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ANN AND GIS-ASSISTED METHODOLOGY FOR WIND RESOURCE ASSESSMENT (WRA) IN SARAWAK

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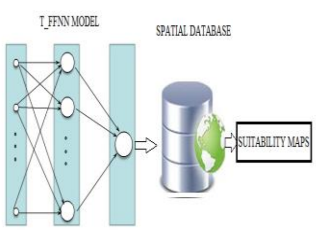
Graphical abstract



Abstract

Wind energy is a reliable, clean source and has emerged as one of the dependable, and the best performing developing renewable energy around the world. It has insignificant environmental impacts, compared to other energy sources. In Sarawak, Malaysia, wind resource varies depending on the location. An inadequate number of wind stations are the major obstacles that slow down the growing of green energy in the region. Site selection is a crucial issue for potential investors and policy makers. This paper examines the spatial distribution and the amount of potential wind power and energy densities for wind energy production and suitable locations in Sarawak. A geographical Information System (GIS) assisted methodology, which includes wind speed, power and energy densities using the existing wind station and based on the newly developed prediction model called topographical neural network (TNN) were used. Kriging interpolation was employed for a simple interpolation of data between locations. The results show that the northeast, northwest and coastal regions have better prospects of wind energy. The studied GIS methodology can be applied for identification of the most suitable locations for wind energy harvesting. The developed maps can further be used in micro-siting and economic evaluation analysis.

Keywords: GIS, wind energy, power density, kriging interpolation, Sarawak

1.0 INTRODUCTION

Energy and environment are the most important concern in today's world. Fossil energy source (coal, gas and petroleum) pollutes the lower layer of the atmosphere, and boost the incidences of global warming directly or indirectly. Renewable energy solutions are naturally abundant, and a major competitor of conventional resources of energy. Among the renewable energy sources, wind power is thought to be the rapidly developed in terms of cumulative and yearly installed capacity [1, 2].

Several research works are being done to examine the potential of wind power around the world [3-21]. In Malaysia, some studies have been performed using distribution models, spatial analysis and analytical assessment of wind power potential [22-29]. To be specific, two studies are identified in the case of Sarawak. Development of the wind map of Sabah and Sarawak using linear strength correlation method [30]. Research study on wind and solar power prospects at five locations in Sarawak [31]. Limited data point underscores the accuracy and usability of the developed energy maps in [30]. The Details of wind energy evaluations, statistical modeling and spatial analysis were covered in [31]. In the conclusion, the researchers suggested the establishment of a wind station in the eastern part of the state.

Wind speed prediction is another most important area need to be reviewed in this manuscript. Wind speed prediction models can be catalogued into physical, statistical and machine learning methods [32]. Prior to the soft computing era, wind speed prediction was normally carried out using kinematics approaches, examples devotional theory, mass-consistent code models and etc [33]. Because of stochastic and ill-define nature of wind speed, it is extremely complicated to generate a reliable mathematical algorithms that will take into account all these irregularities. Furthermore, no mathematical model either physical or numeric will give a perfect definitive solution [34]. As such, soft computing, such as fuzzy logic, neural network (NN) and neurofuzzy that involves parallel computing of complex variables are discovered to be more reliable. Fuzzy logic and neurofuzzy were mainly used for a short prediction. However, it is difficult to develop a fuzzy membership rules for a large number of input variables. ANNs have been applied in a wide prediction application with acceptable accuracy [35]. ANNs have been verified in tackling nonlinear problems, which are hardly to be achieved mathematically. ANNs are trained to solve problems, rather than programmed to do so. Based on these advantages, many researchers have applied ANN for solving prediction challenges [36, 37].

A GIS is widely applied for the generation of wind energy maps, but mostly based on the available wind stations located within the region [38, 39]. Because of time and cost, in this study, a prediction model was used to reproduce additional wind speed data in the areas that are not directly covered by measurement instrument. Based on the predicted and ground-station data, an isovent wind atlas map of Sarawak at 10-40 m heights are proposed.

The research presented here, covers wind resource assessment (WRA), and wind maps generation via ground stations and topographical prediction models. This study is the first of its kind in the state of Sarawak which aims to generate a high-resolution wind speed and energy maps, based on measured and predicted data and in terms of the most fitted wind speed distribution models.

