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ORIGINAL ARTICLE

Forecasting Malaysian overnight Islamic interbank rate using the Box-Jenkins model

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ABSTRACT – Modelling the overnight Islamic interbank rate (IIR) is imperative to define the IIR performance as it would help the Islamic banks to adjust its costs of funding effectively and facilitate the policy makers to regulate a comprehensive monetary policy in Malaysia. The IIR framework which has been regulated by Bank Negara Malaysia under dual banking and financial system has always been overlooked in most previous studies in modelling the financial instruments rates. Therefore, it is vital to select the appropriate model as it resembles with the features of the IIR. The study assesses the forecasting performance of overnight IIR using the Box-Jenkins model. The suggested Box-Jenkins model has been applied to the Malaysian overnight IIR (in percentage) from 02/01/2001 to 31/12/2020. The empirical results determine that ARIMA (0,1,1) is the most appropriate model in forecasting overnight IIR as the model provides the smallest Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). In multistep ahead forecasting, it can be summarised that ARIMA (0,1,1) model is able to trail the actual data trend of daily Malaysian overnight IIR up to 5-day ahead within 95% prediction intervals.

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INTRODUCTION

In Malaysia, a dual banking and financial system have been implemented concurrently since 1963 comprising Islamic and conventional banking systems. In the Islamic banking system, the Overnight Policy Rate (OPR) framework provides a significant influence on the Islamic Interbank Money Market (IIMM) rate or called as Islamic Interbank Rate (IIR). According to IIMM on its official website, IIR is known as the weighted average rate of the *Mudharabah* interbank investment in a day at the IIMM in Kuala Lumpur, which of the individual rates being weighted correspondingly by the volume transactions at those rates. The IIR has been recognized in compliance with the Shariah principle to ensure Islamic and conventional financial institutions perform the transactions of fund surplus and deficit to be in accordance with Islamic Law. Any advice and approvals regarding the governance, methodology and calculation of IIR are done by two independent committees that are the Islamic Benchmark Committee and Shariah Committee [1].

In this study, the Malaysian overnight Islamic interbank rates are recorded daily throughout January 2001 until December 2020. The time series analysis on the overnight IIR time series is performed to portray its components in terms of its trend performance, cycles, seasonality and volatility level to provide an appropriate forecasting analysis [2]. Therefore, understanding the pattern of the IIR data is crucial for Bank Negara Malaysia (BNM) to ascertain whether the stress on the rate arises from demand, supply or other external elements and whether the intervention by the government is needed to alleviate the rate particularly in the money market.

Now, Malaysia is attentively containing the COVID-19 outbreak and the government has taken several measures to accommodate the monetary policy by cutting the OPR to revive the economy**.** More leniency in monetary policy given during COVID-19 containment would safeguard people incomes as well as ensure businesses are afloat. But, there is a concern that arises on the banks' profitability level due to they earn lower interest or profit incomes during this period. By evaluating and forecasting the IIR performance, it alerts the banks to strategise upfront so that they can control costs of funding very well and to charge proper base and deposit rates to ensure they to remain profitable. Thus, the requirement to provide an appropriate model that can predict the future pattern of the Malaysian IIR is very imperative in this study.

Note that, the nature of IIR data is a univariate financial time series data. One of the well-known time series methods in various research practices is the Box-Jenkins model [3]. The Box-Jenkins model is usually applied in research practices related to the interest rate in a country either as the forecasting, the benchmark or as the integrated model [4-7]. Generally, the previous studies focus on forecasting the domestic or conventional interest rate of a nation, without particularly focusing on the Islamic interbank rate. Hence, by looking at this angle and narrowing the gap, the main issue in this study is to construct a forecasting model of Malaysian IIR performance using the Box-Jenkins model. One issue related to the Box-Jenkins model is its fixture that involves one-step-ahead forecast, which is not very impactful for real data due to its constraint of the forecast period. Therefore, the next issue that has been deliberated in this study is evaluating multistep ahead forecast on the IIR data using the Box-Jenkins model. Hence, this study proposes extensive forecasting of Malaysian overnight IIR using the Box-Jenkins model.

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LITERATURE REVIEW

The study of economics and finance data for modelling and forecasting purposes using the Box-Jenkins model is supported by many researchers. Some of the recent studies are detailed out in Table 1.

Table 1. Selected studies in economics and finance using Box-Jenkins models.

Researcher	Data	Model	Methods/Procedure
Mallick and Mishra, 2019	• Monthly data of different interest rates in India (treasury bills of up to 14 days/15-91 days/92-182 days/183-364 days, call money rates, 1-year/2-year/4-year/5-year/10-year/15-year government dated security) • Data over 219 months (Jan 2000 to March 2018)	Autoregressive Integrated Moving Average (ARIMA)	• Variable reduction technique: PCA • Descriptive statistics (mean, variance, skewness, kurtosis, JB Test and correlation analysis • Stationarity and Seasonality test: x^2 goodness-of-fit test, ADF-test, PP, KPSS • Parameter estimation: AIC, BIC, OLS, MLE • Forecasting: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12 and 13-step ahead, RMSE, MSE, MAPE, RMSE/Standard Deviation • Stress period selection: rolling average method on Indian volatility index (VIX)
Rossetti *et al.*, 2017	• Annual daily overnight interbank interest rates from 11 countries • Data Jan 2000 - Dec 2011 (for 252 working days) • Brazil, India, Russia, China, South, Africa, Argentina, Chile, Mexico, USA, Japan, Germany	ARIMA-ARCH, ARIMA-GARCH, ARIMA-EGARCH, ARIMA-TGARCH, ARIMA-PGARCH	• Series behaviour and descriptive statistics (kurtosis, skewness and distribution) • Normality test: JB Test • Stationarity test: ADF Test, KPSS Test • All data differenced once, except for South Arica, differenced twice • Parameter estimation: BIC, HQ, AIC, standard error • Diagnostic test: ARCH-LM, normal, *t*-distribution • No discussion on forecasting part
Ahmed *et al.*, 2017	• 6-month rates of KIBOR • Data for a period of 2012 – 2015 • 927 observations	ARMA, ARIMA	• Graphical analysis, descriptive analysis • Stationarity test: ADF Test, the first difference • Parameter estimation: Durbin Watson, AIC, SIC, HQ criterion, log-likelihood • Forecasting:1-step, RMSE, MAE, MAPE, TIC
Omekara *et al.*, 2016	• Monthly commercial banks interest rate data on time deposits in Nigeria • Data for 2005 – 2015 • In-sample: 2005 – 2014 • Out-of-sample: 2015	ARIMA, Intervention ARIMA, State Space	• Model identification: Differencing & ADF test • Parameter estimation: MLE, AIC • Diagnostic checking: ACF, PACF • Forecasting: Up to 12-step ahead, RMSE • Intervention ARIMA: Abrupt / Permanent change – duration and nature of impact observation
Gough *et al.*, 2014	• Monthly and weekly UK, Germany, Japan and the US interest rates • UK data: 15, 20 and 25-year Treasury yield spreads relative to the 1-month yield	Discrete time ARMA, ARFIMA	• Stationarity test: First difference, standard deviations, ADF Test, PP Test, KPSS • Parameter estimation: Discrete model, Gaussian likelihood function, MLE, AIC, BIC • Forecasting: 1-step ahead forecast, mean and variance of forecast errors, MAPE, RMSE, CDIR, application of Vasicek and Merton Models
Dinh, 2020	• Annual Vietnam and China's credit growth to Gross Domestic Product (GDP) • Data for a period 1996 – 2017 • 44 observations • Out-of-sample: GDP ratio of 2018	ARIMA	• Financial ratio analysis – basis Gap analysis (credit –to-GDP ratio) • Trend and seasonality-exponential smoothing • Model identification: Correlation diagrams, the linear dependence of time-lag values, random errors • Stationarity test: 3-degree difference • Parameter estimation: R-squared, BIC, RMSE • Forecasting: Up to 5-step ahead, RMSE • Johansen Co-Integration, Error Correction model

Table 1. Selected studies in economics and finance using Box-Jenkins models (continued).

