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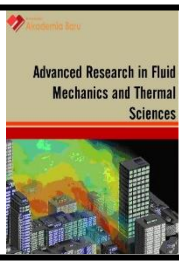

Development of an Improved Hybrid Back propagation ANN for Low Wind speed prediction and Wind Energy Evaluation

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ABSTRACT

Wind energy is clean, reliable, and affordable renewable energy which can be harnessed during the day and night. Before a wind turbine is installed, wind resource assessment (WRA) must be conducted in order to evaluate the wind power potential. The most important parameter in WRA is the wind speed values. The traditional ways of measuring wind speed could not be relied on, due to time constraint and cost. Because of these problems, a prediction model using deep learning is proposed in paper to solve the lingering problem. The objective of this paper is to develop a machine learning, prediction model using available data. Wind data were obtained from Malaysia Meteorological Department (MMD) for a period of ten years starting from 2008-2018. The wind energy evaluation was conducted at 10m-40m meters, respectively. In the areas with limited data or without data a prediction model was developed using different Artificial Neural Networks (ANNs) structures. The model was trained, tested, and validated using measured wind speed in the nearby location. The optimized model in terms of less structure with high prediction accuracy was selected for the final prediction has a correlation value of 0.952. A detailed wind resource assessment was conducted in the areas based on most fitted wind speed distribution model. It was found that Weibull and Rayleigh fitted the wind speed in the areas examined. At the end of the analysis, low wind speed turbine was selected for the wind farm sitting; the results show that wind energy can be harnessed for small Pico scale application such as rural electrification, and grain grinding. Because, in all the cases the wind power density falls within class 1 ($P_D \leq 100$ W/m^2). The outcomes of this study would be useful for policy makers to implement 3-Es Model (Earth-Energy and Empowerment) in rural and remote areas of Sarawak.

1. Introduction

Fossil fuels such as (coal, petroleum and natural gas) are the major sources of greenhouse gases (GHG), because when those sources are burnt as fuels they released carbon dioxide, which cause air

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pollution in the lower layer of the atmosphere. In the twenty century, attention is being devoted to replace the dirtiest sources of green and sustainable energy. In addition to the environmental worries cause by the use of fossil fuels, the resources are finite, because it was discovered and utilized. According to experts, fossil fuels last for 10 to 11 decades [1]. However, renewable energy sources are infinite sources, the can be renewed, or which can be naturally replenished. In general, renewable energy is gaining more attention in recent times, because the prices of solar and wind energy are cheaper when compared with fossil fuels. As we know, energy is important for sustainable economic and infrastructural developments. Rapid developments in urban areas, especially densely populated areas have contributed immensely in energy needs.

As a developing nation, Malaysia is purely fossil-based dependent energy source country about 90% of its energy mix comes from conventional sources. In line with green energy policies of the country, different policies have been formulated in order to encourage and boost the application of renewable energy in the country. In the tenth Malaysia energy plan, the country targeted 5% of the energy mix from renewable under small renewable energy programs (SREP) [2]. Though, the main goal of all the policies is to minimize the use of fossil fuel so as to combat climate change and safeguard the environment. As the country is strategically situated, thus Malaysia possesses quite substantial renewable energy sources such as hydro, solar, biomass and wind.

Electrical power line distribution in Sarawak is quite challenging, even stepping down of high voltages; 330 kV-132-kV-33kV-11kV transmission lines. This is the main reasons for using light and portable diesel generators in some rural and remote areas. Other problems associated with the diesel generators are fuels and maintenance. The end products of burning fossil fuels are the major causes of GHG. Providing electrical energy is a prerequisite requirement to ease their day to day socioeconomic life. Another government program was introduced to ease the lack of access to electricity in rural area. This program called mini rural program MRP, but unfortunately, the source of energy is via diesel powered generators which works on a shift basis during the day and night [3].

Wind power is a clean source of energy; it has been used decades ago for sailing ships, grain grinding, and water pumping. In recent times, wind energy is becoming popular for electrical power generations. Wind energy can provide energy from Pico scale to large scale in both urban and rural areas. And wind energy can be harnessed during the day and night and does not require any accessories, unlike solar energy which is a daylight dependent source, and requires accessories for converting available solar radiation into alternative current for instance, charge controller and inverter.

To convert the available energy in wind into electricity, it is paramount to know the detail characteristics of the particular area, because wind varies in terms of location, speed and height. Because of the aforementioned reasons, it is necessary to conduct a wind resource assessment with a high degree of accuracy. Wind speed and wind speed distribution are important parameters in studying wind energy potential. The wind speed class of the area must be known; afterward the distribution model that fits the wind speed value must be obtained, before the potentiality assessment is conducted.

