Pertanika J. Sci. & Technol. 29 (1): 31 - 58 (2021)

PERTANIKA JOURNALS

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

Forecasting Wind Speed in Peninsular Malaysia: An Application of ARIMA and ARIMA-GARCH Models

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ABSTRACT

In the global energy context, renewable energy sources such as wind is considered as a credible candidate for meeting new energy demands and partly substituting fossil fuels. Modelling and forecasting wind speed are noteworthy to predict the potential location for wind power generation. An accurate forecasting of wind speed will improve the value of renewable energy by enhancing the reliability of this natural resource. In this paper, the wind speed data from year 1990 to 2014 in 18 meteorological stations throughout Peninsular Malaysia were modelled using the Autoregressive Integrated Moving Average (ARIMA) to forecast future wind speed series. The Ljung-Box test was used to determine the presence of serial autocorrelation, while the Engle's Lagrange Multiplier (LM) test was used to investigate the presence of Autoregressive Conditional Heteroscedasticity (ARCH) effect in the residual of the ARIMA model. In this study, three stations showed good fit using the ARIMA modelling since no serial correlation and ARCH effect were present in the residuals of the ARIMA model, while the ARIMA-GARCH had proven to precisely capture the nonlinear characteristic of the wind speed daily series for the remaining stations. The forecasting accuracy measure used was based on the value of root mean square error (RMSE) and mean absolute percentage error (MAPE). Both ARIMA and

ARTICLE INFO

Article history:
Received: 6 July 2020
Accepted: 5 November 2020
Published: 22 January 2021

DOI: https://doi.org/10.47836/pjst.29.1.02

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ISSN: 0128-7680
e-ISSN: 2231-8526

ARIMA-GARCH model proposed provided good forecast accuracy measure of wind speed series in Peninsular Malaysia. These results will help in providing a quantitative measure of wind energy available in the potential location for renewable energy conversion.

Keyword: Forecasting, modelling, renewable energy, time series method, wind speed

INTRODUCTION

In this rapid population growth, the energy demand has increased to support human consumption. The negative effect is energy usage has increased the demand on energy resulting in depletion of natural resources and will cause a harmful effect towards the environment (Ajayi et al., 2014). To overcome this issue, many developed countries are now focusing on conserving the non-renewable energy by switching to renewable energy sources like wind and solar. Wind power is one of the natural sources of renewable energy that is experiencing the fastest growth is the wind energy. Unlike solar energy, wind power can provide energy throughout day and night since it does not require any sunlight (Petinrin & Shaaban, 2015).

Many researchers have studied wind speed modelling and forecasting using various models which were developed in improving the wind speed forecasting accuracy (Chang et al., 2016; De Freitas et al., 2018; Norrulashikin et al., 2018; Sharma & Singh, 2018). According to Erdem et al. (2014), there are two main aspects to be considered in building a wind speed prediction model which is to predict the mean wind speed and the wind speed volatility. Commonly used models include autoregressive (AR) model, moving average (MA) model (Akcan, 2017), autoregressive moving average (ARMA) model (Lujano-Rojas et al., 2011), and autoregressive integrated moving average (ARIMA) model (Radziukynas & Klementavicius, 2014). These models assume that the occurrence of turbulence in the wind speed is constant or in other words, homoscedastic. However, wind speed series can exhibit the characteristics of nonlinear variance where it is often referred to as volatility and may vary over time. Therefore, the presence of nonlinear variance in a model needs to be investigated before any prediction is performed. If the error estimation for this variation of wind speed is underestimated, the prediction model might fail to provide accurate wind speed forecasting that will cause serious problems in the operation of wind turbine (Engle, 2001).

Hence, this study was conducted to propose a forecasting model using the ARIMA model. The proposed model with the presence of serial autocorrelation and effect of heteroscedasticity in the residual part of the series would be treated using the Generalized Autoregressive Conditional Heteroskedastic (GARCH) model. A related study by Masseran (2016) used an ARIMA-ARCH model to investigate the effect of mean and volatility of the wind speed. Yan et al. (2016) suggested the ARIMA-GARCH model for forecasting a short-term wind speed series. The proposed model had successfully managed to capture the heteroscedasticity of wind speed series and gave a higher prediction accuracy compared to the ARIMA model. Based on Lojowska et al. (2010), the advantage of modelling using ARMA-GARCH model is that it has the capability to handle the dominant criteria of the data series, which is distribution, time dependence structure as well as periodicity. For the purpose of wind speed forecasting, Grigonytė & Butkevičiūtė (2016) used the ARIMA model to forecast a short-term wind speed in Latvia and the forecasting accuracy for the proposed model was based on root mean square error (RMSE) and mean absolute percentage error (MAPE) and mean absolute error (MAE) which allowed to establish an optimal model structure. While Sharma and Ghosh (2016) used MAPE in measuring the short-term wind speed forecasting in India and the finding suggested that ARIMA-GARCH model yielded smallest value of MAPE compared to other proposed models.

The aim of this study was to develop a time series model of daily wind speed series in Peninsular Malaysia. Box-Jenkins ARIMA model was used to model the series of each 18 stations and 15 stations were found to have a serial correlation and heteroscedastic effect in the residuals of the proposed model. Therefore, an ARIMA-GARCH model that is proven to help in capturing the serial autocorrelation and the heteroscedastic effects of a time series process was used. This hybrid model would help to overcome the linear limitation of ARIMA model for the purpose of obtaining a time series model that yielded higher accuracy of forecasting results.

MATERIALS AND METHODS

This research used a daily wind speed series collected from Malaysian Meteorological Department (MMD) which consisted of data from 1990 to 2014. Data of daily wind speed series from 18 meteorological stations throughout the Peninsular Malaysia were chosen for this study from different regions. The last 365 days of daily wind speed data for each station would be considered as the out-sample data which will be compared with the forecasted daily wind speed series based on the best fitted model. In this study, time series analysis was applied due to the ability to interpret the presence of internal structure that might occur to the data point taken over time. For instance, the condition of serial autocorrelation and heteroscedastic effects should be taken into account in the analysis.

Data Description

The daily wind speed data from 18 different locations in Peninsular Malaysia with a duration from 1/1/1990 to 31/12/2014 were used in this study. The location in Peninsular Malaysia were divided into 4 regions, namely: northern, east coast, central, and southern. The northern region consists of stations that are located in Perlis, Kedah, Pulau Pinang and Perak, while the east coast region consists of stations that are located in the state of Kelantan, Terengganu, and Pahang. The central region consists of stations that are located in Selangor, Kuala Lumpur, and Putrajaya, and the southern region consists of stations that are located in Negeri Sembilan, Melaka, and Johor. The detailed information on the stations used in this study are given in Table 1 while Figure 1 shows the location of the stations on the map of Peninsular Malaysia.