2.0 METHODOLOGY

2.1 Study Area Description

Sarawak is one of the two states located in the eastern part of Malaysia popularly known as the island of Borneo. Situated in between $109^0 36'$E - $115^0 4^0$'E longitude and latitudes 2^0 0'N-$5^0$0'N. The state has a total area of 124,000 km^2 and a population of 2,639, 839 as of 214. The study area and principal wind station marked in red are shown in Figure 1.

2.2 Data Collection

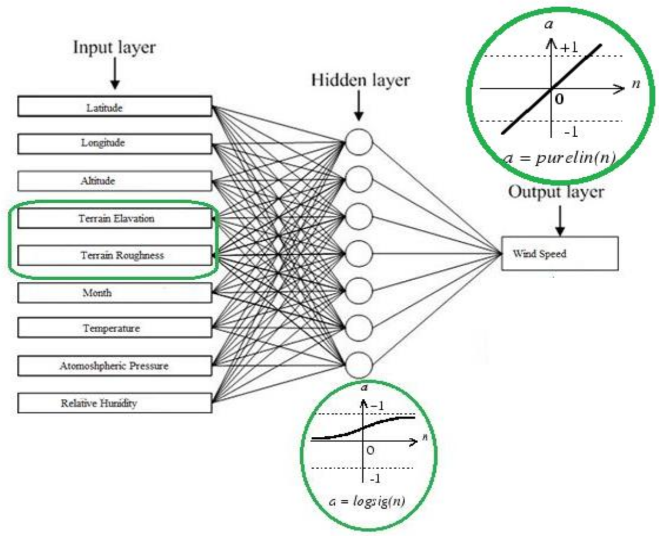
Meteorological and geographical data used in this study was obtained from the Malaysia meteorological department (MMD). The data comprised of daily average hourly wind speed, temperature, atmospheric pressure and relative humidity for a period of ten years (2003-2012) from Kuching, Sibu, Bintulu, Sri Aman and five years worth of data from (2008-2012) from Kapit, Limbang and Mulu. The data were acquired at standard meteorological level of 10 m height.

Terrain data can be acquired from diverse methods, for instance world-wide-web, department of survey and etc. In Malaysia, a non-restricted topographical map is obtainable at department of survey (JUPEM) for study reasons. To build a digital elevation model (DEM), the current study utilized two software programs, GEPlot and Google Earth. The distance between the areas was scanned at 100 m curve interval. By making use of markup tool available in Google Earth, the data points were being identified. World Geodetic System (WGS 84) was utilized to produce the latitude and longitudes of each sample location. The coordinates were exported to Terrain Zonum Solution (TZS) which is available free online in order to extract the DEM data. Based on the developed DEM; the terrain data were viewed and saved in an independent database. The surface roughness class was developed by means of GEPlot. As a result of a large forest in the study area, substantial interest has been given to the forest; a canopy Sarawak forest model was created. The model was solved by applying two drag forces F_{r1} and F_{r2}.

2.3 Neural Network Model (ANN) Development

ANN is a soft computing technique that is widely accepted for solving nonlinear systems without the need of any mathematical functions. ANN learns by examples, it has been applied for solving many engineering problems, because of its simple structure, faster computation time, high accuracy, parallelism, less noise and fault tolerance. Based on these advantages, it has been used for the prediction applications.

Figure 1 Principal wind station at eight-ground station in



Sarawak

Figure 2 Topographical Feedforward neural network (T-FFNN) model topology

In this study, a feedforward neural network (FFNN) with back propagation topology was designed and the scripts were coded using NN toolbox 7.2 [40] to predict the wind speed in twenty-seven locations based on the available eight stations in Sarawak. The model has nine inputs (latitude, longitude, and altitude, month of the year, temperature, atmospheric pressure, relative humidity, terrain elevation and roughness variation), while, monthly wind speeds as the objective function.

Log sigmoid and Purelin transfer functions were used in the hidden and output layer. To take the full advantage of the ANN, single layer architecture 9-202-1 with a step of 5 was selected. Theoretically, it has been proven that the number of neurons in the hidden layer is sufficient for this structure [14, 18]. Summary of the design is shown in Figure 2 and Table 1.

