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Forecasting Electricity Consumption in Malaysia using Holt-Winters' Exponential Smoothing, SARIMA and FB Prophet

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Abstract

Electricity consumption forecasting plays a vital role in supporting power system reliability, efficient energy planning and sustaining economic and country development. With rising demand, robust and accurate forecasting models are important to support development and decision making. This study aims to apply and compare different time series forecasting models to predict future electricity consumption in Malaysia across total, local domestics and local commercial sectors. Holt-Winters' method, Box-Jenkins Seasonal ARIMA (SARIMA) model and FB Prophet model were used and forecast evaluation is conducted using Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The future electricity consumption was forecasted using the most accurate forecasting model. The dataset consist of 78 observations for each of the sectors and was obtained from January 2018 to June 2024 based on Department of Statistics Malaysia. (DOSM) website. During statistical analysis it revealed that each model's outcomes are very similar to each other in terms of the fitted values are plotted closely with the actual values indicating all models able to effective capture the underlying trend and seasonality in the data. During the forecast evaluation comparison, it shows that for total electricity consumption, FB Prophet model outperforms Holt-Winters' methods and SARIMA model with lowest MAPE, MAE and RMSE values. This outcome is also similar for the local domestic and local commercial data forecasting analysis. Hence, this model is selected as the best forecasting model with high accuracy. The use of larger datasets is recommended to further improve models' understanding of historical patterns to deliver good and more accurate predictions.

1. Introduction

Energy Consumption forecasting plays a major role in ensuring a stable power supply, efficient energy planning and sustaining economic and country development. High accurate demand forecasting supports decision-making in grid operation, energy policy formulation and others. The methods and material used to generate electricity vary differently depending on resources and geography. To sustain the population lifestyle and country's operation, the demand for electricity has increased over the years. It is crucial for electricity companies such as Tenaga Nasional Berhad (TNB) to cooperate with the government sector to visualize and gain meaningful insights into electricity consumption. Hence, forecasting electrical consumption is essential to country's development for planning and expansion of facilities in the electrical sector as well as saving cost, improving the reliability of power systems and conducting decision-making [1].

To conduct forecasting analysis, there are few methods and models that are used in the research. Firstly, Holt-Winters Method or known as Triple Exponential Smoothing, introduced by Holt (1957) and Winters (1960) is an extension from exponential smoothing. It captures the seasonality that is present in the data [2]. It consists of two variants which is Additive and Multiplicative model and react differently to the seasonality. This method also consists of three smoothing levels which is level (l_t), trend $(b_t)$and seasonality (s_t). Previously, this method was used in forecast electricity consumption of Malaysia's residential sector [3].

Another method is by using Autoregressive Integrated Moving Average (ARIMA) model or known as Box-Jenkins Model. It was a relatively popular forecasting tool to conduct forecasting analysis and which highly dependent on historical data for effective short-term forecasting. As electricity consumption are recorded at a monthly frequency and shown seasonal behaviour, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is used to account for non-seasonal and seasonal components. A study conducted uses ARIMA model to forecast electrical consumption in Morocco which proofed that this model can be used on mid-term and long-term development [4].

FB Prophet was another forecasting method developed by meta company and introduced in 2017. This method is similar to ARIMA model in terms of trend and seasonality but introduces new component which is holiday component. *h(t)*. Even though this model is primarily used in marketing and financial sector and more, it can be corporate into energy consumption analysis which was conducted previously [5].However, in this study, the FB Prophet model is applied using trend and seasonal components only without using holiday effects due to the monthly data of the electricity consumption.

These three methods and models were commonly used to conduct forecasting analysis. For example, Holt-Winters' model was used to create a framework for high frequency data to forecast electrical consumption along with other methods [6]. Another related research is comparative research between Holt-Winters' and ARIMA statistical model which was conducted for energy prediction by using high frequency data [7]. Lastly, researchers [8] investigate electrical consumption for year 2020 to 2023 by using FB Prophet model and other machine learning techniques.

The study aims to evaluate and compare the performance of three time series forecasting models, specifically Holt-Winters method, SARIMA model and FB Prophet model, to forecast electricity consumption across three sectors which is total, local domestics and local commercial. The forecasting accuracy is then evaluated using Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) to identify the most reliable and accurate approach.