Table 1

Coordinates for 18 stations used for wind speed data collection in Peninsular Malaysia

Location	Station	Latitude	Longitude
Chuping	NS1	6°28'47.0"N	100°15'36.1"E
Langkawi	NS2	6°20'13.0"N	99°43'35.4"E
Bayan Lepas	NS3	5°17'43.4"N	100°16'06.6"E
Butterworth	NS4	5°27'53.9"N	100°22'59.2"E
Lubok Merbau	NS5	4°47'42.9"N	100°53'46.6"E
Sitiawan	NS6	4°13'17.1"N	100°42'05.5"E
Kota Bharu	ES7	6°09'12.6"N	102°18'41.0"E
Kuala Terengganu	ES8	5°22'59.3"N	103°06'28.8"E
Cameron Highland	ES9	4°29'04.0"N	101°22'17.4"E
Kuantan	ES10	3°46'22.9"N	103°12'42.3"E
Subang	CS11	3°07'52.0"N	101°33'09.8"E
Petaling Jaya	CS12	3°06'26.0"N	101°38'52.9"E
Sepang	CS13	2°43'54.2"N	101°42'10.5"E
Melaka	SS14	2°15'17.2"N	102°14'36.0"E
Mersing	SS15	2°26'42.6"N	103°49'52.6"E
Batu Pahat	SS16	1°52'14.5"N	102°59'25.6"E
Kluang	SS17	2°01'41.6"N	103°19'14.0"E
Senai	SS18	1°38'20.3"N	103°39'57.0"E

ARIMA Model

In time series analysis, the Box-Jenkins method is the commonly used method to model a wind speed time series data. The first step is model identification which include measuring the stability of the mean and the stationarity of the time series. The transformation approach is needed if the data does not satisfy these conditions. This can be done by observing the time series and ACF plots of the collected wind speed data. A hypothesis testing using the

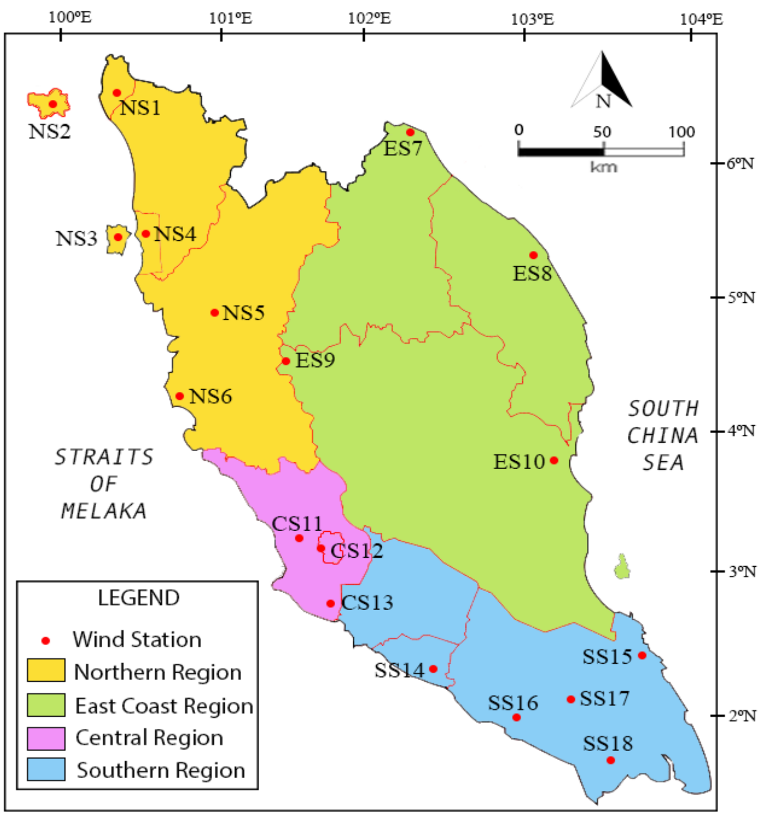


Figure 1. Location of wind stations in Peninsular Malaysia

Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test can be used to determine the stationarity of the wind speed time series data, where the null hypothesis is the data series is stationary (Kwiatkowski et al., 1992). The formulation for the KPSS test is given by Equation 1:

$$y_t = \beta t + r_t + \varepsilon_t. \quad [1]$$

Note that r_t=r_(t-1)+u_t , where r_t represents a random walk while u_t are iid (0, σ_u^2). For a p-value that is significantly low than 0.05, the null hypothesis will be rejected which indicates that the wind speed series in not stationary and requires a differencing approach. For the model selection, autocorrelation function (ACF) and partial autocorrelation function (PACF) plot provides the information on the potential models where it identifies the number of terms for autoregressive order p and moving average order q (Miswan et al., 2015).

The general form of autoregressive integrated moving average ARIMA (p, d, q) can be defined as Equation 2:

$$\varphi(B)(1-B)^{d}y_{t}=\theta(B)\varepsilon_{t} \qquad [2]$$

where y_t and ε_t are the observed values of wind speed series and the random error terms at time period t, respectively. φ_1, φ_2, φ_3,…, φ_p are the autoregressive coefficients with order p. d is the order of differencing, and θ_1, θ_2, θ_3,…, θ_q are the moving average coefficients with order q. B is the backward shift operator, while, φ(B) and θ(B) are polynomials of order p and q respectively, and defined as follows (Wang et al., 2015):

$$\varphi(B)=1-\varphi_{1}B-\varphi_{2}B^{2}-\cdots-\varphi_{p}B^{p}$$

$$\theta(B)=1-\theta_{1}B-\theta_{2}B^{2}-\cdots-\theta_{q}B^{q}.$$

Serial Correlation

A statistical inference of time series analysis will be affected by the presence of serial correlation. A fitted model is appropriate or accurate if the residuals has the conditions of zero mean, homoscedastic, independent, and normally distributed (Jamaludin et al., 2016; Yürekli et al., 2005). One of the very useful diagnostic tools to measure the existence of a serial autocorrelation for residuals in the stationary ARIMA model is using the Ljung-Box (LB) test (Kim et al., 2004). The null hypothesis was set to the absence of serial autocorrelation in the residuals from the ARIMA model and was performed towards the residuals of a fitted ARIMA model instead of the original time series data. The decision making for the test is based on Equation 3:

$$Q=T(T+2)\sum_{k=1}^{L}\frac{r_{k}^{2}}{(T-k)}\,; \qquad [3]$$

where T is denoted as the length of the time series, k represents the number of parameters to be estimated in the model, r_k^2 denotes the sample autocorrelation at lag k, and L is the number of autocorrelation lag to be tested. The Q-statistics in Equation 3 approximately follows a chi-square distribution with L degree of freedom (Wang et al., 2015).

The Autoregressive Conditional Heteroscedasticity (ARCH) Effect

Besides checking for the presence of serial correlation, the test to check on the existence of heteroscedasticity in the residual of the model should also be performed. The result can also be supported by performing ARCH Lagrange Multiplier (LM) test to determine the existence of heteroscedasticity in the residuals of the model.

Engle's Lagrange Multiplier Test for the ARCH Effect

Uncorrelated time series models might still have a serial dependence due to the dynamic conditional variance process. The existence of an ARCH effect in the ARIMA model occur if the model exhibits autoregressive conditional heteroscedasticity. If the ARCH effect is neglected, the consequences might result to large arbitrary loses in asymptotic efficiency which will lead to an extreme rejection of the standard test for the mean autocorrelation (Sjölander, 2011). To assess the significance of an ARCH effect, Engle (1982) proposed a methodology using Lagrange Multiplier (LM) test to assess the presence of ARCH effect based on the regression. The decision making of this test is based on Equation 4:

$$e_t^2 = \hat{a}_0 + \sum_{s=1}^{q} \hat{a}_s e_{t-s}^2 \qquad [4]$$

where e_t is the residual series and a_s is the estimated coefficients of the fitted model. In this test, the null hypothesis is set to be that there is no existing ARCH component up to order q; i.e. a_s=0 for all s=1, 2, …., q. The alternative hypothesis is there are presence of ARCH components in at least one of the estimated a_s coefficients (Yusof et al., 2013). The test statistics for this test is given by TR2. It follows a chi-square distribution with q degree of freedom, where R denotes the sample multiple correlation coefficient based on the computation from the regression in Equation 4, and T is the number of observations (Wang et al., 2005).