For each reference station, the data were segmented into three parts 70, 20 and 10%, for the training, testing and validation (Table 2). Prior to the training all the data were normalised using maximum-minimum approach to a scale of [-1, 1].

Table 1 Summary of the network design

Number of Designed Model	40 networks for each study area
Training Function (algorithm)	L–M
Neurons	7-202 with a step of 5
Performance	MSE
Transfer Function	Log-Sigmoid (LogSig) and linear (Purelin)
Learning rate, maximum fails and epoch	0.2-0.4, 20 and 0-1000 with a step of 10

To overcome the slow convergence associated with FFNN using gradient descent, resilient propagation and quasi-momentum algorithms, Levenberg-Marquardt (LM), which has local maxima, minimum mean squared error (MSE) and fast convergence was employed The training process was followed according to the MSE and the regression value *R*. The number of epochs varied from 0-1000 with a step of one until the difference between the inputs and target is minimal, that is until the optimum network is attained.

Once the training is completed, the simulation is carried out to obtain the weights and biases of the ANN and can be used to develop the mathematical function. The performance of the network was assessed using statistical measures correlation coefficient *R*, and mean absolute percentage error (MAPE). These values were obtained mathematically using the following equations:

$$R = \frac{\sum_{i=1}^{N}\left(t_i - \bar{t}\right)\left(o_i - \bar{o}\right)}{\sqrt{\sum_{i=1}^{N}\left(t_i - \bar{t}\right)^2} \cdot \sqrt{\sum_{i=1}^{N}\left(o_i - \bar{o}\right)^2}} \quad (1)$$

$$MAPE(\%) = \left(\frac{1}{N}\sum_{i=1}^{N}\left|\frac{t_i - o_i}{t_i}\right|\right)100 \quad (2)$$

where N is the number of data, and t_i, o_i are the target value and ANN predicted value, respectively, of one data point i. The bars indicate the average value.

Table 2 Reference and target station used for the training and testing validation

Reference Station	Target areas	Data
Kuching	Samarahan, Serian and Lundu	2003-2012
Miri	Kula Baram and Marudi	2003-2012
Sibu	Mukah, Sarikei and Kanowit	2003-2012
Bintulu	Matu and Tatau	2003-2012
Sri Aman	Betong, Saratok and Lubok Antu	2003-2012
Kapit	Belaga and Song	2008-2012
Limbang	Lawas and Sundar	2008-2012
Mulu	Bario and Ramudu	2008-2012

3.0 RESULTS AND DISCUSSION

For each reference station considered, forty networks were formulated. It was found that the optimum network in terms of faster processing time with acceptable MSE was 9-152-1 (i.e. 9 inputs, 152 neurons in the hidden layer and 1 output) in all the cases. Thus, this architecture was used in order to predict the wind speed values in the non-monitored locations.

The error function graphs during the training, a case of Sibu is shown in Figure 3. Based on the training data sets, the MSE in the order of minimum, maximum was 0.000345-0.000879. A small oscillation due to roughness change can be seen. The best performing network has a coefficient R-value of 0.9954 and the toughest network of R 0.8732 occurred at Mulu as depicted in Figure 4.