Researcher	Data	Model	Methods/Procedure
Nyoni, 2019	• Annual Indian Rupee/USD exchange rate • Data 1960 – 2017 • Out-of-sample forecast: 2018 – 2027	ARIMA	• Descriptive statistics: mean, median, maximum, minimum, standard deviation, skewness, kurtosis • Stationarity test: graphical, ADF, the first difference • Model identification: random walk models • Parameter estimation and diagnostic checking: AIC, ADF Test, stability test • Forecasting: 1 & 10-step ahead, ME, MAE, RMSE, MAPE, Theil's U Statistics
Nyoni, 2018	• Annual Naira/USD exchange rate in Nigeria • Data for a period 1960 – 2017 • 57 observations • Out-of-sample forecast: 2018 – 2022	ARIMA	• Descriptive statistic: mean, median, maximum, minimum, standard deviation, skewness, kurtosis • Stationarity test: graphical, ADF, the first difference • Model identification: ACF, PACF plots • Parameter estimation and diagnostic checking: AIC, residuals correlograms and ADF Test • Forecasting: 1 & 5-step ahead, MSE, RMSE, MAE, MPE, MAPE, Theil's U, Confidence Ellipse
Yildiran and Fettahoglu, 2017	• Daily USDTRY exchange rate in Turkey • Data 3/1/2005-8/3/2017 • 3,069 observations	ARIMA	• Descriptive statistics: minimum, Q1, median, mean, Q3, maximum, time series plots • Stationarity test: hypothesis testing, difference • Diagnostic checking: ADF Test • Forecasting: 1, 6 & 12-step ahead, absolute means, average absolute deviations

There are many forecast models in dealing with interest rates or interbank rates data such as the state-space model [7-8], Cox-Ingersoll-Ross model [9-10] and Nelson-Siegel model [5] and [11]. The three-factor Nelson-Siegel model is widely practised by central banks and monetary policy makers due to its great performance, however, the model causes many estimation issues due to its extreme non-linear results [5] and [12]. Although, these models achieve certain effects in modelling and forecasting the interest rates or interbank rates data, many studies in recent years applied the Box-Jenkins model due to its good performance in signifying various possible models to be considered to provide adequate insights to the series [4], [6], [7] and [13]. Therefore, this study proposes a univariate model and evaluates multistep ahead forecasting performance of the Malaysian overnight IIR data using the Box-Jenkins model by employing the Maximum Likelihood Estimation (MLE) method to get more robust parameter estimates as elaborated further in next chapter.

METHODOLOGY

This chapter theoretically describes the concepts and methodologies used in the study to develop a univariate forecasting model for Malaysian overnight IIR data.

Box Jenkins models

Box-Jenkins model consists of five types of models which are divided into two categories that are stationary models and nonstationary models [14]. The stationarity in time series models involves a special class of stochastic processes of which is centred on the assumption that the process remains in a state of statistical equilibrium. The models are classified as stationary when their probabilistic properties do not show any trend or seasonality and the models have reached a constant mean and variance [14].

Therefore, the stationary model comprises of three models namely autoregressive (AR), moving average (MA) and autoregressive moving average (ARMA). Whereas the nonstationary model comprises two models are autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA). The stationary models (AR, MA and ARMA) will be applied to time series data that have stationary behaviours in-mean and in-variance and do not show any seasonal pattern in the series. Otherwise, the nonstationary models will be applied in modelling time series data which showing some trends (ARIMA) or seasonality (SARIMA) in the series.

An AR model is related to a value from a time series y_t which has been regressed on previous values $(y_{t-1},\ y_{t-2}, \dots, y_{t-p})$ from that same time series. In general, the AR (p) model is defined by Equation 1,

$$y_t = c + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots + \varphi_p y_{t-p} + a_t, |\varphi_i| < 1, i = 1,2, \dots, p \quad (1)$$

where y_t and a_t are the observed value and random error at time t, $y_{t-1}, y_{t-2}, \dots, y_{t-p}$ are the predictors up to lag p, p is the autoregression order, $c = \mu(1 - \varphi_1 - \varphi_2 - \cdots - \varphi_p)$ is a constant and $\varphi_1, \varphi_2, \dots, \varphi_p$ are the p orders of autoregressive parameters. AR (p) model uses past values of the forecast variable in a regression.

A MA model uses past forecast errors$(a_{t-1}, a_{t-2}, \dots, a_{t-q})$ in a regression-like model. The MA (q) model of order q is given by Equation 2,

$$y_t = \mu + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_p a_{t-q}, |\theta_j| < 1, j = 1,2, \dots, q \quad (2)$$

where y_t and a_t are the observed value and random error at time *t*, μ is the mean of the MA model, $\theta_1, \theta_2, \dots, \theta_q$ are the MA (q) parameters of order q and $a_{t-1}, a_{t-2}, \dots, a_{t-q}$ are the error predictors up to lag q (previous values).

An ARMA with order p and q model is the combination between AR (p) and MA (q) models. The ARMA (p,q) model is given by Equation 3, where $c = \mu(1 - \varphi_1 - \varphi_2 - \dots - \varphi_p)$.

$$y_t = c + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \dots + \varphi_p y_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_p a_{t-q} \quad (3)$$

An autoregressive integrated moving average of order p and q with the order of differencing, d, is written as ARIMA (p,d,q) model. The ARIMA (p,d,q) model using backshift operator is given by Equation 4,

$$\varphi_p(B)(1-B)^d y_t = \theta_q(B) a_t \quad (4)$$

for $|\varphi_i| < 1, i = 1,2, \dots, p$ and $|\theta_j| < 1, j = 1,2, \dots, q$ and $d \neq 0$ and $\nabla = (1 - B)$; where y_t and a_t are the observed value and random error at time *t*, p and q are the order of AR and MA models respectively, d is the order of differencing, B is the backshift operator and which $\varphi_p(B) = 1 - \sum_{i=1}^{p} \varphi_i B^i$ for AR model and $\theta_q(B) = 1 - \sum_{j=1}^{q} \theta_j B^j$ for MA model.

Seasonal autoregressive integrated moving average, SARIMA (p,d,q)(P,D,Q)$_S$ model is an extension of the ARIMA model to handle seasonal trend of time series data. The equation of the SARIMA model is given by Equation 5,

$$\Phi_P(B^S)\varphi_p(B)(1-B^S)^D(1-B)^d y_t = \Theta_Q(B^S)\theta_q(B) a_t \quad (5)$$

where y_t and a_t are the observed value and random error at time *t*, $\Phi_P(B^S)$ and $\varphi_p(B)$ are the AR for seasonal and nonseasonal, $(1-B^S)^D$ and $(1-B)^d$ are the difference operators for seasonal and nonseasonal, $\Theta_Q(B^S)$ and $\theta_q(B)$ are the MA for seasonal and nonseasonal, p, d and q are the orders for nonseasonal AR terms, differencing and MA terms respectively. Then, P, D and Q are the orders of seasonal AR terms, differencing and MA terms respectively. S refers to the number of time steps for a single seasonal period. Note that, the random errors, a_t for all the aforementioned equations are assumed as independent identically distributed (*iid*) sequences taken from a continuous distribution with zero mean and constant variance of σ^2 which can be denoted as $a_t \sim iid(0, \sigma^2)$.

Stages in modelling and forecasting using Box-Jenkins models

Box-Jenkins modelling encompasses a four-stage iterative procedure of time series namely model identification, parameter estimation, diagnostic checking and lastly forecasting. The procedures of the Box-Jenkins modelling have been graphically visualised by Figure 1 of which Box-Jenkins is abbreviated as BJ. Meanwhile, the time series cross-validation is applied in the Malaysian overnight IIR data by using a typical ratio of estimation to forecast that is 90 to 10 [15].