In this study, two areas of Sarawak (Lawas and Bario) were selected as reference station with data available from 2008 to 2018. A prediction model using soft computing model will be used to predict the wind speed in the areas without wind station based on the knowledge of wind speed at the reference station.

Prediction of wind speed is being done based on mathematical models and soft computing techniques. Nowadays soft computing, such as neural network, fuzzy logic, support vector machines etc are found to be more acceptable. In recent times, several studies were carried out to predict the wind speed using machine learning methods. Three models (multilayer feed-forward neural network

(MLFFNN), support vector regression with a radial basis function (SVR-RBF) and adaptive Neuro-fuzzy inference system (ANFIS) that is optimized with a partial swarm optimization algorithm (ANFIS-PSO)) were developed and trained using different algorithms to predict wind speed, wind direction and energy output of the wind turbine. It was found that SVR-RBF model outperforms the MLFFNN and ANFIS [1]. A new intelligent method to predict short-term and medium term wind power was proposed. The method hybridized a particle swarm optimization (PSO) algorithm and applied to train the Type-2 fuzzy neural network (T2FNN) which is called T2FNN-PSO. Real wind farm data were used as a case study to validate the effectiveness of the proposed method [2]. A framework to predict wind speed using three models was reported, wavelet transform was used to decompose the wind speed into subsets. The lower frequency subset wind speed and neural network were used to predict the wind speed based on machine learning. The findings show the proposed method could be used to predict wind speed with optimal efficiency [3].

The wind energy assessment has been carried out in Malaysia, with high ratio studies conducted in west Malaysia (peninsular). In the east Malaysia, attempts have been made in Sabah, with few studies in Sarawak. Potential of wind energy was conducted using observed wind speed in northern parts of West Malaysia using Weibull and Hargreaves method analysis [4]. A similar study was reported using two years wind speed from 2006 to 2007 [2]. Ten locations in west Malaysia were statically analyzed to find the most suitable wind power site in a study conducted using three years data available [5]. Spatial estimation of wind speed and wind energy evaluation was studied in Masseran *et al.,* [6]. Wind speed was characterized based on three seasons experienced in Malaysia [7]. Comparative assessment of wind and diesel power source was evaluated and analyzed in Anwari [8]. Wind speed characteristics and wind turbine analysis were conducted in a few locations in west Malaysia using available wind data, the authors showed the possibility of wind energy application despite light wind experienced in the equatorial region [9]. A regional assessment of wind speed and wind power evaluation showed wind power density in some of west Malaysia is suitable to turn moderate wind turbines [10]. A study conducted by Darus *et al.,* [11] showed wind power potential in suitable in Perhentian Island. Although, the apex data used in the study were from January to December 2010. Perlis wind data were analyzed and the final outcomes showed the possibility of using small wind turbine [12]. A study conducted at some locations in west Malaysia showed east coast regions possessed high potential to harness the wind power [13]. Wind speed, theoretical forecasting was reported in Sapuan, Razali and Ibrahim [14]. Distribution of wind speed based on seasonal variation in west Malaysia was evaluated and reported [15]. The work showed areas wind high and low wind speed distribution. In northern Peninsular, wind energy evaluation in Perlis was also studied [16], similar findings were indicated as noted in Daut *et al.,* [12]. Maximum wind speed and distribution of wind direction in Malaysia was thoroughly assessed [17], results showed wind speed and direction varies depending on locations. Another study conducted in the east coast Malaysia demonstrated the suitability of using wind power for small and medium scale [18]. Technical evaluation and assessment conducted on Penang Island showed the average wind power density is suitable to run a moderate wind turbine in the region [19]. Assessment of wind power in Pahang was reported [20], Weibull, Gamma and Lognormal fitted the wind speed of the areas analyzed. Wind energy evaluation at two locations in west Malaysia (Kudat and Labuan) was carried using Weibull and Rayleigh; both areas have wind energy potential for small scale applications [21]. Evaluation of wind power and energy mapping was preliminary conducted, findings showed the areas with little and huge potentials [22-23].

