

An Artificial Intelligence Strategy for the Prediction of Wind Speed and Direction in Sarawak for Wind Energy Mapping

S.M. Lawan, W.A.W.Z. Abidin, S. Lawan and A.M. Lawan

Abstract Accurate and reliable wind speed and direction prediction is one of the necessary concepts in implementing a wind energy system. In this paper, meteorological and geographical variables were modeled via artificial neural networks (ANNs), taking terrain elevation and roughness class into account. The feedforward neural network (FFNN) with back propagation trained with Levenberg–Marquardt algorithm was utilized, with wind speed and direction as the target function in each model. The results obtained using the formulated topographical models showed a regression value R in the range of 0.8256–0.9883. The optimum network based on the lower mean square error and fast computation time was 9-152-1. Thus, the developed topographical feedforward neural network (T-FFNN) is efficient to predict the wind speed and direction properly.

Keywords Wind speed · Wind direction · Neural network · Sarawak

1 Introduction

Renewable energy resources are the major competitor of the fossil fuels such as coal, gas, and petroleum. Fossil fuel depletes with time, moreover, the resources are available in some regions around the world. Wind power is an indirect solar potential, which is clean, freely available, environmentally friendly, widely distributed, and naturally abundant almost anywhere around the globe. It has been applied decades

S.M. Lawan (✉) · W.A.W.Z. Abidin
Department of Electrical and Electronic Engineering, Faculty of Engineering,
Universiti Malaysia Sarawak (UNIMAS), Sarawak, Malaysia
e-mail: 13010004@siswa.unimas.my

S.M. Lawan
Department of Electrical Engineering, Kano University of Science and Technology,
Wudil, Nigeria

S. Lawan · A.M. Lawan
Faculty of Science, Department of Mathematical Science, Bayero University Kano (BUK),
P.M.B 3011 Kano, Nigeria

ago for sailing ships, machine grinding, windmills, and crop handling. Recently, it has become popular for electrical power generation.

The development of wind energy has reached a large scale in terms of annual installed capacity. Large-scale wind farms are linked to the electrical power transmission lines; meanwhile, small wind turbines rated from few watts up to 10kW are being used for stand-alone application to provide electricity to the isolated, remote, and rural locations [1–3]. Notwithstanding, many professionals have claimed that the wind potential remains unharnessed. In fact, 2014 is another remarkable year for wind turbine installation. Currently, wind turbine producers are yet to meet up with the present demands [4, 5].

Wind resource assessment (WRA), micrositing and sizing of wind turbines are prerequisite requirements that must be performed during the technical feasibility stage. The essential aspect that needs to be considered is the stochastic and unpredictable nature of wind speed. It is well known that a small deviation of wind speed will lead to a large error in the wind power output [6]. Because of this, wind speed prediction is essential for analyzing the performance of wind turbine system.

Many published studies have demonstrated the usefulness of wind speed and direction prediction models and this helps in siting of wind energy systems. Those techniques are usually classified into persistence, numeric weather prediction (NWP), statistical, stochastic, and method based on soft computing (artificial neural network (ANN) and fuzzy logic).

In the persistence approach, the accuracy drops with an increase in prediction time horizons. NWP method was based on the kinematics equations, which involve meteorological parameters. Examples, AIOLOS mass-consistent code numerical models [7]. COMPLEX and NOABL models were tested in the united kingdom (UK) [8]. Modified AIOLOS based on thermal stratification [9]. Multigrid solution via three-dimensional solver [10]. Moreover, according to [7], on the account of unpredictable nature of wind speed, it is difficult to generate a reliable algorithm that will take into account of all those irregularities, with acceptable accuracy. Furthermore, it has found that no mathematical model either physical or numeric will give a perfect definitive solution [11]. Meteorologist ordinarily uses the method to predict future samples.

A statistical and stochastic strategy mainly aims short samples. In the era of soft computing, neural network (NN), support vector machine (SVM), simulated annealing (SA) and fuzzy logic are found to be more appropriate [12–16].

