A Methodology for Wind Energy Evaluation in Complex Terrain Regions of Sarawak

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Abstract: Wind power is the safest, cleanest resource and has emerged as the speediest growing renewable energy in terms of annual installed capacity. Before a wind-drive system is set up, thorough wind resource assessment (WRA) must be conducted. In this paper, a methodology based on ground-station and topographical neural network modeled data is proposed to study the wind energy potential, in the monitored location and areas not covered by directly measurement instrumentation at Kuching. A new topographical feed forward neural network (T-FFNN) back propagation trained with Levenberg-Marquardt (LM), which consists of three layers was used to model the wind speed profile. The daily 10 m height, average hourly measured wind speed data for a period of ten years (2003-2012) for eight stations operated by Malaysia Meteorological Department (MMD) were used for the training, testing and validation. The geographical, meteorological and synthesized topographical parameters were used as input data, whereas the monthly wind speeds as the objective function. The optimum topology with maximum mean absolute percentage error of 6.4 % and correlation value of 0.9946 between the reference measured and predicted was obtained. The predicted monthly wind speed varied from 1.3-1.98 m/s with an average annual wind speed of 1.62 m/s. The characteristics of ground -based station was analyzed and presented. It was found in all the areas examined that the wind power falls within a low power density class ($P_D \leq 100 w/m^2$). Results from the micro-sizing showed an annual energy output (AEO) in the range of 4-12 MWh/year.

Keywords: Wind energy; Neural network; Complex terrain; Sarawak

1. Introduction

Wind technology stages are developing energy systems around the entire world, in reaction to boost pressure, to lessen CO_2 amounts and reliance on non-renewable fuels[1]. Energy and the environment play a crucial role in the national economy. In this regards, the need for energy cannot be over emphasized. According to a recent survey conducted by [2], The requirement of energy is swiftly progressing in Malaysia. The country's energy need is anticipated to develop periodically at the rate of 3.5% to reach 146.7 Mtoe in 2030, which is a 2.6 % boost from 2002. Amongst the fossil fuels, coal is forecasted to grow at the accelerated rate of 9.7 % per year, succeeded by natural gas at 2.9 % and oil at 2.7 % [3]. The demand for commercial energy in Malaysia is projected to continue its upward trend from 1244 Petajoule (PJ) in 2000 to an estimated 2218 PJ in 2010, and it is presumed to retain on advancing in forthcoming years [4].

The drift of the energy mix in Malaysia indicated a perpetual reduction in the portion of oil and petroleum products share and steady improvement in coal demand; Figure 1 displays the percentage of primitive commercial energy supply sources. The government of Malaysia has formulated a series of energy policy in order to boost other sources of energy apart from oil and gas. In this regards, a small renewable energy policy was introduced. This program

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encouraged the application of small renewable energy systems such as micro-hydro, biomass, solar and small-scale wind turbines.

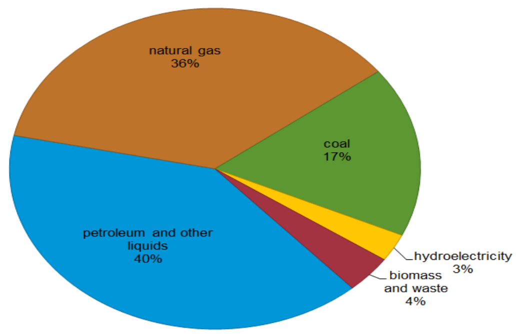

Figure 1. Malaysia Energy Consumption

Wind is available source of energy that is clean, freely available and naturally abundant almost anywhere around the world. However, the availability of the wind resource that will drive the wind system varies depending on the location. Wind turbine operates by transforming the moving energy in the wind. At the beginning of the rotation, wind turbine transforms the kinetic energy in the wind into mechanical power. This useful power is often utilized for particular tasks (including milling grain or pumping water), or a generator can change this mechanical energy into electrical power.

It is well-known that the available power varies directly proportional to the cubic of wind speed. A little fraction variation of the wind speed will lead to a significant error in the output power. Therefore, detailed knowledge of the wind speed characteristics is prerequisite requirements need to be addressed during the technical and feasibility stages. The analysis of the wind speeds mainly involves the application of proper statistical examination, the wind speed distribution modeling, and the wind speed prediction. From the survey conducted, the wind power assessments are performed based on mean wind speed, direction of the wind flows, and variation of the wind speed with heights. For sure, this requires reliable long-term historical wind data sets. Research study based on those techniques has been conducted by employing statistical modeling, Weibull, Rayleigh, and Gamma functions, and reported the achieved wind power densities in different countries. For example, [5-10].

Wind speed varies with time and space; prediction of the wind speed value requires proper modeling tool for greater transformation and utilization wind system. In recent times, the study of wind speed prediction has been a growing concern for many researchers [11-14] across the globe. However, in less developed countries few studies have carried out, due to lack of expertise and the farm operators has minimal knowledge on WRA.

Malaysia meteorological department (MMD) is an agency in the country, which has a mandate to carry out wind monitoring. In Sarawak, there are an insufficient number of wind stations. Barely 8 out of 16 have the wind speed records. In view of that two studies have been published in [15] and [16]. Besides, most of the areas in the states do not possess usable wind station for this purpose. In the case of this study, the wind station is established in Kuching where interest in renewable energy is minimal. Because of the wind speed non-linearity characteristics, physical models tend to generate a higher number of errors, moreover, it is difficult to generate a definitive solution [17, 18]. Based on the aforementioned problems, a suitable prediction model is required. Recently, attention has been devoted to solving an intricate problem of non-linear problems by means of soft computing, such as fuzzy logic and neural network (NN). The fuzzy logic procedure has some constrains, mainly the data samples are limited to short-term prediction, difficulty in selected input parameters, it involves a large number of fuzzy set membership and high processing time. NNs apart from being the simple structure, parallelism, fault tolerance and fast computation time, it has been widely used in many prediction applications. In this study, a NN is proposed to study the complex dependence of wind speed in the areas where wind station is not available, by considering the terrain shape and roughness class changes in a complex terrain environment of Sarawak.