In the eastern part of Malaysia different studies were conducted thoroughly, the studies conducted in Sabah can be categorized into two, wind energy evaluation at different locations conducted using Metar Data [24], northern part of Kudat [25], wind energy evaluation and mapping

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[23]. In Sarawak, few studies were conducted from 2012 to date. The studies are; introduction of topography for wind energy evaluation considering the complex terrain in Sarawak [26-27], ANN and GIS mapping of wind energy [28], wind power potential in Kuching [29], potential of T-FNNN in monthly wind speed prediction and energy mapping [30], using prediction model and ground data considering terrain variations and using terrain nonlinear soft computing methods [31]. The listed study concentrates in either one location or using models to predict the wind speed. Due to the variable nature of wind speed, and location differences, there is a need to use updated wind speed data in different location to study wind energy potential, especially in the rural and remote areas, and also to see how possible the wind speed prediction model could be applied in rural and remote areas [32].

2. Methodology

2.1 Study Area Description

Sarawak is a largest state in Malaysia in terms of area per square kilometer (Land mass), the state is strategically situated in the GPS coordinates 2°30'0.00" N 113°30'0.00" E, with an altitude of 1788 m. The estimated population was 2.7900,000 according to the department of statistics Malaysia, this stands at 86 persons per square kilometer. The study locations (Bario and Lawas) are shown in Figure 1. Bario is situated in the northeast of Sarawak with an altitude of about 3,500 feet above sea level. Lawas is a small town in Limbang region, the area is 3,811.9 square kilometers, the distance of Lawas from the Sarawak city capital is about 1,200 km.

2.2 Data Collection

Wind data can be obtained via different methods; some researchers conducted experiments, while others used meteorological data or published data in books or magazines [33]. Wind data observed in meteorological were used in most scientific studies [34].

Fig. 1. Study area location

In this paper long-term wind speed data are needed, because of the aforementioned reasons, meteorological data observed at Lawas and Bario stations for a period of ten years starting from 2008 to 2018 were used as shown in Table 1. The data were measured using standard meteorological equipment's rotating cup anemometer and wind vane. The data station pole is positioned at 10 m altitude using mild steel. The average hourly, daily wind speed and direction were stored in a permanent memory located in the equipment. Figure 2 shows the wind station in one of the study areas.

Table 1
Data Location and Period of Measurements

Location	Altitude (m)	Data Measurement Period
Bario	1,021	2008-2018
Lawas	85	2008-2018

Fig. 2. Location of Wind station in Lawas

It is equally important to know how prediction model data were obtained, there are two data used in the process of soft computing model development [33]. Meteorological data were observed from the two principal stations (Bario and Lawas) were used as inputs while the wind speed data as the target input. The data covers all the seasons experienced in Sarawak so as to ensure proper model is achieved in terms of seasonal variation and pattern variation are captured during the training, testing and validation. The variables were selected based on wind formation and subsequently validation analysis using correlation analysis was performed.

2.3 Machine Learning Model Development

As a result of the ill-defined nature of wind speed, wind speed prediction must be performed with utmost accuracy. Prediction is categorized into four classes, Physical, statistical and method using artificial intelligence or combination of them. A hybrid method based on two structures proved to give accurate predictions with minimal acceptable errors [4]. Because of the intermittent nature of wind speed when is propagated in the atmosphere. A modified hybrid ANN (restricted Boltzmann machine (RBM) and back propagation neural network (BPNN)) is proposed in this paper. The wind speed values *W(x)* is represented in Eq. (1). A restricted Boltzmann machine is a generative stochastic artificial neural network that can learn a probability distribution over its set of inputs. An RBM is a quite different model from a feed-forward neural network. They have connections going both ways (forward and backward).

$$W(x) = \{x_1, x_2........x_n\} \tag{1}$$

The models consist of a series of Radian Basic Function Networks (RBFNs). The first input layer in the network is represented as N. The number of inputs in the hidden layer is reducing gradually with a variation of epochs. The output layer has one unit that is the wind speed (target function). The optimal mapping of the parameters can be found using a space allowed between the structures by using bat algorithms to avoid the RBM+BPNN to memorize the whole data (personal experience). Two steps were used in the training of conventional ANN. The pre-training phase used reinforces learning. Because of the coupling of two ANN two layers were considered, the visible layer and the hidden layer as shown in Figure 3.