2. Methodology

In this section, the summary of the dataset used in this study is provided. The methods and models used in forecasting analysis which are Holt-Winters' Exponential Smoothing, ARIMA model and FB Prophet Models were discussed. Additionally, the forecast evaluation metrices including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) were also discussed in this section.

2.1 Data Description

The dataset used in this study is the electrical consumption in Malaysia in different sectors from year 2018 to June 2024. The data was obtained from Department of Statistics Malaysia. (DOSM) website. The dataset spans 6 years and 6 months which is from January 2018 to June 2024 and three sectors are used for this study, which was total, local domestic and local commercial. The dataset consists of 78 observations for each sector then splits to ratio of 8:2. The training data consists of 56 observations and testing data with 22 observations. The forecast analysis is then carried out using Minitab and Python.

2.2 Holt-Winters' Exponential Smoothing

Holt-Winters' method also known as Triple Exponential Smoothing (TES) is one of the most popular methods used in forecasting techniques. This method is suitable for data that omits trend and seasonal behaviour which can affect forecasting accuracy. There are two variations to this method which are additive and multiplicative model. Both models consist of three smoothing parameters which are level (l_t), trend $(b_t)$and seasonality (s_t), where level (l_t) represent the average value of the series after removing trend and seasonality, trend (b_t) describe the overall direction of the series and seasonality (s_t) captures the seasonality effect added into the data [9]. Holt-Winters' Additive model can be expressed as in Eq. (1) to Eq. (4.). Multiplicative models are similar to the Eq. (1) to Eq. (4) where calculation is focused on multiplicative and division

$$Level, l_t = \alpha(Y_t - S_{t-p}) + (1-\alpha)[l_{t-1} + b_{t-1}] \quad (1)$$
$$Trend, b_t = \gamma(l_t - l_{t-1}) + (1-\gamma)b_{t-1} \quad (2)$$
$$Seasonality, s_t = \delta(Y_t - l_t) + (1-\delta)S_{t-p} \quad (3)$$
$$Forecasting, \hat{Y}_t = l_{t-1} + t_{t-1} + S_{t-p} \quad (4)$$

where
l_t = level at time t,
α = weight of the level
b_t = trend at time t
γ = weight of the trend
s_t = seasonal component at time t
δ = weight of the seasonal component
p = seasonal period
Y_t = data value at time t
$\hat{Y}_t$ = Fitted value at time t

2.3 Box-Jenkins Seasonal ARIMA (SARIMA) Model

Box-Jenkins model, also known as Autoregressive Integrated Moving Average (ARIMA) model. This model is continuously studied and used in forecast research due to its applicability. When time series data exhibits a seasonal pattern, the model can be extended to the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to incorporate seasonal components. Several steps are required to build a SARIMA model. First step is to check the consistency of variance in the data and optionally apply Box-Cox transformation when the data variance is not consistent. Then, the stationary of the data is visualized by plotting time series plot to observe the pattern of the data. ACF and PACF are plotted to identify non-seasonal and seasonal components and to determine whether it fulfils the rules of the model. Table 1 shows the identification of the SARIMA model.

Table 1 Identification of SARIMA model

ACF	PACF	Model
Decay to zero with exponential pattern	Cuts off after lag p	AR(p)
Cuts off after lag q	Decay to zero with exponential pattern	MA(q)
Decay to zero with exponential pattern	Decay to zero with exponential pattern	ARIMA (p, q)
Significant spike at lag 12	Cuts off after lag 12	Seasonal AR(P)
Cuts off after lag 12	Significant spike at lag 12	Seasonal MA(Q)
Mixed seasonal and non-seasonal patterns	Mixed seasonal and non-seasonal patterns	SARIMA (p, d,q)(P,D,Q) s

where
p = the order of non-seasonal autoregressive component
d = number of non-seasonal differencing
q = the order of non- seasonal moving average component
P = the order of seasonal autoregressive component
D = number of seasonal differencing
Q = the order of seasonal moving average component
s = seasonal period

