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ELECTRICAL & ELECTRONIC ENGINEERING | RESEARCH ARTICLE

Wind energy assessment and mapping using terrain nonlinear autoregressive neural network (TNARX) and wind station data

Salisu Muhammad Lawan^{1,2*} and Wan Azlan Wan Zainal Abidin²

Abstract: This paper presents the potential of generating wind power using soft computing model and ground station data. In reality, the process of wind resource assessment is to set up an experiment in the targeted locations, and measure the wind speed and direction. In this paper, a prediction model based on the terrain based neural network named terrain nonlinear autoregressive neural network (TNARX) is proposed to forecast the wind speed in the areas not covered by measurements using a ground station located nearby. The model has meteorological, physical and topographical as input, while the wind speed is the target variable. The suitability of the proposed model was judged using statistical measures. The paper shows characteristics of wind speed and the most prevailing wind directions. The variation of wind speed at 10–40 m heights was obtained and presented. Wind speed distribution modelling was carried out using five statistical models. It was found that Weibull and Gamma fits the wind speed of the studied areas. Wind power and energy density results show the areas falls within class 1, which is possible for harnessing energy content in wind for small scale purposes.



Salisu Muhammad Lawan

ABOUT THE AUTHORS

Salisu Muhammad Lawan had earlier worked in several industries, both local and international, before becoming a Senior Lecturer at the Department of Electrical Engineering, Kano University of Science and Technology, Wudil where he had taught courses such as computer programming, digital electronics and renewable energy engineering. Salisu Muhammad Lawan obtained a B. Eng (Electrical) from Bayero University, Kano (BUK) and M. Eng in Electrical/Electronic Engineering specializing in software Engineering. He later obtained a PhD on Renewable Energy from Universiti Malaysia Sarawak (UNIMAS). He is a registered engineer with council for the regulation of engineering in Nigeria COREN and a member of the Nigerian Society of Engineer (NSE). He is a seasoned researcher with current interests in Soft Computing and Renewable Energy Systems. He is a pioneer Director, Centre for Renewable Energy and Climate Change, (CERECC) at the Kano University of Science and Technology, Wudil, where he leads research works on renewable energy resources and technologies.

PUBLIC INTEREST STATEMENT

Energy is vital for day to day activities, the generation of electricity via conventional sources (Petroleum, Gas and Coal) increases environmental worries, and other hazardous effects. Renewable energy sources are clean energy that can be generated via natural resources. Wind as one of the renewable energy is the safest and fastest growing renewable energy in terms of annual installed capacity. Before a wind system is built, details wind resource assessment must be conducted. Prediction and measurements of wind speed are one of the prerequisite steps that must be performed. In this reported work, an improved soft computing model was developed to predict wind speed in the areas where wind monitoring station is not installed. The analyzed results showed the availability of wind energy potential for small scale applications, such as remote village electrification, grain grinding, etc. The findings of this paper will be useful to policy makers, potential investors and wind turbine manufacturers.

Subjects: Power & Energy; Renewable Energy; Electrical & Electronic Engineering

Keywords: wind; wind speed; wind power; artificial neural network; Sarawak; Bintulu

1. Introduction

Fossil fuels (coal, oil, and gas) are limited options, which wipe out as time passes; in addition, they are expensive and contaminate the atmosphere. This effect is the motivation for the utilization of sustainable energies. Alternative energy solutions, like wind, solar, geothermal, hydro, biomass, and ocean thermal energy have enticed raising concern nearly across the whole world due to the fact of their essentially infinite and non-polluting characteristics (Al-Nassar, Alhajraf, Al-Enizi, & Al-Awadhi, 2005; Anyi, Kirke, & Ali, 2010; Carolin Mabel & Fernandez, 2008; Karim, 2012). Wind energy is most likely much more acceptable because of the current market, and wind technology remains to get strength across the globe.

Wind power is considered as being a developing subject, and lots of wind turbine firms are encountering difficulties to meet up with the market need. The fact is, 2014 was a fantastic year for the world wind sector with more than 35 GW of mounted plants. The final put in capacity brought up by 11% during this year, having virtually 318 GW (GWEC, 2013). Because of this rapid development of wind energy, specialists assert that the substantial potential of wind power is still unexploited, particularly in the less-developed nations (Abbes & Belhadj, 2014). Over these countries, the deficiency of efficient data and experience in prospecting and analyzing local wind prospective is the most important hindrance that holds back the progress of green energy. In addition, government officials and farm managers are usually non-experts in wind energy.

Numerous scientific studies with divergent concepts on wind energy assessment are already conducted all over the world, particularly to figure out the potentialities of regional wind sites for wind power technology (Akdağ & Dinler, 2009; Akpınar & Akpınar, 2005; Bagiorgas, Assimakopoulos, Theoharopoulos, Matthopoulos, & Mihalakakou, 2007; Bekele & Palm, 2009; Chang, 2011). For example, wind power assessment using two parameter Weibull function was analyzed in (Mostafaeipour, Sedaghat, Dehghan-Niri, & Kalantar, 2011), Wind energy potential assessment based on Weibull and Rayleigh was extensively investigated and concludes that the wind power can be harnessed for commercial used in the United Kingdom (Abbes & Belhadj, 2014). Prediction of wind speed and wind power based on artificial intelligent method for short-term to long term was successfully carried out and validated in a study reported by Ahmad and Anderson (2014), Ak, Li, Vitelli, and Zio (2012), Alkhatib, Heire, and Kurt (2012), Anand, Saravanan, and Muthaiah (2013), Ball, Purcell, and Carey (2004), Bilgili, Sahin, and Yasar, (2007) and Carolin Mabel and Fernandez (2008).

In all the listed studies above, the authors developed soft computing and validated it using error analysis methods using available data within the region. Each of the investigators examined the wind energy prospects working with meteorological stations' information obtainable based on a simple set of variables, which includes wind power, energy densities, and wind speed. Malaysia is a non-contiguous nation and is not overlooked; the revealed researches are offered (Albani & Ibrahim, 2014; Albani, Ibrahim, & Yong, 2009; Anwari, Rashid, Muhyiddin, & Ali, 2012; Daut, Razliana, Irwan, & Farhana, 2012; Islam, Saidur, & Rahim, 2011). The listed studies have considered different locations and provided analyses to justify their findings. In addition, a few studies have been discovered for the case of Sarawak, building the wind map of Sabah and Sarawak (Wahab, 2004), and wind and solar potentials at five locations of Sarawak (Jakhrani, Othman, Rigit, & Samo, 2013) and wind and photovoltaic possibilities at five areas of Sarawak (Albani & Ibrahim, 2014).

Until recently, the authors of the current paper have formulated a novel neural network (NN) model for wind speed prediction, in the areas in which wind speed measurements are not accomplished, as well as produced a wind map at 10–40 m elevations for wind power application (Muhammad, Abidin, Chai, Baharun, & Masri, 2014).

In line with the literary works, because of different geographical disorders and variations in roughness over the length of the location, considerable modifications in wind speed distribution within local vicinity occur. This is verified because wind resources fluctuate based on the area regardless of studies describing the country.

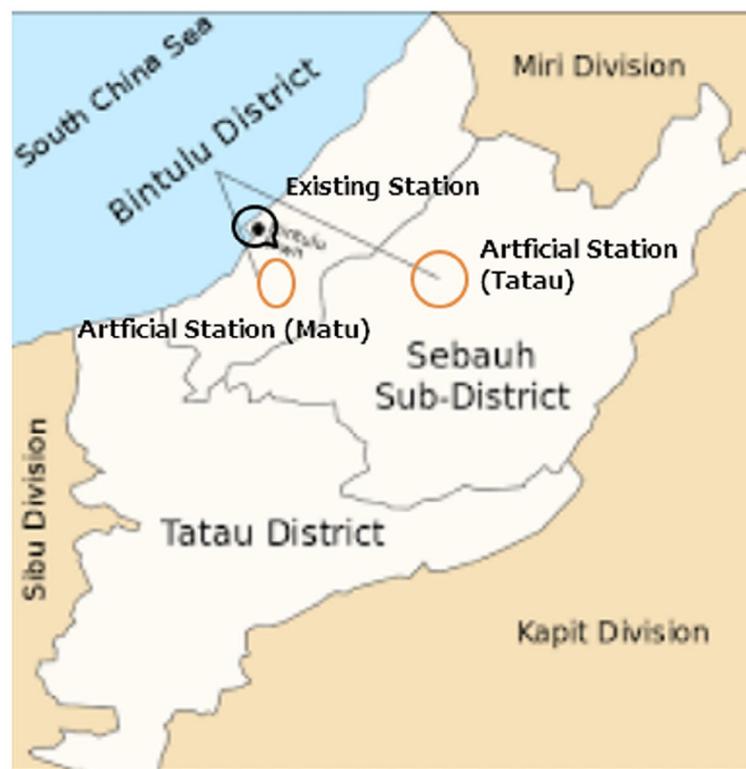
A site-by-site assessment is crucial to get appropriate wind speed and energy patterns in the country. Moreover, going over all of the previously mentioned studies in the Malaysian perspective, no studies targeted on Sibiu. This paper looks into wind power potential and the analysis of wind turbine overall performance for non-connected mode purposes in the rural and remote areas of Bintulu in Sarawak, Borneo.