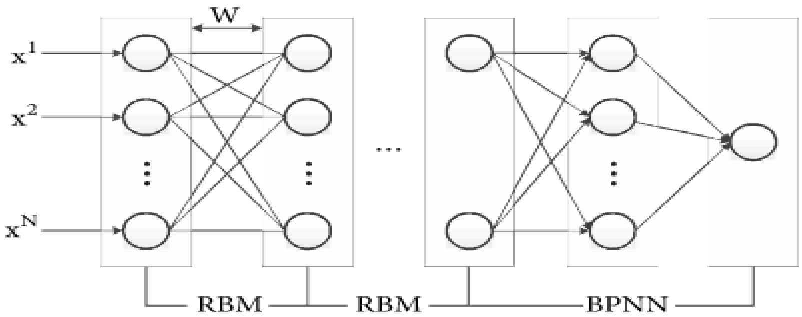

Fig. 3. Hybrid Model Based on Casacded RBM and BPNN

Several optimizations were carried out to find the best possible model, based on connecting weights, offsets and learning rate. The model parameters were fed into the model by experiments approach, and then updated using an iterative procedure. This procedure is time consuming, but with the help of bat algorithm optimal parameters were selected using less time. All the network structures were developed in Matlab/Simulink (R2018B).

The developed hybrid architecture receives the inputs and targeted data to produce the output data. The training of the hybrid model was performed using partitioned data as practiced in statistical analysis. The purpose of this phase is to determine the best design. For the performance after designing cross coupled and K-fold validations were carried out. The K-fold cross validation method is an improvement of cross-couple validation, improving generalization of the hybrid model was also implemented the purpose of doing this is to check the ability of the model to predict as expected. The training procedure includes the following

I. Step 1. Select the training features from the input variables according to the dimension reduction method mentioned
II. Step 2. Based on the input features selected in Step 1, the regression tree model is built on its traditional way with k fold cross validation without pruning.
III. Step 3. The above two steps are repeated until the size of random forest model reaches the threshold

The testing process is carried out to measure the performance of the trained network, which can be measured to some extent by the errors on the training and validation sets and the testing data; or by performing a linear regression analysis between the network response and the corresponding targets. The regression coefficient, ***R*** with values close to one indicates that there is a strong correlation between the targeted outputs and network outputs while the values that are close to zero indicates otherwise. In order to measure network performance in terms of its R-value, the best network is trained once again using both training and validation sets as the whole training data. Its performance is then assessed using the testing data. A fully trained network should be able to predict lightning from this set of unseen data and it is evaluated by measuring the R-value. The ANN algorithm for the whole process described above can be represented in a block diagram as in Figure 3.

2.4 Wind Resources Estimation

2.4.1 Statistics of the wind speed data

Self-application software using a spreadsheet (MS-Excel 2017) was specially designed to carry out statistical analysis. The mean wind speeds, standard deviation, standard error of mean, kurtosis, skewneness of the data were analyzed and computed. The equation used to get the mean wind speed and standard deviation is: is the mean μ_X, defined by the formula

$$\mu_X = \bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{2}$$

The statistics most often used are the variance and the standard deviation $\sigma_X = \sqrt{\sigma_X^2}$. We have

$$\sigma_X = \sqrt{\frac{1}{n}\left\{\sum_{i=1}^{n} X_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} X_i\right)^2\right\}} \tag{3}$$

It is easy to show that the variance is simply the mean squared deviation from the mean.

2.4.2 Wind speed at upper altitude

The standard wind speed is measured at 10m based on metrology standard, to compute the wind speed at upper heights, Eq. (4) (Hellman equation) was applied taking friction factor into consideration:

$$\left[\frac{v_2}{v_1}\right] = \left[\frac{h_2}{h_1}\right]^{\alpha} \tag{4}$$

Where v_1, v_2 are wind speed at height h_1 and h_2 and α is a friction factor of the area =0.1432 is used for neutral and stable condition [30-31].

2.4.3 Wind direction

Wind speed and direction are important during WRA, the wind speed is to see how strength the wind flow, while the wind direction is to judge the most dominant direction of wind speed flows in an area. Thought, the wind direction plays an important role during the wind farm design and installation. The outcomes play a role during sitting of the turbine. In this paper the directional data were analyzed and plotted using Matlab m files plot command.

2.4.4 Wind speed distribution models

The different statistical models are being used to model the wind speed. The purpose of doing this, is to judge which statistical model fitted the wind speed data. Based on the fitted model, the wind energy potential is studied. In this work, two most widely used tested and robust models were selected, Weibull and Rayleigh. Their parameters c (wind speed values in m/s) and k (wind speed stability, which is dimensionless) were computed using Easy-Fit software.