The GARCH Model

Generalized Autoregressive Conditional Heteroscedastic (GARCH) model was developed by Bollerslev (1986). It helps the ARIMA (p, d, q) model to capture the heteroscedastic effect in a time series process. In modelling a univariate time series, let y_t=μ_t+ε_t denote the mean equation with respect to time t, where the conditional mean of y_t is represented by μ_t, while ε_t is denoted as the shock at time t and the equation is ε_t=v_t σ_t where it follows a distribution of ε_t~ iid N (0,1). Then, the conditional variance of y_t denoted by σ_t^2, that follows a GARCH (p,q) model can be expressed in Equation 5:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 \qquad [5]$$

where the value of $\propto_0$ is always positive, while the sum of $\propto_\iota$ and $\beta\iota$ is less than 1 up to order p and q. The coefficient of parameters that represent ARCH and GARCH are represented by $\propto_i$ and β_i, respectively.

The ARIMA-GARCH Model

The ARIMA-GARCH model is known to have two procedures where the first part models the linear part of the wind speed series using ARIMA model, while the residual part consists of the nonlinear data (Yaziz et al., 2013). Then, using the GARCH model, the residuals that display only the nonlinear pattern will be modelled and the combination of the ARIMA model and GARCH error component will give a model that can capture the dynamics of the wind speed series which can be used to forecast wind series. The standard GARCH (1,1) model was used to capture the heteroscedastic effect of the time series process in this study.

Forecasting Accuracy Measures

The final part of this study was to forecast the wind speed data based on the best fitted proposed model as well as examine the adequacy and accuracy of the proposed model. The adequacy and accuracy checking involve the investigation of the error terms in the proposed model. This study would use RMSE and MAPE as forecasting accuracy measures which are given by Equation 6 and 7:

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(\widehat{y_j} - y_j\right)^2} \; ; \qquad [6]$$

$$MAPE = \frac{1}{n}\sum_{j=1}^{n}\frac{|(\widehat{y_j} - y_j)|}{y_j} \times 100 \; ; \qquad [7]$$

where the sample size is denoted by n, while $\widehat{y_j}$ is the predicted value based on proposed model at time j and y_j is the observed value at time j. According to a study by Moreno et al. (2013), the MAPE can be considered as one of the commonly used methods to measure forecasting accuracy since it has a feature that is reliable, easy to interpret, clarity of presentation, support of statistical evaluation, and it uses all the information related to the error (Moreno et al., 2013). The interpretation for the typical MAPE value which was explained by Lewis (1982) are presented in Table 2.

Table 2

Interpretation of typical MAPE values

MAPE	Interpretation	MAPE	Interpretation
< 10	Highly accurate forecasting	20 – 50	Reasonable forecasting
10 – 20	Good forecasting	> 50	Inaccurate forecasting

RESULTS AND DISCUSSION

Descriptive Statistics

Figure 2 illustrates the central tendency, the dispersion, and the skewness of the wind speed data. The outliers present in the boxplot for each station represent a high wind speed reading in a certain time and location. The presence of these extreme values in wind speed data is very pronounced in data processing. Based on Figure 2, the median of the data for all wind stations were in the range of 6 m/s to 9 m/s. The dispersion of the data that represented by the tail of the boxplot showed a wide dispersion which also indicates volatility. The boxplot also shows that all stations exhibited a positive skewness. It means that the wind speed series for all stations in Peninsular Malaysia were not normally distributed. Therefore, in order to capture the variability and volatility, the Box-Jenkins methodology was applied to model the wind speed data for all wind stations in Peninsular Malaysia.

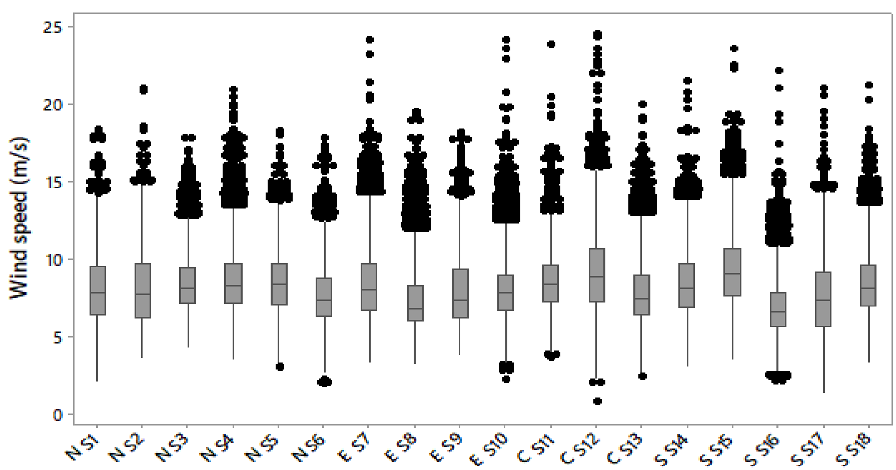
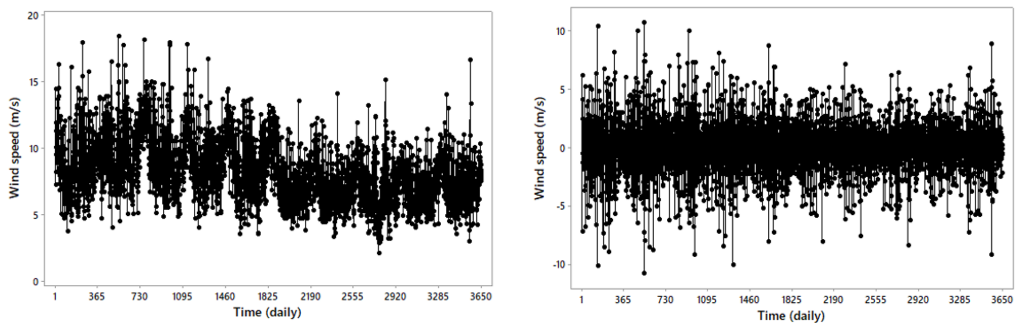