2. Methodology

Technical examination of renewable energy utilization can be performed in a number of diverse plans with different levels of approaches. The sequence of the methodology employed in this study is described systematically in Figure 2.

A. Study Area and Data Collection

Kuching is the metropolis and the most populated city in the state of Sarawak in Malaysia.[19], located in between latitudes of 1.53 and 110.34 in the east of longitude (Figure 3). It is also the capital of the state. The city located on the Sarawak River at the southwest tip of the state of Sarawak on the island of Borneo and covered an area of 431 km^2 with a population about 570,407.The selected study area wind station is located 11 km south of Kuching city center. The target areas from the location of wind station are Samarahan (1.46^0, 110.500), Serian (1.16^0, 110.57^0) and Lundu (1.66^0, 109.85^0), which are separated from a distance of 25.9, 64.37 and 84.00 km respectively [20].

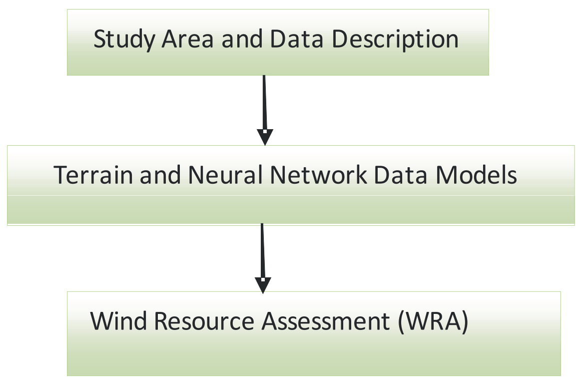

Figure 2. Sequence of the Methodology

Measured daily average hourly data, wind speed, direction, relative humidity, temperature, and atmospheric pressure for a period of 10 years starting from 2003 to2012 were collected from MMD. The data were acquired at 10m mast steel using state-of-the-art weather monitoring system, they were continuously observed in a step of 10 minutes, and average over 1-hour before it was transferred into data electronic data acquisition system (Figure 4).

Figure 3. Location of the Wind Station

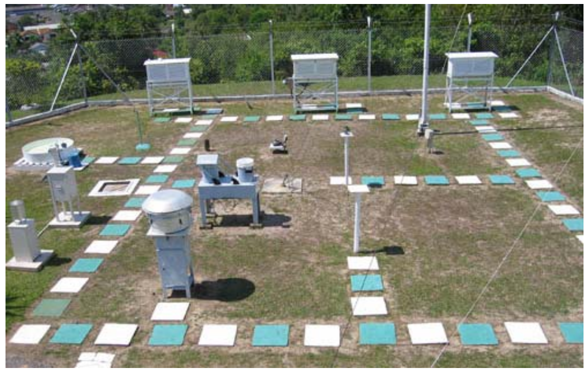

Figure 4. Wind Monitoring Station (MMD)

B. ANN System Modeling

Artificial Neural Networks (ANNs) are among the most efficient learning methods currently used to solve complex problems and have been used in several prediction domains ([21]. ANN is a mathematical model that attempts to simulate the networks of neurons found in the brain, consist of layers of interconnected computational units called neurons that can learn from experience.

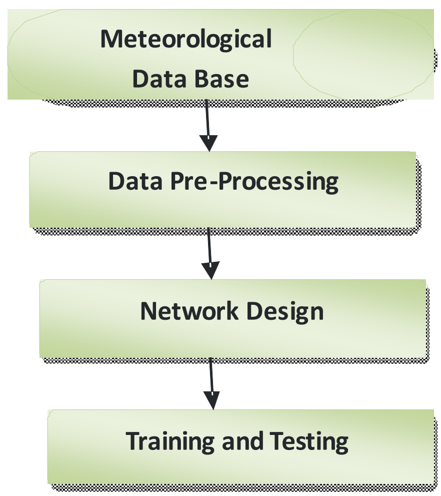

Figure 5. ANN Design Flow Process

Numerous NN architectures have been suggested. The best application of NNs in the wind speed prediction has been feed-forward network (FFN) using log-sigmoid hidden neurons function [22]. FNN was adopted with modifications in this study, to successfully develop a prediction model; the following steps were taken for processing and analyses of data for the development of the model (Figure 5).

Prior to the application of the meteorological data sets, that was obtained from MMD; a terrain data model (DEM) was developed using GEPlot and Google. An unrestricted map available at JUPEM (is the sole control organization liable for giving a premium quality survey and mapping products and services to the government). The map was digitized using GEPlot; the distance between the locations of the 30 m contour interval was established. By means of marking tools available on the Google Earth, the latitudes, and longitude points were obtained from each sample point base on the world geodetic system (WGS84). All the values were exported into terrain zooming solution (software free online), and the ground

elevation data sets were obtained. Ahead of the training, all the data used as inputs and targets were normalized in the series of [-1-1] using the minimum and maximum technique.
A three-layer (input, hidden and output) FNN with back propagation was coded using Matlab 7.2. (Figure 6). Eight geographical and meteorological parameters (latitude, longitude, altitude, month, terrain elevation, temperature, atmospheric pressure and relative humidity) were considered as model inputs, while a monthly wind speed as the target function. The situation of identifying the optimum number of neurons is the hidden layer also very prominent. The number of neurons applied in the hidden was varied from 5-202 with a step of 5. Log-Sigmoid and Purelin transfer functions have been utilized in the hidden and output layers. To overcome the problem associated with the gradient descent algorithm in the FNN, a faster algorithm Levenberg-Marquardt (L-M) which has local maxima and fast convergence was employed. To ensure the data used in the training has exceeded the number of weights, nine years data sets (2003-2011) were employed for the network training and one year worth of data (2012) was applied for testing the model effectiveness.