On the other hand, in order to guarantee the prediction reliability for nonlinear time series, these techniques have some difficulties such as the problems in selecting input parameters, the complexity of computation time, and so on. In particular, one of the issues of fuzzy logic is the difficulty to determine the precise weights and the degree of each rule; moreover, it involves fuzzy sets and interval numbers. The application of ANN presents a series of advantages such as self-adaptive, parallelism, simple structure, rapid training speed, fast convergence fault tolerance. Based on these advantages, the ANN model has been widely formulated for various nonlinear applications [17]. The application of NN for the prediction of wind speed varies depending on the prediction timescale, that is, from short term up to long term. Many

researchers [4, 18–21] have applied different forms of NN for wind speed prediction using different meteorological and geographical data. However, none of the listed studies have considered the influence of terrain shape and roughness changes. Nowadays, special attention has been put into the prediction of nonlinear and nonstationary time-varying data using ANNs, because of their widespread approximation functionality. It is generally acknowledged that ANN is the most suitable for the wind speed prediction [2, 22, 23]. The main objective of this paper is to present a novel ANN models named topographical feedforward neural network (T-FFNN) for predicting monthly wind speed and direction for Sarawak is proposed.

This research was carried out based upon the obtainable average hourly data at eight ground stations under the control of the Malaysia Meteorological Department (MMD). The rest of the paper is structured as follows. First, in depth wind speed and direction prediction using an extended proposed ANN and geographical information system (GIS) assisted methodology are discussed. Subsequently, the predicted and developed wind map results are analyzed. Lastly, purposeful findings are drawn.

2 Wind Speed and Direction Prediction Using ANN

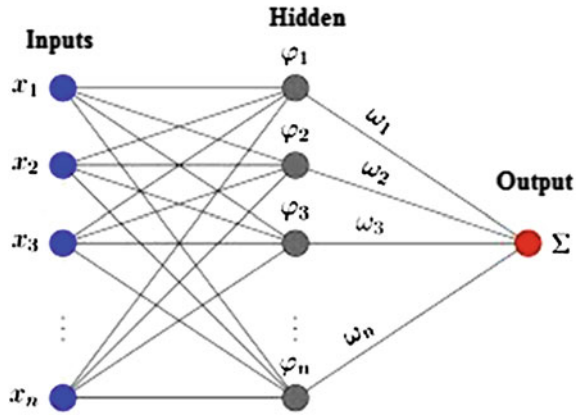
Wide application of wind energy system necessitates accurate and precise estimation of wind speed/direction, which has a direct effect on the energy output. Traditionally, this can only be possible by using anemometer and wind vane to carry out experiments. However, in rural and remote areas, where obstacle-free wind resources are available, these devices or wind monitoring stations are not available. The goal of this paper is to provide a solution for estimating the abundant resource based on the knowledge of existing wind station in Sarawak, Malaysia. In fact, prediction tool is one of the best approaches for estimating wind speed and direction in non-monitored locations, which can help in designing of the wind energy systems, prior to micro-sizing and siting.

In wind engineering, ANNs have been widely used for the prediction of wind speed where a wind turbine is expected to operate [2, 22, 23].

ANNs are mathematical techniques constructed to perform a variety task, such as incremental learning, pattern recognition, process control data mining prediction, and financial modeling. They learn by examples and produce a future unseen data. ANN mimics human being brain system, which consist of layers of parallel element unit called neurons.

The neurons are connected to large number of weights over which the signal is passing; the neuron receives the input through the input layer and multiple by a weight generally performs nonlinear operations and produce an output. The most successful ANN used for the prediction is feedforward neural network (FFNN) using log-sigmoid [14, 15]. For these reasons, one hidden layer FFNN with backpropagation was adopted in this paper to examine the complex dependency of wind speed in the locations where wind station is not available, taking terrain shape and roughness height into consideration.

