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Univariate and Multivariate Regression Models for Short-Term Wind Energy Forecasting

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Abstract: Wind energy resource is a never-ending resource that is categorized under renewable energy. Electricity generated from the wind when the wind blows across the wind turbine system produces high kinetic energy once it goes through the wind blades, rotating and turning it into useful mechanical energy. That motion of the generator produces electricity. However, in Malaysia, the inconsistency in terms of wind speed required for wind turbines to operate efficiently and generate a suitable amount of electrical power is a major problem. Different locations have different weather parameters that affect wind speed and wind energy production. Wind energy forecasting is performed in this paper using linear, nonlinear, and deep learning models for a small-scale wind turbine. The paper focuses on comparing and correlating the performance of univariate and multivariate input parameters with wind speed as its primary feature using short-term forecasting with a time horizon of 1 hour ahead. The set location is at Mersing, Johor, where it is prominently one of the locations in Malaysia with a constant and high amount of wind speed. It is found that Huber Regressor, Gradient Boosting, and Convolutional Neural Network (CNN) are shown to be powerful in prediction. Huber Regressor has the best Mean Absolute Error (MAE) of 0.597 and Root Mean Square Error (RMSE) of 0.797, while Gradient Boosting has the best learning rate (R^2) at 0.637. CNN has the best MAPE at 30.861 and is shown to be the most optimum forecasting model for a univariate parameter. The results show that the outcome of the evaluation does not vary significantly depending on the criteria chosen in the data selection.

Keywords: : Wind energy, Linear Regression, Deep learning, Wind speed forecasting, Deep learning.

1 Introduction

The Energy generation authorities, countries, and energy companies are paying more attention to renewable energy sources due to their nonpolluting nature for power plants that rely on the combustion of fossil fuels, such as coal or natural gas, which will be exhausted in the future [1-3]. Wind energy is one of the most important and potentially useful sources of energy from renewable energy sources. For instance, in 2019, the worldwide wind power market grew by 19%, with over 60 GW of generation capacity contributed to the world's electric grids. About 102 nations have commercial wind generating capacity all around the world, enough to produce an estimated 5.9% of worldwide electricity generation. Fig.1 shows the annual additions and global capacity of wind power during the last ten years [2, 4-8]. In terms of wind operation, when the wind blows past a wind turbine, it produces high kinetic energy that once it passes through, the blades will rotate and turn it into mechanical energy [9, 10]. That spin of the generator produces electricity [9, 11]. Wind turbines are not easily portable; therefore, proper analysis of wind energy potential for promising locations should be done [12, 13]

Wind energy is becoming sought after as a source of renewable energy [1, 5, 7, 12]. However, in Malaysia, the inconsistency in terms of the wind speed required for wind turbines to operate in order to generate electricity is still a major problem [6]. Different locations have different weather parameters that affect wind speed and wind energy production [14-16]. In Malaysia, it is suggested that the prospective for wind energy generation depends on the availability of wind resource [17, 18]. Due to the uncertain nature of wind, it is found to vary according to location.

In the literature, an investigation of the wind-resource analysis was carried out in Kudat to increase the preliminary result of wind energy [6, 18, 19]. Those data were collected by the Malaysian Meteorological Department (MMD) station for the year 2004 until 2012. Therefore, the great and prominent for commencing a wind energy farm is selected

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from created energy maps. For annual energy production calculations and the most fitting ones were used on the micro sitting analysis, wind turbines with nominal powers 6 kW, 10 kW, and 15 kW were designated. The lowest wind speed was 4.3 m/s, while the highest interpolated wind speed in the selected site was 5.4 m/s [6, 18]. The most common wind directions were Northeast (NE) and Southwest (SW). It proves that Malaysia has the potential in developing wind farms in case of the optimal locations is chosen based on wind energy potential. However, few parameters must be taken into consideration to accurately forecast wind energy [20].

