidly die down to zero. On the other hand, the order $q$ in the Moving Average Model "$MA(q)$" is also determined by considering the ACF and PACF of an estimated errors which the ACF that differs more than $q$ period will rapidly die down to zero and the figure of PACF will quickly die down to zero. In addition, we also consider the combination of $AR(p)$ and $MA(q)$ model, the Mixed Autoregressive Integrated Moving Average: $ARIMA(p,d,q)$ which the ACF and PACF that differ more than $p$ and $q$ period will die down fast to zero respectively. We can observe that if the order "$p$" and "$q$" of the $ARIMA(p,0,q)$ are both equal to zero, this model is commonly known as a White Noise Model.

$$Y_{t+h|t} = \varepsilon_t \quad \text{where;} \quad \varepsilon_t \sim IN(0, \sigma_A^2)$$

Moreover, if the order "$p$" and "$q$" of $ARIMA(p,d,q)$ for the time series that is transformed to become a stationary time series by differentiation method are both equal to zero, this model is commonly known as a Random Walk Model which will also be used to compete with the classical $ARIMA(p,d,q)$ and the $ARIMAX(p,d,q)$ in this paper. This procedure is similar to the study of Jesus & Jaroslava (2005).

$$Y_{t+h|t} = Y_t + \varepsilon_t \quad \text{where;} \quad \varepsilon_t \sim IN(0, \sigma_A^2)$$

To estimate the parameter used in the forecasting models, "$ARIMA(p,d,q)$ and $ARIMAX(p,d,q)$", we apply the method of maximum likelihood estimation (ML) which will be performed by SAS version 9.3.

To consider the estimated forecasting errors calculated from each forecasting model, we also apply the illustration of the Theoretical Autocorrelation Function (ACF) and Theoretical Partial Autocorrelation Function (PACF) of an estimated error. If the property of white noise exists, the model is suitable for a forecasting purpose. Moreover, we also apply the Box-Pierce Chi-Square Statistic to examine the autocorrelation of an estimated error, which the degree of freedom ($d_f$) equals to the number of sample autocorrelation of the estimated error ($K$) minus the number of parameters used in the forecasting model ($m$), which is shown as follow:

$$Q = n \sum_{k=1}^{K} \rho_k^2(\varepsilon)$$

where;

$\rho_k(\varepsilon)$ is the autocorrelation function of the estimated error.

$n$ is the number of error value of the observed time series after adjusted to become a stationary time series.

$K$ is the number of the autocorrelation of the estimated error used to calculate $Q$ value.

## VII. EMPRIRICAL RESULTS

### *A. Determining the Degree of Differencing ($d$) in the Time Series Variable.*

Applying graphic presentation of both ACF and PACF together with the Augmented Dickey-Fuller test statistics to determine the degree of differencing ($d$) for the closed bidding price of the exchange rate ($Y_t$) and the interbank borrowing rate ($X_t$), we found that applying 1st difference transformation ($d = 1$) to the time series could convert the closed bidding price become a stationary time series which is largely supported by the MacKinnon

(1996) one-side p-values as shown in Table I. In addition, the ACF and PACF of the time series are rapidly die down to zero. Even thought, there is only the closed bidding price of the CNH that is statistically significant when we performed the test for unit root in level. However, there are not adequate evidences to show a statistical significant examination when we performed the test for unit root in intercept and trend & intercept. Thus, we applied 1st difference transformation ($d = 1$) to the time series of the CNH.

**TABLE I**
**THE MACKINNON (1996) ONE-SIDE P-VALUES FOR CLOSED BIDDING PRICE OF EACH CURRENCY DENOMINATED IN THB.**

| Currencies | | JPY | CNH | SGD | MYR |
|---|---|---|---|---|---|
| Level | None | .5987 | .0126* | .4926 | .4160 |
| | Intercept | .6234 | .1207 | .6459 | .8804 |
| | Trend and Intercept | .9575 | .0776 | .6975 | .6991 |
| 1st diff | None | .0000* | .0000* | .0000* | .0000* |
| | Intercept | .0000* | .0000* | .0000* | .0000* |
| | Trend and Intercept | .0000* | .0000* | .0000* | .0000* |

***significant at 95% confident interval**

Considering the stationary for a time series of the interbank borrowing rate of each country, there is only a time series of Singaporean interbank borrowing rate that sufficiently showed a stationary of time series at a zero degree of difference ($d = 0$). The rest of the time series are stationary when we converted by applying the 1st difference transformation ($d = 1$), which the MacKinnon (1996) one-side p-values are guided as shown in Table II.

