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Handling Volatility and Nonlinearity in Wind Speed Data: A Comparative Analysis between ARIMA-GARCH and ARIMA-MLP

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ABSTRACT

One of the notable features of wind speed is its volatility and nonlinearity. Thorough assessment on the presence of these features is crucial to obtain a wind speed forecasting model with higher accuracy. In this study, the conventional time series linear model; ARIMA model was applied to assess the internal structure of the wind speed daily data in two stations in Johor; Senai and Mersing. Due to the existence of some nonlinearity features in the residuals part of ARIMA modelling, two nonlinear models were introduced to capture the internal structure of the residual data. Both conventional time series models; GARCH, and machine learning model; MLP was applied to model the residuals of ARIMA model. The out-sample performance in forecasting accuracy was compared between the ARIMA-GARCH model and the ARIMA-MLP model. The findings proves that MLP model has outperformed GARCH model in capturing the dynamics in the residual data by providing the lowest error measurements. Thus, the machine learning approaches has proven its superiority against the conventional time series nonlinear model in handling the nonlinearity in the daily wind speed series for wind speed forecasting.

1. Introduction

Due to its many advantages in terms of economy and environmental friendliness, wind power becoming one of the most important and effective renewable energy resources. In addition to being readily available and cost-free, it also makes a significant contribution to protect the non-renewable energy resources, reducing air pollution, and managing the carbon monoxide emission [1]. Time series analysis have been extensively utilized in wind speed forecasting, where it can help to assess the internal structure of the wind speed data. Volatility, or variations in variance over time, and

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nonlinearity are some basic properties of wind speed data that is of great concern. These phenomena has a significant impact on wind power generation, but not enough research has been done on it [2].

Numerous methodologies, including statistical, physical, and hybrid approaches, can be used to forecast wind speed [3]. The statistical technique, that includes the time series models and machine learning models, is the most often used method for creating prediction models for wind speed data. The auto regressive moving average (ARMA) and auto regressive integrated moving average (ARIMA) models are two examples of the Box-Jenkins method for linear time series models. On the other hand, the machine learning models includes the multilayer perceptron (MLP) and support vector regressions (SVR), are commonly used nonlinear forecasting models.

Even though the ARIMA time series model is widely known to be powerful and flexible, there have been situations where the internal structure in the wind speed series have prevented the ARIMA model from producing an adequate model. Since ARMA and ARIMA model assume the data are linear, there are some limitation in the performance especially in handling the real-world time series data that are commonly known for the existence of linear and nonlinear patterns [4]. The Box-Jenkins ARIMA model is a frequently used linear model that was used as a benchmark model in investigating the internal structure of a time series data. This model can be widely utilized for wind speed forecasting and can generate precise forecast values when the data has distinctive linear properties.

Strong nonlinearities, on the other hand, need the use of nonlinear models to explain the relationship between input and output data, and these models typically produce predictions that are more accurate than those produced by linear models. Henceforth, a hybrid technique that integrate different model through error series modelling are developed to address the challenges associated with model selection and design with minimal additional work. The combination of linear and nonlinear models will help to significantly increase the forecasting accuracy on the model since it is capable of capturing the specific criteria in the time series data [5].

To handle the presence of volatility and nonlinearity, many researchers have adopted the generalized autoregressive conditional heteroskedasticity (GARCH) models, which is one of the nonlinear time series model, in their efforts to model wind speed data. It has also been demonstrated that combining GARCH with ARMA or ARIMA can significantly improve the model's estimation and forecasting accuracy. To account for the volatility existence in the ARIMA model, Xiang, [6] applied the ARIMA-GARCH model and the finding proved that the combination of ARIMA and GARCH model have provided a higher forecasting accuracy. While Huang and Gu, [7] analysed the time-varying standard deviation of the nonstationary wind speed data using the ARMA-GARCH model and the finding shows that combining these models have significantly improve the forecasting accuracy of the model.