2.4.5 Wind power density

Wind power density is an important parameter that indicates the resource of wind power available per unit area. The power density relies on the air density and cubic wind speed of the studied area. The values were computed using Eq. (5). In addition to wind power density based on wind speed data. Wind power density based on the fitted model was also computed.

$$P = \frac{1}{2}\rho A v_{0}^{\,3}\left(\frac{h}{h_0}\right)^{3\alpha} \tag{5}$$

where
$v_{\circ}$ = known speed for height $h_{\circ}$
h = desired height
α = wind shear exponent value
ρ = is the air density
A = Area perpendicular to wind speed vector (m2)

2.4.6 Quantitative performance of wind turbine

This section deals with wind turbine selection and other calculation related to the amount of energy expected to generate based on the WRA conducted. The wind generator of 1000W Aero-generator 12-24V 3/5 Blades with charge controller, environmental protection was selected for this purpose. The turbine characteristics and power curve are shown in Table 2 and Figure 4 respectively. The annual energy, capacity factor and full load hour per year of the turbine was calculated for a single case.

Table 2
Turbine Characteristics

Model NO.	FD1000
Rated Voltage	
Starting Wind Speed	2.5 m/s
Rated wind speed	9.5 m/s
Cut-out wind speed	40 m/s
Altitude	Adjustable

3. Results and Discussion

The hybrid technique seemed to be tested in case of Lawas and Bario. Wind speed data from ten years is readily available at a time interval of one hour. For the best results, the data were scaled and normalized as they were accomplished for all preceding models. The data were divided into two parts: training data for three years are used to build the prediction model, and two years of data are applied to test the performance of the model. The MSE was also adopted to judge the effectiveness of the predicted and reference values.

Moreover, the optimum network was realized, and the performances were measured by means of the correlation coefficient R. Figure 5 shows the error model graph of MSE against epochs for the targeted villages. As shown in the figure, the curve drops close to the horizontal axis as the number of epoch's increases. The best validation performances are 0.0027357 and 0.0016115, which occurred in 582 and 1,000 epochs for Lawas and Ramuda, respectively. The simulated results of the validation of the proposed method for long-term wind prediction indicate that the estimated wind speed tends to be close to the real measurements, as all of the values of the correlation coefficient are higher than 0.900 as displayed in Figure 6.