2. Data collection method and study area description

The Bintulu District is one of two districts of Bintulu Division in Sarawak, Malaysia. It has a total area of 7,220.40 square kilometres. Bintulu District has a sub-district, which is Sebauh. Bintulu is located in Malaysia country, in Southeast Asia continent (or region). DMS latitude longitude coordinates for Bintulu are: 3°10'0.01"N, 113°1'59.99"E There are two towns in Bintulu District, namely Bintulu and Sebauh. The economy is largely based on the petroleum and natural gas industries. Bintulu has an estimated 85% of Sarawak's known natural gas reserves, or some 42.3 trillion cubic feet (1,200 km³). In addition to export as liquified natural gas, on-shore facilities produce fertiliser, and formaldehyde resins. Bintulu also has about half of Sarawak's crude oil reserves of 500 million barrels (79,000,000 m³), with production wells located some 40 km offshore. Bintulu has around 27% of Sarawak's tropical rainforest, and the timber industry remains a strong component of the Division's economy. Agriculture is relatively minor although growing steadily, with oil palm, rattan and pepper the main products. Deposits of coal have been discovered, but are yet unexploited (Anand et al., 2013).

Sibu is the future most important city in Sarawak following Kuching. Furthermore, the region has dispersed villages close to the city, with an overall populace around 121,000 (GWEC, 2013). In order to examine the potentiality, two areas, Mukah and Kanowit, were chosen to position a synthetic wind station. Figure 1 shows the location of Sibu jointly with the areas that are close by (Portal, 2007).

Figure 1. Position of the existing station and target locations.



Malaysia Meteorological Department (MMD) is in control of the Malaysian synoptic stations and provide data records. The data utilized in this research consist of wind speed, wind direction, temperature, relative humidity, and atmospheric pressure for a period of ten years (2006–2015) assessed at 10 m height. The data were observed every five minutes and averaged over one hour. Further, the daily average data per hour were calculated and saved in the data logger. Based on the average daily data per hour, the monthly and yearly values were obtained.

3. Methodology

The methodology part is split into two sections; the first part is the prediction of wind speed in the determined areas, where wind speed is not assessed, although the subsequent section presents with the analysis of wind energy making use of the ground station and determined by the formulated terrain nonlinear autoregressive neural network (TNARX) model.

3.1. Prediction modelling: Nonlinear autoregressive neural network (TNARX)

Wind speed prediction models are designed in quite a few described scientific studies. The strategies can be classified into persistence, numerical weather prediction, statistics, and neural network (NN). The application of a NN is more precise, inexpensive, extremely effective, and much less time consuming.

Recently, the authors one study (Muhammad et al., 2014) have designed a topographical NN model by taking into consideration nine inputs: latitude, longitude, altitude, month, temperature, pressure, atmospheric pressure, relative humidity, terrain roughness change, and terrain elevation. The digital terrain elevation model (DEM) was generated making use of GEPlot and Google Earth software, in order to acquire terrain elevation data connecting the areas.

A three-layer TNARX was built and coded using the Matlab 7.5 Tool Box and subsequently script files were written (Kalogirou, 2000). The neuron in the hidden layer varied from 2–450 with a step of two. Theoretical studies have proven that a single hidden layer is adequate in these types of topologies to estimate a complex nonlinear function (Philippopoulos & Deligiorgi, 2009, 2012; Philippopoulos, Deligiorgi, & Kouroupetroglou, 2015). The Log-Sigmoid activation function was utilized in the hidden layer and Purelin is employed to the output layer. In order to get a differential function between the input and output variables To overcome the slow convergences associated with the feedforward neural network (FFNN) using the descent gradient, the Lion Optimization Algorithm (LOA) by means of application designer in the Matlab environment was introduced as a result of the lesser mean square error and shorter processing time.

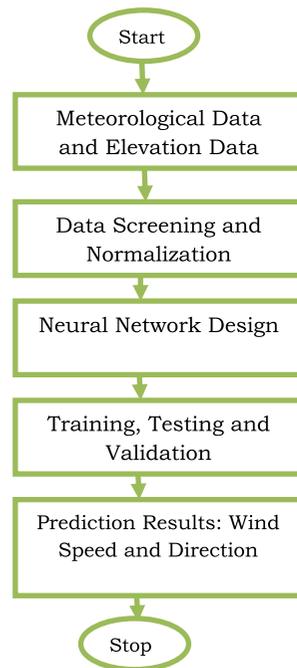
Before the network training, the input data were normalized using lowest and highest strategies in $[-1, 1]$ for all inputs lie 1–80, while $[0, 1]$ scale was used for inputs above 80. The data used in the training, testing, and validations were partitioned into three parts by years: 2006–2014, 2015, and 2016, accordingly. Simulations were executed to calculate the wind speed values in the aimed locations. The iterations were frequently carried out until the best possible network was obtained (i.e. the error between the input and output variables is minimal with little computation time). Information for the procedures involved is shown in Figure 2. Likewise, the same processes were made to ascertain the wind direction in the particular areas using longitude, latitude, altitude, month, wind speed, atmospheric pressure, temperature, relative humidity, terrain elevation, and roughness variation as inputs. Wind direction was employed as the objective function.

To determine the possibilities of wind power within a certain location, many techniques need to be conducted. With this part, the wind resource analysis is carried out as follows.

3.2. Wind speed data analysis

All the obtained data were processed to identify any unacceptable and absent data. The total number of observed data was 3,653 of which eight data points were found to be invalid. An evaluation practice was carried out applying the Newton forward and backward, linear interpolation, and cubic

Figure 2. Process of EFFNN development.



spline methods, which were executed by using a self-developed application in Microsoft Excel 2016. The characteristics of the assessed wind speed at the ground station situated in Miri were evaluated on a daily, monthly, seasonal, and annual basis. The most predominant wind directions were eventually plotted using the Matlab plot command.

3.3. Wind speed at upper height above 10 m

As observed in several research, the suggested elevation for measuring the surface wind speed, recommend based on the standard meteorological association, is 10 m. To analyze the potentiality of wind energy at higher level (20–40 m) heights, exactly where wind-driven generators are anticipated to work, the most widely applied power law model was employed. Its equation is shown below (Abbes & Belhadj, 2014; Sen, 2012).

$$\frac{v_2}{v_1} = \left(\frac{h_2}{h_1} \right)^\alpha \quad (1)$$

With respect to Equation (1), v_1 and v_2 represent the wind speeds at the desired heights of h_1 and h_2 , and α is the friction coefficient. Its value depends on so many factors, such as time, location, roughness, and atmospheric layer stability. Numerous research followed the ratio 1/7 (0.143) for stable and neutral conditions (Islam, Rahim, Solangi, & Saidur, 2012; Ray, Rogers, & McGowan, 2006), Fripp and Wisler (2008) have implemented 0.09 and 0.20 during the day and night. An idea has also been made for the application of a logarithmic equation (Abbes & Belhadj, 2014). For that reason, and data access, this research utilized Equation (2) in finding the friction coefficient.

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

where Z_0 is the roughness length of the locations.