Although time series models are frequently employed in the construction of forecasting models, some researchers have come to the conclusion that the existing time series models are unable to handle the volatility and nonlinear properties [8-10]. In the past few years, a number of research have suggested to combine the machine learning model, which is the nonlinear forecasting model, with the time series model to anticipate the dynamic fluctuations of meteorological variables like wind speed data. Computer intelligence is able to solve difficult nonlinear issues thanks to machine learning techniques. A hybrid wind speed prediction technique based on the ARIMA and artificial neural network (ANN) models is presented by Jiao [11]. The ARIMA-ANN model performs better than the other two in the three prediction tests that were conducted using the ANN, ARIMA, and ARIMA-ANN models. While Junior *et al.*, [12] selected two nonlinear machine learning model; MLP and SVR models, to be combined with the linear time series model; ARIMA model, in order to capture both linear and nonlinear criteria in the real-world time series data.

The main contribution of this paper is a hybrid wind speed forecasting models, that aims to explore the moist suitable combination of linear and nonlinear models that are capable in capturing the dynamics in the time series data and provides the best forecasting model. Firstly, ARIMA model will be the benchmark model in investigating the internal structure of a time series data. Any presence of volatility and nonlinearity in the residuals of ARIMA model will indicate the incapability of the model in capturing the dynamics of the wind speed data. Therefore, this study selected two nonlinear forecasting models; GARCH and MLP models, to handle any presence of volatility or nonlinearity criteria in the wind speed data. In this step, the residuals obtained from ARIMA models are modelled and forecasted using the GARCH and MLP model. Finally, the forecasts values from ARIMA will be combined with the forecasts of residuals from GARCH and MLP model, respectively, will results in the hybrid of ARIMA-GARCH and ARIMA-MLP model. The performance of each models will be compared based on the forecasting performance measure. The model with the lowest error measurements will be selected as the best model, which will conclude the superiority of the model in handling the dynamics in the wind speed data.

2. Methodology

2.1 Study Area and Data Description

This study employed the daily wind speed data collected from Malaysia Meteorological Department (MMD) at two stations in Peninsular Malaysia; Mersing and Senai, Johor. Senai wind station is situated in the airport area, whereas Mersing wind station is in the Mersing district particularly coastal area. Before any analysis is performed, the data series will be pre-processed to capture the presence of any missing values that is common problem in the real-world time series data collection.

Managing missing data is crucial because it can cause uncertainty in the data analysis process by impacting statistical estimators' properties, such as means and variances, and it can result in a loss of power and incorrect conclusion [13]. The typical method to handle the existence of missing values in time series data is the mean imputation method. This technique functions by substituting the mean of the available wind speed data for the missing value that exists at a specific wind station.

In time series data analysis, the descriptive analysis helps to determine overall structure of the datasets. The descriptive statistics will emphasise the internal criteria in the data of wind speed series. It gives the central tendency properties, which include the mean value, the standard deviation value, which represents the dispersion of a data, and the data distribution, which includes the value of skewness. The average wind speed recorded at each station are given by the mean value. The deviation of data from the mean can be obtained by calculating the value of standard deviation. While the distribution of the data can be explained by the skewness value. These three descriptive statistics values can be expressed in the following way:

$$\text{Mean}, \bar{v} = \frac{1}{n}\sum_{i=1}^{n} v_i \tag{1}$$

$$\text{Standard deviation}, s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(v_i - \bar{v})^2} \tag{2}$$

$$\text{Skewness} = \frac{1}{n \times s^3}\sum_{i=1}^{n}(v_i - \bar{v})^3 \tag{3}$$

where *n* is the sample size, v_i represents the observed value of wind speed data with regards to *I*, whereas $\bar{v}$ and s are the mean and standard deviation, respectively.

2.2 Linear Modelling
2.2.1 ARIMA model

The Box-Jenkins approach, often known as the autoregressive integrated moving average (ARIMA) model, is commonly used in statistical time series modelling to develop a model to forecast future wind speed. In general, the mathematical representation of ARIMA (*p, d, q*) model can be expressed as follows:

$$\varphi(B)(1-B)^d v_t = \theta(B)\varepsilon_t \tag{4}$$

Here, v_t is the empirical wind speed values and ε_t represents the term of random error at time *t*. φ_1, φ_2, φ_3,..., φ_p are the coefficient of autoregressive (AR) of order p, and θ_1, θ_2, θ_3,..., θ_q are the coefficient of moving average (MA) of order q. d is the differencing order. While, $\varphi(B) = 1 - \sum_{i=1}^{p} \varphi_i B^i$ and $\theta(B) = 1 - \sum_{j}^{q} \theta_j B^j$ are the polynomials of order *p* and *q*, respectively, where *B* is the backward shift operator. Hence, the combination of AR and MA with differencing order *d* will form an ARIMA (*p, d, q*) model as such):

$$v_t = \mu + \varphi_1 v_{t-1} + \varphi_2 v_{t-2+} \dots \varphi_p v_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q} \tag{5}$$