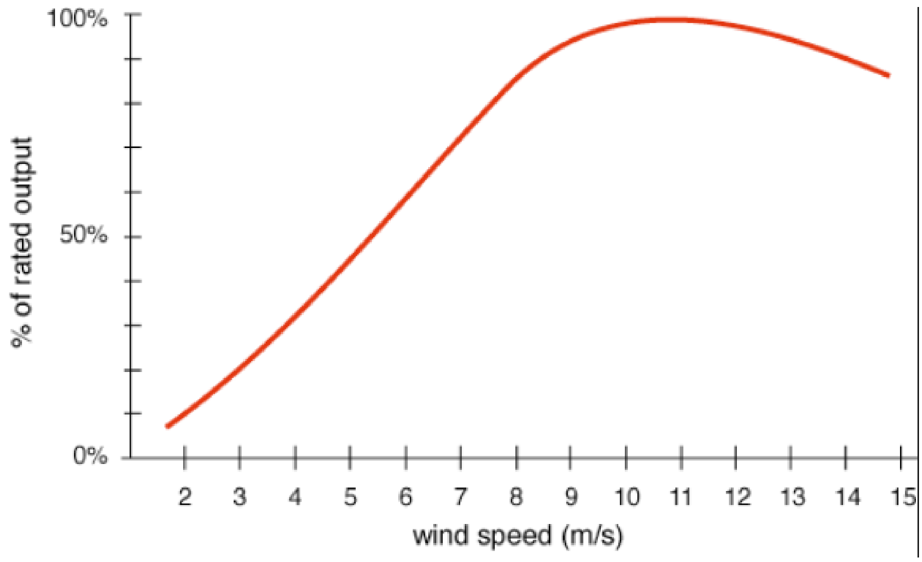

Fig. 4. Power curve of the wind turbine

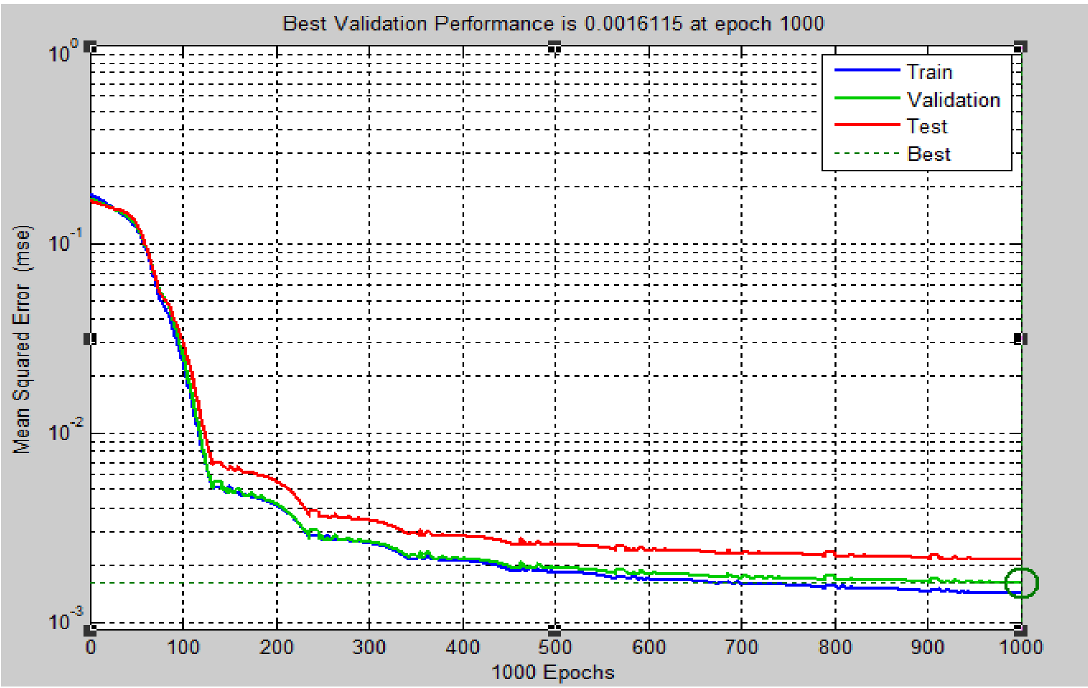

Fig. 5. Error model during the training

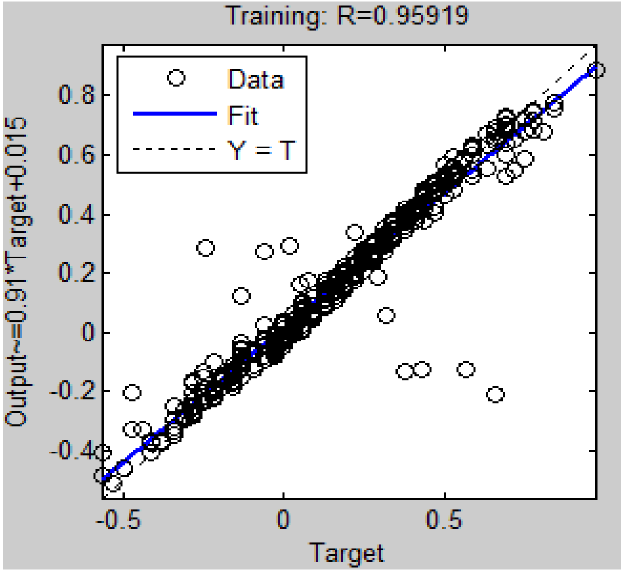

Fig. 6. Correlation diagram for the hybrid model

As shown in Figure 7, the predicted wind speed and actual measured wind speed show small deviation, but their correlation is 0.87. Thus, this demonstrates the possibility of using the developed model. The good outcome of the results obtained in both stations for a period of ten years indicates that the mean hourly daily wind speed is above 1.5 m/s. The maximum wind speed observed at the station was 4.8 m/s, while the minimum value for the period was 0.4 m/s. The identical structure observed from all the stations is a result of unequal heating of the atmosphere by the sun.