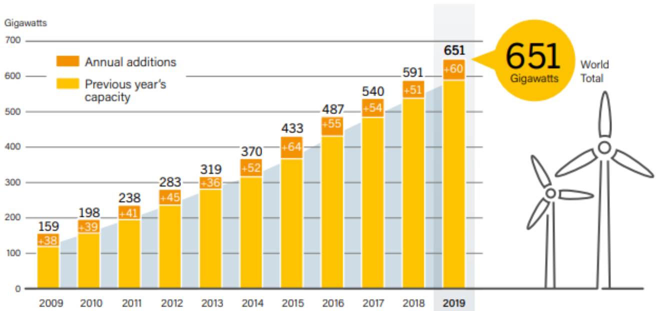

Fig.1: Annual additions and global capacity of wind power during 2009-2019[5].

Therefore, to get the most suitable location for wind turbines installation, this study proposes to build a forecasting algorithm of wind energy production based on different parameters. In this paper, short-term wind power forecasting is done with a time horizon of 1 hour ahead. Short term forecasting is preferred due to the features are weather dependent and has unstable nature. Such forecasting can give insight to investors as well as consumers of wind energy to decide on the suitability of wind turbine installation across the peninsular of Malaysia.

Regression analysis is also used as it mathematically portrays the relationship between independent variables and the dependent variable. It can predict the mean value of the dependent variable to provide an accurate approximation of the wind speed and availability. The dependent variable described is the wind speed, as it is a primary input to calculate wind energy. H. Demolli, et al. [21] used a regression model for long-term forecasting and achieved good results for xGBoost, Support Vector Regressor (SVR) and Random Forest with LASSO regressor being the worst. J. Jung, et al. [5] applied Artificial Neural Network (ANN) and merged with Fuzzy logic creating ANN-Fuzzy for forecast, providing excellent performance. As this paper covers a large number of samples performance comparison is also done using the deep learning method. Using the backpropagation algorithm, deep learning detects intricate structure in big data sets to specify how a machine should compute the representation in each layer from the previous layer [22].

2 Literature Review

2.1 Wind Speed

Wind speed forecasting is important for wind turbine-based energy conversion systems as it contains information about power system planning and also allows adaptive monitoring of wind turbine units in the wind farm [23]. A study has discussed that wind power potential analysis should not consider wind speed data from or near airports, particularly if the data come from low wind speed regions and instead should be measured at an open and flat area, where fewer obstacles and surface roughness are present [24, 25]. Based on this study outcomes, it was proven that there are two areas with the best wind power potential where the annual mean power (W/m²) potentials of 32.50 and 85.61 which are in Kuala Terengganu and Mersing, respectively. Another paper agreed on promising future success in Kudat and Mersing where from potential analysis based on the capacity factor, these areas are capable to develop and install medium capacity of wind turbine power. In this regard, the medium rated power of a wind turbine (600 kW) could generate electricity with capacity factor surpassing 20% [26].

2.2 Wind Direction

The directions of the wind and wind farm's design have a vital influence on wind farm implementation and energy harvesting. This shifts the wake cones' orientation and position. In this regard, the variation in wind direction or wind farm architecture results in changes in the interaction between wakes (overlapping area) [27]. Multiple wakes can consequently affect the power output of wind turbines. A wake will begin to spread as the wind flow proceeds downstream and will gradually return to free stream settings. The downwind turbine is said to be shadowed by the turbine producing the wake when awake intersects with the swept area of a downwind turbine. When wake occurs, the speed of the turbine will decrease and might cause turbulence of the wind thus affecting energy potential.

2.3 Humidity

It is well-known that the dry air density is lower than the humid air density. The humid air is preferable that could be reduced the entire mixer density results in lower power for wind turbine application, which in turn reduce the content of water vapour. Still, Abdul-Kareem et.al. [28] found that inadequate the amount of moisture composition towards wind energy sources at average annual established the minimum altitude requirement that was consumed in the power plant of Nasiriyah (44 m for $\alpha = 0.3$; 32 m for $\alpha = 0.4$). Meanwhile, as the altitude is visible at a higher position, it has been growing. The level of misfortune on the annual ordinary sodden air pressure (due to the sheer effects of relative viscous) is insufficient and varies in the surrounding (0.847% and 1.106%) at high position (15 m and 71 m) individually. Humidity is a notable source of corrosion that could contribute to wind turbine faults and thus reducing wind energy. The paper recommended the influence of humidity on the mean of wind power (annually) is low and that the proportion of losses on the mean of moist airpower (due to the cause of humidity) decreases with an increase in altitude compared to dry air. Therefore, these factors must be taken into consideration before choosing the site of wind farms.