Simulations were carried out to calculate the wind speed values in the targeted regions. During the training process, the weights are set one at a time using surface roughness data connecting the reference area and a target location. So that the desired input/output relation of the network was realized. The iterations are frequently performed until the differences between the real output of the network and the preferred output is equal to a negligible value. Thus, indicating that no additional improvement in the system can be made. It is quite notable that; expanding the learning process could lead the ANN to memorize the training data sets and behaves in weak generalization capability of the ANN model. The design function weights and biases of the ANN are obtained once the training is completed. The statistical method correlation *R,* mean absolute percentage was applied to the evaluation of the model performances. The values were obtained mathematically using equation 2.1 and 2.2 respectively.

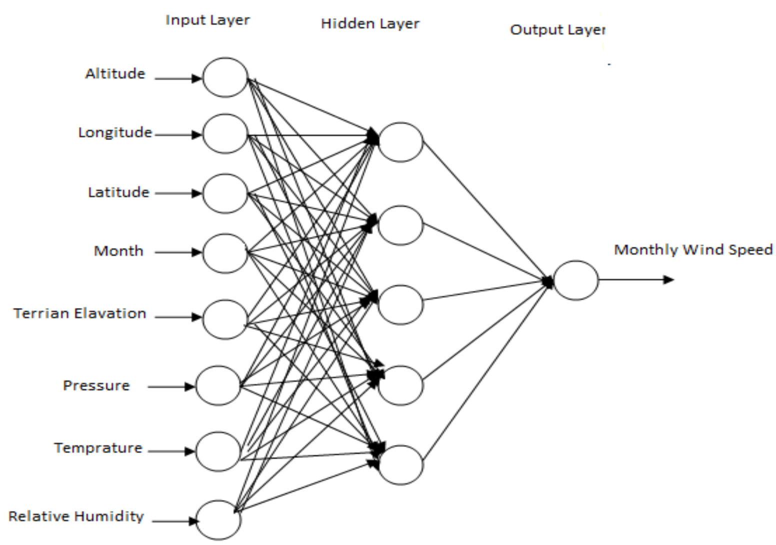

Figure 6. Sample of ANN Model with five Neurons

$$\boldsymbol{R} = \frac{1}{n-1}\sum_{i=1}^{n}\frac{(t_i-\bar{t})}{S_t}\frac{(o_i-\bar{o})}{S_o} \tag{1}$$

Here, $\bar{t}$ and $\bar{o}$ are the means of *t* and o Likewise, S_t and S_o are the standard deviations of each variable.

$$MAPE = \frac{\frac{\sum_{i=1}^{N} |O_i - t_i|}{O}}{n} * 100 \quad (2)$$

C. *Wind Resource Evaluation*

To carry out a study on wind energy potential in a given area, many published studies have proposed the steps need to be followed. In this paper, the following techniques were formulated. Preprocessing data analysis, wind speed characteristics, wind speed variation with height, air density changes computation, statistical distribution of the wind speed values and WRA. Measured wind speed data sets were screened in order to detect any missing or invalid data. Validation process was performed using self-developed application in Microsoft excel spreadsheet software. The validation results showed that out of 3653 barely 1% were missing. Hence, this gives a total recovery rate of 99% measurements are credible and effectively represent the wind data sets. The monthly mean wind speed and direction was plotted, in an effort to describe the characteristics of the average values of wind speed and directional data over the examined area.

C.1. Variation of Wind speed with Height

Wind speed at ground level is merely zero. To achieve the representational level of wind speed at upper heights where a wind turbine is expected to work. A well-known wind shear equation was adopted; its equation is shown by [23, 24]. The values of wind speed were obtained at 20-40 m heights which are suitable for small-scale applications [25] is obtained using :

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$$\frac{v_2}{v_1} = \left(\frac{h_2}{h_1}\right)^{\alpha} \quad (3)$$

where wind velocities from a different altitude to a hub height at which the turbine is expected to be installed, knowing the velocities v_1 and v_2 measured at height h_1 and h_2 respectively, and α is the roughness coefficient, and can be approximated using Equation 2.4 as described by [26].

$$\alpha = 0.0910\log_{10} Z_0 + 0.016(\log_{10} Z_0)^2 + 0.24 \quad (4)$$

C.2. Air Density

Air density is another important parameter that is linked with the power density; in many reported studies, the values are assumed constant at standard conditions. Because of the availability of meteorological data, the values were computed taking into account, temperature, relative humidity, and height of the anemometer at 10-40 m, using Equation 2.5, which is an extended version of the conventional air density equation:

$$\rho = \frac{p}{R_d T} * h(t) \quad (5)$$

where p is the atmospheric pressure, R_d is the relative humidity, T atmospheric temperature and h (t) represent altitude

C.3. Wind Speed Distribution Modeling

In modeling wind speed distribution, Weibull function is the most widely used in the literature, but the reliability of the model varies depending on how accurate the parameters were calculated. To assume this, without performing any statistical measures, it might lead to errors.

Table 1. Statistical Distribution Models

Name	PDF/CDF	Remarks
Weibull	$p(v)=\frac{k}{c}\left(\frac{v}{c}\right)^{k-1}\exp\left\{-\left(\frac{v}{c}\right)\right\}^{k}$ v>0, k,c >0 $P(v)=\int_0^{\infty} p(v)dv = 1-\exp\left\{-\left(\frac{v}{c}\right)\right\}^{k}$	Where c is the scale parameter measured in m/s and k stands for shape parameter, which has no unit.
Rayleigh	$p(v)=\frac{2v}{c^2}\exp-[v/c]^2$	Is a special case of Weibull model in which the value of k=2
Gamma	$f(x:\alpha,\beta)=\frac{x^{\alpha-1}}{\beta\Gamma(\alpha)}\exp\left[-\frac{x}{\beta}\right]$ x>0, α,β>0 $F(x)=\frac{\Gamma(x/\beta)_{\alpha}}{\Gamma(\alpha)}$	Where $\Gamma(x)$ is an incomplete gamma function
Lognormal	$f(x:\mu,\delta)=\frac{1}{x\delta\sqrt{2\pi}}\exp\left[-\frac{1}{2}\left(\frac{\ln n-\mu}{\delta}\right)^2\right]$ x>0, s>0,8□µ8 $F(x)=\phi\left(\frac{\ln x-\mu}{\delta}\right)$	Where Ø is the Laplace integral
Erlang	$f(x)=1-\exp\left[\frac{-x}{\beta}\right]\sum_{i=0}^{m-1}\frac{x^i}{\beta^i i}$	where a is an integer, contrary to the Gamma distribution, the Erlang does offer a cumulative distribution function.