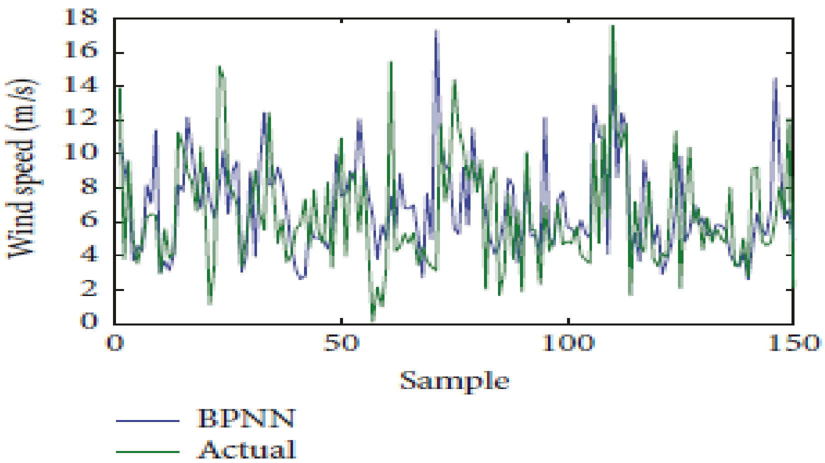

Fig. 7. Comparion between predicted and oberved wind speed

As expected, the wind speeds at 40 m are higher, the result is shown in Table 3 in the case one station located in the studied area. The average annual wind speed at 10m and 40 m heights are above 2.5 m/s and 4.5 m/s. Though, the friction factor was maintained at neutral and stable condition at 0.1432. So, a wind turbine with a cut-in wind speed of 2.0-2.5 could run throughout the year in this particular location.

Table 3
Wind speed at 10m and 20m heights

Month	10 m	40 m
January	2.92	4.59
February	2.92	4.66
March	2.96	4.66
April	2.98	4.70
May	2.97	4.68
June	2.97	4.67
July	2.01	4.74
August	2.01	4.74
September	2.93	4.61
October	2.91	4.56
November	2.92	4.59
December	2.96	4.65
Annual	2.78	4.75

The directional plot shows the dominant wind direction. Figure 8 cases of two locations. Wind directions are shown by means of wind roses divided circular approach was utilized as an indicator. The locations are Bario, and Ramuda. However, these directional values show the general trends of seasonal variations. The data from the presented location are expected to serve as a guide for wind turbine installation. Most of the wind blows 180^0-200^0 (WSW) at the Bario and 125^0-145^0 (WNW) at Ramuda when 90^0 is positioned north.

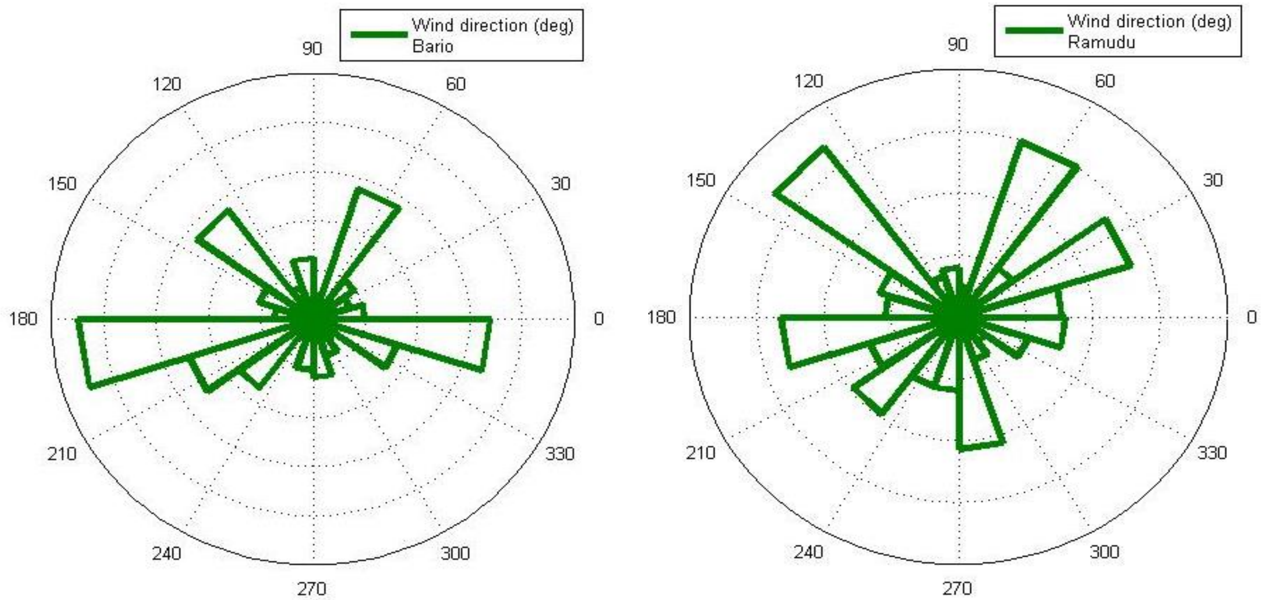

Fig. 8. Wind rose at Bario and Ramuda

Two distribution models were selected in order to judge which model suit and fit the wind speed. It was found that Weibull fit the data well, followed by the relight model in all the cases examined. A sample of the results in the case of one predicted station is shown in Table 4. It is clear from the table based on three statistical analyses; the Anderson–Darling (AD) test is a statistical test of whether a given sample data is drawn from a given probability distribution. In statistics, the Kolmogorov–Smirnov test (K–S test or KS test) is a nonparametric test of the equality of continuous. And A chi-squared test (CS), also written as χ^2 test, is any statistical hypothesis test where the sampling distribution of the test statistic is a chi-squared distribution when the null hypothesis is true. The errors found in Raleigh model are higher compared to Weibull model, based on the stated reasons, Weibull model was ranked as the first.