2.4 Linear Regression

Linear regression is a form of a mathematical model used to approximate the dependency relationship between two variables for better understanding by the association of input and output numerical variables. Furthermore, it is manipulated by the statistical algorithm and machine learning algorithm. In other words, it is also considered as a linear model that forecasts a linear relationship between the input variables (x) and the single output variable (y). The output (y) can be calculated from a linear combination of the input variables (x). Moreover, linear regression is used for solving linear relationship between the target and one or more forecasters. For error forecasting using linear regression, the data are simulated using six models which are defined by:

i. LASSO Regression
LASSO is defined as least absolute shrinkage and selection operator. Basically, it applies to shrinkage conditions where data values are shrunk towards a middle value, like the mean. It is well suited for multicollinearity or to automate certain parts of model selection, some sort like variable selection or parameter removal.

ii. Ridge Regression
It is a method to generate a parsimonious model when the numbers of forecaster variables in a set that exceeds the numbers of observation. It shrinks the coefficients to minimize the model complexity and multi-collinearity.

iii. Huber Regression
A regression technique that is robust to outliers. The idea is that this technique is less sensitive to outliers in data than the squared error loss.

iv. LASSO Least Angle Regression (LARS)
The LARS algorithm could provide a series of estimation production of which variables are suitable to insert, as well as their coefficients. Hence, the algorithm will exploit the special formula for the LASSO issue and consequently provides an efficient route to calculate the solutions simultaneously.

v. Passive Aggressive Regression
The parameter determines a tolerance for forecasting errors and is based on Hinge loss function. Analogous to standard hinge loss but is designed to work with continuous data. The algorithm is passive when a correct classification occurs while aggressive when it looks for a new weight vector that is near the previous value.

vi. Elastic Net
This mode applies to overcome the restriction of the LASSO. Elastic Net is a regularized regression method that linearly combines the L1 and L2 penalties of the LASSO and Ridge methods.

2.5 Non-Linear Regression

Non-linear regression is different from linear regression in which the linear equation has only one basic form. However, nonlinear equations can create in variable forms. If the equation does not fulfil the linear equation requirement, thus it is considered non-linear. Eight models were tested out and can be defined as:

i. K-nearest Neighbor (KNN)
KNN is a non-parametric algorithm, which means that it does not make any forecasting about the primary data. It makes its selection according to the proximity to other data points regardless of what features the numerical values represent.

ii. Decision Trees
It implements a tree-like model of decisions. Each internal node represents a “test” and considers as one result. Every branch classified as the outcome of the test, while each of the leaf nodes indicates a class label (decision is made after computing all data). The pathway from root to leaf of the tree model represents organization principles.

iii. AdaBoost
AdaBoost is a short form of (Adaptive Boosting). It focuses on arrangement issues and aims to translate a series of poor classifiers into a robust arrangement.

iv. Bagging
Bagging or also known as Bootstrap Aggregation uses the concept of bootstrap. Bootstrap is a sample of dataset replacement. It is defined that the new dataset is formed from existing dataset samples with a random selection of where a given row may behave repeated samples.

v. Random Forest
Random Forest is randomly creating and merges with multiple decision trees into one “forest”. It is a collection place of decision models in order to enhance accuracy rather than relying on a single learning model. The difference between this approach and the standard decision tree algorithms is that the root nodes feature splitting nodes are generated randomly.

vi. Extra Trees
It is a joint learning technique that corresponds based on Decision Trees. Extra Trees is similar to Random Forest, where it assembles multiple trees and separate nodes using random subsets of features, but with two key differences: it does not bootstrap observations, but nodes are split on

random splits, not precise splits.

vii. Gradient Boosting
Gradient Boosting trains many models in a gradual, stabilizer and consecutive manner. It obtains from gradients which mainly involved by the loss function. The loss function is a measurement that determines how perfect the model's coefficients are at fitting the basic data.

viii. SVMR
SVMR is derived as Support Vector Machine Regression, it is a monitored learning algorithm that could manage to sort data and divided into two categories to build the model as it is initially trained. It implies a technique named kernel trick to transform data which do an auto search for an optimal boundary within the possible outputs.