Figure 2. Boxplot of 18 wind stations in Peninsular Malaysia

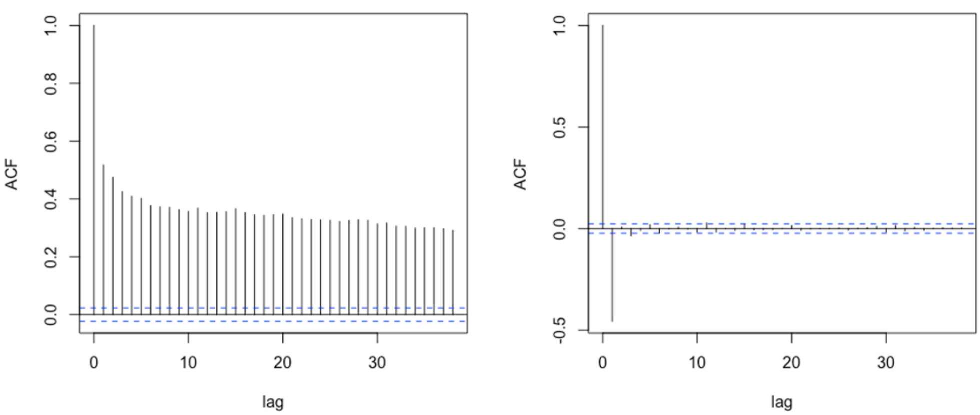
ARIMA Model

The first step in building a time series model using the Box-Jenkins methodology is the model identification. This step is intended to determine whether the differencing is required in order to obtain a stationary time series. In practical sense, a stationary time series is known to vary around a constant mean level over time, with a constant variance. This can be determined by observing the time series plot and ACF plot of the wind speed data. It also can be done by performing the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, where it tests the presence of a unit root in a time series data.



(a) (b)

Figure 3. Time series plot of station NS1; (a) observation data and (b) after first difference.



(a) (b)

Figure 4. ACF plot for station NS1; (a) observation data and (b) after first difference.

The time series plot in Figure 3 (a) shows that the mean and variance of wind speed series in station NS1 change over time. This indicates that the time series was not stationary. The plot presented in Figure 4 (a) also proves that station NS1 was not stationary due to the slow decay displayed in the ACF plot. This suggest that the data must undergo differencing. A non-stationary time series can be transformed to stationary if the differences among pairs of observation at lags are calculated. After the first differencing approach was applied, Figure 3 (b) and Figure 4 (b) show that the wind speed data in station NS1 are stationary. To support the findings, the KPSS test was performed to determine the stationarity of the daily wind speed time series data, where the null hypothesis was the data series is stationary. For a p-value that was significantly lower than 0.05, the null hypothesis would be rejected which indicated that the wind speed series was not stationary and required a differencing approach. The results of KPSS test for stationarity are presented in Table 3 where the findings concluded that five stations showed a stationary wind speed series, while 12 other stations satisfied this condition after first differencing (d=1).

Table 3
The KPSS test for stationarity of the daily wind speed series

Station	Observation Data			First Differencing		
	KPSS Level	p-value	Stationary	KPSS Level	p-value	Stationary
NS1	20.699	< 0.01	NO	0.0012	> 0.1	YES
NS2	0.0619	> 0.1	YES	-	-	-
NS3	0.0827	> 0.1	YES	-	-	-
NS4	3.8562	< 0.01	NO	0.0028	> 0.1	YES
NS5	3.1419	< 0.01	NO	0.0011	> 0.1	YES
NS6	20.181	< 0.01	NO	0.0015	> 0.1	YES
ES7	14.028	< 0.01	NO	0.0012	> 0.1	YES
ES8	24.312	< 0.01	NO	0.0010	> 0.1	YES
ES9	0.2554	> 0.1	YES	-	-	-
ES10	25.534	< 0.01	NO	0.0008	> 0.1	YES
CS11	0.0848	> 0.1	YES	-	-	-
CS12	2.000	< 0.01	NO	0.0015	> 0.1	YES
CS13	3.0304	< 0.01	NO	0.0013	> 0.1	YES
SS14	9.7655	< 0.01	NO	0.0009	> 0.1	YES
SS15	5.3813	< 0.01	NO	0.0011	> 0.1	YES
SS16	1.9574	< 0.01	NO	0.0026	> 0.1	YES
SS17	22.39	< 0.01	NO	0.0016	> 0.1	YES
SS18	0.2095	> 0.1	YES	-	-	-

After satisfying the stationarity condition, the next step in Box-Jenkins method is the parameter estimation. In this step, the orders of AR(p) and MA(q) for each station were identified using the PACF and ACF plots, respectively. Figure 5 illustrates the ACF plot and PACF plot of station NS1 after first differencing approach is done.

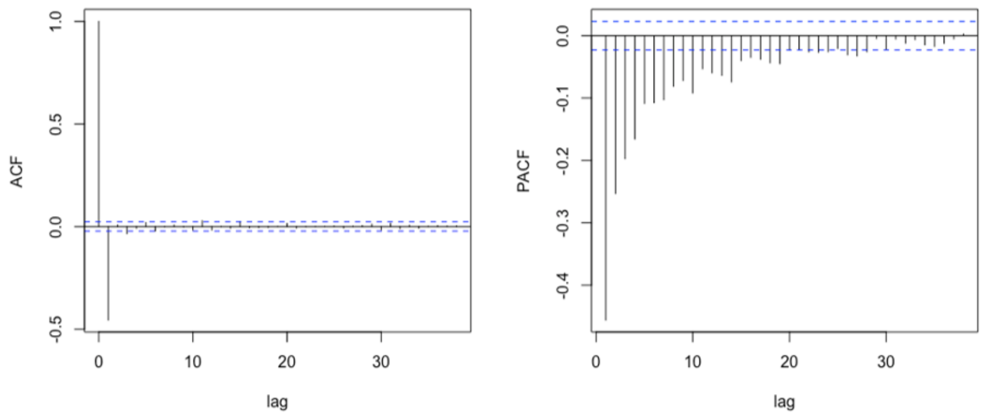


Figure 5. ACF and PACF plot for station NS1 after first difference

Few models were selected for ARIMA (p, d, q) based on these two plots, and the best model was selected based on the Akaike information criterion (AIC) values where the model with the lowest AIC value was selected as the best model for ARIMA model estimation. These steps were repeated on the remaining stations and the results of the best fitted ARIMA model for wind speed series for each station are shown in the Table 4.

Table 4

Model parameter estimates using the ARIMA (p, d, q) model for daily wind speed series

Location	Station	Model	Coefficient	Estimates	Standard Error
Chuping	NS1	ARIMA (2,1,1)	AR(1)	0.1858	0.0134
			AR(2)	0.1031	0.0132
			MA(1)	- 0.9329	0.0057
Langkawi	NS2	ARIMA (1,0,1)	AR(1)	0.5106	0.0628
			MA(1)	-0.2069	0.0709
Bayan Lepas	NS3	ARIMA (1,0,1)	AR(1)	0.8738	0.0892
			MA(1)	-0.8338	0.1008
Butterworth	NS4	ARIMA (1,1,2)	AR(1)	0.4906	0.0583
			MA(1)	-1.3395	0.0625
			MA(2)	0.3432	0.0621