There are three procedure in modelling using the Box-Jenkin ARIMA (*p, d, q*):

i. Model identification. The variables must be checked for stationarity and seasonality in this stage. The ACF and PACF plots were then examined to determine which component should be included in the model.
ii. Parameters estimation. This stage is carried out to acquire the best coefficient for the selected ARIMA model using the computational approach based on the maximum likelihood estimation (MLE) method. To select the most appropriate ARIMA (*p, d, q*) model, the parsimonious model will be chosen based on the model with the lowest AIC value [14].
iii. Diagnostic checking. This stage will assess the adequacy of the chosen model by determining whether the estimated model meets the stationary univariate method specifications.

The diagnostic checking part will, the internal structure of a time series data will be determined. To assess the presence of serial correlation and volatility in the data series, the Ljung-Box Q statistics can be tested on both residuals and squared residuals, respectively [15]. The results can be confirmed by running the ARCH Lagrange Multiplier (LM) test to look for any evidence of a volatility in the fitted model's residual data. The formulation for Ljung-Box Q statistics and ARCH (LM) test are shown in Eq. (6) and Eq. (7), respectively.

$$Q = T(T+2)\sum_{k=1}^{L} \frac{r_k^2}{(T-k)} \tag{6}$$

$$\varepsilon_t^2 = \hat{a}_0 + \sum_{s=1}^{q} \hat{a}_s \varepsilon_{t-s}^2 \tag{7}$$

2.3 Nonlinear Time Series Model
2.3.1 Generalised Autoregressive Conditional Heteroscedastic (GARCH) model

The Generalised Autoregressive Conditional Heteroscedastic (GARCH) model is essentially a generalisation of Bollerslev's (1986) ARCH model. The generic version of the GARCH (r, s) model for conditional heteroscedasticity can be written as $y_t = \mu_t + \varepsilon_t$, where μ_t is the conditional mean for y_t, while ε_t is the shock at time *t,* as such; $\varepsilon_t = \sigma_t z_t,\ z_t \sim iid\ N(0,1)$. Here, the variance equation for GARCH (r,s) model can be expressed as:

$$\sigma_t^2 = \propto_0 + \sum_{i=1}^{r} \propto_i \varepsilon_{t-i}^2 + \sum_{i=1}^{s} \beta_i \sigma_{t-i}^2 \tag{8}$$

where $\propto_0 > 0$ and $\sum_{i=1}^{\max(p,q)} (\propto_i + \beta_i) < 1$. $\propto_i$ are the parameters coefficient for ARCH and β_i are the parameters coefficient for GARCH. In a situation where all values of the coefficient β are zero, ARCH model will replace the GARCH model.

2.3.2 ARIMA-GARCH model

To develop the ARIMA-GARCH model, there are two main procedures that can be considered. At the beginning, the linear component is estimated using ARIMA model and followed by obtaining the residual series, ε_t, as in Eq. (4) [16]. In the second stage, the GARCH model is employed to model the residuals that solely include the nonlinear pattern. The ARIMA model is hybridised with the GARCH model's error component, resulting in a model that is known to be capable of handling the internal structure in the wind speed daily data and predicting the future datasets of wind speed series. Based on past literatures [17,18], the GARCH (1, 1) is the simplest form of GARCH model. Henceforth, the GARCH (1,1) will be applied in this study to model the residuals of ARIMA model in capturing any internal structure exist in the error term of the ARIMA model.