2.6 Deep Learning

Deep learning is a subset of machine learning in artificial intelligence that has networks capable of learning unsupervised from data that is unstructured or unlabeled.

i. Convolutional Neural Network (CNN)
CNN takes in an input image, assign importance to various aspects in the image and be able to differentiate one from the other. One dimensional CNN (CNN1D) is used in this research because it is time-series data.

ii. Multilayer Perceptron (MLP)
MLP is a feedforward neural network consisting of interconnected neurons transferring information to each other, having similar characteristics to the human brain.

iii. Long Short-Term Memory (LSTM)
LSTM has feedback connections in which it takes time and sequence into account and have a temporal dimension.

iv. Recurrent Neural Network (RNN)
RNN is a subset of LSTM designed to recognize patterns in sequences of data, such as numerical times series data. Its feedback loop connects to their past decisions, ingesting their own outputs moment after moment as input.

3 Methodology of Wind Energy Forecasting

Local datasets comprising suitable weather parameters will be tested using a few different models. From there, few models are tested out to calculate its error. The best model with the least error will be identified to suit the proposed forecasting. Python software is used for simulation because it can be utilized for complex mathematics processing with superior performance needs. There will be some collision on wind electricity generation capacity and operating characteristics at the period of wind speed fluctuations. Generally, the starting to rotate most small wind turbines, the wind speeds are 2 m/s. In addition, the typical cut-in speed is 3.5 m/s when a small turbine starts to produce electricity [29]. Since Malaysia annually does not generate a high amount of wind speed, we are looking into building a forecasting model that suits small scale wind turbines. Through simulation, we will pick the location and time in which the wind speed constantly exceeds 4 m/s. Short term wind energy forecasting with a time horizon of 1 hour ahead is looked into due to the instability and unpredictable nature of weather conditions. The flow chart of forecasting methodology is shown in Fig. 2.