Fig. 1 T-FFNN for wind speed/direction prediction



Theoretically, it has been validated that a single layer design is satisfactory to approximate any nonlinear problems [5, 24]. Figure 1 shows a fully connected three layers topology of the proposed model for wind speed and direction prediction. Fully connected implies that the output from each of the input and hidden layer is distributed to all of the neurons in the subsequent layer. However, feedforward signifies that the network has not any directed cycle.

Although, there is no restriction regarding the adoption of transfer functions, it can be any mathematical function such as tangent, hyperbolic, logarithm, or combination of both like log-sigmoid, hyperbolic tangent, or Purelin. In this paper, log-sigmoid and Purelin (Fig. 2, [2]), activation functions were selected in order to obtain the differential function between the output and input variables, whose mathematical formulas are expressed in Eqs. 1 and 2 accordingly [25].

$$f(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

$$f(x) = x \tag{2}$$

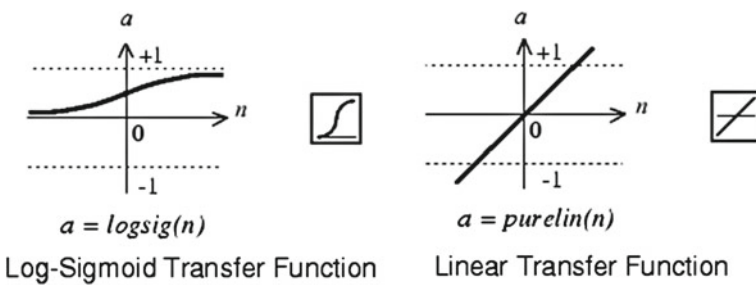


Fig. 2 Log-Sigmoid and purelin activation functions

Yet another most important phase in the course of designing an ANN is the training phase, simply because ANN is trained to solve a problem instead of programmed to accomplish this. The supervised training was adopted in this study. Monthly average data were feed in and the network learned by comparing the measured with the estimated. The error difference is propagated back from the output layer via hidden layer to the input layer and the weights on the connection between the neurons are updated as the error is backpropagated using Levenberg–Marquardt (LM). The goal of selecting LM was to assure speedy processing and furthermore to overwhelm the slow convergence associated with the conventional algorithm such as descent gradients and resilient propagation.

FFNN can mathematically approximate multivariate function to any level of accuracy if an adequate number of the hidden layer neurons are available. To avoid underfitting and overfitting in determining the number of optimal neurons in the hidden layer. This research work considered that the number of weights must not exceed the data used for the training. Hence, 9-7-1 topology was used with a step of five in all the designed models.

A MATLAB editor was used to the write the scripts file and implemented in the NN Toolbox. The developed models have 9 inputs latitude, longitude, altitude, and month of the year, temperature, atmospheric pressure, temperature and relative humidity, terrain shape and roughness height. Meanwhile, the output is the monthly wind speed for the wind speed prediction. In the case of wind direction, as the objection function (model 2). The network has latitude, longitude, altitude and month of the year, temperature, atmospheric pressure, temperature, and wind speed, terrain shape and roughness height. After the ANN training, the network was simulated to get the weights /biases, and can be applied to formulate the mathematical function.

The appropriateness of the designed models was assessed according to two statistical methods, the correlation coefficient (R) and mean absolute percentage error ($MAPE$). These values are mathematically described by the following equation [18, 26].

$$R = \frac{\sum_{i=1}^N (t_i - \bar{t}) \cdot (o_i - \bar{o})}{\sqrt{\sum_{i=1}^N (t_i - \bar{t})^2} \cdot \sqrt{\sum_{i=1}^N (o_i - \bar{o})^2}} \tag{3}$$

$$MAPE(\%) = \left(\frac{1}{N} \sum_{i=1}^N \left| \frac{t_i - o_i}{t_i} \right| \right) 100 \tag{4}$$

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

3 Isovent Lines Mapping and Maps Production

Wind energy mapping of the study area was generated using ARCGIS 9.3 software. The base maps of Sarawak at 1: 1,25,000 were digitized in order to obtain the shape files. The coordinate of the ground and predicted station were converted from degrees, minutes, seconds to the decimal unit. The World Geodetic System (WGS) of 1984 was applied for the definition of the coordination system and it was used in generating contour lines. Series of interpolation were conducted to select the best method that fits the wind speed and energy data of the studied area. It was found that Kriging method provides better accuracy for the spatial analysis carried out. This methodology has been verified in various studies [27, 28].