The general form of SARIMA (p, d, q)(P,D,Q)s can be expressed by a backshift notation in Eq. (5)

$$\emptyset(B^s)\,\emptyset(B)(1-B)^d(1-B^s)^D Y_t = \Theta(B^S)\theta(B)\varepsilon_t \quad (5)$$

where AR and MA are expressed as:
Non-seasonal components:
AR: $\emptyset(B) = (1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p)$
MA: $\theta(B) = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$
Seasonal components:

SAR: $\Phi(B^s) = (1 - \Phi_1 B^s - \Phi_2 B^{2s} - \ldots - \Phi_p B^{Ps})$
SMA: $\Theta(B^s) = (1 - \Theta_1 B^s - \Theta_2 B^{2s} - \cdots - \Theta_Q B^{Qs})$
ϕ = parameter estimate of non-seasonal AR
θ = parameter estimate of non-seasonal MA
Φ = parameter estimate of seasonal AR
Θ = parameter estimate of seasonal MA
B = backward shift operator
e_i = random errors

2.4 FB Prophet Method

Prophet model, known as FB Prophet, was used on time series data which contain strong seasonality [10]. Prophet model is introduced by meta company in 2017. Prophet model can detect monthly seasonality which can affect forecasting accuracy. The model is built by using python coding which shortens the forecasting time and minimal work. Due to the monthly aggregated nature of electricity consumption data, holiday effects were not included in this study. The suggested mathematical expression for Prophet model [11] is shown in Eq. (6)

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \tag{6}$$

where
$g(t)$ = trend in the data
$s(t)$ = seasonality in the data
h(t) = *holiday component*
ε_t= error term

2.5 Forecast Evaluation

Forecast Evaluation is crucial to understand which model can accurately forecast the outcome towards real-world data. Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) are used to evaluate the model accuracy in this research. To determine which model has the highest forecasting accuracy, the MAPE value must be less than 10% along with low value of RMSE and MAE. The equations of MAPE, MAE and RMSE are shown respectively in Eq. (7) to Eq. (9).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(y_t - \widehat{y}_t\right)^2}{n}} \tag{7}$$

$$MAE = \frac{\sum_{i=1}^{n} \left|y_y - \widehat{y}_t\right|}{n} \tag{8}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left|\frac{y_t - \widehat{y}_t}{y_t}\right| \tag{9}$$

where
y_t = actual value at time t
$\hat{y}_t$ = forecast value at time t
n = sample size

3. Results and Discussion

Although forecasting analysis was conducted for total, local domestic and local commercial electricity consumption, detail graphical results are presented only for total electricity consumption as it represents overall demand trends in Malaysia, while results for other sectors are summarised to avoid repetition.

3.1 Initial Time Series Plot

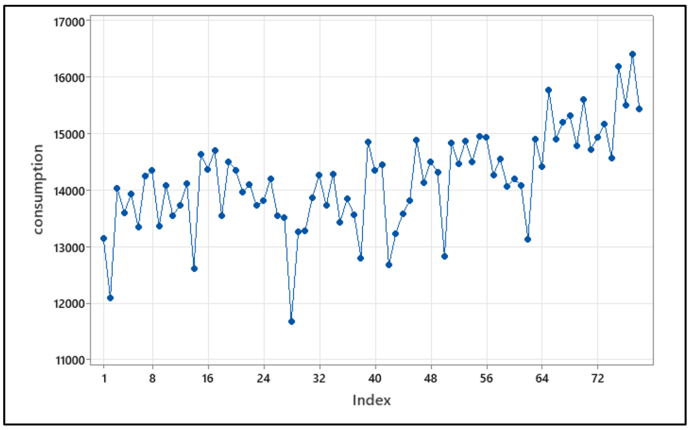
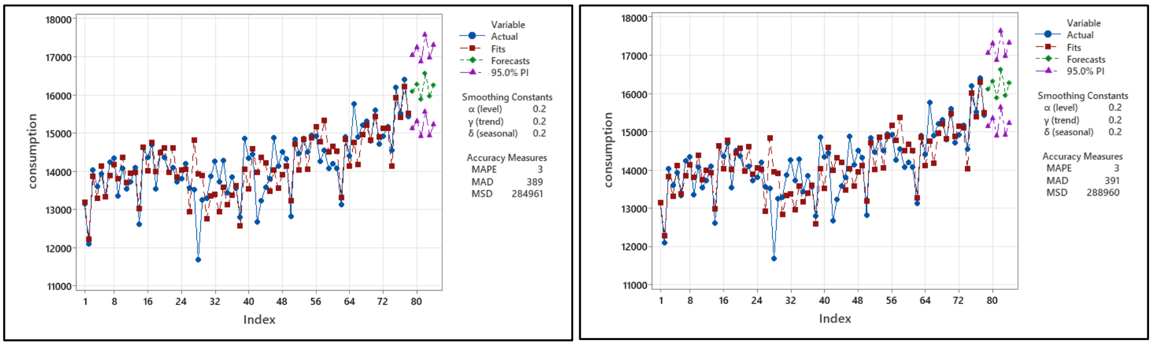