3.4. Effects of air density on wind power

The generation of wind energy relies upon on the air density. It is vital parameters that need to be addressed during the technical feasibility phase. The models proposed in the literature for computing air density vary from the required meteorological input parameters. The main concern of those

approaches is the fact that they use average daily data that do not effectively give precise indication about the system. Additionally, the traditional models never take into account sufficient meteorological variables for instance, moisture content (humidity), which can be a very essential feature, particularly in a tropical environment like Malaysia whereby humidity could attain almost 100%. Their value is calculated in terms of the ideal gas formula by looking at the elevation variance, temperature and relative humidity. The improved equation is:

$$\rho(h, r_d) = \frac{P}{RT} e^{-\left[\frac{gh}{RT} * r_d\right]} \text{ (kg/m}^3\text{)} \tag{3}$$

where p , r_d , T and h are atmospheric pressure, relative humidity, temperature and height.

3.5. Statistical modelling for wind speed data

To examine the wind power potential in a given location, statistical models have been proposed and utilized. In statistical theory, the probability density function (pdf) of a steady random variable is a function that is often included to acquire the probability that a random variable usually takes a value in a given span. From the wind engineering perspective, pdfs have been utilized to describe the distribution of wind speed in a given area. In addition, PDFs serve as a statistical modelling of random wind speed variations. Weibull and Rayleigh are classified as the most frequently applied models. In addition to these functions, Gamma, Erlang, and Lognormal were included in this paper (Table 1).

The suitability of each model was judged based on the three goodness-of-fit tests (GOF): Anderson-Darling (AD), Kolmogorov-Smirnov (KS), and Chi-Square (CS) (Table 2). Numerous parameter evaluation models are made available in the literature. The most utilized method was the maximum likelihood method (MLM); many experts have applied MLM extensively (Al-Nassar et al., 2005; Azad, Rasul, & Yusaf, 2014; Dike, Chineke, Nwofor, & Okoro, 2011; Gualtieri & Secci, 2014; Mohammadi, Mostafaeipour, Dinpashoh, & Pouya, 2014; Muhammad et al., 2014; Palma, Castro, Ribeiro, Rodrigues, & Pinto, 2008). In view of the overwhelming consensus, the MLM was employed, and implemented using Easy-Fit software version 5.0.

3.5.1. Most probable wind speed and wind speed carrying the maximum energy

Additional parameters, which need to be analyzed, include the most probable wind speed (V_{mp}) and the wind speed carrying maximum energy (V_{MaxE}). Though the most probable wind speed is not directly linked to the assessment of wind energy in a certain region, it is important to wind turbine

Table 1. PDF and CDF models

PDF	Equation PDF and CDF	Equation	Remarks
Weibull	$p(v) = \frac{k}{c} \left(\frac{v}{c}\right)^{k-1} \exp\left\{-\left(\frac{v}{c}\right)^k\right\}$	3	$v > 0, k, c > 0$, where c is the scale parameter measure in m/s and k is the shape parameter which has no unit
	$P(v) = \int_0^{\infty} p(v)dv = 1 - \exp\left\{-\left(\frac{v}{c}\right)^k\right\}$	4	
Rayleigh	$p(v) = \frac{2v}{c^2} \exp\left[-\left(\frac{v}{c}\right)^2\right]$	5	Rayleigh is a special case of the Weibull function with $k = 2$
Gamma	$p(v) = \frac{v^{k-1}}{c \Gamma(k)} \exp\left[-\frac{v}{c}\right]$	5	Where $\Gamma(v)$ is an incomplete Gamma function
	$P(v) = \frac{\Gamma\left(\frac{v}{c}\right)^k}{\Gamma(\alpha)}$	6	
Lognormal	$p(v) = \frac{1}{vc \sqrt{2\pi}} \exp\left[-\frac{1}{2} \left(\frac{\ln v - c}{c}\right)^2\right]$	7	Where \emptyset is the Laplace integral function.
	$P(v) = \emptyset\left(\frac{\ln v - k}{c}\right)$	8	
Erlang	$p(v) = 1 - \exp\left[-\frac{v}{k}\right] \sum_{i=0}^{c-1} \frac{v^i}{k^i i!}$	9	Where α is an integer, contrary to the Gamma
	$P(v) = \left[-\left(\frac{c}{v-c}\right)^\alpha\right]$	10	

Table 2. GOF models

GOF	Equation	Number
KS	$D = \text{Max}(D^+, D^-), D^+ = \text{Max}\left(\frac{1}{n} - F\left(\frac{1}{n} - F(x_i)\right)\right)$	11
	$D^- = \text{Max}\left(F(x_i) - \frac{i-1}{n}\right)$	12
AD	$A^2 = -n - \frac{1}{n} \sum_{i=1}^N (2i - 1) [\ln F(x_i) + \ln(F(x_{n+1+i}))]$	13
CS	$\chi^2 = \sum_{i=1}^k \frac{(O_i - E_i)^2}{E_i}, E_i = F(x_2) - F(x_1)$	14

makers. The values were obtained analytically according to the Weibull model, whose equations are provided in 15 and 16, accordingly.

$$V_{mp} = c \left(\frac{k-1}{k} \right), \text{ (m/s)} \tag{15}$$

$$V_{maxE} = c \left(\frac{k+2}{k} \right), \text{ (m/s)} \tag{16}$$

where V_{mp} and V_{maxE} represent the most probable wind speed and wind speed carrying the maximum energy by the wind, while, c and k are the scale and shape parameters for the Weibull function.

3.6. Wind power, wind power density and wind energy density

After knowing the best performing distribution model that suits the wind speed, the next stage is to identify the potential of wind power per unit area, which is known as power density. The available power is the most important in finding the wind energy potential. It is basically separate and does not depend on the kind of wind energy generator.

$$P_a = \frac{1}{2} \rho (h, r_d) v^3 \tag{17}$$

$$P_w = \frac{1}{2} \rho (h, r_d) c^3 \Gamma \left(1 + \frac{3}{k} \right) \tag{18}$$

$$P_G = \frac{1}{2} \rho (h, r_d) c^3 \Gamma(k(k+1)(k+2)) \tag{19}$$

$$P.E(\%) = \frac{(P_{w,G} - P_a)}{P_a} \tag{20}$$

where P_a , P_w , and P_G represent the wind power densities for the actual, Weibull, and Gamma functions, ρ is the air density, and c and k are the model parameters, which represent the scale and shape of the distribution models.

The power density is obtained based on the measured and predicted wind speed Equation (17) and the two most fitted models (Equations (18–19)), while the errors in computing the wind power densities are obtained using Equation (20) (Azad et al., 2014; Celik, 2003; Keyhani, Ghasemi-Varnamkhasti, Khanali, & Abbaszadeh, 2010; Mohammadi et al., 2014). Energy density is acquired using Equations 21–23 for the preferred time T . In this paper, the value of T is 8760 h.

$$E_a = \frac{1}{2} \rho (h, r_d) v^3 * T \tag{21}$$

$$E_w = \frac{1}{2} \rho (h, r_d) c^3 \Gamma \left(1 + \frac{3}{k} \right) * T \quad (22)$$

$$E_G = \frac{1}{2} \rho (h, r_d) c^3 \Gamma (k(k+1)(k+2)) * T \quad (23)$$

where E_w , E_w , and E_G are the energy densities based on the observed, Weibull, and Gamma distribution models.

3.7. Analysis of selected wind turbine systems

Immediately after determining the wind power potential of a particular location, the next phase is to execute the optimum design of the determined wind generators for the reason of strengthening the energy generation of the farm. This process is often considered as micro-siting analysis. It is remarkably considerable, generally for the reason that there are several factors to take into consideration, such as the prevalent wind direction, the surface roughness and terrain slope difference, which have an impact on wind movement in the area under evaluation. Well-established software programs, such as computational fluid dynamics (CFD), Wind Atlas and Application Program Software (WAsP), 3-Tier, 3-DEM, WindSim, and WindPro are used in lots of research.

These computer software assist in the determination of more prosperous designs. In this paper, Windographer software was used to calculate the wind field in the examined area based on the measured and predicted data. Comparable to the showcased software packages, Windographer functions are made up of three-dimensional solvers to identify the Reynolds-Average Navier-Stokes (RANS) equations based on the well-known turbulence model (Abbes & Belhadj, 2014; Moussavi & Kashkooli, 2013).