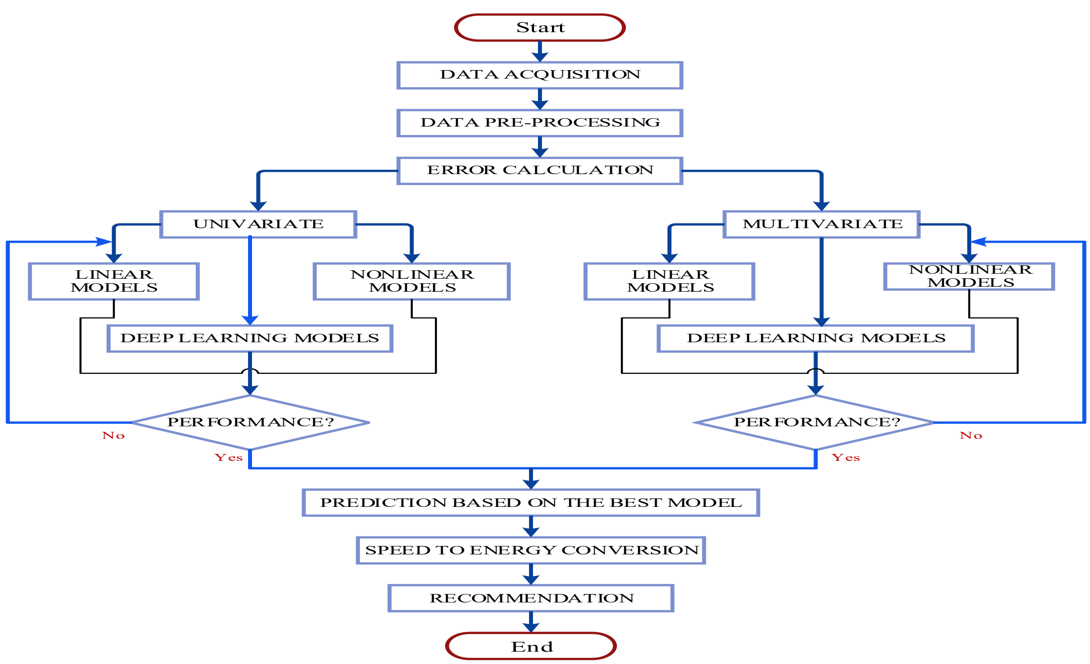

Fig.2: The flow chart of the forecasting.

3.1 Wind Data Acquisition

The dataset is taken from National Centers for Environmental Information (NOAA) [30]. The location chosen is Mersing, Johor because its average speed is between 3 to 4 m/s which shows promising potential for installation as the small-scale wind turbine that is used for justification with the cut-in speed of 2.0 m/s. Their samples are taken per hour from the year 2007 to 2018. The data includes characteristics such as wind turning path, humidity, ambient temperature, and wind speed, all of which are required for wind power generation. Based on the method used, the data samples of wind speed variable, air temperature variable, humidity variable, and wind direction variable are shown in Figurs 3-6.

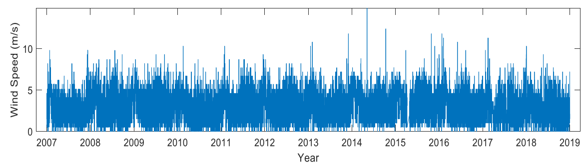

Fig.3: Wind speed variable

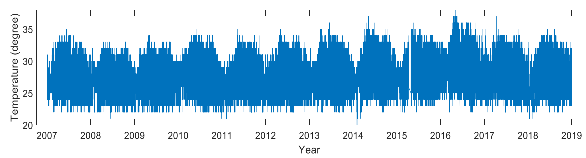

Fig.4: Air temperature variable

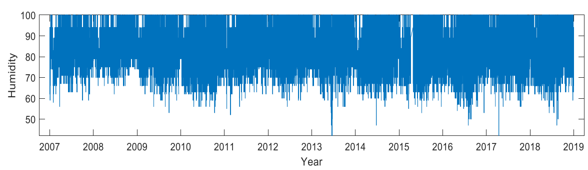

Fig.5: Humidity variable.

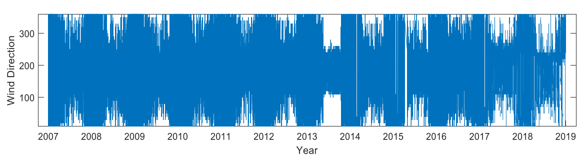

Fig.6: Wind direction variable.

3.2 Wind Data Pre-processing

Basically, this is a data mining approach that is altering raw data into an intelligible format. Real-world data is often lacking, inconsistent and incomplete in certain trends or behaviors and most likely to embrace with many errors. It refers to methods for removing, replacing, and finding missing/bad data. Identification of abrupt changes and local extrema can assist to spot conspicuous data directions. In the datasets, some data are missing. Therefore, its median is calculated using surrounding hour values to fill in the missing data. Pre-processing also ensures that the datasets obtained are accurate so that the project will result in the least error possible.

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3.4 Forecasting Error

To test out the accuracy of forecasting, errors are calculated between an actual and forecasting value. Errors are calculated using linear and non-linear regression. Inputs are separated into two categories: univariate where the input is only wind speed and multivariate which the parameters consist of wind direction, wind speed, humidity and temperature. In order to obtain a more accurate model, root mean squared error (RMSE), mean absolute error (MAE), R squared (R2) and mean absolute percentage error (MAPE) parameters were used for model comparison and model performance. The calculation for RMSE, MAE, R2 and MAPE are defined as follow.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - y_j)^2} \tag{1}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - y_j| \tag{2}$$

$$R^2 = 1 - \frac{\sum_i (y_i - y_j)^2}{\sum_i (y_i - \bar{y})^2} \tag{3}$$

$$MAPE = (\frac{1}{N}\sum \frac{|y_i - y_j|}{|y_i|}) * 100 \tag{4}$$

The specifications of the wind turbine are taken from a small-scale wind turbine in Universiti Tenaga Nasional (UNITEN), Malaysia. The generation of wind energy will be calculated to validate the results.