Fig. 1 Initial Time Series Plot for Total Electricity Consumption

Fig. 1 illustrates the initial time series plot of total electricity consumption. The overall trend for this initial time series plot shows a positive upward trend with significant fluctuation throughout the observation This indicates that there are seasonality present in the data due to strong seasonal pattern with regular cycles. However, there are few very significant peaks which shown to be outliers. The lowest point of the data point is plotted between index 24 to 32 which corresponds to end of year 2019 to August year 2020. This time period indicates the starting point of pandemic factor in Malaysia which cause the electricity consumption to plumage significantly, but it increased back with similar pattern across the observation

3.2 Holt-Winters' Model Result Findings

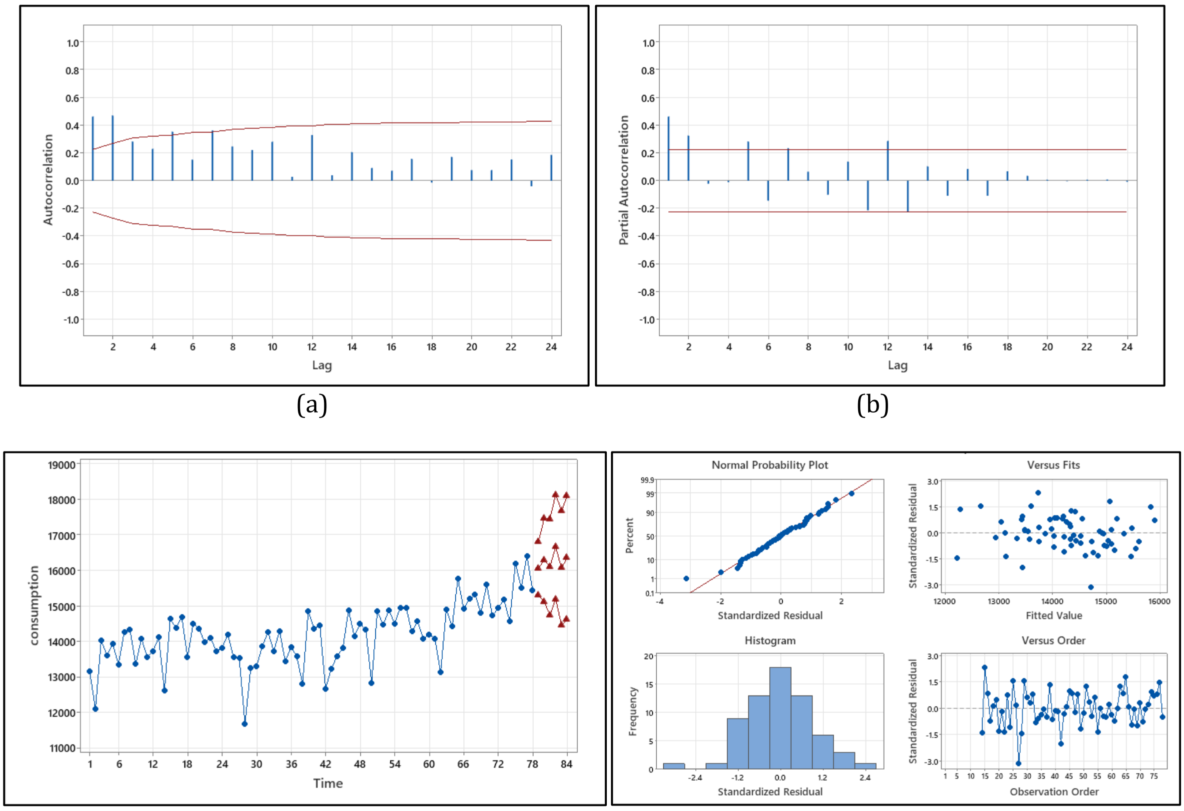


(a) (b)