The software allows the user to determine the potential of each location. By utilizing our produced wind speed and energy maps using GIS software at 10–40 m heights (a sample at 10 m is shown in (Figure 3)), wind energy system sitting may be accomplished.

To avert the wake effects and wake-induced fatigue loads, a spacing of at least 7–10 wind turbine rotor diameter is usually recommended in many wind energy books in an attempt to achieve the best cost-effective power generation (Burton, Jenkins, Sharpe, & Bossanyi, 2012). On account of the low wind speed in the tropical zone, a vertical axis wind turbine (VAWT) is extensively installed for the reason that the design gets wind speed from all directions. For that reason, the wind turbines are placed a minimum of five rotor dimensions away from each other.

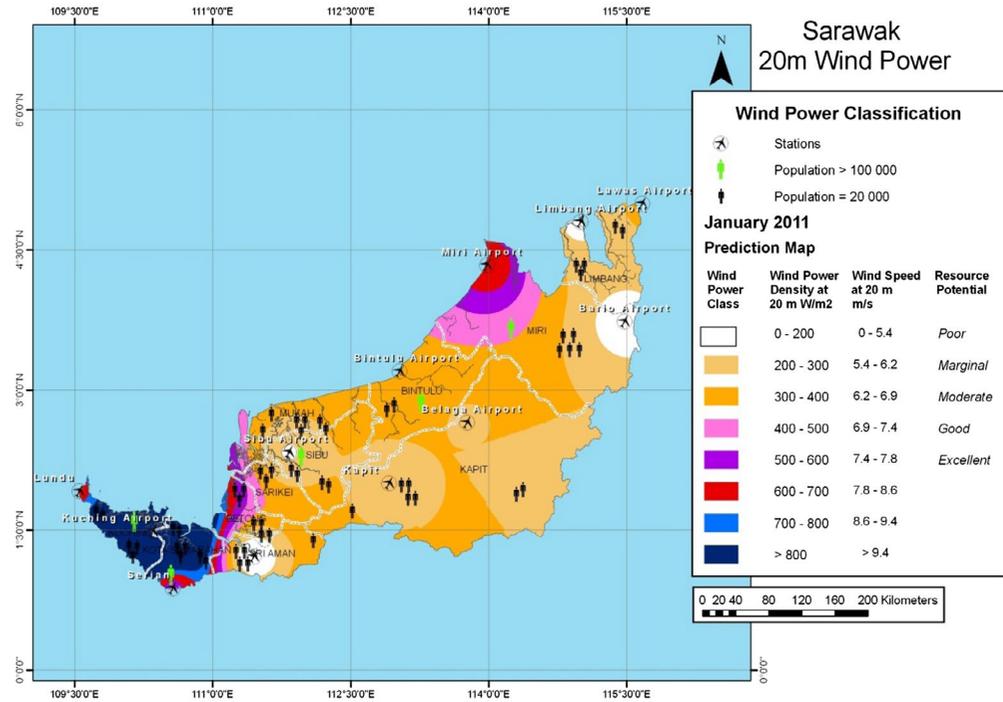
The selection of wind turbines is usually carried out using the power performance curve and the wind speed pattern in area under study. The average wind power output can be extracted using Equation (24).

$$\bar{P}_a = \int_0^{\infty} P_a(v) f(v) dv \quad (24)$$

where $P_a(v)$ stands for turbine power output for a constant wind speed v .

A 75 kW Inerjy EcoVert vertical axis small wind turbine is preferred for the purpose of analysis, the properties of which are given in (Muhammad et al., 2014). Different models are accessible to

Figure 3. A sample of wind speed map of Sarawak at 20 m.



simulate the power production curves. In this paper, the Chebyshev steady state is applied to estimate the numerical model designed by the VAWT curve Equation (25), based on the optimum power of 30% inside the air stream that goes through the rotor (Burton et al., 2012).

$$P_a = \frac{P_r}{1 + \exp -(cv - 5.09)} \quad (25)$$

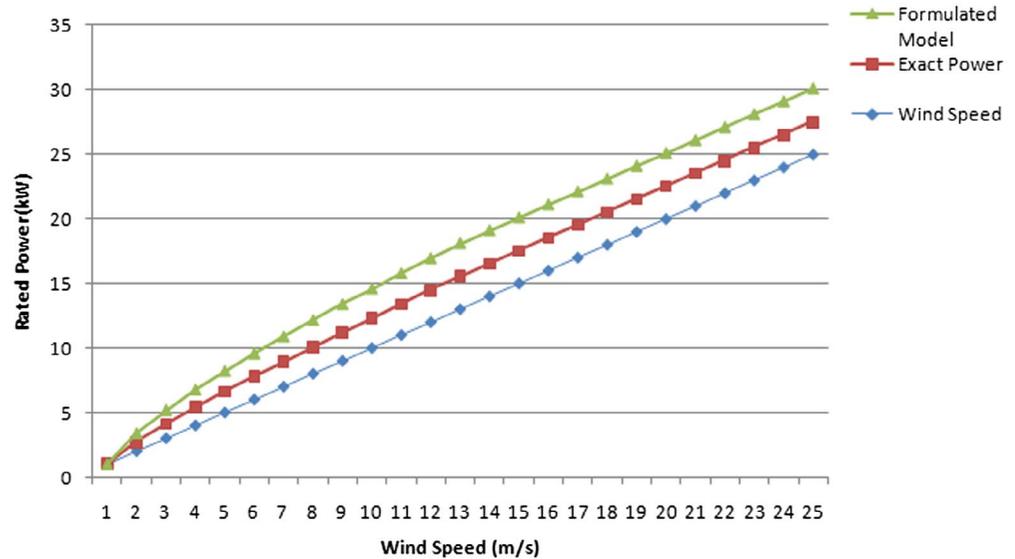
where P_r is the rated wind turbine power, and parameter c is dependent on the rated wind speed of the chosen wind system. The estimated solution of the model was acquired via Maple Software, and the formula is provided by the following expression:

$$c = c_1 \exp(c_2 * v) + c_3 \exp(c_4 * v) \quad (26)$$

The acquired values of c_1 , c_2 , c_3 and c_4 are 4.36, -0.43, 0.98 and -0.07, respectively. Equations (25) and (26) were validated using a 75 kW commercial wind turbine power curve, taking pitch control into account. Figure 4 shows the affirmation results. In accordance to the diagram, there is a robust relation between the power characteristics of a 75 kW VAWT in which the rated wind speed is 12 m/s.

This confirmed the possibility of resolving integral Equation (24) numerically by means of Chebyshev polynomial interpolation. The 12-monthly energy output was computed by multiplying the average wind power output by 8760/year. Additionally, the capacity factor (C_p), which is the ratio between the average power delivered to the rated power, was acquired.

Figure 4. Wind power based on exact and formulated model.



4. Results and discussion

4.1. Training, testing and validation simulation outcomes

A T-FFNN wind speed prediction was developed and coded using Matlab Tool Box. The best network was 9-250-1. The training was performed for the Bintulu reference station to predict the wind speed values in two areas (Matu and Tatau).