Table 4
GOF Summary for Ramuda

S/No	Distribution	KS		AD		CS	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Rayleigh (2P)	0.29271	2	179.83	5	988.38	2
2	Weibull	0.13452	1	27.581	2	281.32	1

The power density was computed at 10 m and 40 m heights. The potential of average annual wind power density will lead to the class of wind power in the area. The wind power density was computed using the desired equation stated in the methodology section. The result is tabulated in Table 5. As shown in the table wind power density varies in terms of height and month. The minimum and maximum wind power density based on the Weibull fitted model are 4.05 W/m^2 and 4.69 W/m^{2}at 10m heights. While based on the observed wind speed the minimum and maximum values are 4.01 and 4.96 W/m^2. The error values are in the range of 0.10-0.21. As expected, the wind power density at 40 m is higher than that of 10 m. The computed wind power densities at 40 m based on Weibull and actual data in the case of one station are in the range of minimum maximum 39.11 W/m^2 and 42.05 W/m^{2}and 38.65 41.20 W/m^2. The error values are in the range of 0.04 -0.16. The average wind power densities at 10 m and 40 m based on fitted model and observed data are 4.31 W/m^2, 4.62 W/m^2 and 40.54 W/m^{2}and 33.76 W/m^2. According to the national renewable energy laboratory (NERL), the wind power density at 10-40m falls within class 1, power density less-than or equal to 100 W/m^2. This class is considered as low energy yield, which is suitable for small power generation.

Table 5
Power Density at 10 m and 40 m Height

	10 m			40 m		
Month	P_W	P_A	Error	P_W	P_A	Error
Jan	4.59	4.34	0.11	42.05	41.01	0.09
Feb	4.62	4.38	0.10	41.60	41.20	0.04
Mar	4.69	4.38	0.13	41.77	41.20	0.05
Apr	4.37	4.11	0.12	40.44	40.98	0.05
May	4.16	4.96	0.10	39.84	40.20	0.07
Jun	4.19	4.84	0.19	39.11	38.67	0.05
Jul	4.14	4.85	0.16	40.08	38.77	0.15
Aug	4.22	4.93	0.15	39.98	39.10	0.10
Sep	4.43	4.01	0.21	41.02	39.47	0.16
Oct	4.13	4.91	0.11	40.02	39.00	0.11
Nov	4.14	4.89	0.13	41.16	38.91	0.14
Dec	4.05	4.83	0.12	39.36	38.65	0.08
Annual	4.31	4.62	0.14	40.54	33.76	0.09

Based on the selected wind turbine as discussed above, the energy produced was estimated. The wind energy Table 6 shows the results of energy production that is anticipated in the selected location. The outcomes are tabulated based on the annual energy output, (AEO), capacity factor (CF) and full load hours (FLH) of the selected 1000 W with 3-5 blade turbine at 10m and 40 m heights. The energy production at 10 m and 40 m are 5905.52 kWh/year and 9,717.27 kWh/year. The ratio stands at 1:1.8.

Table 6
Energy production of the 1000W wind generator

	10 m	40 m
AEO (kWh/year)	5905.52	9,717.27
CF (%)	3.10	6.31
FLH (Hour/year)	104.80	265.91

4. Conclusions

The objective of this study is to evaluate the potential of having wind energy in the remote areas, using a reliable wind speed prediction model and data available at the ground station. An improved hybrid intelligent model using RBM and BPNN model was designed, trained, and tested. The results show the capability of using the model to generate the wind speed data. In addition, to prediction model, WRA assessment was conducted in selected remote location. The outcome of the evaluation shows that the wind speed and wind power density fall within class 1, which is suitable for small and medium wind power development. Quantitative energy production using a selected wind turbine was carried out. As expected, the AEO, CF and FLH show the energy yield is suitable for remote area application. Prospects cost analysis and model comparison with other traditional wind speed prediction could be a future study.

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