Table 4 *(Continued)*

Location	Station	Model	Coefficient	Estimates	Standard Error
Lubok Merbau	NS5	ARIMA (1,1,2)	AR(1)	0.6452	0.0863
			MA(1)	-1.5047	0.0930
			MA(2)	0.5198	0.0883
Sitiawan	NS6	ARIMA (3,1,1)	AR(1)	0.0910	0.0127
			AR(2)	0.0246	0.0126
			AR(3)	-0.0184	0.0126
			MA(1)	-0.9557	0.0043
Kota Bharu	ES7	ARIMA (1,1,2)	AR(1)	0.5605	0.0322
			MA(1)	-1.3219	0.0367
			MA(2)	0.3249	0.0365
Kuala Terengganu	ES8	ARIMA (2,1,1)	AR(1)	0.2803	0.0125
			AR(2)	0.0915	0.0124
			MA(1)	-0.9849	0.0062
Cameron Highland	ES9	ARIMA (2,0,0)	AR(1)	0.4921	0.0261
			AR(2)	0.0305	0.0262
Kuantan	ES10	ARIMA (2,1,1)	AR(1)	0.0919	0.0118
			AR(2)	0.0675	0.0117
			MA(1)	-0.9770	0.0048
Subang	CS11	ARIMA (1,0,1)	AR(1)	0.9522	0.0291
			MA(1)	-0.9254	0.0355
Petaling Jaya	CS12	ARIMA (2,1,1)	AR(1)	0.0552	0.0155
			AR(2)	0.0343	0.0154
			MA(1)	-0.9513	0.0062
Sepang	CS13	ARIMA (1,1,1)	AR(1)	0.1224	0.0137
			MA(1)	-0.9888	0.0033
Melaka	SS14	ARIMA (1,1,2)	AR(1)	0.7459	0.0377
			MA(1)	-1.5496	0.0429
			MA(2)	0.5629	0.0401
Mersing	SS15	ARIMA (1,1,2)	AR(1)	0.6731	0.0362
			MA(1)	-1.4005	0.0408
			MA(2)	0.4196	0.0370

Table 4 *(Continued)*

Location	Station	Model	Coefficient	Estimates	Standard Error
Batu Pahat	SS16	ARIMA (1,1,2)	AR(1)	0.8653	0.0469
			MA(1)	-1.7653	0.0529
			MA(2)	0.7686	0.0517
Kluang	SS17	ARIMA (1,1,2)	AR(1)	0.7066	0.0524
			MA(1)	-1.5504	0.0580
			MA(2)	0.5648	0.0549
Senai	SS18	ARIMA (1,0,1)	AR(1)	0.9352	0.0214
			MA(1)	-0.8738	0.0301

After parameter estimation, the next step of the Box-Jenkins methodology is model diagnostic checking. In this step, the residual of a fitted ARIMA model was tested for the presence of serial autocorrelation and heteroscedasticity.

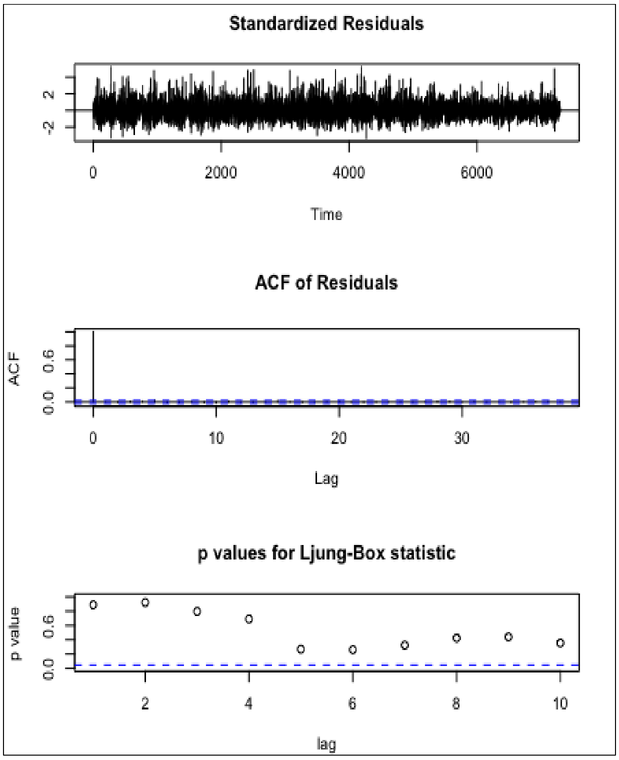


Figure 6. Diagnostic checking results for station NS1

Figure 6 shows the results of diagnostic checking using the Ljung-Box test for station NS1. The null hypothesis for the Ljung-Box test was set to be no serial autocorrelation in the residual of the fitted ARIMA (p, d, q) model. Based on the plot, the residuals of the wind speed series in station NS1 has a zero mean and constant variance. The ACF plot exhibits no correlation in the residuals of the series. The p-value for Ljung-Box test also confirmed that the residuals of the series were uncorrelated. This step was performed towards the remaining stations and the results are simplified in Table 5. The results of Ljung-Box test for the residuals in Table 5 are given into two parts; the figures represent the p-values for residuals up to lag 10 followed by the p-value for residuals up to lag 20. In addition, to prove that the square residuals are not a sequence of white noise, the Ljung-Box test was also performed on the squared residual of the wind speed series.

Table 5

The Ljung-Box test for the residuals and squared residuals of the fitted ARIMA (p, d, q) model of daily wind speed series

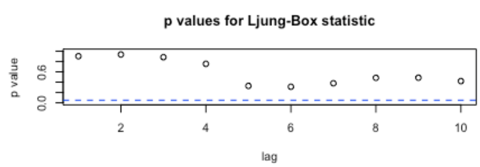
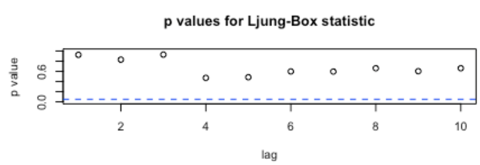
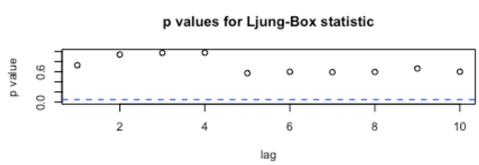
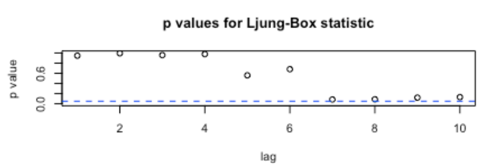
<table>
<tr><th rowspan="2">Station</th><th rowspan="2">ARIMA Model</th><th colspan="3">p-value for Ljung-Box Statistics</th></tr>
<tr><th colspan="2">Residuals</th><th>Squared Residuals</th></tr>
<tr><td>NS1</td><td>ARIMA (2,1,1)</td><td>
</td><td>0.4028</td><td>2.2e-16</td></tr>
<tr><td>NS2</td><td>ARIMA (1,0,1)</td><td>
</td><td>0.0011</td><td>2.2e-16</td></tr>
<tr><td>NS3</td><td>ARIMA (1,0,1)</td><td>
</td><td>0.7637</td><td>0.00167</td></tr>
<tr><td>NS4</td><td>ARIMA (1,1,2)</td><td>
</td><td>0.2838</td><td>2.2e-16</td></tr>
</table>