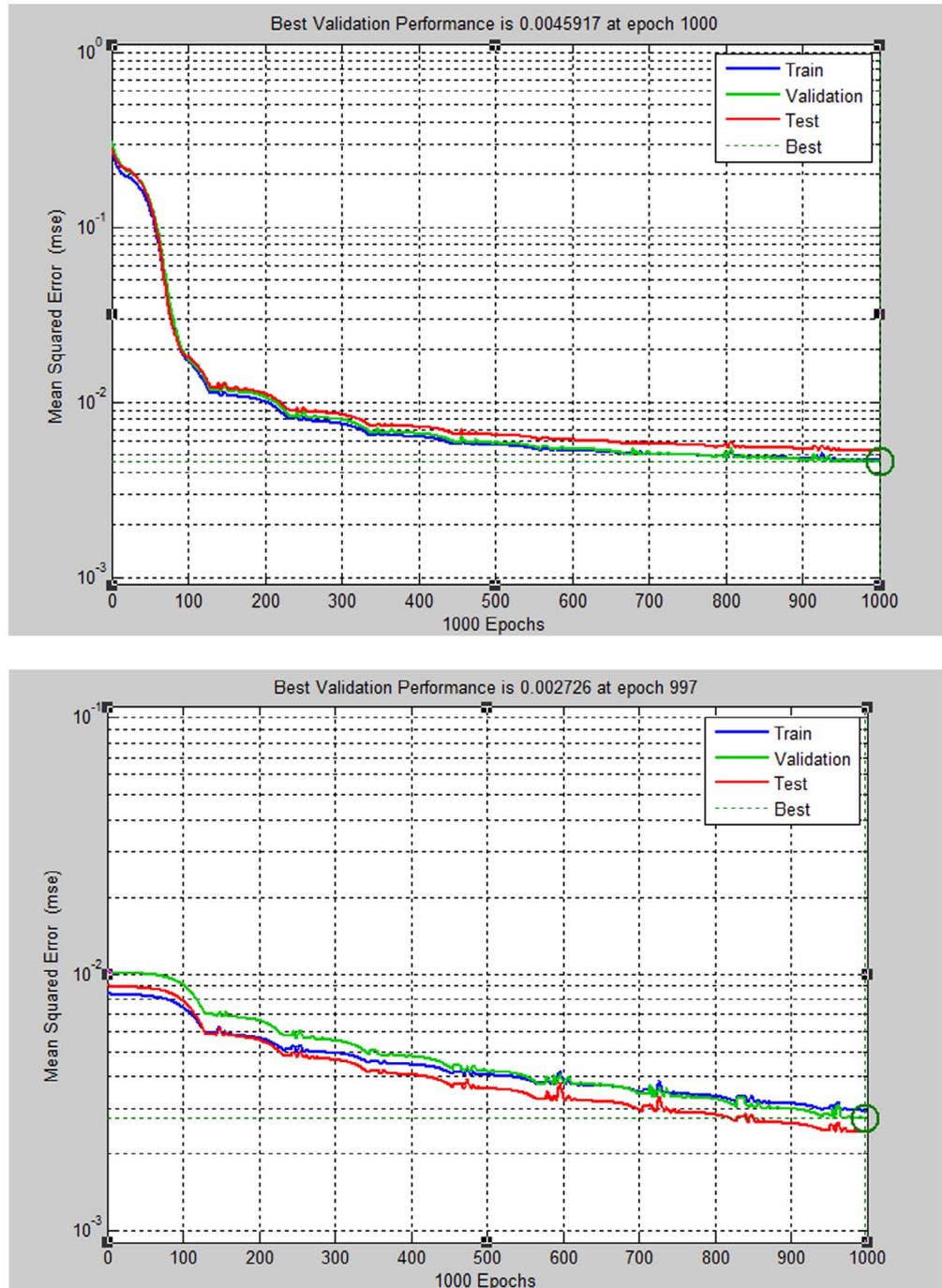
Bintulu is a referral station employed to predict the values for wind speed at three targeted locations (Matu and Tatau). Three years of observed wind speeds were used for the training, testing, and validation of the TNARX model. The highest possible number of 1,000 epochs was used for the training procedure; the performances of the network and training algorithm were analyzed based on the correlation R between the predicted and the actual wind speeds.

The reduction of MSE during the training is illustrated in Figure 5. The MSE obtained for the targeted areas (Mukah, Sarikei, and Kanowit) are 0.0017543, and 0.00171007, respectively, and no further development can be made. The optimum network has correlation factors of R values 0.9875, and 0.98651; 0.99199, and 0.99179; and 0.99534, and 0.99541 for Matu, and Tatau for the learning, testing, and whole data sets, respectively (Figures 6 and 7). The results obtained in this particular case shows the ability of the developed model to predict wind speed using the nearest available ground wind station.

The values are within the acceptable and reliable range, though a lower value of R has been reported in the literature, such as 0.7882 in Akinci (2011) and higher values of 0.0988 and 0.974 were noted in Gomes and Castro (2012). It is useful to note that the values of R vary depending on the type of the data employed, model training, type of algorithm, and terrain conditions. Based on these findings, the developed TNARX model used in this case is considered precise and robust in terms of prediction accuracy.

Once the training process is completed, the generated weights and biases of the developed TNARX are determined and can be used to formulate a mathematical function for the wind speed and

Figure 5. ANN training (a) Matu (b) Tatau.



direction, in terms of normalised data, activation functions used in the hidden and input layer. The equations for calculating the wind speed and direction become:

$$v_m = \left| 10.956 \left[\left\{ \left(\frac{125.067}{1 + e^{-9.067(XW_1 + B_1)}} \right) W_2 + B_2 \right\} + 1 \right] + 19.98 \right| \quad (27)$$

Figure 6. Correlation between ANN and reference based on training data sets for (a) Matu and (b) Tatu.

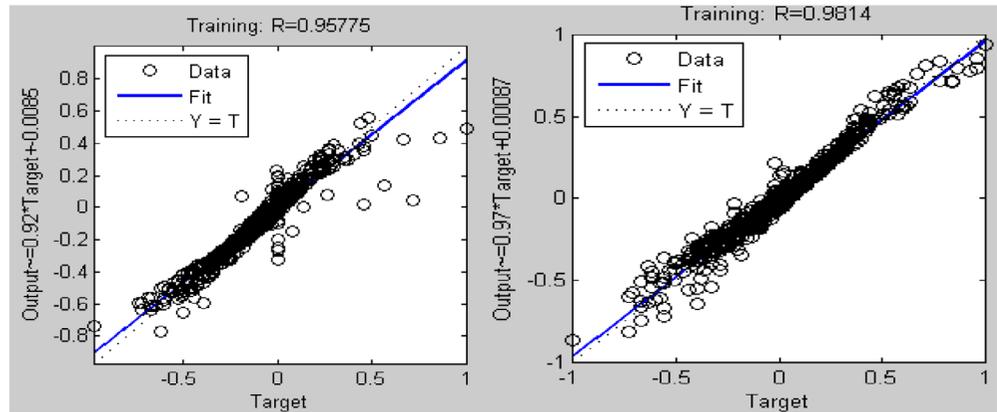


Figure 7. Regression between ANN and reference based on whole training data sets for (a) Matu and (b) Tatu.

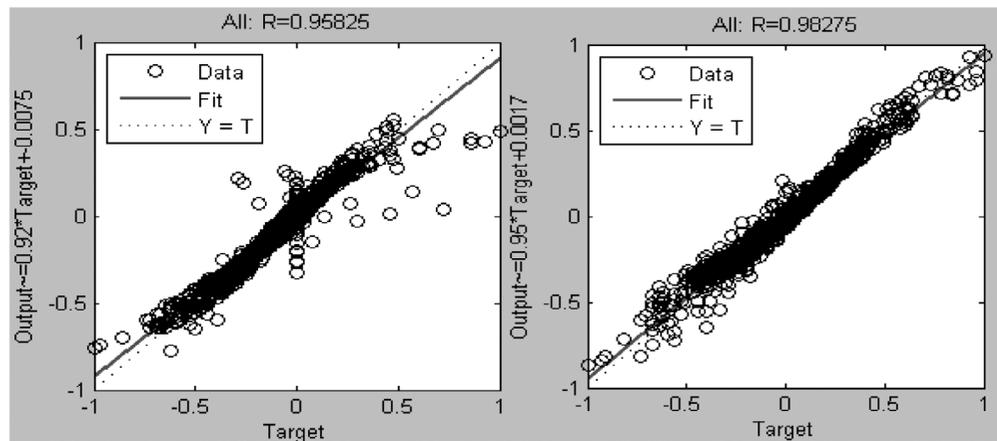
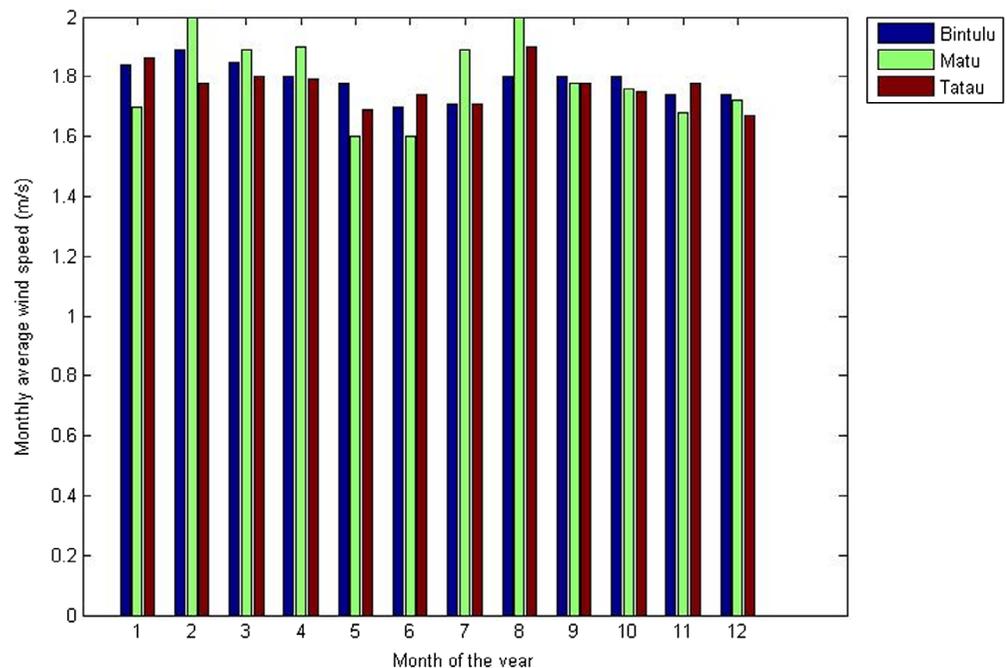