Table 2. Goodness of Fit Model Description

Name	Equation	Remarks
KS	$D=Max(D^+,D^-)$, $D^+=Max(\frac{1}{n}-F(x_i))$ $D^-=Max(F(x_i)-\frac{i-1}{n})$	The data are made up of a randomly sample X_1, X_2,..., X_n of dimension and related to some unknown distribution function, denoted by $F(x)$, and the sample is a random sample
AD	$A^2=-n-\frac{1}{n}\sum_{i=1}^{N}(2i-1)[\ln F(x_i)+\ln(1-F(x_{n-1+i}))]$	Compare the fit of an observed CDF to an expected CDF. This test gives higher weights to the tails than KS test and the test statistic
CS	$\chi^2=\sum_{i=1}^{k}\frac{(O_i-E_i)^2}{E_i}$, $E_i=F(x_2)-F(x_1)$	where Oi denotes the observed frequency and Ei denotes the expected frequency where F denotes the CDF of the distribution under consideration and x_1, x_2 are the lower and upper limits for bin i.

Hence, five most widely applied models (Weibull, Rayleigh, Lognormal, Erlang and Gamma) (Table 1) were selected. The suitability of each model was judged based on

Kolmogorov-Smirnov (KS), Anderson-Darling (AD) and Chi-Squared (CS) tests (Table 2). The parameters of the fittest model were obtained via maximum likelihood method (MLM).

C.4. Most Probable Wind Speed and Wind Speed Carrying Maximum Energy

The most probable wind speed signifies the most prevalent wind velocity for a distributed wind probability function. The greatest wind energy taking the wind speed can be determined by the scale parameter and shape parameters of the Weibull distribution function. These values are obtainable based on Weibull model; the most probable wind speed and the wind speed carrying maximum energy are obtained using the following Equation [27]:

$$\boldsymbol{V}_{\boldsymbol{mp}} = \boldsymbol{c}\left(1 - \frac{1}{\boldsymbol{k}}\right) \text{ (m/s)} \tag{6}$$

$$V_{\max E} = c\left(1 + \frac{2}{k}\right)^{\frac{1}{k}} \text{ (m/s)} \tag{7}$$

C.5. Wind Power and Energy Density

The average wind power represents the available mean wind power per unit area. The equation is given (2.8), based on the fitted model Weibull and Gamma, the power density is expressed using (2.9-2.11):

$$\boldsymbol{P_a} = \frac{1}{2}\rho(\boldsymbol{h}, \boldsymbol{r_d})\boldsymbol{v}^3 \tag{8}$$

$$P_w = \frac{1}{2}\rho(h, r_d)c^3\Gamma(1 + \frac{3}{k}) \tag{9}$$

$$\boldsymbol{P_G} = \frac{1}{2}\rho(\boldsymbol{h}, \boldsymbol{r_d})c^3[\boldsymbol{k}(\boldsymbol{k}+1)(\boldsymbol{k}+2)] \tag{10}$$

$$\boldsymbol{P.E(\%)} = \frac{(\boldsymbol{P_{w,G}} - \boldsymbol{P_a})}{\boldsymbol{P_a}} \tag{11}$$

The error in computing the power density is provided by (equation 2.11): Wind energy density described the potential as a function of time (equation 2.12-2.14).

$$\boldsymbol{E_a} = \frac{1}{2}\rho(\boldsymbol{h}, \boldsymbol{r_d})\boldsymbol{v}^3 * \boldsymbol{T} \tag{12}$$

$$\boldsymbol{E_w} = \frac{1}{2}\rho(\boldsymbol{h}, \boldsymbol{r_d})\boldsymbol{c}^3\Gamma(1 + \frac{3}{\boldsymbol{k}}) * \boldsymbol{T} \tag{13}$$

$$\boldsymbol{E_G} = \frac{1}{2}\rho(\boldsymbol{h}, \boldsymbol{r_d})\boldsymbol{c}^3[\boldsymbol{k}(\boldsymbol{k}+1)(\boldsymbol{k}+2)] * \boldsymbol{T} \tag{14}$$

C.6. Micro-sitting Analysis

As soon as wind potential in a particular location is determined, wind farm designers need to search for maximum structure of turbines in order to optimize the strength development of the wind energy. This technique regarded as “micro-siting,” is extremely significant considering that it requires a variable factor like the predominant wind direction, surfaces convenience, and the visible effect. As reported in many scientific literatures, it is more fitting to express the wind power in terms of average wind speed and swept area. Hence, the wind energy depends on the cubic values of the wind speed of wind energy conversion system (WECS). The kinetic power available in a driving airstream is given by:

$$\boldsymbol{P} = \frac{1}{2}\rho \boldsymbol{A}\boldsymbol{V}^{3} \tag{15}$$

where P is the power in the wind, (Watts), ρ is the calculated air density, in Kg/m^3 .A is the cross sectional flow rate and V is the wind speed in (m/s).