2.4 Machine Leaning Model
2.4.1 Data pre-processing

Data division is an important stage in the modelling process, where this method is classified as supervised or unsupervised [19]. There are no standardised rules for partitioning data into training, validation, and test sets. Most studies divide data in one of two ways: based on domain expertise or arbitrarily [20]. The training set is part of the model fitting, where it serve as the sample data. The validation set is the collection of data that is set apart when the training is performed. The validation set are known to helps in two ways; (i) model performance assessment while model training is performed, (ii) aid in the selection of the best parameter for the machine learning model [21]. The validation procedure provides information that can be used to fine-tune the model's hyperparameters, preventing overfitting. Lastly, the testing set is applied for the evaluation of the model's ability to generalise, and its error from the testing set can be utilize as the tool to compare the performance of other prediction models. Consequently, the machine learning model in this study are divided into three groups; 60% training sets, 20% validation sets, and 20% testing sets.

2.4.2 Multilayer Perceptron (MLP) Model

A basic feed forward neural network model, sometimes referred to as a three-layer multilayer perceptron (MLP), should be assessed before going on to a more sophisticated model. One popular feed-forward artificial neural network (ANN) for wind speed forecasting is the MLP model. It consists of at least three layers, each of which consists of units stacked in layers: the input layer, one or more hidden layers, and the output layer. The nodes of the hidden layer process the input values that are received by the first layer, the input layer. The output layer will then produce the desired output after this [22]. The MLP model's processing elements are all recognised as interconnected nodes connected by flexible weights. Each node receives input signals, which are essentially the output of other nodes. Each node's output in this case is determined by the weighted input, bias, and activation function. Figure 1 illustrated a simple MLP network that consist of one input layer, one hidden layer, and 1 output layer.

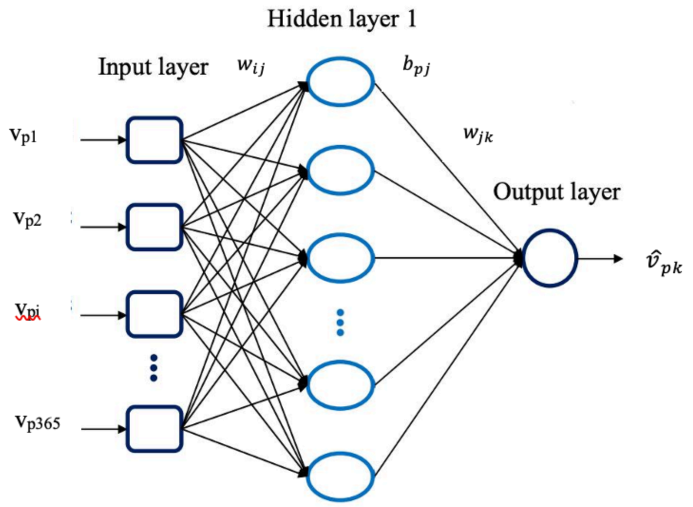


Fig. 1. The MLP architecture of one hidden layer with one prediction output

The formulation applied to come up with the output value b_{pj}, by the hidden layer, based on input pattern V_{pN} : v_{p1}, v_{p2},..., v_{pN} can be express as follows:

$$b_{pj} = f_j\left(\sum_{i=1}^{N} w_{ij} \cdot v_{pi} + \epsilon_j\right) \tag{9}$$

where f is the activation function for hidden neuron, w_{ij} is the connection weight for input neuron *i* and hidden neuron *j*, v_{pi} is the input signal based on input neuron *i* for pattern *p*, and ϵ_j represents the threshold for hidden neuron *j*.

The mathematical formulation for the output in output neurons are similar to the neurons in the hidden layer which is:

$$\hat{v}_{pk} = f_M\left(\sum_{j=1}^{L} w_{jk} \cdot b_{pj} + \epsilon_k\right) \tag{10}$$

where $\hat{v}_{pk}$ are the output signal based on output neuron *k* for pattern *p*, f_M are the activation function for output neuron *M*, w_{jk} are t the connection weight for hidden neuron *j* and output neuron *k*, b_{pj} is the output signal from hidden neuron *j* for pattern *p*, and ϵ_j represents the threshold of output neuron *k*.

The training parameters for number of inputs, number of hidden neurons, activation function, loss function, optimizer, learning rates, batch size, and number of epochs, are determined based on the previous literatures. The selected parameter values will be tested according to the trial-and-error basis [23]. The training parameters used in modelling using the MLP is summarized in Table 1.