Table 5 *(Continued)*

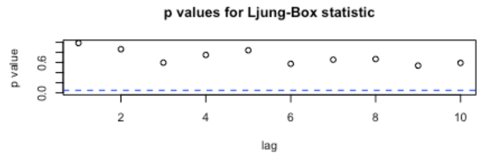
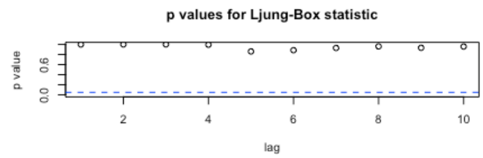
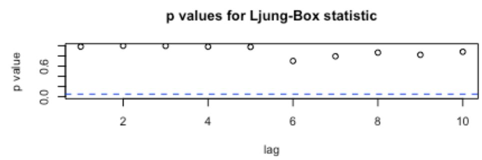
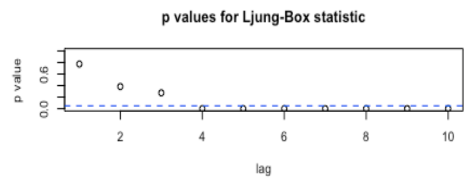
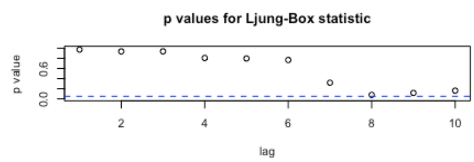
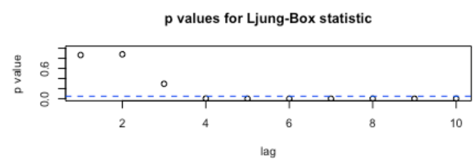
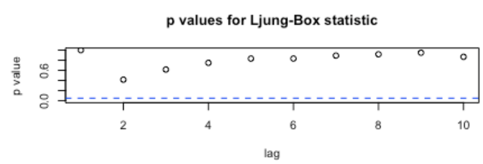
<table>
<tr><th rowspan="2">Station</th><th rowspan="2">ARIMA Model</th><th colspan="3">p-value for Ljung-Box Statistics</th></tr>
<tr><th colspan="2">Residuals</th><th>Squared Residuals</th></tr>
<tr><td>NS5</td><td>ARIMA (1,1,2)</td><td></td><td>0.211</td><td>0.4394</td></tr>
<tr><td>NS6</td><td>ARIMA (3,1,1)</td><td></td><td>0.8291</td><td>2.2e-16</td></tr>
<tr><td>ES7</td><td>ARIMA (1,1,2)</td><td></td><td>0.4634</td><td>2.2e-16</td></tr>
<tr><td>ES8</td><td>ARIMA (2,1,1)</td><td></td><td>0.0037</td><td>2.2e-16</td></tr>
<tr><td>ES9</td><td>ARIMA (2,0,0)</td><td></td><td>0.0608</td><td>0.01968</td></tr>
<tr><td>ES10</td><td>ARIMA (2,1,1)</td><td></td><td>0.0048</td><td>2.2e-16</td></tr>
<tr><td>CS11</td><td>ARIMA (1,0,1)</td><td></td><td>0.7672</td><td>0.985</td></tr>
</table>

Table 5 *(Continued)*

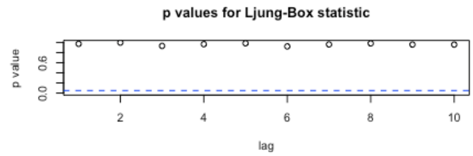
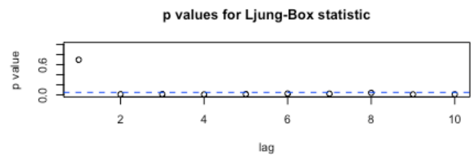
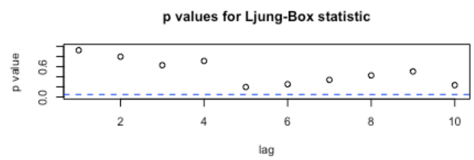
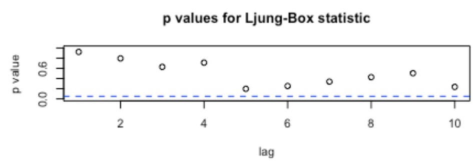
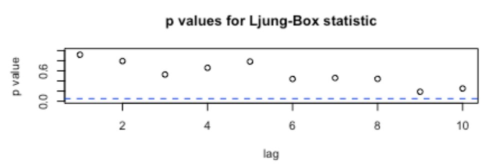
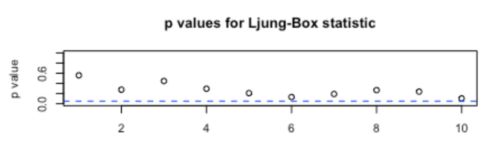
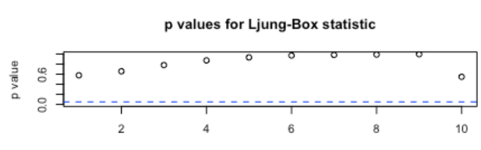
Station	ARIMA Model	p-value for Ljung-Box Statistics		
		Residuals		Squared Residuals
CS12	ARIMA (2,1,1)		0.9718	0.00294
CS13	ARIMA (1,1,1)		0.0486	0.00587
SS14	ARIMA (1,1,2)		0.1366	1.098e-13
SS15	ARIMA (1,1,2)		0.1366	1.098e-13
SS16	ARIMA (1,1,2)		0.3976	2.2e-16
SS17	ARIMA (1,1,2)		0.1932	2.2e-16
SS18	ARIMA (1,0,1)		0.6180	0.157

Table 5 shows that the p-values of the Ljung-Box test for stations NS2, ES8, ES10, and CS13 show a clear evidence to reject the null hypothesis of no serial autocorrelation. It means that the wind speed daily series in these stations shows the presence of autocorrelation in the residual of the series. Other stations did not show the presence of serial autocorrelation in the residual of the daily wind speed series. On the other hand, the Ljung-Box test for the squared residuals with a p-value less than 0.05 indicates the presence of ARCH effect in the residuals of the series. Based on the results presented in Table 5, three stations were found to be not affected by ARCH effect, which was station NS5, CS11, and SS18. The remaining 15 stations showed that the residuals were a sequence of white noise which also indicated the presence of ARCH effect in the daily wind speed series. Therefore, to conclude on the presence of heteroscedasticity in the series, the LM test was applied towards the residuals of the fitted ARIMA models and the result are presented in Table 6. The null hypothesis for this test is there is no ARCH effect presence in the residual of the models. For a p-value that is lower than 0.05, the null hypothesis is rejected which indicates that the model residuals significantly exhibit an ARCH effect.