Figure 8 illustrates the chosen wind turbines and their power curves, whereas technical specifications are summarized in Table 3. The Siemens SWT-2.3-113 wind turbine is the decisive option for low to moderate wind conditions, like countries in the equatorial. The revolutionary direct drive generator and a new, optimized quantum blade are paired to extract as much energy as possible from the wind. With a low 105 dB noise level, the turbine is one of the quietest wind turbines on the market. At normal condition, best wind turbines acquire about 50 % of the theoretical optimum power of 30% within the air stream that moves through the rotor [28]. Thus:

$$\boldsymbol{P_a} = 0.3*\frac{6}{\pi}\left(\tfrac{1}{2}\boldsymbol{r}\boldsymbol{A}\boldsymbol{V}_a^3\right) = 0.35\boldsymbol{A}\boldsymbol{V}_a^3 \tag{16}$$

where P_a is the average wind power output (kW), and V_a is the average wind speed (m/s).
The energy is the function of power (P) in watts and time (t) in hours. Thus, the annual energy production of wind turbine can be computed from:

$$\boldsymbol{AEO} = \frac{\boldsymbol{P_a} * 8760}{1000} = 3.1\boldsymbol{A}\boldsymbol{V}_a^3 \tag{17}$$

where:
AEO = Annual energy output (kWh)
8760 = stands for the number of hours in a year
A = Area of swept by wind turbine rotor (m^2)

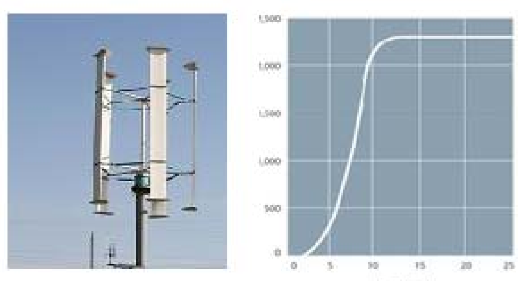


Figure 8. Siemens VAWT Wind Turbine and Power Curve

V_a= Average wind speed (m/s)

Table 3. Technical Specifications of Wind Turbines

Description	Siemens SWT-2.3-113
Rotor type	5-blade
Rotor diameter (m)	113
Swept area (m^2)	10,000
Rated power (kW)	2.3
Cut-in-wind speed (m/s)	1.5
Cut-off-wind speed (m/s)	15
Tower Height	Site specific

The capacity factor (C_F) describes the wind turbine generators (WTG's) actual strength outcome for the year divided up by the energy output if the machine worked on its performing power output for the whole year. The C_F is mostly based on the characteristics of the wind regime, together with the turbine and generator capabilities. This facilitates in generating the wind consumption effectiveness (WCE) which is calculated by (2.18) [29]:

$$C_f = \frac{P_a}{P_r} * 100 \tag{18}$$

3. Results and Discussion

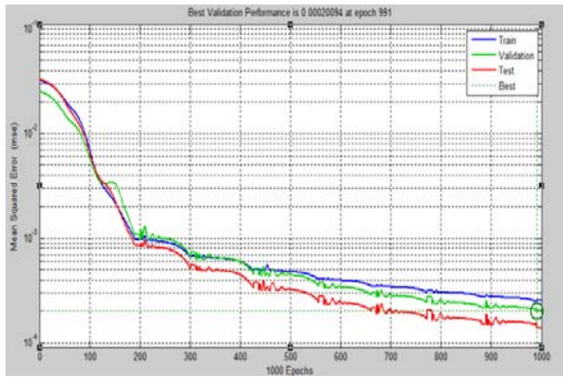
A. Simulation Results

For the NN design, the model is used to predict the values of wind speed at Serian, Samarahan, and Lundu. The number of neurons in the hidden layer, the type of activation function, and learning algorithm were carefully selected. Since the NNs' performances should be compared with those from the observed near stations, the input/output vectors are applied. For the better convergence of the proposed NNs, the sample data were normalized between -1 to 1.

It was discovered experimentally, that working with 152 neurons in the hidden layer coupled with L-M training algorithm offered the most efficient overall performance, and the lowest prediction error as shown in Figure 8 and 9, respectively. The training was stopped at 1000 epochs in which no further improvement can be made. The MSE between the ANN and reference data was drastically reduced to 0.0020094, 0.001883 and 0.0015626, at best valuation periods of 991, 976 and 996 for Samarahan, Serian and Lundu. Another important aspect that can be observed during the training phase is that, from 0-100 epochs, the training, testing and validation curves are oscillation-free. This is clearly understandable due to geostrophic wind characteristics. Furthermore, small oscillations' were noticed because of terrain elevation changes.

Figure 9 also presents the training plots regression between the predicted values of wind speed and the actual ones based on the training set for the Kuching reference station. To examine the effectiveness of the overall model, a set of predefined data in the template were feasted into the model and the predicted values were acquired consequently. Figure 10 shows the predicted results of the suggested model. In all the three cases, the regression values are above 0.9000, which implies a high relationship between the control and predicted wind speed. A much lower than this has been reported in [30, 31].

A comparison between monthly-predicted wind speeds at the targeted station was made with the ones obtained from the nearest neighbor wind speed. The results are depicted in Figure 11. As shown in the figure the maximum predictable wind speed was about 2.0 m/s, which occurred at Lundu, while the lowest possible value of 1.3 m/s was realized at Serian. The long-term mean annual wind speed for ground and artificial stations are 1.7 1.8, 1.6 and 1.7 m/s. Again, to show in-depth analysis concerning the prediction model, a comparison was made with the observed wind speed using the control station in the area due to the identical climatic characteristic. From January to December, the predicted and measured values at control station show similar trends. For instance, in January the control station located in Kuching has an average monthly wind speed of 1.71 m/s, while, the model-based values for Samarahan, Serian and Lundu are 1.8 m/s, 1.6 m/s and 1.9 m/s. The mean absolute percentage error (MAPE) was 5.5%, 4.62 and 14.45%. The highest value occurred in Lundu will probably be due to the high distance from the control. The variation is because of the dynamic nature of wind speed, because of site-specific behavior of wind speed, and different training data sets employed and terrain variation. Furthermore, the correlation coefficient between these stations were computed and presented in Table 4. The result shows the values of the wind speed in Kuching correlates well when compared to the reference station followed by Samarahan and then Serian.