Table 1
The training parameters for the MLP model

Parameter	Descriptions
Number of Input	365-day time steps [24,25]
Number of Hidden Neurons	32, 64, 128, 256, 512 [26]
Loss function	Mean squared error loss [27]
Optimizer	Adam optimizer [28]
Activation function	Rectified linear unit (ReLU)
Learning Rates	0.001 [29]
Batch Size	512 [25]
Epochs	Range between 100 to 500 [30]

2.3.4 ARIMA-MLP model

A hybrid model is, in general, an attempt to integrate linear and nonlinear models into one. With ARIMA and MLP, a number of researchers have developed a hybrid model based on the idea of separating the model for linear and nonlinear components of time series. Zhang's [31] hybrid technique is a popular method for creating a hybrid model for prediction. It can be broadly stated as follows:

$$v_t = L_t + N_t \tag{11}$$

where the linear and nonlinear components, respectively, are computed from wind speed data and denoted by L_t and N_t. In this study, the ARIMA model will extract the linear component, and the residuals, ε_t from the linear model will only contain nonlinear component, which may be expressed as follows:

$$\hat{v}_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i v_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{12}$$

where $\hat{L}_t$ is estimated by the ARIMA model at time *t* and is applied to calculate the residual series. The next step is to performed a nonlinear modelling with the aim to capture the nonlinear patterns from the residuals ε_t using the MLP model to form:

$$\varepsilon_{tMLP} = f_{MLP}(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-n}) + \epsilon_{tMLP} \tag{13}$$

At this point, f_{MLP} represented the nonlinear functions for MLP with *n* input and ϵ_{tMLP} is the error term. To obtain the final model of ARIMA-MLP, the out-sample forecast from MLP, $\widehat{N}_{tMLP}$ was added up with the forecasted value from ARIMA model, $\hat{L}_t$ to form a combined forecast as below:

$$\hat{v}_{t-MLP} = \hat{L}_t + \widehat{N}_{tMLP} \tag{14}$$

The development of the ARIMA-MLP model can be done in two steps, to sum up the hybrid methodologies from [31]. To capture the linear component of the series, the wind speed dataset will first be fitted to the ARIMA model. Second, the predicted value will be obtained by feeding the ARIMA model's residuals into the MLP model. In order to get the combined forecast, the forecast values of residuals from MLP will then be added to the values predicted by the ARIMA model to produce ARIMA-MLP model.

2.5 Forecasting Performance Measure

To conclude the superiority of the selected nonlinear models, the difference between the observed and predicted wind speed series will be calculated. The RMSE, MAE, and MAPE are used to assess forecasting performance. The equations are written as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\widehat{v_\iota} - v_i)^2} \tag{15}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|(\widehat{v_J} - v_i)\right| \tag{16}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|(\widehat{v_J} - v_i)\right|}{v_i} \tag{17}$$

where v_t and $\hat{v}_t$ represents the empirical and theoretical wind speed daily data sets, while *n* denotes the sample data. Here, model with lowest error measurements from RMSE, MAE, and MAPE will then be selected as the most promising model, which concluded its superiority in capturing the nonlinearity in the wind speed data.

3. Results

3.1 Descriptive Statistics

Prior to doing exploratory data analysis, the wind speed data underwent pre-processing. It was observed that only a tiny proportion of missing values, specifically less than 5%, were present in the wind speed data series for each station. Consequently, the absent data values in each dataset were approximated using the Mean Imputation method. Subsequently, the wind speed data is analysed, and the descriptive statistics for each dataset are presented in Table 2.