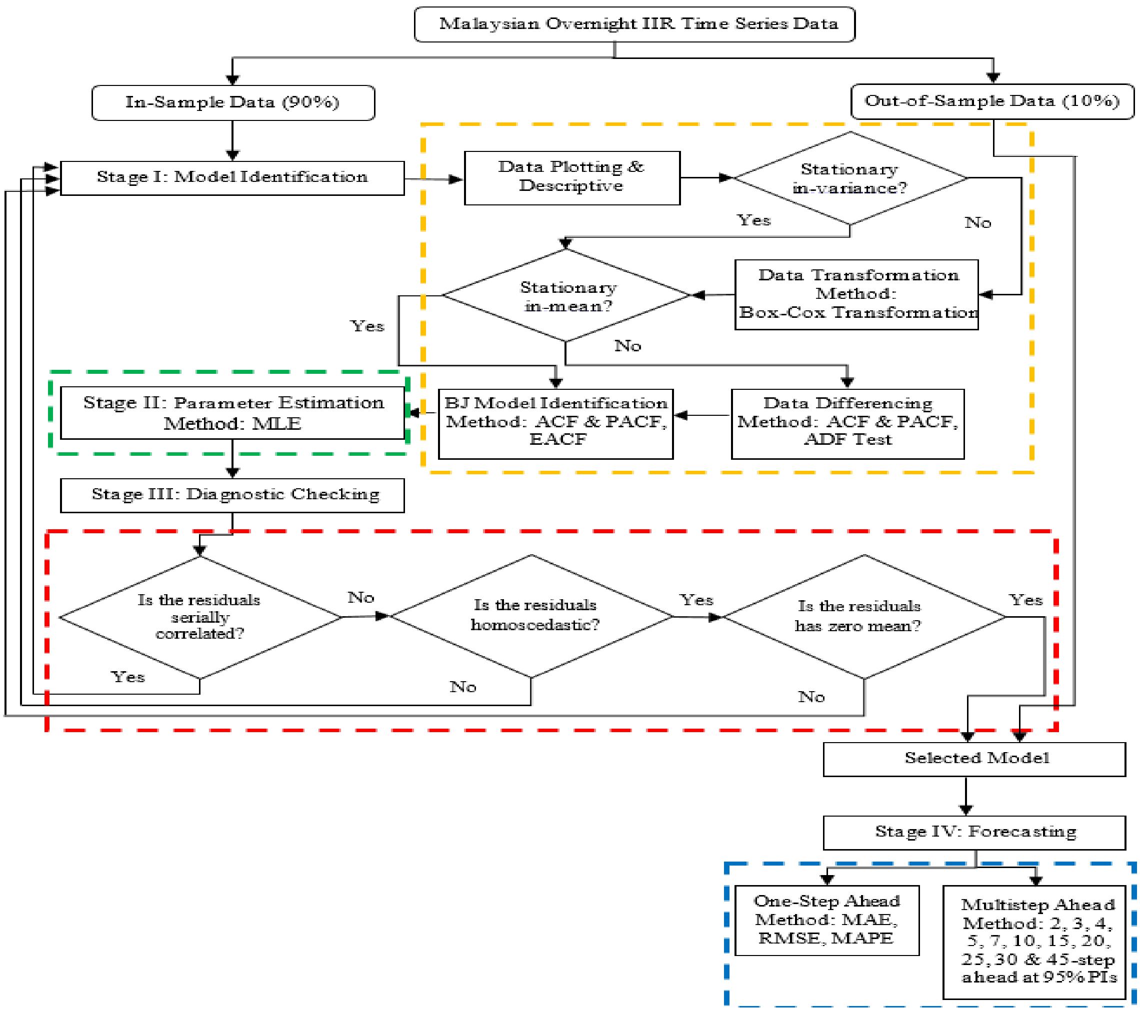


Figure 1. Proposed modelling procedures using the Box-Jenkins model.

Stage I: Model identification

The first step in model identification is involving data transformation and differencing. The Box-Cox transformation is employed to stationary the data in-variance. The plots of the autocorrelation function (ACF) and partial ACF (PACF) of the in-sample data are used as the basic tools in checking the stationarity in-mean as well as in identifying the order of the time series model. The ACF plot reflects the linear relationship between the time series observations separated by lag k and representing the order of q for the MA model, while the PACF plot represents the order of p for the AR model. Then, the in-sample data are differenced to achieve stationary in-mean. The unit-root test known as Augmented Dickey-Fuller (ADF) test is used to prove the stationarity of the differenced time series data. The null hypothesis of the ADF test is the time series data is nonstationary in-mean. Tsay and Tiao (1984) suggested a new approach using the extended autocorrelation function (EACF) to determine the p and q orders. The EACF output is a two-way table in which the rows represent order p (AR) and the columns represent order q (MA) [2]. The EACF main attribute for an ARMA model is the triangle of "O" has an upper left vertex at the (p,q) position. The EACF Table denotes the symbols of "X" and "O" of which "X" means the absolute value of the corresponding EACF is greater than or equal to two times its standard error. Meanwhile, "O" means the corresponding EACF is less than two times its standard error in modulus. The EACF standard error can be calculated as $2/\sqrt{T}$, where T is the number of in-sample time series data.

Stage II: Parameter estimation

The MLE method is widely applied in the Box-Jenkins modelling to find the parameter values that optimize the probability of obtaining the data that have been studied. In MLE, it minimizes the sum of squared errors (SSE) given by $SSE = \sum_{t=1}^{T} \epsilon_t^2$. The application of the model estimation in selecting the best significant Box-Jenkins model must fulfil the following conditions: two times the value of standard error < value of model coefficient and the p-value $\leq \alpha$. Then, the model is selected in Information Criterion (IC) test measured by Akaike's Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (BIC/SIC) values. In the model selection criteria, the model that has the smallest value of the AIC/BIC are the most preferred.

Stage III: Diagnostic checking

In the diagnostic checking stage, the chosen models are tested in the aspects of serial correlation, heteroscedasticity or ARCH effect and zero mean in the residuals time series data. The chosen model is considered well fitted if the residuals values, $\hat{a}_t$, are relatively small, no ARCH effect or constant and finite variance and zero mean. If the model does not meet the assumptions of the white noise criteria, the process of Stage I to Stage III is repeated by using a new selected model until a satisfactory model can be identified.

Stage IV: Forecasting

The forecasting stage is continued once the satisfactory model is identified. The out-of-sample time series data are employed in the model to obtain the forecast results. In this study, the method of one-step and multistep ahead are used in the forecasting evaluation. In this stage, the minimum mean absolute error (MAE), root mean squared error (RMSE) and mean absolute percentage error (MAPE) are measured for the cross-validation purpose as given by Equation 6-8, respectively, where y_t and $\hat{y}_t$ are the observed and forecast values at time t and n is the number of time t.

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |y_t - \hat{y}_t| \tag{6}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}} \tag{7}$$

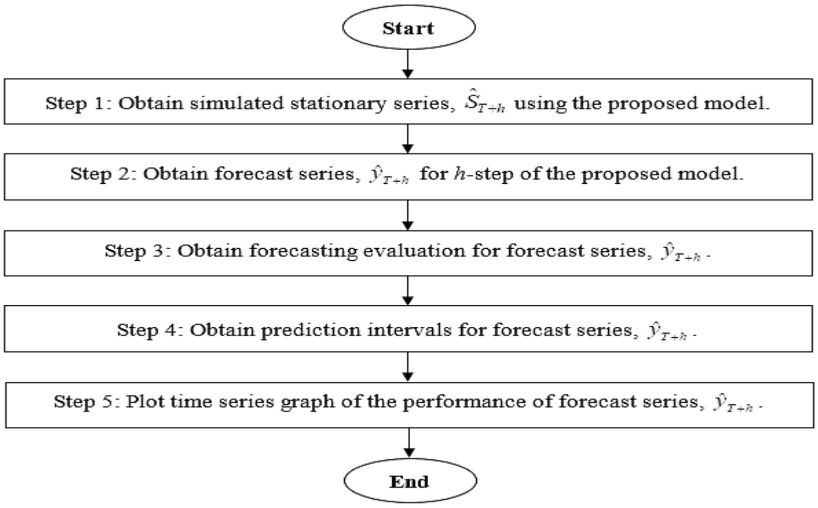
$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n} \left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{8}$$

The accuracy of the forecasts can be expressed by calculating probability limits on either side of each forecast or also known as prediction intervals (PIs). Computing prediction intervals (PIs) is an important part of the forecasting process as it is useful to quantify the accuracy of the forecast data [15]. These limits may be calculated for any convenient set of probabilities, such as 95%. A 95% PIs for one-step-ahead forecast of y_{T+1} for the random errors at the time t period, a_t normally distributed, is given by Equation 9, where $Var[e_T(1)]$ is the variance of the one-step-ahead forecast error that is defined as Equation 10. The a_{T+1} is referred to as the shock to the series at $T+1$, which is also known as the one-step ahead forecast error at the forecast origin T. In practice, the estimated value of $Var[e_T(1)]$ can be obtained from the variance of the one-step-ahead forecast residuals of the model considered. The PIs in Equation 9 are also applicable to multistep ahead forecasting, i.e. $h = 2,3, \dots, n$, where h and n are the forecasting horizon and the number of out-of-sample time series data. Therefore, the forecasting horizons that have been applied in the study are 2, 3, 4, 5, 7, 10, 15, 20, 25, 30 and 45-days ahead of the overnight IIR [6-7] and [16-19]. Consequently, a $(1-\alpha)100\%$ PIs for h-step ahead forecasting and a_t follows normal distribution is given by Equation 11. The procedure in evaluating the multistep ahead forecasting performance as proposed by Yaziz, Zakaria and Boland (2020) is given in Figure 2.