Table 6

The LM test for the residuals of the fitted ARIMA (p, d, q) model of daily wind speed series

Station	ARIMA Model	Residuals	Squared Residuals
		p-value	p-value
NS1	ARIMA (2,1,1)	2.2e-16	1.928e-05
NS2	ARIMA (1,0,1)	1.029e-08	0.9162
NS3	ARIMA (1,0,1)	0.0449	0.0471
NS4	ARIMA (1,1,2)	2.2e-16	0.0110
NS5	ARIMA (1,1,2)	0.4922	1
NS6	ARIMA (3,1,1)	2.2e-16	2.2e-16
ES7	ARIMA (1,1,2)	2.2e-16	0.9999
ES8	ARIMA (2,1,1)	2.2e-16	0.2241
ES9	ARIMA (2,0,0)	0.0414	0.9448
ES10	ARIMA (2,1,1)	2.2e-16	0.9847
CS11	ARIMA (1,0,1)	0.9865	1
CS12	ARIMA (2,1,1)	0.0056	0.9338
CS13	ARIMA (1,1,1)	0.0175	0.9995
SS14	ARIMA (1,1,2)	3.228e-06	0.5071
SS15	ARIMA (1,1,2)	2.997e-11	1
SS16	ARIMA (1,1,2)	2.834e-16	0.3848

Table 6 *(Continued)*

Station	ARIMA Model	Residuals	Squared Residuals
		p-value	p-value
SS17	ARIMA (1,1,2)	2.2e-16	0.0007
SS18	ARIMA (1,0,1)	0.1865	1

The results in Table 6 show that the 3 stations; NS5, CS11, and SS18 were not affected by the heteroscedasticity effect based on the p-values of the residuals of the LM test. This was also supported by the Ljung-Box test in Table 5 for squared residuals. Hence, it can be concluded that the proposed ARIMA model for these 3 stations are suitable for forecasting the daily wind speed series in the respective location. On the other hand, the remaining 15 stations verify that the ARCH effect was established in the wind speed daily series for these stations. Therefore, to cater the issue of the presence of serial autocorrelation and ARCH effect in the residual of fitted ARIMA (p, d, q) model, GARCH modelling is necessary to model the nonlinear part of the daily wind speed series.

ARIMA-GARCH Modelling

The ARIMA model explains the linear part of the data, while the nonlinear characteristics is explained using the GARCH model which is derived based on the residual series of an ARIMA model. In this study, the method used to model the variance behavior was using the standard GARCH (1,1) model.

Table 7

The result for the estimated ARIMA-GARCH model for wind speed data in Malaysia

Station	Model	Parameter Estimates				Ljung-Box Test	LM Test
		μ	ω	α	β	p-value	p-value
NS1	ARIMA (2,1,1) – GARCH (1,1)	0.0053	0.3363	0.0975	0.8176	0.0521	0.0131
NS2	ARIMA (1,0,1) – GARCH (1,1)	8.1178	1.0888	0.1384	0.6731	0.9053	0.9722

Table 7 *(Continued)*

Station	Model	Parameter Estimates				Ljung-Box Test	LM Test
		μ	ω	α	β	p-value	p-value
NS3	ARIMA (1,0,1) – GARCH (1,1)	8.4873	0.3458	0.0638	0.8489	0.9762	0.9510
NS4	ARIMA (1,1,2) – GARCH (1,1)	0.0003	0.0645	0.0258	0.9615	0.0000	0.1256
NS6	ARIMA (3,1,1) – GARCH (1,1)	0.0018	0.0936	0.0362	0.9376	0.2195	0.0812
ES7	ARIMA (1,1,2) – GARCH (1,1)	-0.0010	0.2578	0.1092	0.8551	0.0077	0.0902
ES8	ARIMA (2,1,1) – GARCH (1,1)	-0.0020	0.1026	0.1191	0.8763	0.0000	0.0007
ES9	ARIMA (2,0,0) – GARCH (1,1)	7.7551	1.7030	0.1552	0.4489	0.6530	0.3274
ES10	ARIMA (2,1,1) – GARCH (1,1)	0.0017	0.0707	0.0543	0.9390	0.7439	0.5164
CS12	ARIMA (2,1,1) – GARCH (1,1)	0.0005	1.6691	0.0647	0.6595	0.4033	0.4569
CS13	ARIMA (1,1,1) – GARCH (1,1)	0.0002	0.0795	0.0169	0.9655	0.6070	0.7862

Table 7 *(Continued)*

Station	Model	Parameter Estimates				Ljung-Box Test	LM Test
		μ	ω	α	β	p-value	p-value
SS14	ARIMA (1,1,2) – GARCH (1,1)	0.0004	0.0115	0.0124	0.9853	0.0119	0.3177
S S15	ARIMA (1,1,2) – GARCH (1,1)	-0.0011	1.5383	0.1468	0.6303	0.13388	0.22325
S S16	ARIMA (1,1,2) – GARCH (1,1)	0.0000	0.2179	0.0679	0.8831	0.7664	0.4526
S S17	ARIMA (1,1,2) – GARCH (1,1)	0.0001	0.0103	0.0294	0.9691	0.14448	0.7983

Table 7 gives the result of the ARIMA-GARCH model. The mean behaviour of the daily wind speed series was modelled using ARIMA model, while the standard GARCH (1,1) model captured the conditional variance in the residuals of the series. In this case, the GARCH model was used to cater the existence of the ARCH effect in the residual of daily wind speed series. The diagnostic checking was conducted once again on the ARIMA-GARCH model. The Ljung-Box test was used to check the presence of serial autocorrelation in the standardized squared residuals from the GARCH model. Based on the p-values in Table 7, it can be concluded that the serial autocorrelation no longer existed in the model except for 4 stations which were NS4, ES7, ES8, and SS14. The test was performed on the residuals of the hybrid model using the LM test to investigate the existence of remaining ARCH effect in the residuals of the model. The results in Table 7 prove that there was still ARCH effect in stations NS1 and ES8. For the stations NS2, NS3, NS6, ES9, ES10, CS12, CS13, SS15, SS16, and SS17, there was enough evidence to conclude that the daily wind speed series were free from the conditional heteroscedasticity. This shows that the ARIMA-GARCH model has precisely captured the dynamics in the wind speed daily series. However, further investigation should be done to treat the presence of serial autocorrelation in time series data collected from the stations NS4, ES7, ES8, and SS14, and the presence of ARCH effect in time series data collected from the stations NS1 and

ES8 using other type of GARCH family models since it has proven to be very successful in describing the volatility dynamics in a short period of time (Jamaludin et al., 2016).

Forecasting Capabilities using ARIMA Model and ARIMA-GARCH Model

The performance of the proposed model was tested based on the capability of forecasting future daily wind speed series. The model was built using the in-sample data and then was projected for 365 days ahead. This forecasted series that is estimated based on the best fitted model was compared with the last 365 of out-sample data and the accuracy of the forecasting model was evaluated from the RMSE and MAPE values where the lowest value indicates a better performance. The results of RMSE and MAPE between the in-sample and out-sample data are given in Table 8. Forecasting interpretation based on Table 1 is also included in the Table 8.

Table 8

The result of forecast accuracy using RMSE and MAPE and forecasting interpretation

Station	Model	In-Sample		Out-Sample		Forecasting Interpretation
		RMSE	MAPE	RMSE	MAPE	
NS2	ARIMA (1,0,1) - GARCH (1,1)	2.4554	23.7161	2.3163	23.7408	Reasonable
NS3	ARIMA (1,0,1) - GARCH (1,1)	1.9921	16.907	2.1799	16.3708	Good
NS5	ARIMA (1,1,2)	1.4156	13.7443	1.4401	15.4814	Good
NS6	ARIMA (3,1,1) - GARCH (1,1)	1.4584	13.7489	1.3166	15.2564	Good
ES9	ARIMA (2,0,0) - GARCH (1,1)	2.1346	19.8658	2.3821	20.3147	Reasonable
ES10	ARIMA (2,1,1) - GARCH (1,1)	1.8198	14.9371	1.6481	14.0077	Good