Fig. 2 Holt-Winters' Additive and Multiplicative model results for total electrical consumption (a) Additive model (b); Multiplicative Model

Fig. 2(a) and Fig. 2(b) illustrate the time series plot of total electricity consumption for Holt-Winters' Additive and Multiplicative model. The fitted values, represented in red squares, follows closely with the actual values, represented in blue dots, in both models. This indicates that both additive and multiplicative model can effectively capture data's underlying seasonal pattern and trend. While the fitted values followed the overall trend and seasonality, there are few data points shown to be plotted away from the actual values. For example, the fitted value for index 29 in both models plotted in opposite direction with the actual value. This suggests the limitation in capturing in significant changes in the data. The forecast value, represented in green diamonds, shows an increase with similar pattern to the historical data. MAPE value for both model shows 3% which indicates that both models can accurately forecast the data.

3.3 SARIMA Model Result and Findings



(a) (b)

(c) (d)

Fig. 3 ARIMA Model results for total electrical consumption with 95% confidence interval (a) ACF plot of the original series; (b) PACF plot of the original series; (c) Time Series plot with forecasted values; (d) Residual plots of SARIMA $(2,1,0)(0,1,2)_{12}$

Fig. 3(a) and Fig. 3(b) illustrate the ACF and PACF plots of total electricity consumption before differencing. The presence of significant autocorrelation at lower lags and at the seasonal lag of 12 indicates that the data contain strong seasonal behaviour, which justifies the use of a seasonal time series model. Fig. 3(c) illustrates the SARIMA model results for total electricity consumption with its forecast plot. The selected SARIMA model in this analysis is SARIMA $(2,1,0)$ $(0,1,2)_{12}$ due to its lowest AIC value, which indicates that it is the best model fit among other models. The SARIMA models understand and follow the historical data behaviour and pattern well. The predicted forecast values, represented in red triangles, indicate an increase trend in electricity consumption. However, the upper and lower limits disperse vastly which suggest that the forecast value can increase or decrease very significantly in between the limits. Fig. 3(d) presents the residual plots of the SARIMA model. The normal probability plot shows that the residuals are plotted closely along the red line, indicating that the data are normally distributed. There are some data points are plotted away from the red line which suggest outlier and needed to be observed. Residual versus fit plot illustrates that the data are scattered around zero with no significant pattern which indicates that the variance is constant. There are some data point plotted away from zero which further proves the outlier is present n the data.

3.4 FB Prophet Model Result and Findings

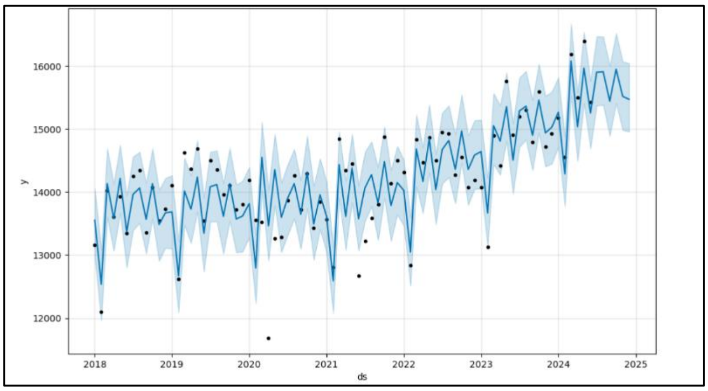


Fig. 4 FB Prophet Model Results for total electrical consumption time series plot of total electricity consumption

Fig. 4 illustrates the FB Prophet model results for total electricity consumption using the time series plot. The solid line represents the fitted and forecasted values, while black dots represent the actual data. The shades region represents the 95% interval which contributes to the forecast horizon over time. Overall, prophet model shows an upward trend in energy consumption, indicating a growth in electricity demand. The fitted values follow the historical data pattern closely, suggesting that the FB prophet model is able to capture the underlying trend and seasonality of the data. The forecasted value indicates an increase in electricity consumption in future periods. The result output is similar to Holt-Winters' model with significant fluctuations observed in the fitted values. However, the forecast pattern suggests that the FB Prophet model produces results comparable to the Holt-Winters' model, suggesting that the model is suitable for forecasting monthly electricity consumption.