4 Results and Discussion

The employed data consist of 3650 daily records from Kuching, Miri, Sibul, Bintulu, and Sri Aman for the period of ten years (2003–2012). In addition, for the remaining stations, Kapit, Limbang and Mulu, the period of observation is 5 years (2008–2012). For the first five stations, the data were segmented from 2003–2009, 2010–2011, and 2012. For the last three stations, 2008–2009, 2010–2011, and 2012 for the training, testing, and validation. Prior to the training, all the data employed were scaled to the range of $[-1, 1]$.

4.1 Topographical Simulation Models

Forty networks were designed and trained. The training was performed according to the mean squared error (MSE). It was identified that the optimum network in terms of fast convergence and lower MSE was 9-152-1 and 9-94-1 for the wind speed and direction models. The number of epochs was varied from 0 to 1000 in a step of one. It was realized that no further improvement could be made once the training reaches between 996 and 1000 epochs. Hence, the training was stopped. Figure 3 shows the error model function obtained during the training of one station. It can be noted from the figure that the after 1000 epochs the MSE reduces drastically between the ANN and measured data. The realized MSE was 0.043821. It should be observed that extended training would result in the ANN to remember training data, which ends up in poor generalization capability of the ANN model.

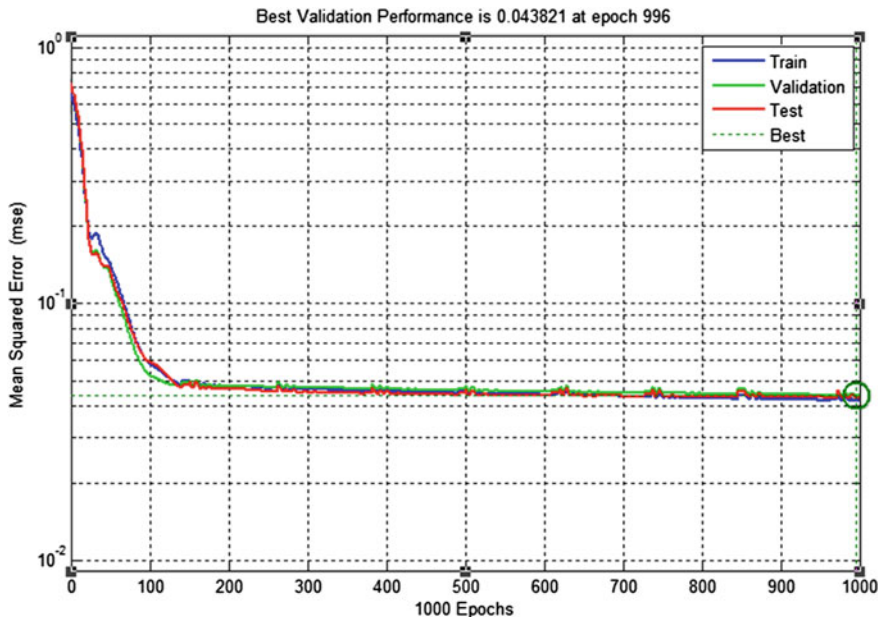


Fig. 3 Sample of the error function during the training (color figure online)

Pertaining to the data normalization, activation function used in the hidden layer and by using the weights and biases generated after the training, the equation for calculating wind speed and direction in the case of one station becomes:

$$v_m = 1.098 \left[\left\{ \left(\frac{2.907}{1 + e^{-2.907(XW_1+B_1)}} \right) W_2 + B_2 \right\} + 1 \right] + 0.337 \quad (5)$$

$$w_D = 0.035 \left[\left\{ \left(\frac{0.072}{1 + e^{-0.062(XW_1+B_1)}} \right) W_2 + B_2 \right\} + 1 \right] + 10.789 \quad (6)$$

where V_m , W_D : are the monthly wind speed/direction, W_1 : Weight between the input and hidden layer, W_2 : Weight between the hidden layer and output layer, B_1 : Biases of the hidden layer, B_2 : Biases in the output layer, X : is the column vector, which contains normalized values of nine input variables.