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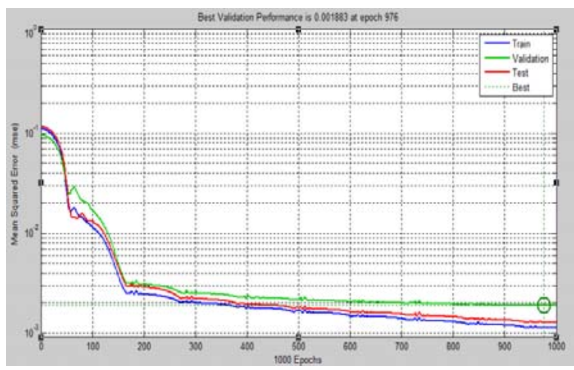

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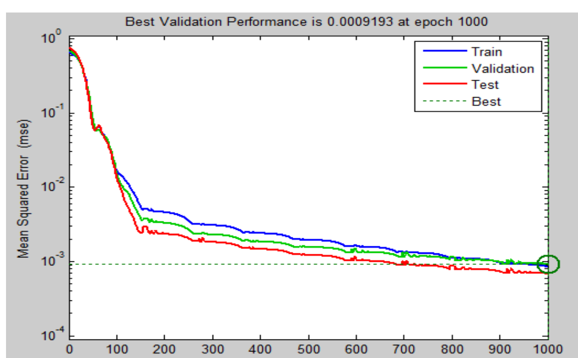
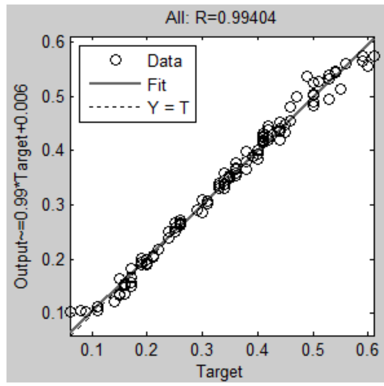


(c)

Figure 9. ANN Training (a) Samarahan (b) Serian (c) Lundu

Table 4. Correlation between Predicted and Neighbor Station

Reference Station	Target Areas	*R*	*MAPE (%)*	*COV*
Kuching	Samarahan	0.812	5.01	0.006
	Serian	0.627	5.63	0.007
	Lundu	0.876	4.28	0.007



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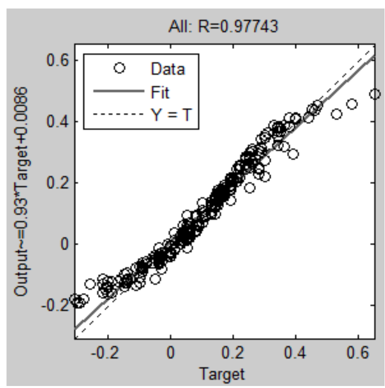

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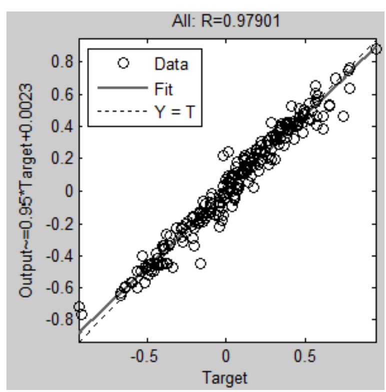

(c).

Figure 10. Regression Between ANN and Reference Based o Training Whole Data Sets for (a) Samarahan (b) Serian (c) Lundu

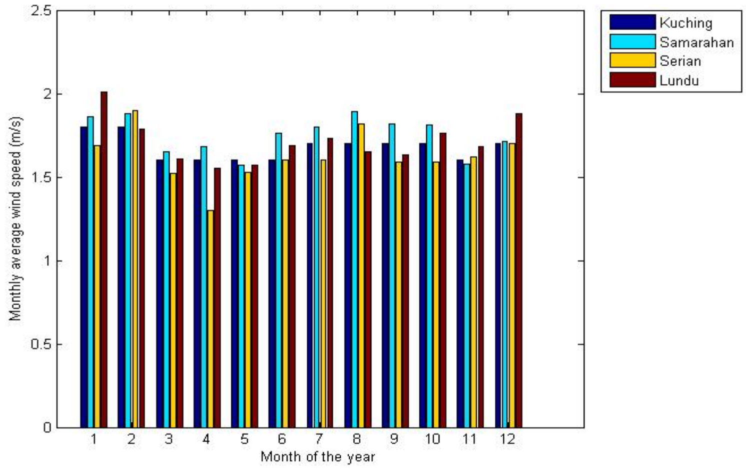

Figure 11. ANN Predicted and Reference Stations

B. Wind Speed Characteristics and Statistical Modeling

Figure11 shows the summarized characteristics of wind speed over the examined study areas. The displayed values indicate data analysis around the measurement interval, from January 2003 to December 2012. The 12-monthly mean value of wind speed is virtually continuous and range from 0:5 to 3.7 m/s. This feature demonstrates the reasonable balance of the wind resource at 10 m over the Kuching The entire mean value is equal to 1.7 m/s.

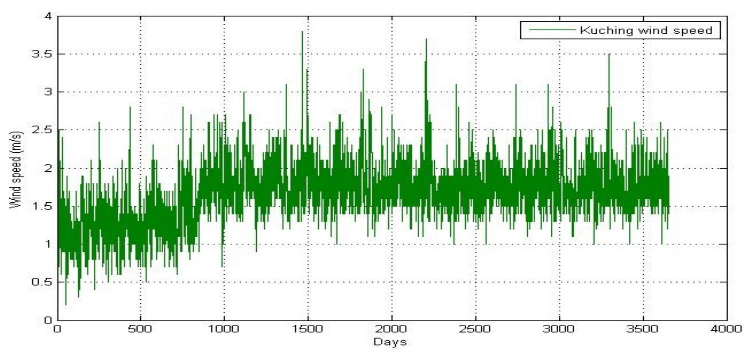

Figure 11. Daily Wind Speed Characteristics at Kuching

Table 4. Goodness of Fit Summary at Kuching

	Distribution	Kolmogorov Smirnov		Anderson Darling		Chi-Squared	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Erlang	0.16859	4	104.33	4	345.95	2
2	Gamma	0.09676	2	26.352	2	288.92	1
3	Lognormal	0.11795	3	46.53	3	366.47	3
4	Rayleigh (2P)	0.27508	5	423.75	5	2353.8	5
5	Weibull	0.09057	1	21.607	1	372.04	4

Figure 12 and Table 4 demonstrates the outcomes of wind speed statistical modeling distribution at 10 m above the ground level (AGL). Ranking one shows the best-fitted model, while rank five pinpoints the poorly performed distribution function. The results show that Gamma and Weibull fit the observed wind speed in the study area. Based on Weibull function the shape parameter k is equal to be 4.93 and the scale parameter reaches to 1.82 m/s. While for Gamma model, the shape parameter is 17.74 and scale value was found to be 0.09 m/s.