**TABLE II**
**THE MACKINNON (1996) ONE-SIDE P-VALUES FOR INTERBANK BORROWING RATE OF EACH COUNTRY.**

| Currencies | | JPY | CNH | SGD | MYR |
|---|---|---|---|---|---|
| Level | None | .0126* | .0993 | .0001* | .4896 |
| | Intercept | .1207 | .4408 | .0000* | .0540 |
| | Trend and Intercept | .0776 | .0051* | .0000* | .0035* |
| 1st diff | None | .0000* | .0000* | .0000* | .0000* |
| | Intercept | .0000* | .0000* | .0000* | .0000* |
| | Trend and Intercept | .0000* | .0000* | .0000* | .0000* |

***significant at 95% confident interval**

***B. Determining the Order ( $p$ and $q$ ) in the ARIMA and ARIMAX Models***

After transformation of time series to become a stationary time series, we orderly considered the possible order $p$ and $q$ of a standalone $AR(p)$ or $MA(q)$ model together with a combination of $ARMA(p,q)$ model of the time series for both $ARIMA(p,d,q)$ and $ARIMAX(p,d,q)$ models.

1. **The Order ( $p$ and $q$ ) in the ARIMA**

The optimal models for estimating the foreign exchange rate under a classical autoregressive intregrated moving average model or "ARIMA" are examined by the graphical illustration of the ACF and PACF which are revealed below:

**Optimal Forecasting Models**

**For THB/JPY:** $p = 0,\ d = 1,\ q = 1$

$$(1-L)^1 Y_t = \delta + (1-\varphi_1 B^1)u_t$$

**For THB/CNH:** $p = 8,11,\ d = 1,\ q = 1$

$$(1-\theta_8 B^8 - \theta_{11} B^{11})(1-L)^1 Y_t = \delta + (1-\varphi_1 B^1)u_t$$

**For THB/SGD:** $p = 0,\ d = 1,\ q = 1$

$$(1-L)^1 Y_t = \delta + (1-\varphi_1 B^1)u_t$$

**For THB/MYR:** $p = 0,\ d = 1,\ q = 1$

$$(1-L)^1 Y_t = \delta + (1-\varphi_1 B^1)u_t$$

2. **The Order ( $p$ and $q$ ) in the ARIMAX**

The same procedures to determine the order "$p$" and "$q$" in the ARIMA are also applied in the process of determining order "$p$" and "$q$" in the ARIMAX, which the optimal models are presented below:

**Optimal Forecasting Models**

**For THB/JPY:** $p = 0,\ d = 1,\ q = 1$

$$(1-L)^1 Y_t = \delta + \psi(L)X_t + (1-\varphi_1 B^1)u_t$$

where ; $\psi(L)X_t$ is represented for

$$(1-\psi_1 B^1 - \psi_2 B^2)(1-L)X_t - \tau + (1-\eta_1 B^1)\omega_t$$

, which $p = 1,2,\ d = 1,\ q = 1$

**For THB/CNH:** $p = 8,11,\ d = 1,\ q = 1$

$$(1-\theta_8 B^8 - \theta_{11} B^{11})(1-L)^1 Y_t = \delta + \psi(L) X_t + (1-\varphi_1 B^1) u_t$$

where ; $\psi(L) X_t$ is represented for

$$(1-\psi_1 B^1 - \psi_2 B^2 - \psi_3 B^3 - \psi_4 B^4 - \psi_8 B^8)(1-L) X_t, -\tau + (1-\eta_1 B^1)\omega_t$$

which $p = 1,2,3,4,8,\ d = 1,\ q = 1$

**For THB/SGD:** $p = 0,\ d = 1,\ q = 1$

$$(1-L)^1 Y_t = \delta + \psi(L) X_t + (1-\varphi_1 B^1) u_t$$

where ; $\psi(L) X_t$ is represented for

$$(1-\psi_1 B^1 - \psi_2 B^2) X_t - \tau + (1-\eta_1 B^1)\omega_t$$

, which $p = 1,2,\ d = 0,\ q = 1$

**For THB/MYR:** ( $p = 0,\ d = 1,\ q = 1$)

$$(1-L)^1 Y_t = \delta + \psi(L) X_t + (1-\varphi_1 B^1) u_t$$

where ; $\psi(L) X_t$ is represented for

$$(1-\psi_1 B^1 - \psi_3 B^3 - \psi_4 B^4 - \psi_7 B^7)(1-L) X_t - \tau + (1-\eta_1 B^1)\omega_t$$

, which $p = 1,3,4,7,\ d = 1,\ q = 1$

### *C. Comparing Forecasting Performances*

Considering the MSE of each optimal forecasting model, we found that the random walk model (RW) outperformed the others in forecasting all foreign exchange rates used in this paper. However, the ARIMA performed as equal as the ARIMAX because there is no different in MSE between these two models. Moreover, we also considered the MAPE for the alternative indicators. We found that RW still performed the best in forecasting the JPY, CNH and SGD. But, it was the worst-performing in forecasting the MYR. We have been clearly seen from the MAPE that the ARIMAX performed better than the ARIMA in forecasting the SGD and the MYR but the ARIMA performed better than the ARIMAX in forecasting the CNH, which are illustrated in Table V. The graphical illustrations of a 30-day ahead forecasting performance are shown in Fig. 1-4.