In accordance with the results displayed in Table 1. The suggested models have the satisfactory precision for calculating wind speed and direction. It is interested to observe that, the T-FFNN models showed improved outcomes on the test data, which verifies the high generalization of the development process. For this reason,

Table 1 T-FFNN prediction accuracy

Model	Data for the development		Data for model test	
	R	MAPE	R	MAPE
T-FFNN-1	0.8256–0.9871	5.46	0.9126–0.9671	4.69
T-FFNN-2	0.90123–0.985	4.29	0.9432–0.9883	3.87

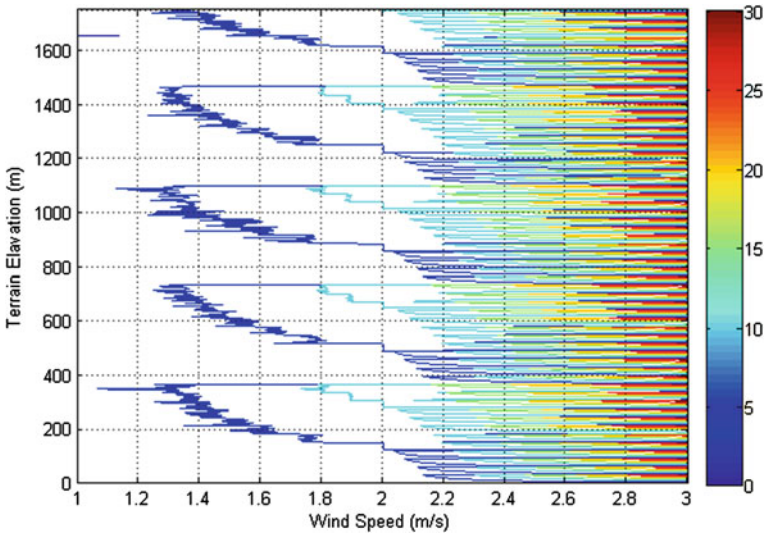


Fig. 4 Interaction effect between wind speed and terrain elevation at $v = 1-3$ m/s

the formulated models can be utilized efficiently to examine the relation between geographical, topographical, and meteorological variables on the wind speed and direction.

To this aim, Eq. 5 was plotted to generate a contours map response of wind speed for change in terrain condition (the shape of the terrain and roughness class) see Fig. 4. It is clear that, the terrain varies depending on the location, and wind speed is affected by the terrain and changes with the roughness of the terrain such as forest, lake, city, etc. From the figure, it is noticeable that the changes are more pronounce at higher wind speed, however, wind speed in the range of 1 m/s to about 2.2 m/s (class from 0–5 and 5–10) has limited effect on the wind flow within the studied area.

4.2 Wind Atlas Map of Sarawak at Various Elavations

The isovents map of Sarawak was developed based on the procedures discussed in the previous section. The generated map was based on the long-term measured and