Table 2
The statistical descriptive of daily wind speed data

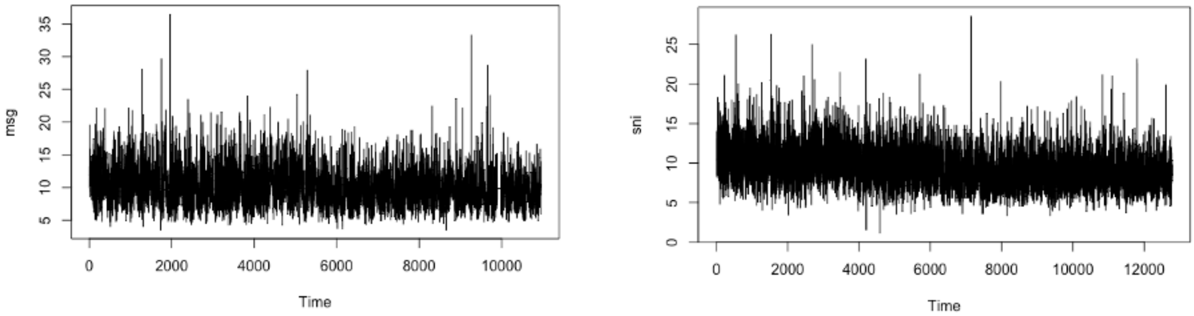
Station	Mean	Standard Deviation	Skewness
Mersing	9.892	2.784	1.128
Senai	9.228	2.354	0.881

From the results presented in Table 2, the mean of wind speed for Mersing and Senai stations can be categorized in a high range speed. The standard deviation also shows that the wind behavior for both stations is in a good consistency. A skewness value serves as an indicator of the direction in which outliers are present. When the skewness is positive, the outliers are located more to the right and closer to the mean on the left side.

It also suggests that a distribution has exceptional values towards its positive end. A highly skewed distribution is shown by Mersing stations, which produced a skewness value of more than one. Senai, on the other hand, seems to be somewhat skewed, with a skewness level between 0.5 and 1. When data points favour one side of the distribution, the underlying data have a high degree of skewness. This indicates that there are more outliers in the wind speed data, with a higher percentage of extreme values recorded on a higher scale.

3.2 ARIMA Modelling

As part of the Box-Jenkins methodology, a time series plot is generated to assess the presence of seasonality or trend in the data series. The charts in Figure 2 indicate that the wind speed series does not exhibit discernible trend or seasonality, as it remains consistently variable rather than fluctuating at a consistent level.



(a) (b)

Fig. 2. The time series plot for station in (a) Mersing and (b) Senai

Subsequently, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is employed to assess the stationarity of the time series. The unit root test results for Mersing and Senai stations indicate that both data series are non-stationary, as evidenced by a p-value that is less than 0.01 for the KPSS test shown in Table 3.

Table 3
The KPSS test for stationarity

Station	Observed Data			First Differencing		
	KPSS Level	p-value	Stationary	KPSS Level	p-value	Stationary
Mersing	7.381	< 0.01	NO	0.0012	> 0.1	YES
Senai	44.949	< 0.01	NO	0.0012	> 0.1	YES

This is further corroborated by the consistent decline observed in the ACF plots for both sites. In order to address the issue of nonstationarity, it is necessary to apply differencing to obtain datasets that exhibit stationarity. The KPSS test yields a p-value of more than 0.1 for station Mersing and Senai after applying the first differencing. This implies that the series, after being differenced once, exhibits stationarity.

This conclusion is additionally reinforced by the ACF plot, which exhibits a rapid decline to zero. The ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots are utilised to determine the appropriate component to include in the ARIMA model once the series achieves stationarity after differencing. The plots demonstrate that, for d=1, the possible combinations are p=0, 1, 2 and q=0, 1, 2. The study reveals that the Mersing station's ARIMA (1, 1, 2) and the Senai station's ARIMA (2, 1, 2) exhibit the lowest AIC values as shown in Table 4. Henceforth, the final ARIMA model for Mersing station is ARIMA (1, 1, 2), while Senai station is ARIMA (2, 1, 2).

Table 4
The AIC value for the potential ARIMA models

Tentative ARIMA Model	AIC values	
	Mersing	Senai
ARIMA (0,1,1)	42027.05	45513.70
ARIMA (0,1,2)	41802.27	45470.85
ARIMA (1,1,0)	43521.38	48895.63
ARIMA (2,1,0)	42962.31	47782.52
ARIMA (1,1,1)	41728.66	45466.96
ARIMA (1,1,2)	**41628.48**	45427.25
ARIMA (2,1,1)	41640.57	45452.07
ARIMA (2,1,2)	41630.35	**45422.91**

In order to determine the appropriateness of the potential model, diagnostic checks will be performed on both of these models. Table 5 shows that the residual of the ARIMA model in both stations do not possesses any serial correlation.