Figure 8. Comparison between predicted and observed monthly wind speed.



$$v_m = \left| 10.598 \left[\left\{ \left(\frac{156.126}{1 + e^{-12.126(XW_1 + B_1)}} \right) W_2 + B_2 \right\} + 1 \right] + 10.463 \right| \tag{28}$$

where V_m is the monthly wind speed, W_d is the monthly wind direction. W_1 is the weight between the input and hidden layer, W_2 is the weight between the hidden layer and output layer, B_1 is the bias of the hidden layer, B_2 , bias in the output layer, X is the column vector, which contains normalised values of nine input variables.

To illustrate the relationship between the estimated wind speed and those measured at the station in the area, a graph displaying the values was plotted in Figure 8. The predicted wind speed at Bintulu shows a comparable pattern. The values of the predicted wind speeds are within the threshold values of the observed data

4.2. Wind speed characteristics of the studied areas

A complete of 3653 hourly average wind speed data sets are accessible, of that 0.22% from the observations are lacking, as displayed in Table 3. The data present some variation features of wind speed and are skewed in the positive direction, meaning that all the density functions vary from the normal distribution in the positive route.

Four diversified interpolations are used to determine the finest strategy. The strategies made use of comprise the Newton backward interpolation technique, which provides the roughest outcomes when in comparison to the other methods. The cubic spline provides the most successful approximation for the station (Table 4), that is certainly, the error is modest and the values of prediction precision and reliability are high, for the station deemed. Applying the performance indicator, the coefficient of determination (R^2) is 0.85. The value is within an satisfactory array as described previously in Coville, Siddiqui, and Vogstad (2011). The results signify that cubic spline methods present highly effective over-all functionality for providing missing wind speed values, followed by the linear interpolation approach and the Newton forward method.

The wind speed time-series applied in this paper comprises hourly mean values assessed in eight ground-based stations in Sibuluan, from January 2006 to December 2015. The day-to-day average per hour wind speed is evaluated as shown in Figure 9, in which the day-to-day mean wind speed varies from 0.4–4.8 m/s, and the average total annual wind speed is 2.3 m/s. The worked out values are

Table 3. Summary of the percentile of missing wind speed values

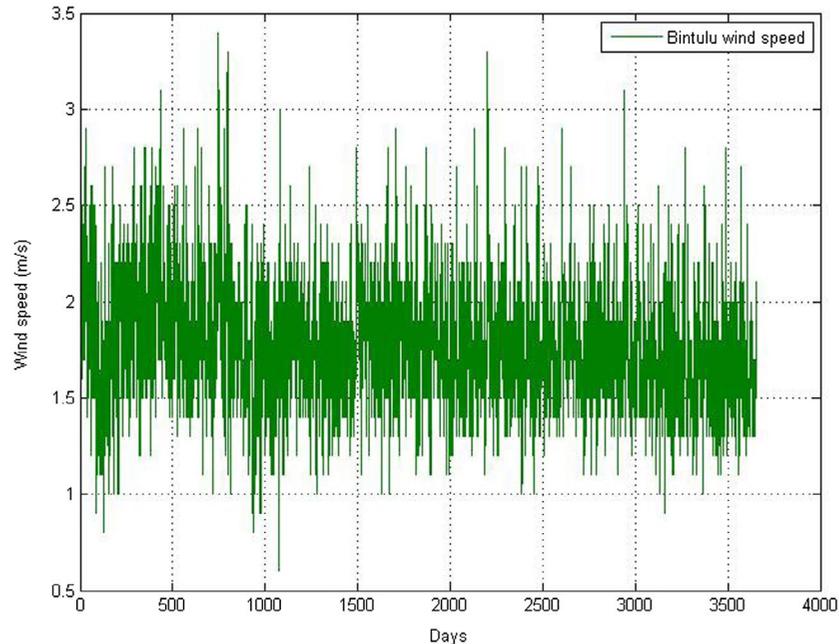
Items	Bintulu	Total
Number of observations	3,653	3,653
No of valid data points	3,640	3,640
Missing values	13	13
Percentage	0.36%	0.22%

Table 4. Effectiveness of methods based on station

Station	Methods	Prediction accuracy	Coefficient of determination (R^2)	Mean absolute error (MAE)	Root mean square error (RMSE)
Miri	NB	0.67	0.59	3.42	8.78
	NF	0.63	0.54	3.89	8.04
	Li	0.89	0.81	2.19	7.66
	CS	0.93	0.86	2.05	4.65

Notes: NB: Newton Backward, NF: Newton Forward, Linear Interpolation, CS: Cubic Spline.

Figure 9. Variation of daily average wind speed for ten years (2006–2015).



found within class 1 that is (<5.0 m/s at 10 m) as categorized based on the conventional wind energy and meteorological association (WEA, 2012) and backed in some revealed investigation research work (Olaofe & Folly, 2012; Oyedepo, Adaramola, & Paul, 2012).

Directional data is another most important parameter during the micro-siting, and it plays a great role in WRA and wind farm design. Although the chosen wind turbine is the vertical axis, which receives wind from all directions, it will help in selecting the most dominant path in order to yield more wind power. In this regard, the observed and predicted wind direction was plotted via the Matlab plot command, and the results are shown in Figure 10. As shown in the diagram, 0, 90, 180, and 270 degrees represent the east, north, west, and south directions. It can be seen from the figures, the northeast region is substantially productive. The most dominant wind directions for micro-siting of a wind energy system are, in order, Based on the figure it can be observed that in all the three cases, the most suitable directions falls within the range of 3,250–3,400 (SEE) while the lowest measured wind is placed 90° for Bintulu, Matu and Tatau.

4.3. Wind friction coefficients and calculated wind speed at 20–30 m elevations

To compute the difference of wind speed at hub elevations, in which wind turbines will be required to operate, the wind shear values were worked out analytically using Equation (2). The result obtained was 0.373. The shear value does not provide in depth facts on the site wind characteristics at various altitudes, but it will give most important information and facts about the terrain surface and the visibility of the location (Burton, Jenkins, Sharpe, & Bossanyi, 2011). In contrast with the most commonly implemented (0.1432), it is obvious that the effects of the friction shear coefficient of Sarawak differ relying on the location.

The primary goal of calculating vertical gradient wind speed changes is to find out the fraction of wind speed at higher altitudes. Table 5 demonstrates the synopsis of the calculated wind speeds at 10–40 m altitudes. In line with the tabulated results (Table 5), as expected, the estimated wind speeds are higher than those acquired at 10 m in the study area. Likewise, about 15%; 23% and 28% of wind speeds at 20, 30, and 40 m, accordingly, above the ground are greater than wind speeds at the representative level of measurement. The results indicate that the wind speed of Bintulu is reasonably moderate for a wind turbine to capture more energy at higher altitudes above the ground, especially at 20–40 m elevations. Mainly because the average annual wind speed is higher than

Figure 10. Wind direction for ten years (2006–2015) at Bintulu, Matu, and Tatau.