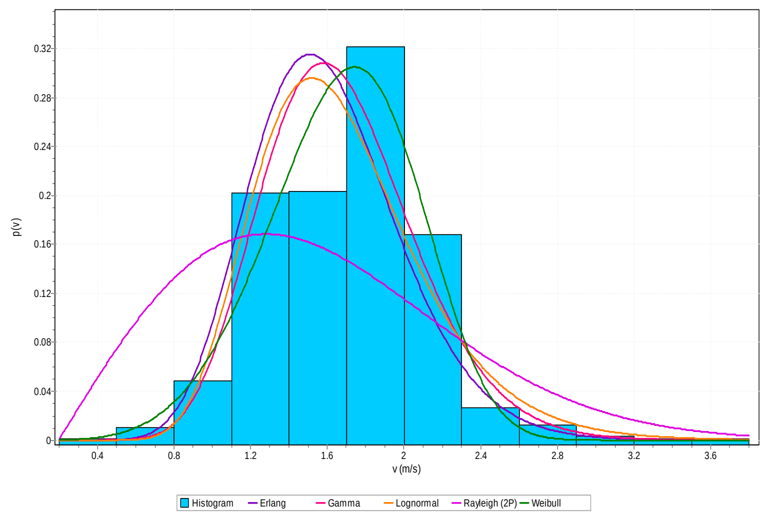

Figure 12. Distribution Modeling of Wind Speed

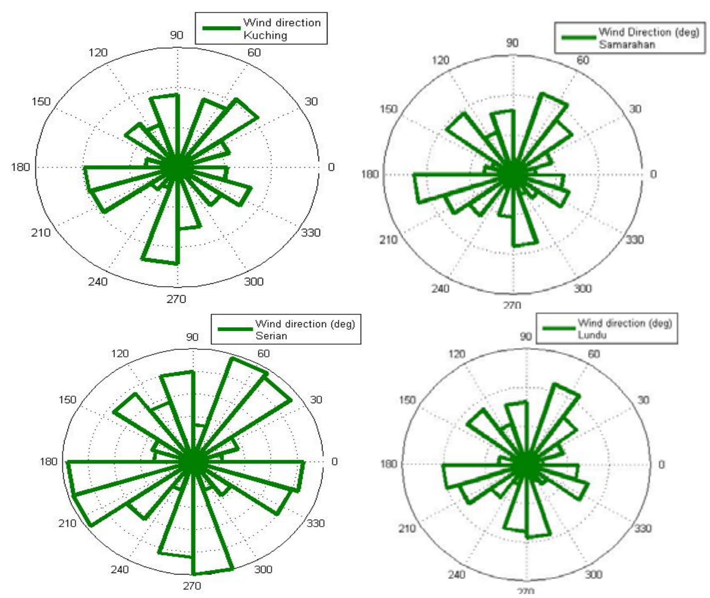

Figure 13: Wind Direction for Ten Years (2003-2012) Kuching, Samarahan, Serian and Lundu

The most probable wind speeds (V_{mp}) and wind speed carrying maximum energy (V_{maxE}) varied with time and space. The minimum and maximum values of (V_{mp}) and (V_{maxE}) at Kuching are 0.65 m/s at 10 m and 1.91 m/s at 40 m, which happened in the month of march and February and 2.8-5.74 and 2.8m/s at 10 m and 5.74 m/s at 30 m. The mean annual values of (V_{mp}) and (V_{maxE}) was 0.78 m/s, 1.09 m/s, 1.52 m/s, 1.54 m/s and 2.90 m/s, 4.10 m/s, 5.62 m/s, and 5.58 m/s.

Additionally, predominant wind directions were studied and determined. This phase is equally important, considering that it permits to boost wind farm siting. Matlab software was utilized to project the distribution of wind direction data. Figure 13 shows the wind rose drawn for 12 sectors when 90^0 is placed in the north position. The diagrams reveal the significance of winds spitting out from the north-west and western areas. The wind blows more predominantly at 260^0-270^0, 180^0-200^0, 50^0-70^0 and 180^0-210^0 in Kuching, Samarahan, Lundu, and Serian. In some regions, other directions were also feasible.

The values of air density were obtained using equation 2.5; the result shows that the mean value is 1.165kg/m^3. The monthly values range from 1.158-1.169 kg/m^3. Based on that, the average value was applied in the computation of wind energy density. The variation of wind speed from the observed level of measurement shows an increase of 14%, 26%, 31% and 42%. While the shear coefficient (friction factor within the study area was α=0. 239).

C. *Wind Power and Energy Density*

The power densities calculated from the measured probability density distribution and those obtained using the most fitted models are shown in Table 5. The power density shows a significant month-to-month variation, the minimum power densities occur in Kuching, Samarahan, Serian and Lundu have values of 2.37 and 27.30 W/m^2, 2.24-26.87 W/m^2, 1.27-27.20 W/m^2 and 2.16-14.76 W/m^2 based on measured wind speed data sets at 10-40m. However, the power densities were also computed based on fitted mathematical model. The minimum and maxim mum values of power density at 10-40 m heights are 1.55-31.42 W/m^2 for the Weibull function and 1.31-35.68 W/m^2 for the Gamma model.