$$\hat{y}_T(1) \pm Z_{0.025}\sqrt{Var[e_T(1)]} \tag{9}$$

$$Var[e_T(1)] = Var(a_{T+1}) = \sigma_a^2 \tag{10}$$

$$\hat{y}_T(h) \pm Z_{\alpha/2}\sqrt{Var[e_T(h)]} \tag{11}$$



RESULTS AND DISCUSSION

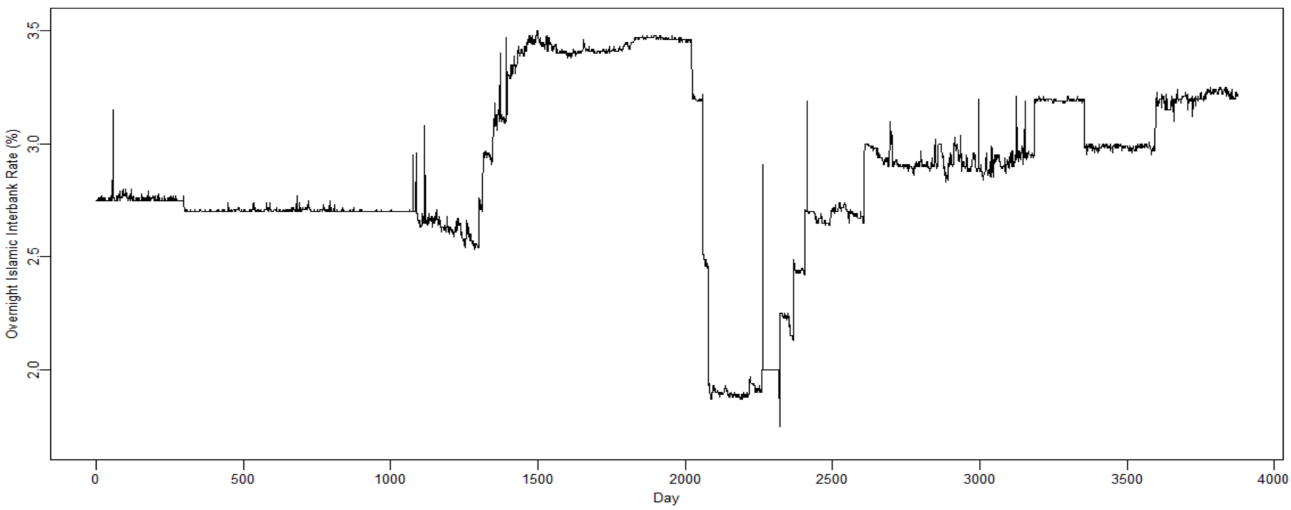
The dataset

A total of 4,305 Malaysian overnight IIR data starting from 2 January 2001 to 31 December 2020 which covering for 20-year performance period are used in this study. The data are represented in percentage (%). The data refer to the daily weighted average rate of the *Mudharabah* interbank investment at the IIMM in Kuala Lumpur of which each rate is being duly weighted by the transactions of volume at respective rates. The Malaysian overnight IIR data are retrieved from IIMM's official website[1]. The estimation ratio for in-sample data to forecast out-of-sample data used in this study is 90:10. The in-sample period used to determine the Box-Jenkins model is from 2 January 2001 to 25 March 2019, covering 3,875 daily overnight IIR data and resulting in 3,875 daily return values. Meanwhile, the out-of-sample period used to validate the forecast is from 27 March 2019 to 31 December 2020, covers 430 daily overnight IIR data and resulting in 430 daily return values.

Stage I: Box-Jenkins model identification

Figure 3 shows the time series plot of the in-sample Malaysian overnight IIR from 2 January 2001 to 25 March 2019. The figure shows that there are random, irregular and nonseasonal patterns of the series in the whole period selected in this study. From the early period of the series performance, the series are likely stable until it surpasses the 1,000th day (around January 2005) whereby the series started to show low and high fluctuation trends. A drastic drop in the series was recorded after 2,000 days which occurred in early 2009 due to the impact of the 2008 Financial Crisis. After that, the series are showing a moderate upward trend before it goes back to a significant downward trend because of the COVID-19 outbreaks in 2020.

Table 2 presents the descriptive statistics for the in-sample data. As shown in the table, the mean of the series is positive. The twofold difference between the maximum and minimum values confirms the volatility in Malaysian overnight IIRs which is likely to have been triggered by the economic instability and other unprecedented events that characterized the rates over the years. The skewness is in negative value which implying that the distribution of the series is non-symmetric and skewed to the left, as shown in Figure 3. The positive kurtosis of 0.5870 specifies that the distribution has heavier tails and a sharper peak than a normal distribution.



1 The dataset can be retrieved from https://iimm.bnm.gov.my.

Table 2. Descriptive statistics of in-sample data.

Description	Statistics
No. of Observations	3,875
Minimum	1.7500
Maximum	3.5000
Mean	2.8832
Standard Deviation	0.3783
Skewness	-0.5859
Kurtosis	0.5870

In the hypothesis testing on mean for the in-sample data, the test statistics generated is 474.43 with a p-value equals to 0. Since, $(p - value = 0) < (\alpha = 0.05)$, then the null hypothesis of zero mean is rejected at a 5% significance level. Therefore, the mean is not equal to zero. Meanwhile, for hypothesis testing on the data skewness, the test statistics generated is 14.8896 with a p-value equals to 0. Since, $(p - value = 0) < (\alpha = 0.05)$, then the null hypothesis of zero skewness is rejected at a 5% significance level. Therefore, the skewness is not equal to zero and the distribution of the series is non-symmetric and negatively skewed. In the testing of the data kurtosis, the test statistics generated is equal to 7.4588 with a p-value equals to 0. Since, $(p - value = 0) < (\alpha = 0.05)$, then the null hypothesis of zero kurtosis is rejected at a 5% significance level. Therefore, the kurtosis is not equal to zero and the positive or leptokurtic kurtosis indicates that the data distribution has heavier tails and a sharper peak than the normal distribution of the data. The findings of negatively skewed and leptokurtic kurtosis of the in-sample data have been proved by Figure 4.

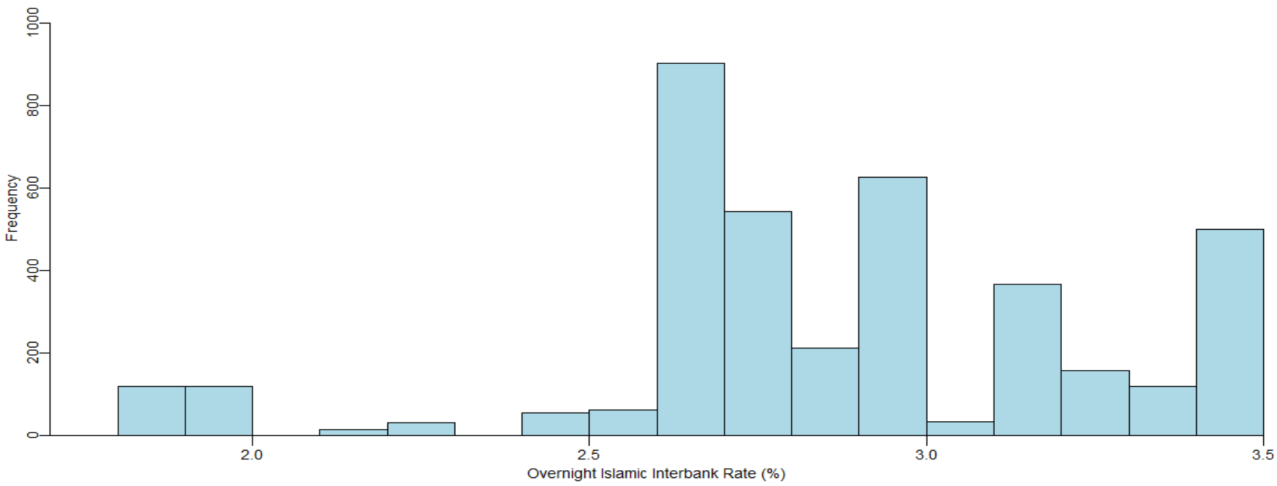


Figure 4. Histogram of Malaysian overnight Islamic interbank rates.

The Jarque Bera (JB) Test is employed to test the normality of the series. The p-value generated is equal to 0 and since, $(p - value = 0) < (\alpha = 0.05)$, then the null hypothesis of the series are normally distributed is rejected at a 5% significance level. Therefore, the distribution of the overnight IIR does not follow a normal distribution.

Figure 5 shows the time series plot of the in-sample Malaysian overnight IIR after went through the first-order differencing. The differencing method has made the series become stationary in-mean as the series are situated closely with one another, and the trend of the series are showing in the same line and static. Again, the ACF and PACF plots have been constructed by using the differenced series to check on the stationarity in-mean, as presented in Figure 6.