Table 8 *(Continued)*

Station	Model	In-Sample		Out-Sample		Forecasting Interpretation
		RMSE	MAPE	RMSE	MAPE	
CS11	ARIMA (1,0,1)	2.1572	18.8206	1.7758	17.3518	Good
CS12	ARIMA (2,1,1) - GARCH (1,1)	1.9336	17.2430	1.8117	15.9246	Good
CS13	ARIMA (1,1,1) - GARCH (1,1)	1.5761	14.8005	1.8743	14.3288	Good
SS15	ARIMA (1,1,2) - GARCH (1,1)	1.9593	15.0709	1.7438	13.7584	Good
SS16	ARIMA (1,1,2) - GARCH (1,1)	1.5367	14.8042	1.3239	13.3581	Good
SS17	ARIMA (1,1,2) - GARCH (1,1)	1.6702	16.0472	1.2368	13.4531	Good
SS18	ARIMA (1,0,1)	2.0314	19.685	1.9686	17.7601	Good

Table 8 shows that the proposed model could forecast the daily wind speed series where the values of RMSE and MAPE of the out-sample data followed closely the in-sample data for ARIMA model and ARIMA-GARCH model. The values of MAPE for the proposed model shows that 11 out of 13 station (85%) gave good forecasts while the other 2 stations (15%) forecasted reasonably well as mentioned in Lewis (1982). Figure 7 shows the distribution of the best fitted model for 13 locations of wind stations in Peninsular Malaysia.

Table 9 shows that the ARIMA and ARIMA-GARCH model could modelled most of the stations in the northern, east coast, central and southern regions. There were 3 stations (16.68%) in the northern, central, and southern regions that could be modelled using ARIMA modelling. For ARIMA-GARCH modelling, 10 stations (55.56%) out of 18 were able to be modelled using the hybrid model. This shows that 13 stations (72.24%) out of 18 wind stations in Peninsular Malaysia were successfully modelled using a time series modelling. These results have proven the ability of the proposed models for wind speed forecasting and may be used to predict the future pattern of daily wind speed series in Peninsular Malaysia. The results of wind speed prediction can be used to provide a quantitative measure of wind energy available in the potential location for renewable energy conversion (Barbosa de Alencar et al., 2017). Further studies are required for the remaining 5 stations (27.78%) that give a non-conclusive result due to failure in modelling the volatility of the daily wind speed using both ARIMA and ARIMA-GARCH.

To check the forecasting performance of ARIMA-GARCH modelling, the 3 stations that had an adequate model of ARIMA was tested once again using ARIMA-GARCH. The forecasting accuracy measure as mentioned in Lewis (1982) for the out-sample for each station are illustrated in Table 10.

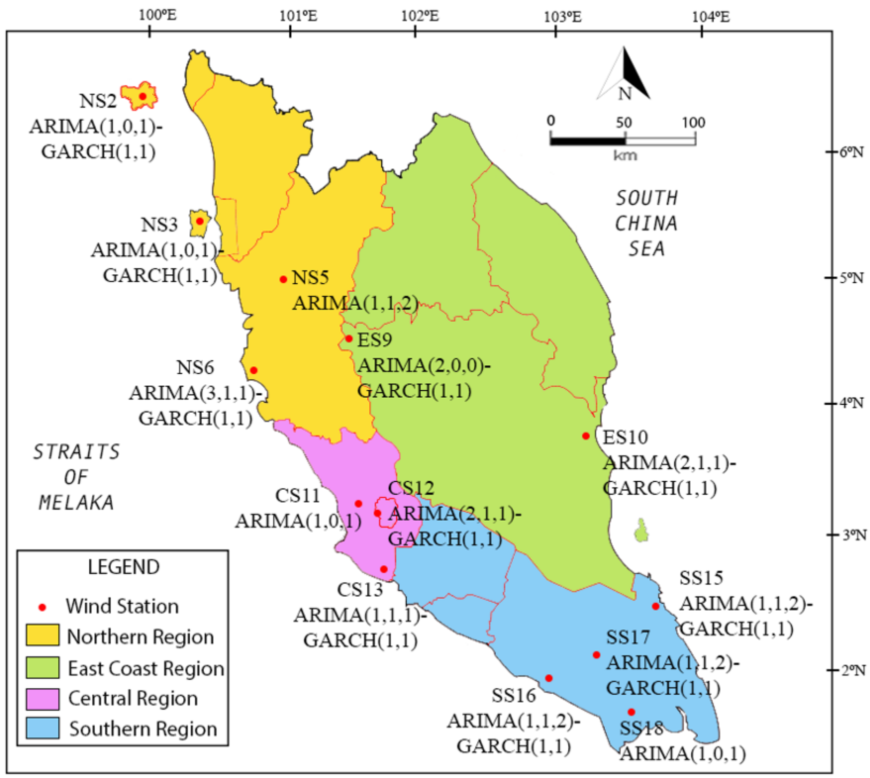


Figure 7. Results of ARIMA and ARIMA-GARCH models

Table 9

Percentage of proposed model based on region of wind stations

Region	Total Station	ARIMA		ARIMA-GARCH		Non- Conclusive	
		Station	Percent	Station	Percent	Station	Percent
North	6	1	5.56%	3	16.67%	2	11.11%
East Coast	4	0	0%	2	11.11%	2	11.11%
Central	3	1	5.56%	2	11.11%	0	0%
South	5	1	5.56%	3	16.67%	1	5.56%
Total	18	3	16.68%	10	55.56%	5	27.78%

Table 10

The result of forecasting performance of ARIMA-GARCH modelling

Location	Station	ARIMA		ARIMA-GARCH		Forecasting Interpretation
		RMSE	MAPE	RMSE	MAPE	
Lubok Merbau	NS5	1.4401	15.4814	1.4529	15.6325	Good
Subang	CS11	1.7758	17.3518	1.7697	16.6947	Good
Senai	SS18	1.9686	17.7601	2.0671	17.6552	Good

Based on these results, it shows that even though the ARIMA model has proven to be adequate in modelling these 3 stations, the ARIMA-GARCH modelling also gives a good forecasting accuracy based on the forecasting interpretation by Lewis (1982). These models can be used in forecasting the daily wind speed in the wind station with a good forecasting result.

CONCLUSION AND FUTURE WORK

This study led to the construction of a time series model of daily wind speed series of 18 meteorological stations in Peninsular Malaysia. The Box-Jenkins ARIMA modelling was used to build a model of wind speed series for each station. In measuring the adequacy of the proposed ARIMA model, 3 stations: NS5, CS11, and SS18, were proven to be suitable for forecasting the wind speed series using the ARIMA model while the 15 other stations are affected by the presence of serial autocorrelation as well as ARCH effects. To overcome the issue, we used the ARIMA-GARCH model for 15 stations. The results show that 10 stations were successfully modelled using the ARIMA-GARCH model while 5 stations required other methods of modelling. Future work is needed to improve the limitation of the ARIMA-GARCH model for the remaining 5 stations. As for the 13 stations that had successfully been modelled using the time series, future work can be done by calculating the wind power density of each stations in Peninsular Malaysia in order to provide a quantitative measure of wind energy available in the potential location for renewable energy conversion.

ACKNOWLEDGEMENT

The authors would like to acknowledge Universiti Teknikal Malaysia Melaka, Universiti Teknologi Malaysia, and those who gave support in carrying out this research under the grant vote number Q.J130000.2654.17J30.

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