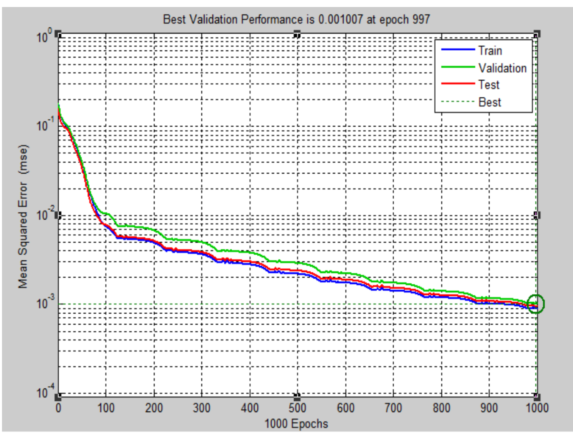


Figure 3 Reduction of MSE during the training

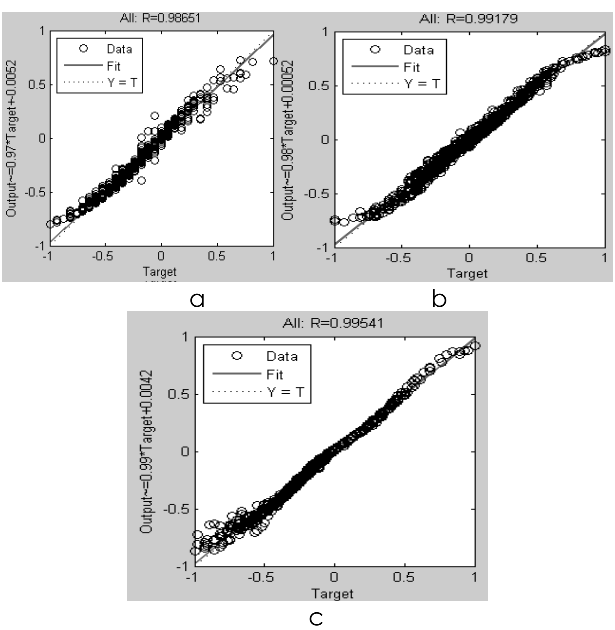


Figure 4 Regression graphs for the whole data sets for (a) Mukah (b) Sarikei (c) Kanowit

A correlation coefficient *R* and mean absolute percentage error (MAPE) were later computed between the predicted and observed wind speed based on the available ground station located in each region. The minimum and maximum values of r were 0.8416-0.912, and the maximum MAPE of 6.46% was realised. A minimum and maximum MAPE of 7.12% and 19.1 have been reported in [18]. Figure 5 shows a comparison between the predicted monthly average wind speeds a case of Sibu. It can be seen that in all the months, the predicted and measured wind speed shows the identical trend. Even though, Kanowit wind speed values are a little bit higher in some months. In all the months, the mean wind speed is above 1.2 m/s at 10 m height.

3.1 Potential of T-FFNN for Wind Speed Prediction

By means of data available at eight-ground stations in Sarawak, and subsequently, a DEM and roughness length data generation models were built. Topographic prediction models with nine inputs and one input correspond to the monthly wind speed were designed, to predict monthly wind speed from January to December for 27 areas within Sarawak consisting of the 8 wind stations with an additional 19 locations where wind station is not installed. Kriging GIS-assisted methodology was used in ARCGIS 9.3 software, for energy mapping of the study area. Samples of the isovent maps are shown in Figures 6-8. It is clear, that the northeast, southwest, and coastal regions have higher prospects of wind power. That is based on the high wind speed, power potential per unit area and energy density.