3.5 Forecast Evaluation

Table 2 Forecast Evaluation Table

Data	Methods	MAPE (%)	MAE	RMSE
Total	Holt-Winters' Additive Model	3.00	389.00	533.82
	Holt-Winters' Multiplicative Model	3.00	391.00	537.55
	SARIMA Model	5.58	878.00	2971.55
	FB Prophet Method (Without Holiday)	2.27	314.55	430.29
Local Domestics	Holt-Winters' Additive Model	3.10	99.80	146.70
	Holt-Winters' Multiplicative Model	3.10	99.80	149.06
	SARIMA Model	6.87	261.1	295.85
	FB Prophet Method (Without Holiday)	2.46	78.54	111.47
Local Commercials	Holt-Winters' Additive Model	4.00	384.00	547.79
	Holt-Winters' Multiplicative Model	4.00	393.00	556.50
	SARIMA Model	4.35	467.30	494.89
	FB Prophet Method (Without Holiday)	3.19	290.50	429.41

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Table 2 summarises the forecasting accuracy of Holt-Winters' model, SARIMA model and FB Prophet model for total, local domestic and local commercial electricity consumption. The forecast evaluation shows that the FB prophet model have the highest forecast accuracy compared to other models across all datasets. The criteria for all three forecast evaluations have been met. FB Prophet model has achieved lowest MAPE value of 2.27%, demonstrating highest forecasting performance. Additionally, MAE and RMSE value achieved by FB prophet model are lower compare to Holt-Winters' Models and SARIMA models, suggesting that the FB Prophet method is bale to capture the underlying trend and seasonality efficiently. Similarly, the performance pattern is observed for local domestic and local commercial electricity consumption, where FB Prophet method consistently achieved lower MAPE, MAE, RMSE values that other models. Although the SARIMA and Holt-Winters' models produced reasonable forecasts, their accuracy was generally lower than FB Prophet method. Hence, the results indicates that the FB Prophet method provides an accurate forecasting approach on electricity consumption across different sectors.

4. Conclusion

This study has successfully achieved its three objectives. Firstly, the time series models for electricity consumption were developed using the three forecasting models (Holt-Winters Exponential Smoothing, SARIMA and FB Prophet Method) for forecast future predictions on total, local domestic and local commercial. Holt-Winters' models and SARIMA models were constructed by using Minitab and FB Prophet method is constructed using python. Next, this research compared and determined the best forecasting models among Holt-Winters' Additive and Multiplicative models, SARIMA model and FB Prophet model using MAPE, MAE and RMSE for evaluation. The result shows that FB Prophet model outperforms other three models with the lowest MAPE, MAE and RMSE value, making it the best forecasting model with the highest accuracy. This finding is consistent across all three datasets, including total, local domestic and local commercials electricity consumptions. Lastly, the research conducted forecasting using FB Prophet model to predict future electrical consumption in Malaysia from July 2024 to December 2024.

For future studies, there were few approaches to improve the analysis of forecasting models. Firstly, it is to increase the number of observations or use large datasets to further increase the forecasting accuracy. This is to ensure that the models understand thoroughly the historical patterns of the data to deliver a good prediction. Additionally, it is recommended to conduct analysis by using other explanatory variables or advance forecasting techniques such as XGBoost to further improve model performance.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Choong Hor Yin; Kamil Khalid;* ***analysis and interpretation of results:*** *Choong Hor Yin; Kamil Khalid;* ***draft manuscript preparation:*** *Choong Hor Yin; Kamil Khalid. All authors reviewed the results and approved the final version of the manuscript.*

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