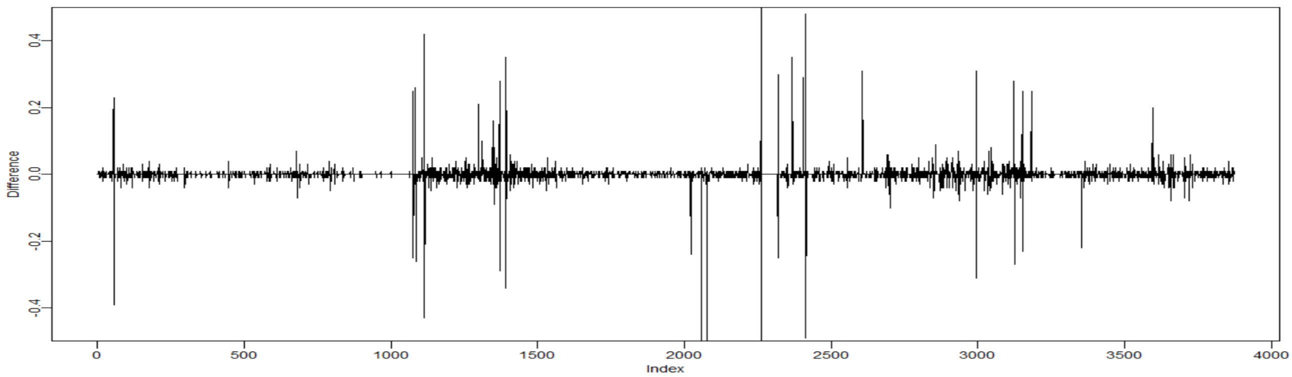


Figure 5. The plot of first-order differenced series of Malaysian overnight Islamic interbank rates.

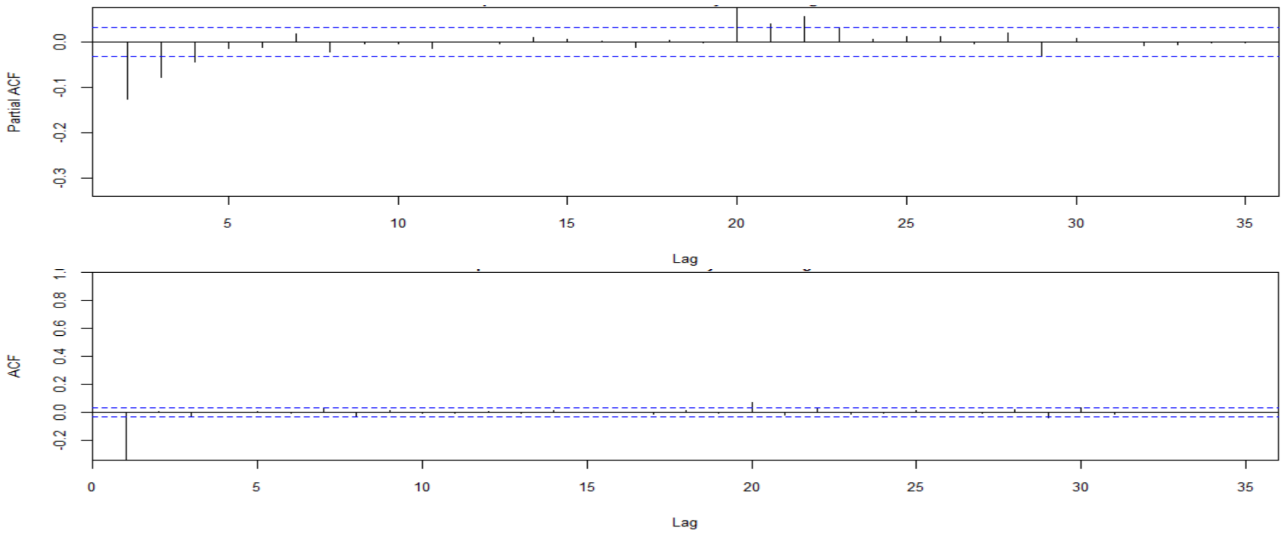


Figure 6. ACF and PACF plots for first-order differenced series.

Figure 6 illustrates that the series approach zero rapidly and most of the lags are within the correlograms or confidence interval lines. Thus, the series is stationary in-mean. The ADF test is conducted to confirm the stationarity. The p-value of the test equals to 0.01. As $(p - value = 0) < (\alpha = 0.05)$, it indicates the null hypothesis of the differenced overnight IIR time series data is not stationary in-mean is rejected at a 5% significance level. Therefore, the ADF test provides the same results as ACF-PACF plots after differencing of which the series by now is stationary in-mean.

Table 3 presents the descriptive statistics of the stationarity in-sample data. It illustrates that the mean of the stationary series is positive. The skewness is maintained in negative value which implying that the distribution of the series is asymmetric and skewed to the left. In other words, the tail of the distribution is longer on the left. The high positive kurtosis value of 212.5994 specifies that the distribution has heavier tails and a sharper peak than a normal distribution.

Table 3. Descriptive statistics of the stationary data.

Descriptive	Statistics
No. of Observations	3,874
Minimum	-0.9100
Maximum	0.9100
Mean	0.0001
Standard Deviation	0.0396
Skewness	-1.7420
Kurtosis	212.5994

In the hypothesis testing on mean for the stationary data, the test statistics of 0.1572 with a p-value equals to 0.8751, indicates the null hypothesis of zero mean is not rejected at a 5% significance level. Meanwhile, the test statistics of data skewness is 44.2642 with a p-value equals to 0, indicates the null hypothesis of zero skewness is rejected at a 5% significance level. Therefore, the distribution of the stationary series is non-symmetric and negatively skewed. In the testing of the stationary data kurtosis, the test statistics generated 2701.0720 with a p-value equals to 0, then the null hypothesis of zero kurtosis is rejected at a 5% significance level. Therefore, the leptokurtic kurtosis indicates that the distribution of the stationary data has heavier tails and a sharper peak than the normal distribution of the data as proved by Figure 7.

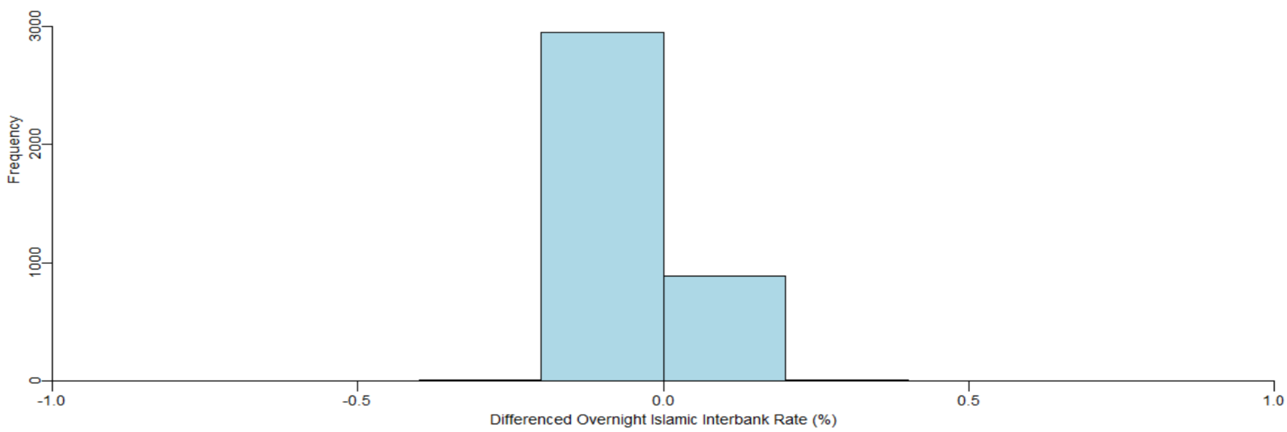


Figure 7. Histogram of first-order differenced series of Malaysian overnight Islamic interbank rates.

The JB Test is employed in the stationary series to support the results of the non-normality of data. The *p*-value generated indicates that the value equals to 0, then the null hypothesis of the stationary series are normally distributed is rejected at a 5% significance level. Therefore, the distribution of the stationary overnight IIR does not follow a normal distribution.

The Ljung-Box (LBQ) Test has been used to test the serial correlation of the stationary series. The overnight IIR series can only be modelled once the data is stationary in-mean and serially correlated [2]. The *p*-value generated at lag 10 [20] specifies that the value equals to 0, then the null hypothesis of there is no serial correlation in the stationary series is rejected at a 5% significance level. This can be concluded that the stationary series of overnight IIR is serially correlated between another, and the Box-Jenkins can be applied to the data.