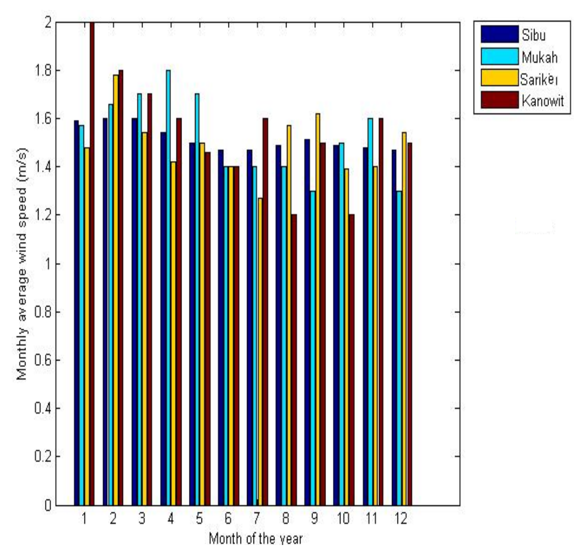


Figure 5 Comparison between the predicted and measured wind speed

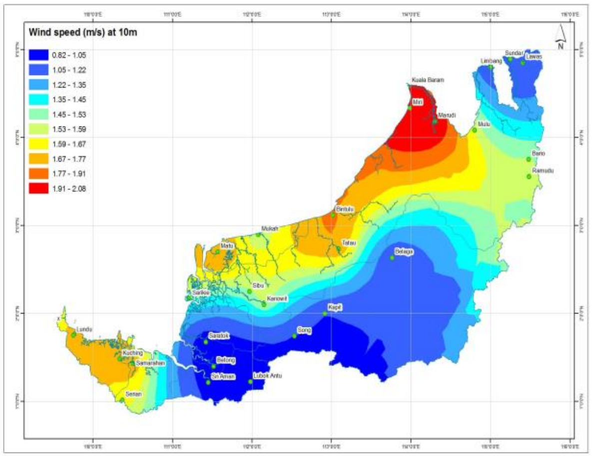


Figure 6 Wind speed map of Sarawak

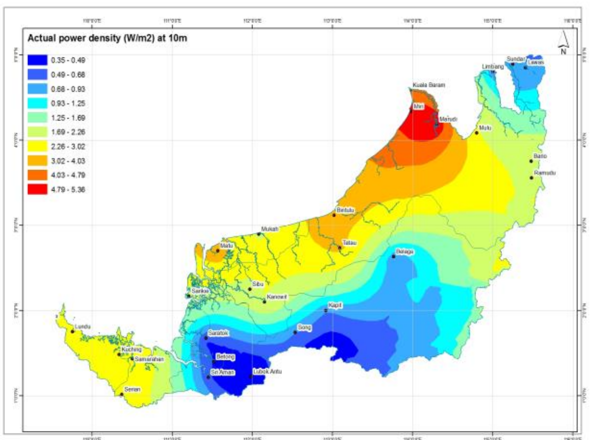


Figure 7 Power density of Sarawak

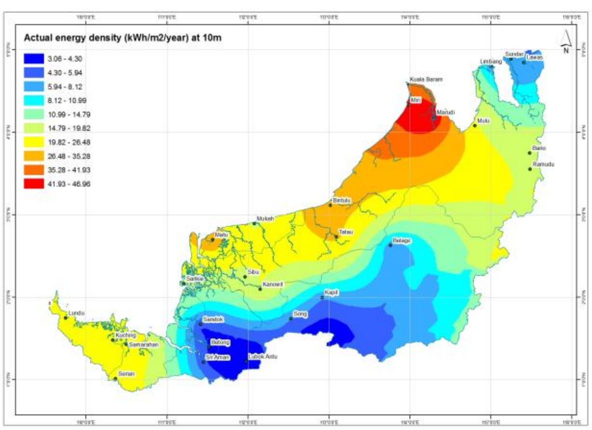


Figure 8 Power energy density map of Sarawak

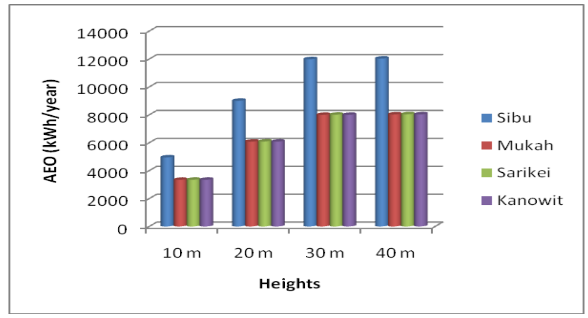


Figure 9 Annual energy output a case of Sibu

3.1 Performances of Wind turbines

The developed maps can be used to determine the annual energy output of the commercial wind turbines. A 10 kW ALEOS vertical axis wind turbine with 1.5 m/s and 2.5 m/s, cut-in and rated wind speed was selected for the analysis. The reason for this selection was based on the characteristics of wind speed in the equatorial. The annual energy output (AEO) obtainable at 10-40 m heights suitable for small-scale application is shown in Figure 9.

4.0 CONCLUSION

The research has demonstrated that the capability of the ANN base model has an acceptable accuracy for modeling the wind speed profile of Sarawak. The contributions of this paper are exploration of general GIS-based terrain roughness length data model synthesis and the development of topographic NN prediction simulation models. The paper demonstrates that the models have an acceptable accuracy with maximum MAPE of 6.4%. It is clearly seen based on the wind atlas map of Sarawak that the northeast and southwest and coastal regions have better potentials. The model is reliable and can be used to predict the wind speed in the location where measurements of wind speed is not done.

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