The Ljung-Box test results on the squared residual from Table 5 suggest the existence of a volatility effect in the residual data from the ARIMA model, as well as a pattern of white noise. This is further confirmed by the findings of the ARCH (LM) test. Thus, it can be concluded that the ARIMA models lack statistical significance and are inadequate for estimating both stations. Instead, a nonlinear model is necessary. Subsequently, the GARCH and MLP models will be incorporated into the ARIMA model to account for the underlying patterns that have been demonstrated to impact the accuracy of the ARIMA model, hence addressing its limitations.

Table 5
The *p*-value for Ljung-Box test and LM test for the potential ARIMA model

Station	ARIMA Model	Ljung-Box test		ARCH (LM) test
		Residuals	Sq. Residuals	
Mersing	ARIMA (1,1,2)	0.230	<0.001	<0.001
Senai	ARIMA (2,1,2)	0.139	<0.001	<0.001

3.3 ARIMA-GARCH modelling

This step is taken to address the issues with the ARIMA model that arise from the volatility being present in the model's residuals. In order to account for the existence of conditional heteroscedasticity, the GARCH model is presented. The GARCH (1,1) model is selected to be used in this study since it is the simple GARCH model and has been used as the benchmark GARCH model by the previous literature in modelling using ARIMA-GARCH model [17,18]. The MLE approach is used to estimate the GARCH model's parameters, and a computational algorithm is used to get the ideal constant and coefficient values for the ARIMA-GARCH model. The estimated ARIMA-GARCH model results for each chosen wind station's wind speed data are shown in Table 6. Based on the results presented in Table 6, it can be concluded that the GARCH model managed to capture the existence of volatility in the residuals of ARIMA-GARCH model for both stations. Following this, the error measurement for ARIMA-GARCH model are calculated to be compared with the ARIMA-MLP model.

Table 6
The ARIMA-GARCH model and the results for ARCH LM test

Station	Model	LM Test	
		Statistics	*p*-value
Mersing	ARIMA (1, 1, 2) – GARCH (1, 1)	12.886	0.230
Senai	ARIMA (2, 1, 2) – GARCH (1, 1)	14.796	0.139

3.4 ARIMA-MLP Modelling

The ARIMA-MLP hybrid model is widely regarded as the most common choice for capturing both linear and nonlinear components in time series data, especially in the domain of wind speed forecasting. When employing this hybrid approach in modelling, the initial stage involves acquiring the residuals from the ARIMA model and subsequently training these values using the MLP model. To determine the ideal number of hidden neurons, we chose five distinct values based on previous research: 32, 64, 128, 256, and 512. A total of five distinct MLP models were trained using the residual values obtained from the ARIMA model. The MLP model with the lowest validation error will be identified as the optimal choice to represent the residual of the ARIMA model for each station.

The findings are succinctly presented in Table 7. The study selects six discrete epochs, spanning from 100 to 500, to investigate the influence of varying epoch counts on the performance of the MLP model. This is done by monitoring the occurrence of underfitting or overfitting during the training process, as indicated in the literature. This procedure establishes the optimal number of epochs for training the model. The loss plot was generated and the ideal number of epochs for the MLP model was selected based on the point where the training loss and validation loss showed the smallest difference and the inflection point in the loss plot was clearly visible.

Table 7 demonstrates that the ideal number of hidden neurons for both stations is 32 since it gives the lowest RMSE values among all five selected number of hidden neurons. While the number of epochs was concluded based on the loss plot obtained in the study with Mersing station requiring 150 epochs and Senai station requiring 300 epochs.

Table 7
The optimal parameters for the ARIMA-MLP model

Station	Optimal Parameter		
	Hidden Layer	Hidden Neurons	Epoch
Mersing	1	32	150
Senai	1	32	300

These models are determined to be the most effective MLP models for capturing the residuals of the ARIMA model. After that, the chosen model is used to forecast the out-of-sample residual data for each station in order to assess the model's performance. The out-of-sample data derived from ARIMA modelling is added to these numbers. Following this, the error measurement for ARIMA-MLP model are calculated to be compared with the ARIMA-GARCH model.