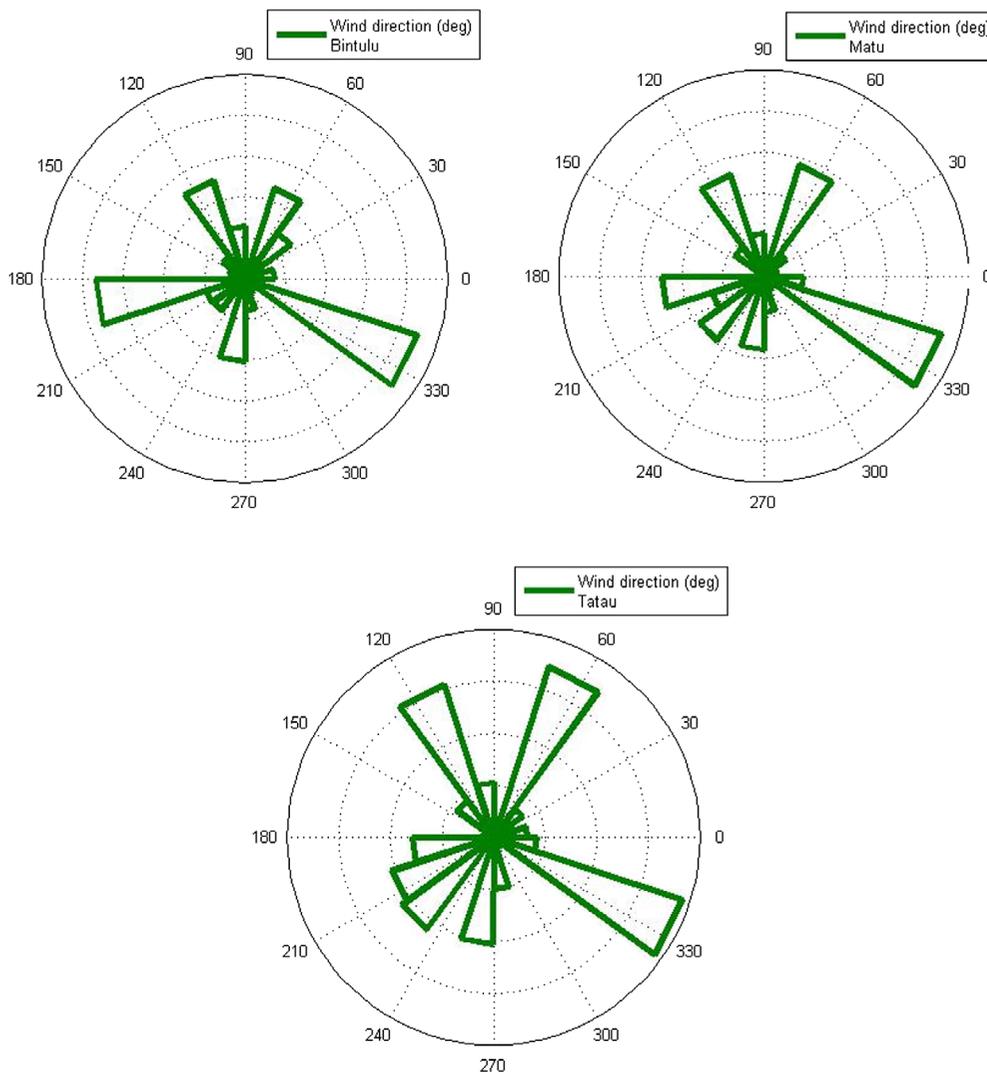


Table 5. Wind speed (2006–2015) at 10–40 m heights in Sibü

Month	Wind speed (m/s)			
	10 m	20 m	30 m	40 m
January	1.59	2.06	2.40	2.67
February	1.60	2.07	2.41	2.68
March	1.60	2.07	2.41	2.68
April	1.54	1.99	2.32	2.58
May	1.50	1.94	2.26	2.51
June	1.47	1.90	2.21	2.46
July	1.47	1.91	2.22	2.47
August	1.49	1.93	2.25	2.50
September	1.51	1.96	2.28	2.54
October	1.49	1.93	2.24	2.50
November	1.48	1.92	2.23	2.49
December	1.47	1.90	2.21	2.46
Annual	1.52	1.97	2.29	2.55

1.9 m/s at 20–40 m altitudes. Hence, a small wind turbine with a cut-in wind speed of about 1.5 m/s can be run within the locations.

4.4. Computed air density based on height and relative humidity in the study area

The monthly mean values at 10–40 m heights varied; the minimum and maximum were 1.154–1.1668 kg/m³. In terms of mean annual air density variation with height, there is a negligible decrease of 0.01 from 10–40 m in a step of 10 m. This clearly illustrates the effect of calculating the value at each examined elevation in order to stay away from overestimating the power potential. The minimum and maximum mean annual air density of the ground-based station of Sibul was 1.159 and 1.162 kg/m³, accordingly. The simulated air densities acquired using simulations work in the course of the roughness height creation in the aimed areas were 1.154 and 1.168 kg/m³ for Mukah and Kanowit, respectively. These values slip within the calculated range, which is attained making use of the meteorological parameters acquired from the wind station situated in Sibul (Table 6).

4.5. Fitted distribution models

Table 7 illustrates the GOF test of the five distributions in the case of Bintulu. The results indicate that the KS, AD, and CS values of the Gamma and Weibull distributions are lower than the values obtained by the Rayleigh, Erlang and Lognormal distributions. The ranking obviously shows that Gamma and Weibull distributions provide a better model for the distribution of wind speeds for these particular station data sets. Furthermore, Rayleigh and Erlang are not suitable to represent the wind speed data for Bintulu.

Table 6. Comparisons of monthly air densities at different heights (2006–2015) at Sibul

Month	$\rho(h, r_h)$ kg/m ³			
	10 m	20 m	30 m	40 m
January	1.158	1.157	1.156	1.155
February	1.162	1.161	1.160	1.159
March	1.163	1.162	1.161	1.160
April	1.162	1.161	1.160	1.159
May	1.162	1.161	1.160	1.159
June	1.162	1.161	1.160	1.159
July	1.162	1.161	1.160	1.159
August	1.162	1.161	1.160	1.159
September	1.162	1.161	1.160	1.159
October	1.162	1.161	1.160	1.159
November	1.162	1.161	1.160	1.159
December	1.162	1.161	1.160	1.159
Average	1.162	1.161	1.160	1.159

Table 7. GOF summary at Bintulu

S/No	Distribution	KS		AD		CS	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Erlang	0.12431	4	62.064	4	525.45	4
2	Gamma	0.06992	1	15.922	1	229.9	2
3	Weibull	0.08156	3	16.644	3	230.03	3
4	Rayleigh (2P)	0.26491	5	370.42	5	2396.3	5
5	Lognormal	0.07412	2	16.013	2	229.9	1

It is essential in this section, to revisit the qualities of wind speed, regarding Bintulu, so as to demonstrate some capabilities linked on this unique area. The station has the higher number of missing wind speed values, and it is characterized by an hourly average wind speed in the range of 0.6–3.4 m/s. This is the sole station exhibits a single dominant wind direction, NE. According to the Table 7, the Rayleigh distribution does inadequately based on AD test, and the error results determined by Gamma and Weibull is extremely insignificant.

4.6. Most probable wind speed and wind speed carrying maximum energy in the examined locations

The two important wind speeds were computed as discussed in the previous section. Their values in the studied area were determined using Equations (15) and (16). At Bintulu the values of V_{mp} and V_{maxE} were also analyzed, and the results show that the minimum and maximum values range from 0.45–1.62 m/s at 10–40 m, which occurred in the months of February and December and 3.17–4.90 m/s respectively. The average values of V_{mp} and V_{maxE} are 1.13 and 3.73 m/s, respectively. In the case of Sri Aman, the highest values of V_{mp} and V_{maxE} are 0.91 and 3.46 m/s, and the lowest values of V_{mp} and V_{maxE} are 0.00 and 2.58 m/s. The lowest null value of the most probable wind speed observed at Sri Aman is a result of the low wind speed recorded in the area.