The previous analysis on the Malaysian IIR series has shown nonseasonal and stationary at the first differenced series. Therefore, these results then reflect ARIMA(p,1,q). Based on PACF and ACF plots of the stationary series as illustrated in Figure 6, it can be suggested that the values of $p = 0,1,2,3,4$ and $q = 0,1$, respectively, of which the standard errors for ACF and PACF are 0.0161, respectively. Therefore, there are ten possible ARIMA models that can be identified namely ARIMA (0,1,0), ARIMA (1,1,0), ARIMA (2,1,0), ARIMA (3,1,0), ARIMA (4,1,0), ARIMA (0,1,1), ARIMA (1,1,1), ARIMA (2,1,1), ARIMA (3,1,1) and ARIMA (4,1,1). Alternatively, the EACF Table has suggested that ARIMA (0,1,1) is the possible Box-Jenkins model for the stationary series, as illustrated in Table 4.

Table 4. The EACF Table for ARIMA (0,1,1) model.

AR/MA	0	1	2	3	4	5	6
0	X	O	O	O	O	O	O
1	X	X	O	O	O	O	O
2	X	X	X	O	O	O	O
3	X	X	X	O	O	O	O
4	X	X	X	O	X	O	O
5	X	X	X	O	X	X	O
6	X	X	X	X	X	X	X

Stage II: Parameter estimation of ARIMA (0,1,1) model

In the parameter estimation stage of the Box-Jenkins model, the MLE is applied to find the parameter values that optimize the probability of obtaining the overnight IIR data that have been studied. The application of the model estimation in selecting the best significant IIR model has fulfilled the conditions of two times value of standard error (SE) is less than the value of model coefficient and the $p - value \le \alpha$. The statistics of the parameter estimation using the model selection criteria have been summarized in Table 5.

By using the MLE method to estimate parameters, ARIMA (0,1,1) was found to be significant at $\alpha = 0.05$ as two times standard error values is lower than coefficient value and the model is preferred due to it provides the smallest AIC and BIC values of -14,575.45 and -14,556.67, respectively. According to the parsimony principle that simple models are preferred as compared to complex models when all things being equal, thus the model of ARIMA (0,1,1) is the most preferred for the next stage. On top of that, the results of the EACF Table as given by Table 4 also agreed with ARIMA (0,1,1).

Table 5. Parameter estimation using model selection criteria.

No	Model	2*SE < Coefficient	AIC	BIC	Significance
1	ARIMA (0,1,0)	No	-14,011.38	-13,998.86	Significant
2	ARIMA (1,1,0)	Yes	-14,485.20	-14,466.41	Significant
3	ARIMA (2,1,0)	Yes	-14,545.88	-14,520.83	Significant
4	ARIMA (3,1,0)	Yes	-14,567.74	-14,536.43	Significant
5	ARIMA (4,1,0)	Yes	-14,573.31	-14,535.74	Significant
6	ARIMA (0,1,1)	Yes	-14,575.45	-14,556.67	Significant
7	ARIMA (1,1,1)	No	-14,575.11	-14,550.06	Not Significant
8	ARIMA (2,1,1)	No	-14,575.63	-14,544.32	Not Significant
9	ARIMA (3,1,1)	No	-14,574.07	-14,536.50	Not Significant
10	ARIMA (4,1,1)	No	-14,572.27	-14,528.44	Not Significant

Stage III: Diagnostic checking of ARIMA (0,1,1) model

In the Box-Jenkins' diagnostic checking stage, the chosen model of ARIMA (0,1,1) has been verified and tested in the aspects of serial correlation, homoscedasticity and zero mean in the residuals of the IIR series. Table 6 shows the descriptive statistics of the IIR series residuals of the ARIMA (0,1,1) model, which shows the zero mean and variance of 0.0014. The skewness is in positive value which implying that the distribution of the residuals of the series is asymmetric and skewed to the right. In other words, the tail of the distribution is longer on the right. The high positive kurtosis value of 189.9865 specifies that the distribution of the residuals has heavier tails and a sharper peak than a normal distribution.

Table 6. Descriptive statistics of the series residuals of ARIMA (0,1,1) model.

Description	Statistics
No. of Observations	3,874
Minimum	-0.7019
Maximum	0.9251
Mean	0.0000
Standard Deviation	0.0369
Skewness	2.7489
Kurtosis	189.9865

The residuals plot as shown in Figure 8 has proven that ARIMA (0,1,1) model errors are uncorrelated as the sign of the residuals are randomly distributed and correlation is almost close to zero. The LBQ Test has been used to validate and test on the serial correlation of the residual series. The $p - value = 0.5260$ generated at lag 10 [20] indicates that the null hypothesis of there is no serial correlation in the series residuals is not rejected at a 5% significance level. Therefore, it can be concluded that the series residuals of overnight IIR are independent and randomly distributed.

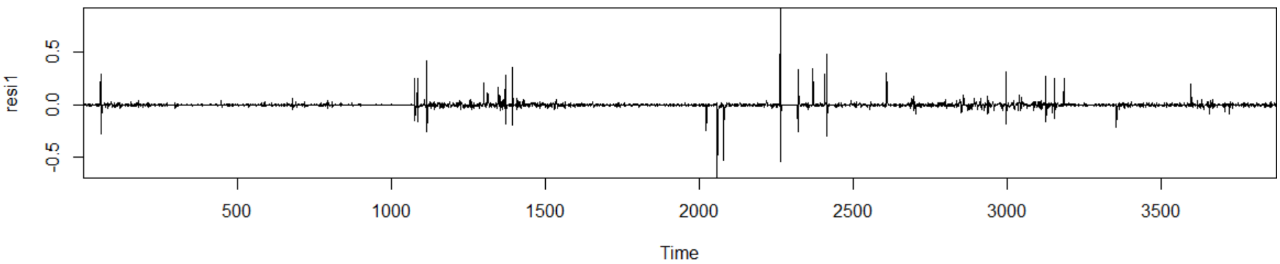


Figure 8. Residuals plot of ARIMA (0,1,1) model.

Figure 9 shows the standardized residual plot, ACF for residuals and *p*-values for Ljung-Box statistics. Based on Figure 9, the standardised residual plot for ARIMA (0,1,1) of the in-sample stationary series illustrates randomness in the residuals with some spikes representing volatility clustering commencing in the middle of the residuals plot. Whereas the ACF of the residuals is relatively small and approximately equals to zero up to lag 35 which supports the independence in the residuals. The *p*-value of 0.5260 of the LBQ Test indicates that there is no serial correlation in the residuals up to lag 10 at a 5% significance level. This reflects that the mean model of ARIMA (0,1,1) to the IIR series is correctly specified up to lag 10. Therefore, the residual series of the model behave as white noise as the series has zero mean, the constant variance of 0.0014 and is serially uncorrelated.

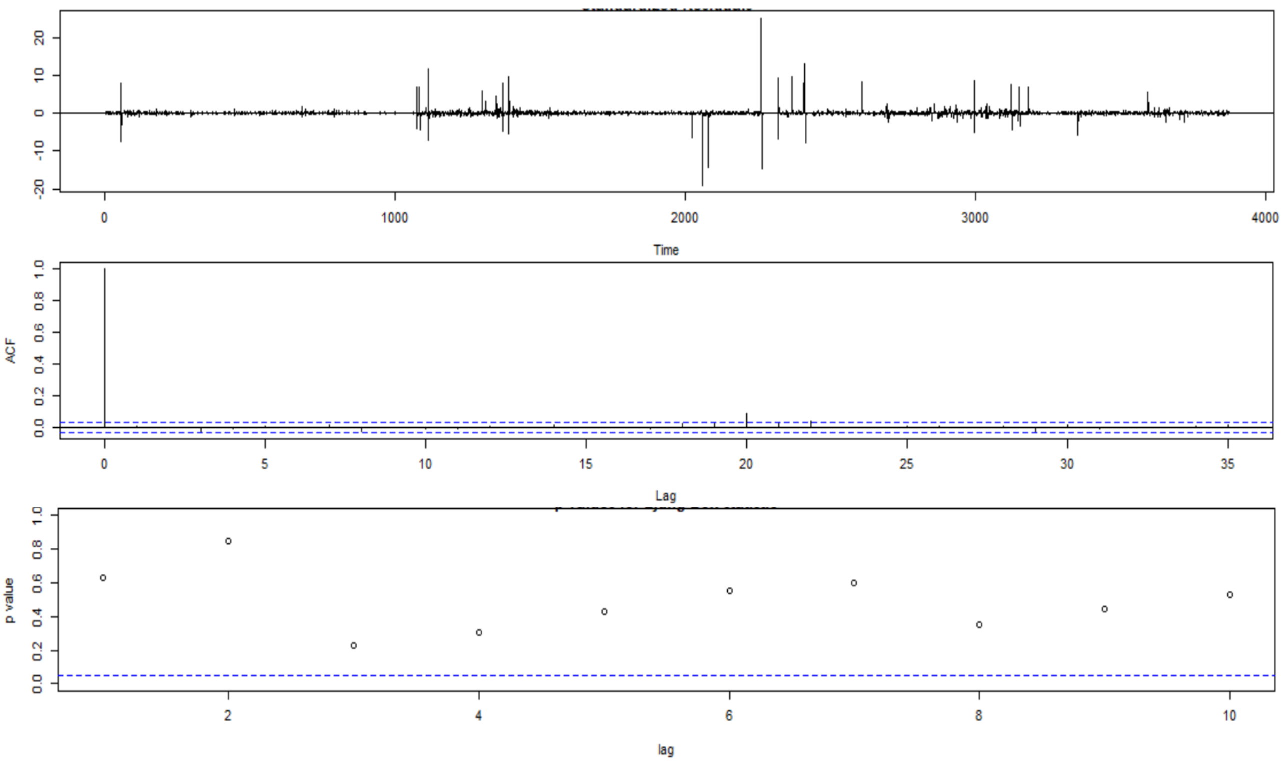


Figure 9. The standardised residual plot, ACF for residuals and *p*-value for Ljung-Box statistics of ARIMA (0,1,1) model.