3.5 Performance Comparison

To ascertain the most accurate model for capturing the wind speed data dynamics, we assessed and compared the RMSE, MAE, and MAPE values of each model in a study on model performance. In general, a model with the lowest error measurement is regarded as good. The performance comparison of the ARIMA-GARCH and ARIMA-MLP models is presented in Table 8.

Table 8
The comparative performance of ARIMA-GARCH and ARIMA-MLP model

Station	ARIMA-GARCH			ARIMA-MLP		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
Mersing	3.491	2.996	37.146	2.261	1.706	17.291
Senai	2.736	2.325	31.920	2.189	1.624	18.072

The performance of the ARIMA-MLP model is generally superior to that of the ARIMA-GARCH model for both stations. The ARIMA-MLP model yields the lowest RMSE, MAE, and MAPE values for both stations, in comparison to the ARIMA-GARCH model. Therefore, the results indicate that the MLP model outperforms the GARCH model in capturing the nonlinearity characteristics of the wind speed data and generating a more precise forecast of wind speed.

Four criteria can be used to categorise the typical value of MAPE, as was discussed in the preceding section by Lewis [32]. A forecasting value of more than 50% falls into the category of "inaccurate" forecasting; a value between 20% and 50% falls into the category of "reasonable" forecasting; a value between 10% and 20% falls into the category of "good" forecasting; and a value less than 10% falls into the category of "excellent" forecasting. The model's predictive power over the out-of-sample datasets is the basis for evaluating the MAPE value. Based on Table 6, ARIMA-GARCH model only able to provide a reasonable forecasting, while ARIMA-MLP model belongs to a good forecasting category.

The percentage of improvements that is based on a higher reduction of error from MAPE value was also measured. As compared to the ARIMA-GARCH model, the error measurement using MAPE values from the ARIMA-MLP model has greatly decreased for Mersing station and Senai station, by 53% and 43%, respectively, according to the data shown in Table 8. Based on these results, this demonstrates how the ARIMA model's drawback can be overcome by combining the MLP model with the ARIMA model, which has demonstrated the capability to handle the nonlinearity feature present in the wind speed data. In consequence, the combination of linear and nonlinear models has also increase the performance of the wind speed forecasting model.

4. Conclusions

The primary aim of this study was to assess the efficacy of the time series model and the artificial neural network model in addressing the nonlinearity present in wind speed data, and determining the superior forecasting model. This was achieved by employing scientific methodologies to assure a high degree of accuracy in the projected data points, closely aligning them with the actual values. This study employed multiple pre-existing models to effectively harness the potential of each model in capturing the nonlinearity present in the wind speed data. A performance comparison was undertaken to select the model that yielded the most accurate forecasting metric, as determined by the lowest values of RMSE, MAE, and MAPE. Therefore, in this study, the ARIMA model was employed to analyse linear patterns, while the GARCH and MLP models were utilised to capture the nonlinearity criterion in the wind speed data. The selection of these two models was based on their widespread applicability in describing nonlinear data.

This study aims to enhance the construction of a forecasting model that can effectively capture the nonlinearity present in wind speed data. A comparison research was conducted due to the nonlinearity observed in the residuals of the fitted ARIMA model. The presence of heteroscedasticity in the fitted ARIMA model was also accounted for by incorporating the GARCH and MLP models, resulting in the creation of the ARIMA-GARCH model and ARIMA-MLP model. The model's superiority was confirmed by comparing the predicting performance measures of these two models, with the

ARIMA-MLP models showing the lowest error measurements. In summary, the ARIMA-MLP model offers a valuable contribution to the field of wind energy by presenting a wind speed model that accurately represents both the linear and nonlinear aspects of the wind speed data series.

Developing a precise wind speed forecast model, specifically for Malaysian authorities, would aid in minimising the likelihood of choosing a suboptimal site for wind farm installation. Hence, future research might involve utilising the ARIMA-MLP model to compute the wind power density. This would offer a precise assessment of the wind energy potential at various wind stations throughout Peninsular Malaysia.

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