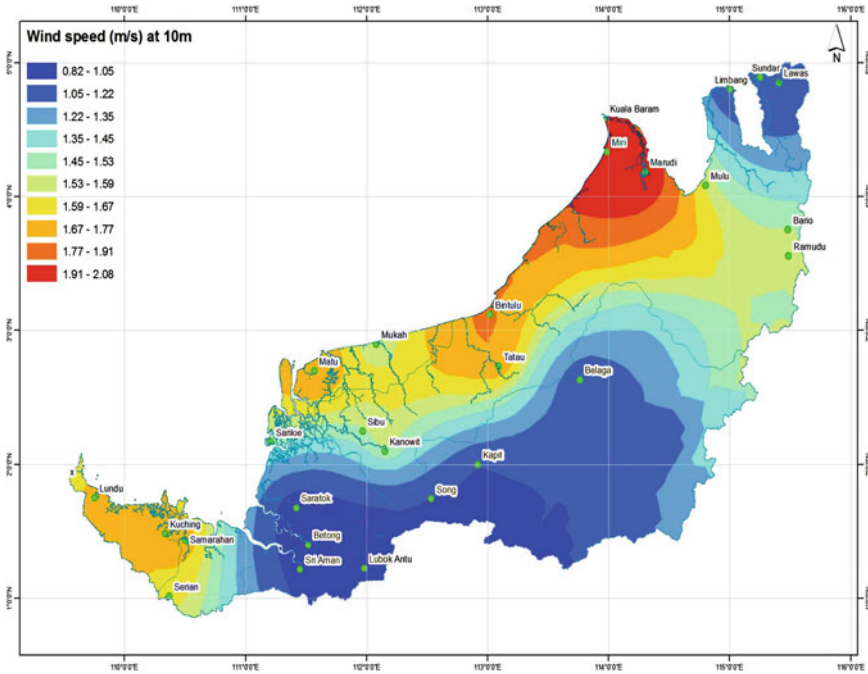


Fig. 5 Long-term wind speed map of Sarawak (color figure online)

predicted wind speed at 10–40 m in heights. Sample of the wind speed, power, and energy density maps are depicted in Figs. 5, 6 and 7 at 10 m in elevation. In all the listed figures, the areas marked red and blue represent highest and lowest potentials respectively.

5 Conclusion

In this paper, the idea of a new wind speed and direction prediction modeling based on the NN considering terrain shape is introduced. The proposed T-FFNN has been analyzed mathematically. The prediction models were used in conjunction with ground-based wind station to construct an isovents wind map of Sarawak that will be useful to policymakers, wind turbine manufacturers, potential investor and structural and bridge engineers.

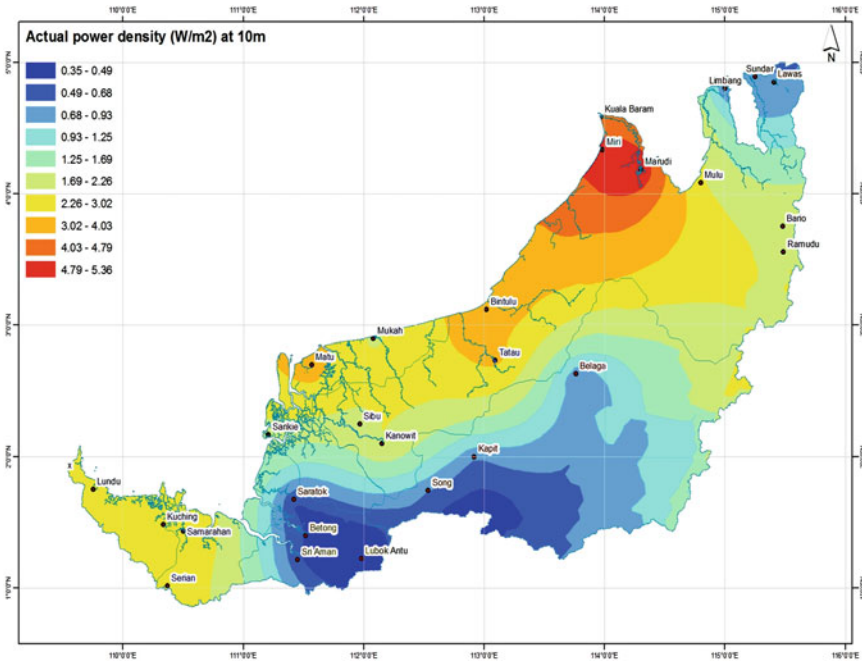


Fig. 6 Long-term power density map of Sarawak (color figure online)