4.7. Available wind power and energy density

Wind power density represents a quantitative amount of wind prospects of a prospective site. At the examined site, the parameter was acquired in accordance to Equations (17), through (19), and the errors in calculating the power densities using the fitted distribution models were obtained using Equation (20).

Figures 11–12 illustrate the results for wind energy density; the values are calculated using the equation specified in the previous section. The highest observed value of the actual, Weibull, and Gamma wind energy density is 98.12, 106.45, and 105.58 kWh/m²/year in February–March and January, respectively and the lowest value for wind energy density is 16.02, 18.75, and 17.92 kWh/m²/year (December) at the considered altitudes, respectively. The highest annual average wind energy density computed is 60.96, 94.13, and 91.57 kWh/m²/year, respectively, the values fall within the work of (Keyhani et al., 2010).

The monthly mean wind speed at Bintulu is also quite modest; the results for wind power density are summarized in Figures 11–12. The actual and modeled (Weibull and Gamma) monthly mean wind power densities range from 2.87–10.73, 3.71–12.38, and 3.21–11.03 W/m² in the months of June and February. An annual average wind power of 4.08–10.71 and 3.33–9.14 W/m² was observed for the measured and modeled data. Similar to the other studied areas, the wind power falls within the low-potential range.

Figure 11. Weibull model fitted wind power density.

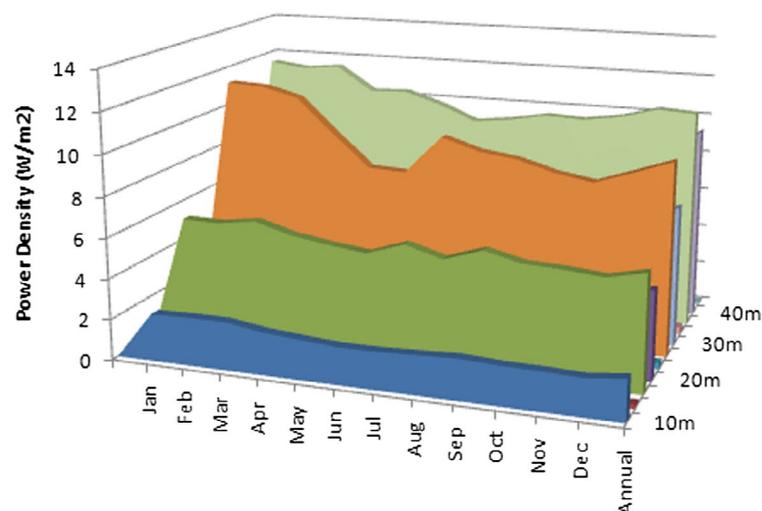
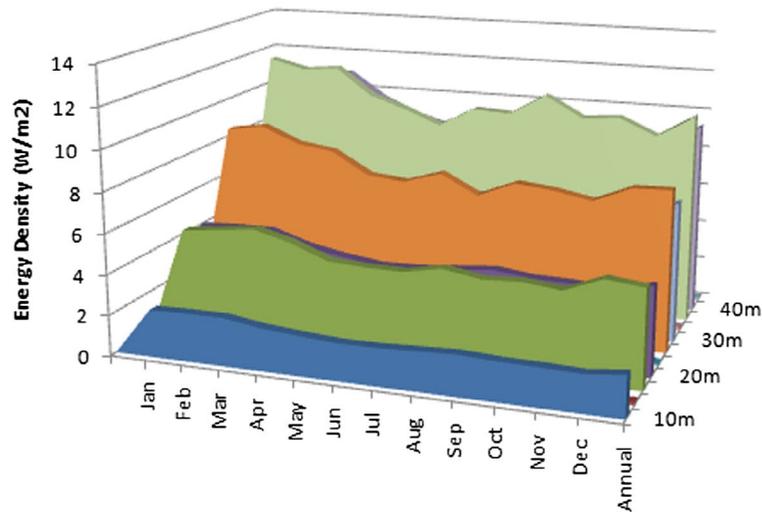


Figure 12. Gamma model fitted wind power density.



Tables 8–9 illustrate the yearly and monthly actual, Weibull, and Gamma wind energy densities of Bintulu; the lowest possible value for annual average wind energy ranges from 25.11–68.57, 34.31–94.01, and 36.25–94.01 kWh/m²/year.

In the aimed areas, related calculations were executed. Tables 8 and 9 present the summary of the predicted power and energy densities based on the fitted models. It can be observed, in the two cases, that the wind power density falls within class less than 100 W/m². The minimum energy density of 19.13 kWh/m²/year was obtained at Kanowit.

4.8. Sizing of small-scale wind turbines system in the areas

The primary intention of this research is to assess the prospective of wind energy using the accessible wind station in the region, and also to estimate the values of wind speed and direction in the non-monitored locations. Assessment of annual energy output AEO, capacity factor, and a load hour was conducted with the support of Windographer software package. The results are depicted in Figure 13.

As expected, the AEO ranges with elevations. In all the analyzed areas, the Bintulu, Matu, and Tatau annual average energy outputs are quite acceptable small-scale wind power generation; the highest possible AEO observed is 10,721.70 kWh/year at Bintulu, and the lowest value of AEO is 3,957.66 kWh/year at Tatau. It is clear, the capacitor factor is categorized within the small-scale application of wind energy as noted by (Oyedepo et al., 2012). The results obviously illustrate the opportunities of setting up small wind drive systems for stand-alone applications, in particular: battery charging, low-powered house and street lighting, crops grinding, and other low-power applications in the areas, specifically the remote island areas.

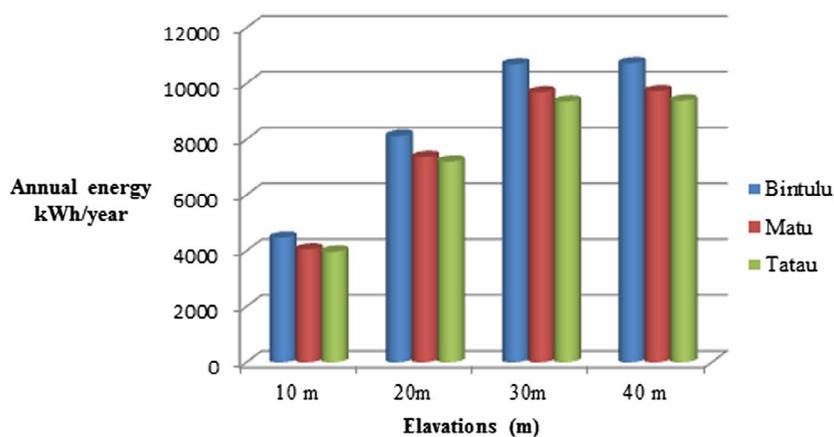
Table 8. Comparisons of wind power density at predicted locations

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
Matu	2.37	12.77	2.80	15.80	2.47	13.56
Tatau	2.70	9.62	3.16	11.03	2.92	10.02

Table 9. Comparisons of wind energy density at predicted locations

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
Matu	20.79	93.14	24.57	111.86	21.68	118.75
Tatau	23.68	84.22	27.69	96.64	26.10	87.81

Figure 13. Computed AEO at different elevation.



5. Conclusions

In this paper, the idea of a new TNARX is introduced. The proposed method has been analysed. The potential of wind energy in the areas with and without stations were studied. The measured daily, monthly and annual mean wind speed characteristics for the ground station were analysed at a representative height, and a vertical gradient mean wind speed at 20–40 m altitude was computed. Furthermore, the measured and predicted most prevailing wind directions were shown. For the wind speed distribution, in addition to the most widely adopted Weibull and Rayleigh models, Erlang, Lognormal, and Gamma functions were included. It was realised that the Gamma and Weibull outperform the other models analysed in all the areas examined. The results of wind power prospects demonstrated that the wind power falls within class 1 ($PD \leq 100 \text{ W/m}^2$) suitable for small scale purposes. In a nutshell, the study shows an improved method for the evaluation of wind energy by means of soft computing model and existing wind station. The findings will be beneficial to policy makers, renewable energy researchers and wind energy investors.

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