**TABLE V**
**THE OUT-OF-SAMPLE MSE AND MAPE – FORECAST PERIOD 2017:02:20 – 2017:03:31**

| | | JPY | CNH | SGD | MYR |
|---|---|---|---|---|---|
| RW | MSE | $9\times10^{-6}$ | $3\times10^{-4}$ | $6\times10^{-3}$ | $1.3\times10^{-1}$ |
| | MAPE (%) | 0.1686 | 0.0679 | 0.1984 | 1.0204 |
| ARIMA | MSE | $6\times10^{-5}$ | $1\times10^{-3}$ | 0.1927 | $5.2\times10^{-3}$ |
| | MAPE (%) | 1.3027 | 0.3236 | 1.5679 | 0.7368 |
| ARIMAX | MSE | $6\times10^{-5}$ | $1\times10^{-3}$ | 0.1910 | $5.3\times10^{-3}$ |
| | MAPE (%) | 1.3027 | 0.3324 | 1.5623 | 0.7413 |

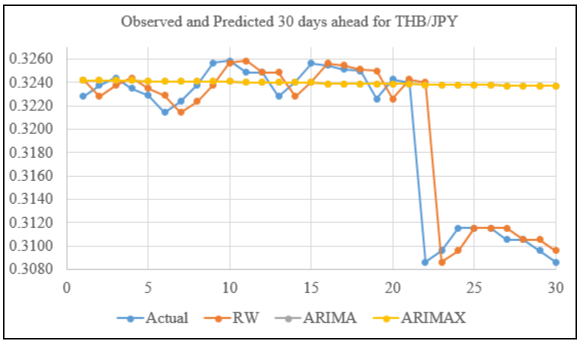



**Fig. 1** Observed and predicted foreign exchange rate 30 days ahead of JYP.

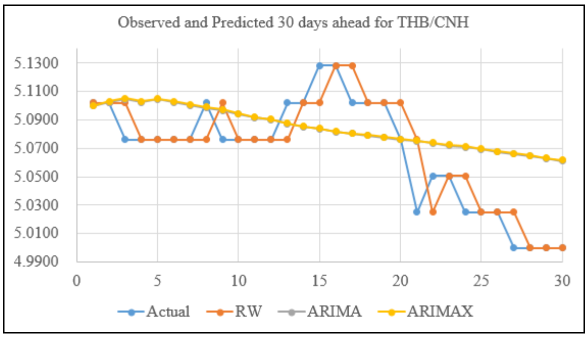



**Fig. 2** Observed and predicted foreign exchange rate 30 days ahead of CNH.

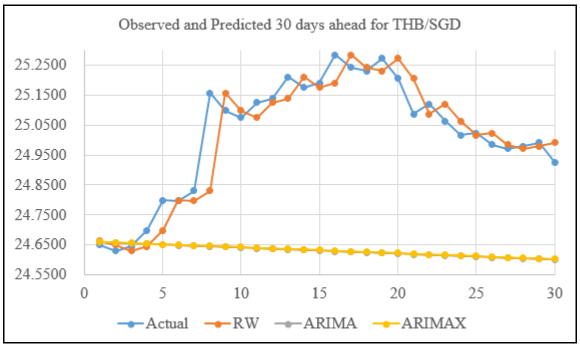



**Fig. 3** Observed and predicted foreign exchange rate 30 days ahead of SGD.

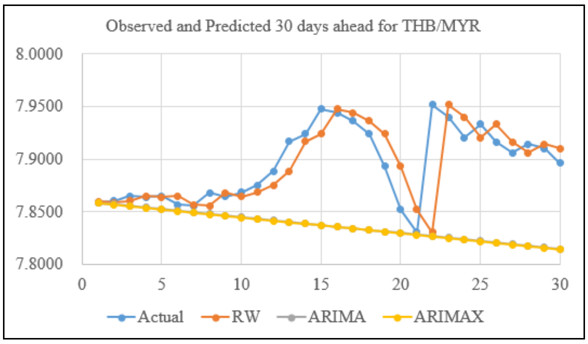



**Fig. 4** Observed and predicted foreign exchange rate 30 days ahead of MYR.

## VIII. DISCUSSION AND CONCLUSION

This study examines the forecasting performances of the classical time series analysis proposed by Box-Jenkin (1970) "ARIMA" and its extension "ARIMAX" on currency exchange rate for Asian. The concept of this study is based on the idea that including the explanatory variable, "interbank borrowing rate" will improve the forecasting accuracy significantly. The forecasting performances of the prospective models used in this paper illustrated that the random walk model (RW) performed the best in forecasting the movement of a foreign exchange rate that exhibits low volatility characteristic. On the other hands, the time series analysis technique proposed by Box-Jenkin (1970) "ARIMA" and also its extension "ARIMAX" performed the best in forecasting the movement of a foreign exchange rate that exhibits high volatility characteristic. We obviously found that when the "ARIMA" and its extension performed an estimation, they were likely to use the most recent forecasted value to be the next observed value. As a result, the estimated errors calculated from these models would be diverged. Therefore, the "ARIMA" and "ARIMAX" models are even so considered as the most efficient model in making a short term forecasting horizon. Nevertheless, improving the long-term forecasting accuracy, the researchers should recursively estimate a forecasting model, "ARIMA" and "ARIMAX", when the most recent observation ($Y_t$) enters.

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