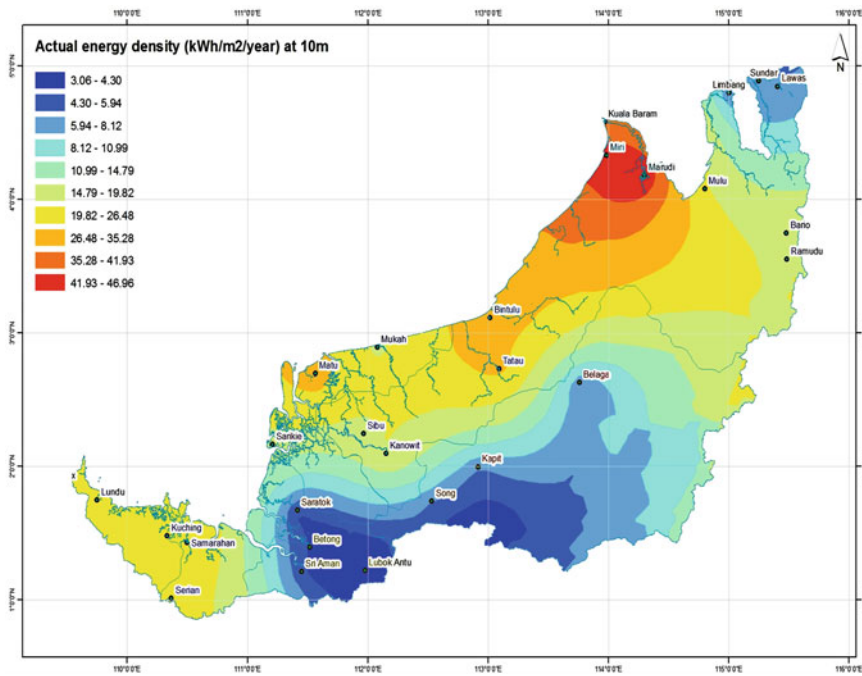


Fig. 7 Long-term energy density map of Sarawak (color figure online)

Acknowledgments The authors duly thanked the support of Universiti Malaysia Sarawak (UNIMAS) who has supported the data used in the research.

References

1. Mabel, C.M., Fernandez, E.: Analysis of wind power generation and prediction using ANN: a case study. *Renew. Energy* **33**, 986–992 (2008)
2. Muhammad, S.L., Abidin, W.A.W.Z., Chai, W.Y., Baharun, A., Masri, T.: Development of wind mapping based on artificial neural network (ANN) for energy exploration in Sarawak. *Int. J. Renew. Energy Res. (IJRER)* **4**, 618–627 (2014)
3. Azad, A.K., Rasul, M.G., Yusaf, T.: Statistical diagnosis of the best weibull methods for wind power assessment for agricultural applications. *Energies* **7**, 3056–3085 (2014)
4. Abbes, M., Belhadj, J.: Development of a methodology for wind energy estimation and wind park design. *J. Renew. Sustain. Energy* **6**, 053103 (2014)
5. Anvari-Moghaddam, A., Monsef, H., Rahimi-Kian, A., Nance, H.: Feasibility study of a novel methodology for solar radiation prediction on an hourly time scale: A case study in Plymouth, United Kingdom. *J. Renew. Sustain. Energy* **6**, 033107 (2014)
6. Lawan, S., Abidin, W., Chai, W., Baharun, A., Masri, T.: The status of wind resource assessment (WRA) techniques, wind energy potential and utilisation in Malaysia and other countries. *J. Eng. Appl. Sci.* **8**, (2013)
7. Ratto, C., Festa, R., Romeo, C., Frumento, O., Galluzzi, M.: Mass-consistent models for wind fields over complex terrain: the state of the art. *Environ. Softw.* **9**, 247–268 (1994)
8. Guo, X., Palutikof, J.: A study of two mass-consistent models: problems and possible solutions. *Bound. Layer Meteorol.* **53**, 303–332 (1990)
9. Focken, U., Heinemann, D., Waldl, H.P.: Wind assessment in complex terrain with the numeric model Aiolos: implementation of the influence of roughness changes and stability. In: EWEC-Conference, pp. 1173–1176 (1999)
10. Dinar, N.: Mass consistent models for wind distribution in complex terrain—Fast algorithms for three dimensional problems. In: *Boundary Layer Structure*, ed, pp. 177–199, Springer, Boston (1984)
11. Focken, U., Lange, M.: *Physical approach to short-term wind power prediction*. Springer, New York (2006)
12. Ahmad, A., Anderson, T.: *Global Solar Radiation Prediction Using Artificial Neural Network Models for New Zealand* (2014)
13. Ak, R., Li, Y., Vitelli, V., Zio, E.: Estimation of wind speed prediction intervals by multi-objective genetic algorithms and neural networks. In: *Acts of the XLVI Scientific Meeting of the Italian Statistical Society, Rome, Italy* (2012)
14. Alkhatib, A., Heire, S., Kurt M.: Detailed analysis for implementing a short term wind speed prediction tool using artificial neural networks. In: *International Journal on Advances in Networks and Services*, vol. 5, pp. 149–158 (2012)
15. Anand, A.P., Saravanan, R., Muthaiah, R.: Threshold prediction of a cyclostationary feature detection process using an artificial neural network. In: *International Journal of Engineering & Technology*, vol. 5, pp. 0975–4024 (2013)
16. Kalogirou, S.A.: Artificial neural networks in renewable energy systems applications: A review. *Renew. Sustain. Energy Rev.* **5**, 373–401 (2001)
17. Kazemi, K., Moradi, S., Asoodeh, M.: A neural network based model for prediction of saturation pressure from molecular components of crude oil. *Energy sources, Part A: Recovery, utilization, and environmental effects* **35**, 1039–1045 (2013)
18. Khatib, T., Alsadi, S.: Modeling of wind speed for palestine using artificial neural network. *J. Appl. Sci.* **11**, 2634–2639 (2011)