3.5 Speed to Energy Conversion

On average, the wind speed in Mersing is about 2.5 m/s which exceeds the cut-in speed for the wind turbine to generate electricity. A constant power of at least 18 kW can be obtained at the location. Speed to energy conversion is evaluated to validate the model using specifications of a small-scale wind turbine installed at the wind energy lab UNITEN. The specifications are as follow in Table 1.

Table 1: Specification of a small-scale wind turbine.

Turbine	
Rated Power	400 W
Cut-in-speed	2.0 m/s
Cut-out-speed	13 m/s
Survival wind speed	50 m/s
Overall Weight	6.8 kg
Rotor/ Generator	
Rotor diameter	1.4 m
Voltage	24 V
Come with	
Mounting Pole On-Grid Inverter/Controllers Rectifier Strip installation	

The most accurate wind speed prediction model is converted into wind energy by the formula in Equation 5:

$$P = \frac{1}{2}\rho A v^3 \quad (5)$$

where Cp = power coefficient, ρ = air density (kg/m³), A = area of wind turbine's blade m²), and v = wind speed (m/s). The area of the wind turbine's blade is calculated from the length of the rotor. Air density is constant at standard temperature and pressure at 1.225 kg/m³ while the power coefficient is set at a value of 0.59 from Betz' Law. Betz Law indicates that the theoretical maximum efficiency for a wind turbine at most can generate a maximum of 59.3% of the kinetic energy from wind to spin the turbine and generate electricity [31].

4 Results and Discussions

The findings of evaluating the linear models employing univariate and multivariate wind data were summarized in Tables 2 and 3. As shown in Table 2, Huber Regression model outperformed all other linear models with the lowest MAE of 0.597. However, the Huber Regression model archived fairly good performance for short-term forecasting when using multivariate data as shown in Table 3. Ridge model generally outperformed with all other linear models for the univariate parameter, but it is comparable (MAE errors) to Huber Regressor and Passive-Aggressive regressor. Huber regressor model introduced a different loss function named Huber loss, which designed to reduce sensitivity to outliers in the wind data compared to the Squared loss function used in other models. This explained the good forecasting performance of Huber method in both univariate and multivariate wind data.

The multivariate wind data is expected to provide better forecasting results than the univariate data. However, the analyzed wind data in this paper is limited to a few multivariate parameters where the missing observations are imputed in the pre-processing stage. These multivariate parameters must exhibit meaningful and statistically significant correlations with the wind speed data to generate more accurate forecasts. The results in Table 3 indicated the absence of the rich correlation structure which made the univariate to provide better forecasting performance.

Table 2: Error Calculation Using Linear Regression for Univariate Parameter.

Models	*MAE*	*RMSE*	*MAPE*	*R²*
LASSO	0.902	1.142	60.609	0.170
Ridge	0.603	0.801	39.547	0.591
Huber Regressor	0.597	0.797	38.583	0.596
Lasso Lars	1.057	1.342	70.741	0.147
Passive Aggressive Regressor	0.666	0.866	44.117	0.523
Elastic Net	0.779	0.984	52.682	0.384

Table 3: Error Calculation Using Linear Regression for Multivariate Parameter.

Models	MAE	RMSE	MAPE	R²
LASSO	0.900	1.195	44.841	0.281
Ridge	0.653	0.890	32.527	0.601
Huber Regressor	0.653	0.894	32.159	0.598
Lasso Lars	1.092	1.411	54.378	0.002
Passive Aggressive Regressor	0.659	0.906	31.440	0.587
Elastic Net	0.768	1.022	38.693	0.475

For nonlinear models, Table 4 and Table 5 compared the performance of different methods on forecasting univariate and multivariate wind data, respectively. The Gradient Boosting model showed the best forecasting performance with an MAE of 0.627 for both univariate and multivariate cases.