Stage IV: Forecasting using ARIMA (0,1,1) model

The model of ARIMA (0,1,1) which has been selected from Stage I to Stage III has been used in the forecasting part using Box-Jenkins modelling. In this stage, the out-of-sample IIR data has been employed to obtain the forecast results as the accuracy of forecasts can only be defined by considering how well a model performs on new data that have not been used when fitting the model [17]. ARIMA (0,1,1) model in the stationary form is given by Equation 12, where S_t, y_t, y_{t-1} and a_t are the stationary series, the observed values, the predictor up to lag 1 (or the previous value) and the random error at time *t*, respectively and σ_t^2 is the conditional variance of S_t.

$$S_t = y_t - y_{t-1}$$
$$S_t = 0.0001 + a_t - 0.4046_{t-1}, \qquad \sigma_t^2 = 0.0014 \tag{12}$$

Table 7 shows the values of actual and one-step-ahead forecast stationary data for the last 10 days of out-of-sample data using the ARIMA (0,1,1) model. The values of MAE and RMSE for stationary data are 0.0162 and 0.0382, respectively. No value of MAPE is produced here as there are existences of zero values in the stationary data. Whereas, the values of MAE, RMSE and MAPE for the out-of-sample forecast Malaysian IIR data are 0.0162, 0.0382 and 0.6940. Based on these values, ARIMA (0,1,1) model is concluded as the appropriate model for modelling overnight IIR using the Box-Jenkins model as it generates very small prediction errors with MAPE below 5%.

Table 7. Actual and one-step ahead forecast stationary IIR data for the last 10 days using ARIMA (0,1,1) model.

Date	Actual Stationary IIR Data	Forecast Stationary IIR Data
17/12/2020	0.0000	0.0026
18/12/2020	0.0000	0.0025
21/12/2020	0.0100	0.0025
22/12/2020	-0.0100	-0.0015
23/12/2020	0.0100	0.0049
24/12/2020	-0.0100	-0.0006
28/12/2020	0.0100	0.0053
29/12/2020	-0.0200	-0.0004
30/12/2020	-0.0100	0.0094
31/12/2020	0.0200	0.0094

Figure 10 illustrates the time series plot of the actual values of the out-of-sample data versus one-step-ahead forecast values of the overnight IIR at one-step-ahead forecasting using the ARIMA (0,1,1) model. Generally, the pattern of the out-of-sample IIR data shows a downward trend due to the events of persistent global downside risk for the first half of 2019 and adverse impact resulted from the emergence of coronavirus pandemic in late 2019. In terms of forecasting, the forecast line coloured in red is almost in parallel with the actual line which is coloured in blue. This promising performance of the Box-Jenkins model in forecasting Malaysian IIR data is supported numerically by Table 8. Note that, there is a one-day lag problem of which the second column (forecast) IIR data can be obtained from the first column (actual) IIR data by shifting the first column one row downward or the today's IIR data is a good forecast for tomorrow IIR data. This is generally the efficient market hypothesis at work, and it is a common circumstance for one-step-ahead forecast.

Table 8 summarizes the values of the actual data, forecast data, 95% lower and upper PIs of the overnight IIR for the last 10 days using the ARIMA (0,1,1) model. The table points out that all the values of the one-step-ahead forecast data are within the 95% PIs which means the preferred ARIMA (0,1,1) model will produce good forecasting results of the overnight IIR as illustrated by Figure 11.

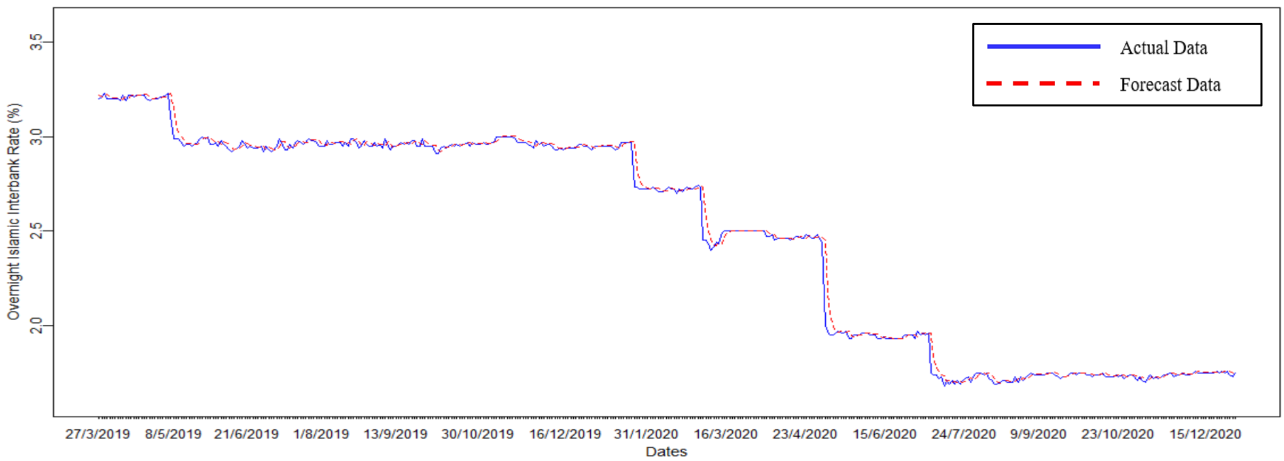


Figure 10. The plot of actual data versus one-step ahead forecast data of the overnight IIR using ARIMA (0,1,1) model.

Table 8. Actual and forecast data, 95% lower and 95% upper intervals for the last 10 days using ARIMA (0,1,1) model.

Date	Actual IIR Data (%)	Forecast IIR Data (%)	Lower 95% (%)	Upper 95% (%)
17/12/2020	1.7500	1.7526	1.6526	1.8525
18/12/2020	1.7500	1.7525	1.6526	1.8525
21/12/2020	1.7600	1.7525	1.6526	1.8525
22/12/2020	1.7500	1.7585	1.6585	1.8584
23/12/2020	1.7600	1.7549	1.6550	1.8549
24/12/2020	1.7500	1.7594	1.6595	1.8594
28/12/2020	1.7600	1.7553	1.6554	1.8553
29/12/2020	1.7400	1.7596	1.6597	1.8595
30/12/2020	1.7300	1.7494	1.6495	1.8494
31/12/2020	1.7500	1.7394	1.6394	1.8393

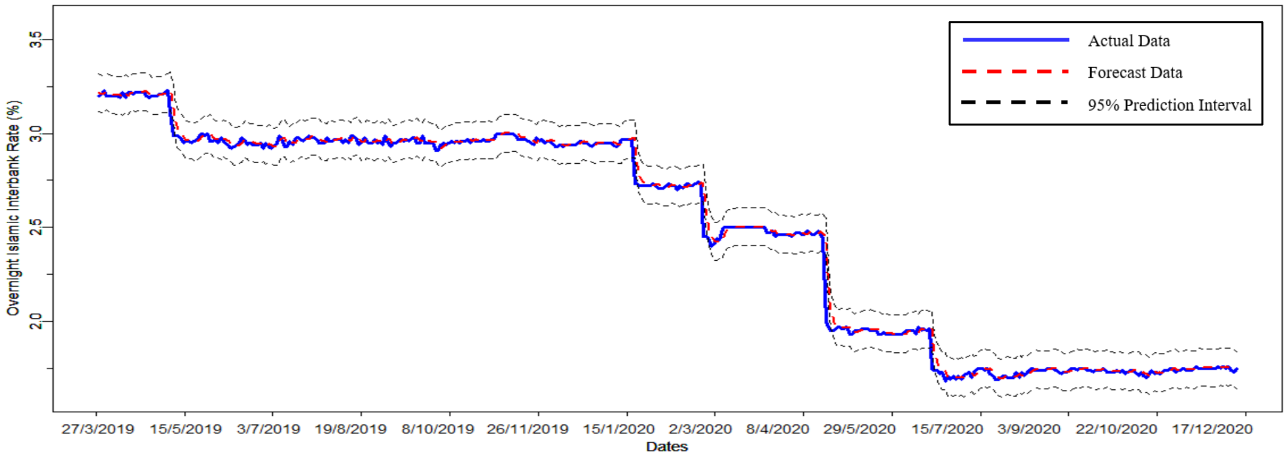


Figure 11. Plot of ARIMA (0,1,1) model with 95% PIs.