In is interesting to note that, the values of power densities of 10-40 m for Samarahan, Serian and Lundu in the order of maximum-minimum falls within class less than 100 W/m^2 based on standard wind association category. This indicates the possibility of running small-scale wind-drive systems in the areas. Based on the recommended power density class Errors in calculating the power densities using the distributions (Weibull and Gamma models) and a comparison to those using the measured probability density distributions were calculated. The highest error value of 0.07% was realized for the Weibull model, while 0.58% was obtained using the Gamma model. Consequently, this demonstrates that the power density as estimated by the Weibull model has a small error compared to Gamma. It is clear, based on the result obtained; the Gamma model was unable to fit the measured wind speed properly. Nevertheless, the Gamma model might be considered for micro sizing, simply for the reason that it fits the wind speed excellently compared to Erlang, Lognormal and Rayleigh functions. For instance, an error of 0.68-0.78% has been noted in [32, 33].

Energy density depends on the power per unit area. The values were obtained using (2.12-2.14). Table 6 shows the achieved energy densities in terms of observed and predicted data and based on fitted distributions. The highest values of wind power based on the measured wind speed are 282.47 kWh/m^2/ year that acquired in Lundu, while the lowest possible value of 11.51 kWh/m^2/ year was realized in Serian. Based on the models the energy density shows slightly upwards/downwards in some location. The maximum and minimum values are found to be 13.59 - 298.50 kWh/m^2/year and 11.46-282.47 kWh/m^2/ year for the Weibull and Gamma models respectively.

Table 5. Power Density Comparison

Station	10-40 m Actual wind power density (W/m^2)		10-40 m Weibull wind power density (W/m^2)		10-40 m Gamma wind power density (W/m^2)	
	Min	Max	Min	Max	Min	Max
Kuching	2.37	23.90	2.37	29.30	2.86	27.20
Samarahan	2.24	26.78	2.24	31.42	2.79	28.99
Serian	1.27	27.20	1.55	29.54	1.31	28.01
Lundu	2.16	14.76	2.24	14.76	2.47	35.68

Table 6. Energy Density Comparison

Station	10-40 m Actual wind energy density (kWh/m^2/ year)		10-40 m Weibull wind energy density (kWh/m^2/year)		10-40 m Gamma wind energy density (kWh/m^2/ year)	
	Min	Max	Min	Max	Min	Max
Kuching	19.22	243.89	28.75	288.12	27.12	266.78
Samarahan	19.65	234.60	19.65	272.26	24.40	253.90
Serian	11.51	238.45	13.59	258.76	11.46	245.34
Lundu	18.90	282.47	19.65	298.50	21.49	282.47

D. Micrositing

For the purpose of energy yield six different wind turbines of various ratings were selected (300 W, 600 W, 1 kW, 3 kW, 5 kW and 10 kW). The analysis was performed using desired equations previously stated in the methodology section. Figure14 depicts the annual energy production generated in the studied locations. The figure signifies the AEO varies depending on the heights, time and wind resource available. It is clear Kuching has higher values followed by Samarahan, but Serian and Lundu are having similar values of AEO. The capacity factor is important for policy makers and manufacturers of wind power system. The minimum values of 1.76% were obtained at 10 m, and the maximum value of 8.7% was realized. It is clear, based on the previous findings the areas falls within the moderate region that is suitable for small-scale application, for instance, remote street lighting, water pumping, grains milling and agricultural and isolated electrification.

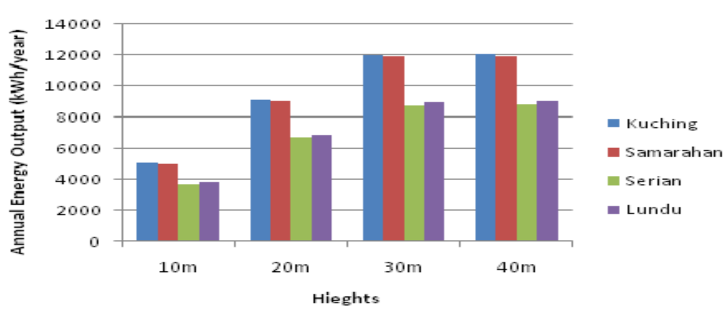

Figure 14. Annual Energy Output at 10-40 m Height

4. Conclusion

Wind energy is clean, freely available alternative that can be applied to a standalone system. In the study presented here, the wind power potential was analyzed in the areas with and without monitoring regimes. Statistical modeling performed shows that the wind speed varies depending on the particular location. It is clear that Weibull and Gamma fits the wind speed data of Sarawak. The wind energy density of all the areas falls within class 1. Power Based on the micro-siting conducted the energy production in all the areas can be harnessed for small-scale application.

Nomenclature and Symbols

Symbol	Meaning
μ	Mean for the lognormal function
c	Scale parameter of the Weibull model
C_f	Capacity factor
E_a	Actual energy density
E_G	Gamma energy density
E_w	Weibull energy density
$h(t)$	Altitude at different time
h_1	Height of wind velocity 1
h_2	Height of wind velocity 2
k	Shape parameter of the Weibull model
o	Output data
o_E	Expected sample
o_i	Observed sample
P	Pressure
p_a	Actual wind power density
P_G	Gamma power density
P_w	Weibull power density
s_o	Standard deviation of output data
s_t	Standard deviation of target data
t	Target data
T	Temperature
v_1	Wind speed at height 1
v_2	Wind speed at height 2
V_a	Average wind speed
v_{maxE}	Wind speed carrying maximum energy
v_{mp}	Most probable wind speed
x_i	Sample data
z_o	Initial roughness height
α	Roughness coefficient
γ	Scale parameter of the Lognormal Model
Γ	Gamma function
β	Scale parameter of the Gamma and Erlang Models
ρ	Air density (kg/m^3)
$\rho(h,r_d)$	Air density in terms of height and relative humidity

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