In Table 4 and Table 5, non-linear models are measured which highlights Gradient Boosting and SVMR produced fewer errors (MAE, RMSE, MAPE) compared to other models in both univariate and multivariate parameters. Similar to the linear models, both univariate and multivariate models shown no significant difference however the multivariate demonstrated better values. KNN, Bagging, Random Forest, Extra trees, and SVMR performed comparably to the Gradient Boosting for the univariate forecast as shown in Table 4. Decision Trees, Extra Tree and AdaBoost methods showed poor performance in Table 4 when compared with others. However, all models performed comparably for the multivariate forecast in Table 5. Similar to the linear models, there is no significant improvement in the forecast performance when using multivariate data to univariate data.

Table 4: Error Calculation Using Non-Linear Regression for Univariate Parameter.

Models	MAE	RMSE	MAPE	R^2
K-nearest Neighbour (KNN)	0.674	0.909	33.789	0.576
Decision Trees	0.920	1.261	43.928	0.184
AdaBoost	0.929	1.1466	55.943	0.325
Bagging	0.646	0.879	32.690	0.603
Random Forest	0.645	0.878	32.692	0.604
Extra Trees	0.647	0.880	32.743	0.603
Gradient Boosting	0.627	0.855	31.847	0.625
SVMR	0.632	0.870	31.343	0.611

Table 5: Error Calculation Using Non-Linear Regression for Multivariate Parameter.

Models	***MAE***	***RMSE***	***MAPE***	***R^2***
K-nearest Neighbour (KNN)	0.670	0.905	33.026	0.588
Decision Trees	0.683	0.947	33.445	0.549
AdaBoost	0.684	0.920	37.131	0.574
Bagging	0.659	0.897	32.525	0.595
Random Forest	0.659	0.897	32.530	0.595
Extra Trees	0.669	0.918	32.938	0.576
Gradient Boosting	**0.627**	**0.849**	31.528	0.637
SVMR	0.628	0.854	**30.871**	0.633

In Table 6, RNN performs the best in terms of RMSE and R^2 compared to other models. CNN and MLP are comparable in which both have almost similar outcome as RNN. LSTM model produces better MAPE however its MAE, RMSE and R^2 have weak performance. Out of the four measured models in Table 7, CNN achieved fairly good performance for its MAE, RMSE and R^2.

For multivariate data in Table 7, it is presumed to have better results than univariate parameters however its accuracy did not improve. Deep learning techniques learn by creating a more abstract representation of data as the network grows deeper, as a result the model automatically extracts features. This could be the problem of deep learning characteristics where it identifies features that are most relevant. The multi-features of a multivariate parameter might affect the accuracy of prediction. Overall, prediction using univariate parameter using the CNN model performs the best compared to other models. The forecasted wind speed is converted into wind energy as shown in Fig.7

Table 6: Error calculation using deep learning method for univariate parameter.

Models	MAE	RMSE	MAPE	R^2
Convolutional Neural Network (CNN)	0.621	0.860	31.311	0.620
Multilayer Perceptron (MLP)	0.626	0.863	31.156	0.617
Long Short-Term Memory (LSTM)	0.752	1.001	30.708	0.485
Recurrent Neural Network (RNN)	0.623	0.855	31.033	0.625

Table 7: Error calculation using deep learning method for multivariate parameter.