In multistep ahead forecasting, the performance of the model has been assessed at multiple horizons of 2, 3, 4, 5, 7, 10, 15, 20, 25, 30 and 45-day ahead at 95% PIs [6-7] and [16-19]. Table 9 shows 1-step to 45-step ahead forecast evaluation results with the number of data that lies within the 95% PIs and forecast errors below 5% using the ARIMA (0,1,1) model. From the table, the values of RMSE are increasing not more than the adequate forecast error of 5% which are aligned with the addition in forecast horizons up to 45-step ahead. Yet, it is difficult to select the appropriate forecast horizon for the preferred model as the value of forecast errors, particularly MAPE is increasing marginally between each other. Therefore, by considering the maximum number of 420 out of 430 actual out-of-sample data or 97.67% that lies inside the 95% PIs, as highlighted in Table 9, then the results state that the 5-day ahead forecast horizon performs the best in Box-Jenkins forecasting as compared to other multistep ahead forecast horizons. It can be concluded that the ARIMA (0,1,1) model can be considered for forecast up to 5-step ahead of daily overnight IIR.

Table 9. Forecast error evaluation at 95% prediction interval for multistep ahead forecasting using ARIMA (0,1,1).

Forecast Horizon (h)	Forecast Error Evaluation			Data Inside 95% PIs	
	MAE	RMSE	MAPE	No. of Data	%
1-day ahead	0.0162	0.0382	0.6940	419	97.4419
2-day ahead	0.0183	0.0461	0.7904	419	97.4419
3-day ahead	0.0211	0.0508	0.8874	419	97.4419
4-day ahead	0.0230	0.0538	0.9884	416	96.7442
5-day ahead	**0.0215**	**0.0442**	**0.9126**	**420**	**97.6744**
7-day ahead	0.0284	0.0686	1.2495	416	96.7442
10-day ahead	0.0347	0.0772	1.5518	406	94.4186
15-day ahead	0.0432	0.0956	1.9268	398	92.5581
20-day ahead	0.0522	0.0948	2.2388	390	90.6977
25-day ahead	0.0646	0.0987	2.6767	375	87.2093
30-day ahead	0.0695	0.1333	3.2783	402	93.4884
45-day ahead	0.1049	0.1684	4.6875	389	90.4651

Figure 12 presents the time series plot of actual out-of-sample data and forecast data at 5-step ahead using the proposed Box-Jenkins model at 95% PIs. The forecasting performance of the ARIMA(0,1,1) model for up to 5-step ahead forecast is proved graphically by the plot as almost all actual data of overnight IIR are within 95% PIs except in several events of significant IIR drops. It shows that the trend of the 5-day ahead forecast of overnight IIR imitates the trend of the actual overnight IIR for the out-of-sample period. Table 10 compares the actual IIR data in May 2020 derived from out-of-sample data with the 5-step ahead forecast IIR and it has been associated with its 95% PIs using the ARIMA (0,1,1) model. Based on Table 10, there is only 1 out of 15 actual IIR data that is not within 95% PIs. This signifies that the preferred Box-Jenkins model is following the trend performance of actual IIR data up to 5-day ahead.

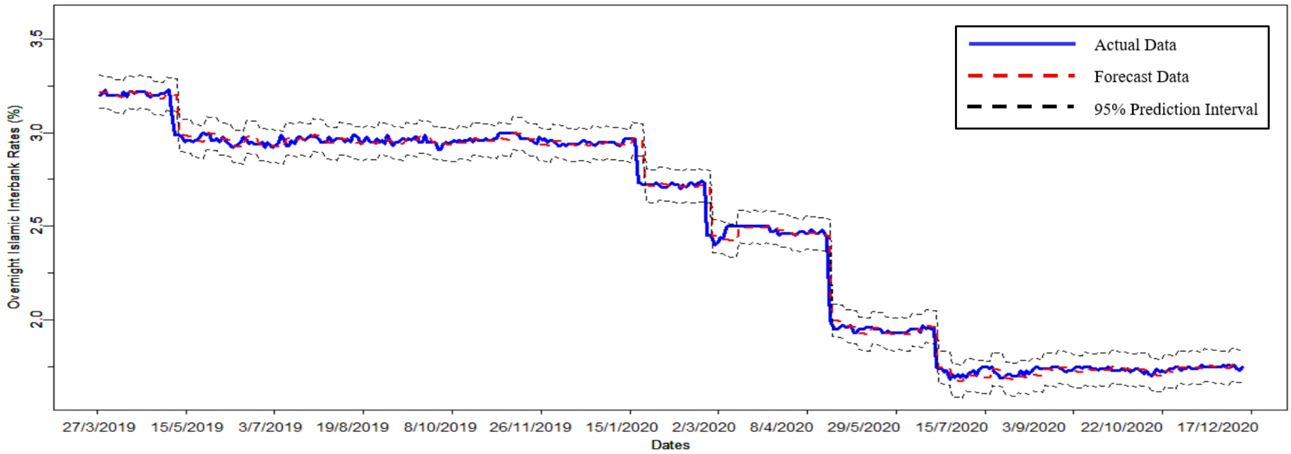


Figure 12. The plot of actual data versus 5-step ahead forecast using ARIMA (0,1,1) model at 95% PIs.

Table 10. Actual IIR, 5-step ahead forecast and 95% PIs using ARIMA (0,1,1) model.

Date	Actual IIR (%)	Forecast IIR (%)	95% Prediction Intervals	
			Lower Interval	Upper Interval
4/5/2020	2.44	2.4516	2.3640	2.5393
5/5/2020	2.00	2.4496	2.3619	2.5372
6/5/2020	1.97	1.9979	1.9103	2.0856
8/5/2020	1.95	1.9958	1.9082	2.0835
12/5/2020	1.95	1.9937	1.9061	2.0814
13/5/2020	1.96	1.9916	1.9040	2.0793
14/5/2020	1.97	1.9896	1.9019	2.0772
15/5/2020	1.96	1.9679	1.8803	2.0556
18/5/2020	1.96	1.9658	1.8782	2.0535
19/5/2020	1.97	1.9637	1.8761	2.0514
20/5/2020	1.93	1.9616	1.8740	2.0493
21/5/2020	1.93	1.9596	1.8719	2.0472
22/5/2020	1.95	1.9279	1.8403	2.0156
27/5/2020	1.95	1.9258	1.8382	2.0135
29/5/2020	1.95	1.9237	1.8361	2.0114

CONCLUSION

This study is aimed to examine the performance of the Box-Jenkins model in forecasting the Malaysian overnight IIR in daily returns. The overnight IIR in Malaysia is constantly changing over time due to the constant changes in the monetary policy set by the government according to certain events that happened in the period. Therefore, the Malaysian overnight IIR time series dataset is selected over a 20-year performance period from 2001 to 2020 to get a better observation over the impacts of the 2008 financial crisis, COVID-19 outbreak and/or other unprecedented events that happened over along the years towards the performance of the Malaysian overnight IIR using the Box-Jenkins model.

Based on the result findings discussed, it indicates that the ARIMA (0,1,1) model produces the smallest RMSE, MAE and MAPE. That means the ARIMA (0,1,1) model is the most appropriate Box-Jenkins model to forecast Malaysian overnight IIR as it produces very high forecast accuracy with marginal error of below 5%. The encouraging results from one-step-ahead forecasting using the ARIMA (0,1,1) model has directed the study in conducting multistep ahead forecasting of the Malaysian overnight IIR. It can be summarized that the ARIMA (0,1,1) model can be considered for forecast up to 5-day ahead for 20 years data series of daily overnight IIR in Malaysia. Therefore, the proposed model in the study can benefit the beneficial parties particularly the financial institutions to predict the future values of the overnight IIR in weekly timeframe.

There are some recommendations that can be considered for future researches like various frequencies of the overnight IIR data sampling (i.e. in weekly, monthly or quarterly) should be measured and compared to provide comprehensive forecasting model of the Malaysian overnight IIR. In addition, the researchers can also establish an overnight IIR forecast model by testing the model in different time period and partition of in-sample against out-of-sample data as they might give tendency on different direction and results.

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