19. Fadare, D.: The application of artificial neural networks to mapping of wind speed profile for energy application in Nigeria. *Appl. Energy* **87**, 934–942 (2010)
20. Sözen, A., Arcaklioglu, E., Özalp, M., Kanit, E.G.: Use of artificial neural networks for mapping of solar potential in Turkey. *Appl. Energy* **77**, 273–286 (2004)
21. Ozgonenel, O., Thomas, D.W.: Short-term wind speed estimation based on weather data. *Turkish J. Elect. Eng. Comput. Sci.* **20**, 335–346 (2012)
22. Lin, W.-M., Hong, C.-M.: A new elman neural network-based control algorithm for adjustable-pitch variable-speed wind-energy conversion systems. *IEEE Trans. Power Electron.* **26**, 473–481 (2011)
23. Musyafa, A., Cholifah, B., Dharma, A., Robandi, I.: Local short term wind speed prediction in the region Nganjuk City (East Java) using neural network. In: *Local Short Term Wind Speed Prediction in the Region Nganjuk City (East Java) Using Neural Network* (2013)
24. Philippopoulos, K., Deligiorgi, D., Kouroupetroglou, G.: Artificial neural network modeling of relative humidity and air temperature spatial and temporal distributions over complex terrains. In: *Pattern Recognition Applications and Methods*, ed. pp. 171–187, Springer, New York (2015)
25. Mohandes, M., Balghonaim, A., Kassas, M., Rehman, S., Halawani, T.: Use of radial basis functions for estimating monthly mean daily solar radiation. *Solar Energy* **68**, 161–168 (2000)
26. Madić, M., Radovanović, M.: An artificial intelligence approach for the prediction of surface roughness in CO₂ laser cutting. *J. Eng. Sci. Technol.* **7**, 679–689 (2012)
27. Ramachandra, T., Shruthi, B.: Wind energy potential mapping in Karnataka, India, Using GIS. *Energy Convers. Manag.* **46**, 1561–1578 (2005)
28. Bui, T.Q., Nguyen, T.N., Nguyen-Dang, H.: A moving kriging interpolation-based meshless method for numerical simulation of Kirchhoff plate problems. *Int. J. Num. Methods Eng.* **77**, 1371–1395 (2009)