Models	MAE	RMSE	MAPE	R^2
Convolutional Neural Network (CNN)	0.644	0.874	31.319	0.548
Multilayer Perceptron (MLP)	0.658	0.908	31.651	0.513
Long Short-Term Memory (LSTM)	0.645	0.885	31.256	0.537
Recurrent Neural Network (RNN)	0.657	0.898	31.859	0.523

Annexation FRT and other requirements to GCs concerning penetration of the PV system to the electric power network is a new topic. Previously, the PV plants connected with the distribution network were not permitted to take any action during the disturbances and had to disconnect directly in case of grid fault. Recently, with the significant rise of the PV farm size, it is required to keep PV units working under either normal or abnormal conditions. Germany and Spain as a leader in the production and installation of PV technology are adopting these new requirements in their GCs [6-8]. On July 2010, German grid code stipulated that PV plant had to be capable to make a limited contribution for the dynamic network support while from January 2011, it was recommended that the PVPP should provide full dynamic network support [2, 6, 9]. Italy has recently adopted a new version of the grid code for distributed generation systems, explicitly including PV, CEI 0-16, 2012 and CEI 0-21, 2014 [10]. Japan had released FRT requirement and measures of PV distributed system in 2011 by the Energy and Industrial Development Organization (NEDO) [11]. The USA applied the requirement for PV integration according to IEEE 1547 standard [12] while Puerto Rico Electric Power Authority (PREPA), which is one of the main public electric power corporations in the United States had released technical requirements for interconnecting wind and solar generation [13]. Australia imposes the requirement in AS4777 standard, where the last update was in 2013 [14] and it follows National Electricity Rules, version 63, which was published by (AEMC) in 2014 [15]. Finally in Malaysia on 21 December 2010, the Grid Code and Distribution Code has been issued by the Energy Commission Malaysia (ECM) but these two codes did not address the FRT capability either for wind or PV integration [16].

This paper introduces comparative study for different national grid codes especially FRT requirements concerning penetration of the PV system to the power network. Also, it proposed FRT regulation regarding PV farm connection to the Malaysian grid.

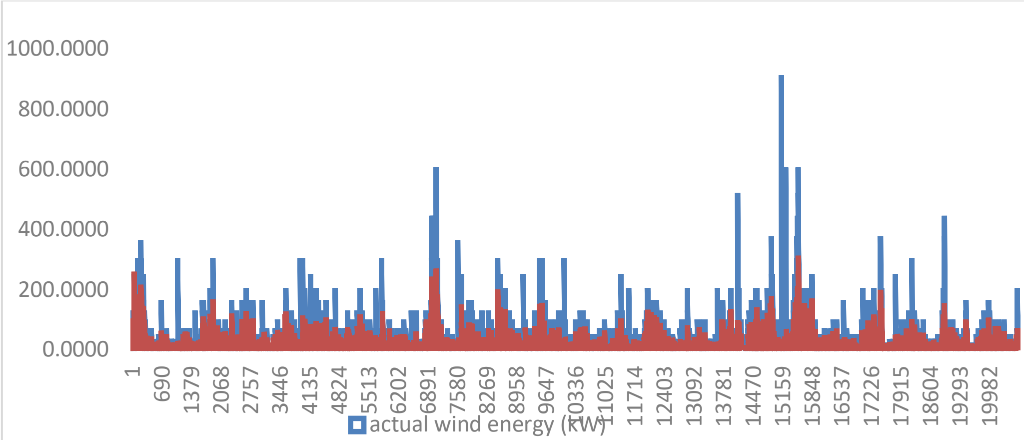

Fig.7: Graph comparison between actual and predicted wind energy using CNN univariate model.

4 Conclusions

Wind speed forecasting is a challenging task due to the intermittent and uncertain nature that exists in wind data. In this paper, various traditional machine learning methods are benchmarked for short-term wind speed forecasting. The forecasting is applied using linear, nonlinear, and deep learning models in univariate and multivariate input parameters. Huber Regressor, Gradient Boosting, and Convolutional Neural Network (CNN) are shown to be powerful in prediction. Huber Regressor has the best Mean absolute error (MAE) of 0.597 and Root Mean Square Error (RMSE) of 0.797 while Gradient Boosting has the best learning rate (R^2) at 0.637. CNN has the best MAPE at 30.861. Overall, CNN univariate model shows the best performance. Generally, the type of feature whether it is univariate or multivariate the performance did not show notable improvement. This could be due to the implemented method is showing better performance when using fewer input data.

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Conflicts of Interest
The authors declare that there is no conflict of interest regarding the publication of this article.

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