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The application of artificial neural networks to mapping of wind speed profile for energy application in Nigeria

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ABSTRACT

Modelling and prediction of wind speed are essential prerequisites in the sitting and sizing of wind power applications. The profile of wind speed in Nigeria is modelled using artificial neural network (ANN). The ANN model consists of 3-layered, feed-forward, back-propagation network with different configurations, designed using the Neural Toolbox for MATLAB. The monthly mean daily wind speed data monitored at 10 m above ground level for a period of 20 years (1983–2003) for 28 ground stations operated by the Nigeria Meteorological Services (NIMET) were used as training (18 stations) and testing (10 stations) dataset. The geographical parameters (latitude, longitude and altitude) and the month of the year were used as input data, while the monthly mean wind speed was used as the output of the network. The optimum network architecture with minimum Mean Absolute Percentage Error (MAPE) of 8.9% and correlation coefficient (r) between the predicted and the measured wind speed values of 0.9380 was obtained. The predicted monthly wind speed ranged from 0.9–13.1 m/s with an annual mean of 4.7 m/s. The model predicted wind speed values are given in the form of monthly maps, which can be easily used for assessment of wind energy potential for different locations within Nigeria.

1. Introduction

In Nigeria, the energy crisis has been a great concern that spanned many decades. At present, the Federal Government is committed to finding a long-term solution to this predicament through the adoption of the Renewable Energy Master Plan (REMP) with a target of increasing the present installation of 5000 MW generation capacity to 16,000 MW by the year 2015 through the exploration of renewable energy resources [1]. In order to realise this goal, the exploration of wind energy resource is one of the key elements of this master plan. The share of wind energy in the national energy consumption has remained on lower ebb, while at present, natural gas, hydroelectricity, fuelwood, and petroleum products constitute 5.2, 3.1, 50.5 and 41.3% share, respectively. This shows that presently, renewable-energy use in Nigeria is split essentially between hydroelectricity and traditional fuel wood [2]. Nigeria as a developing nation, has not given wind energy exploration due attention. Till date, there is no record of wind power plants connected to the national grid [3]. Only a few number of small scale, stand-alone wind power plants have been installed as far back as early 1960s in some northern states mainly to power water pumps and grinding mills such as in Goronyo in Katsina, Kedada in Bauchi and Sayya Gidan-Gada village in Sokoto States [4].

Wind speed profiles are known to exhibit a high variability in space and time. Wind speed modelling and mapping are essential prerequisites in the design and sitting of wind power plants. Therefore, efficient conversion and utilization of the wind energy resource require accurate and detailed knowledge of the wind characteristics of the location [5–8]. In different parts of the world, meteorological data including wind speed distribution is monitored on continuous basis through ground or satellite stations. Such acquired data form a database that is used as input parameters in the exploration of renewable energy resources. In recent times, the study of the wind characteristics and exploration of the associated energy potentials has been an increasing concern of researchers [9–17] in many developed countries. However, the information and exploration as applicable to the developing nations is yet to be addressed.

In Nigeria, the Nigerian Meteorological Services (NIMET) Oshodi, Lagos, which is saddled with the responsibilities of measuring and archiving values of meteorological parameters, has limited number of monitoring facilities installed at the ground stations. Only very few (28) out of the 44 ground stations operated by the agency have adequate and accurate records of wind speed. Hence, inadequate and accurate record of wind speed and other meteorological data remained parts of the major challenges facing engineers and scientists in the field of renewable energy

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applications. The dearth in meteorological data such as wind speed data has led to limited study and hence the exploration of wind energy resources in Nigeria. A few number of studies have been conducted at specific locations [18–25]. In those studies, the wind speed variability was modelled using different analytical tools such as: statistical models including Weibull and Rayleigh distribution functions; stochastic simulation; seasonal autoregressive integrated moving average; linear and multiple regression models.

Table 1
Geographical parameters of the meteorological ground stations.

S/N		Station code	City	State	Latitude (°N)	Longitude (°E)	Altitude (m)
1	Stations used in training	65,001	Yelwa	Kebbi	10.83	4.75	244.0
2		65,010	Sokoto	Sokoto	13.02	5.25	350.8
3		65,015	Gusau	Zamfara	12.17	6.70	463.9
4		65,019	Kaduna	Kaduna	10.60	7.45	645.4
5		65,046	Kano	Kano	12.05	8.20	472.5
6		65,055	Bauchi	Bauchi	10.23	9.82	609.7
7		65,073	Potiskum	Borno	11.70	11.03	414.8
8		65,082	Maiduguri	Borno	11.85	13.08	353.8
9		65,101	Ilorin	Kwara	8.48	4.58	307.4
10		65,108	Shaki	Oyo	8.67	3.38	278.0
11		65,112	Bida	Niger	9.10	6.02	144.3
12		65,123	Minna	Niger	9.62	6.53	256.4
13		65,125	Abuja	FCT	9.25	7.00	343.1
14		65,134	Jos	Plateau	9.87	8.90	586.0
15		65,167	Yola	Adamawa	9.23	12.47	186.1
16		65,200	Iseyin	Oyo	7.97	3.60	330.0
17		65,201	Ikeja	Lagos	6.58	3.33	39.4
18		65,203	Lagos roof	Lagos	6.45	3.40	14.0
19	Stations used in testing	65,208	Ibadan	Oyo	7.43	3.90	227.2
20		65,210	Ijebu-ode	Ogun	6.83	3.93	77.0
21		65,215	Oshogbo	Osun	7.78	4.48	302.0
22		65,222	Ondo	Ondo	7.10	4.83	287.3
23		65,229	Benin	Edo	6.32	5.10	77.8
24		65,243	Lokoja	Kogi	7.78	6.73	62.5
25		65,250	Port – Harcourt	Rivers	4.85	7.02	19.5
26		65,257	Enugu	Enugu	6.47	7.55	141.8
27		65,264	Calabar	Cross river	4.97	8.35	61.9
28		65,275	Ogoja	Cross river	6.67	8.80	117.0

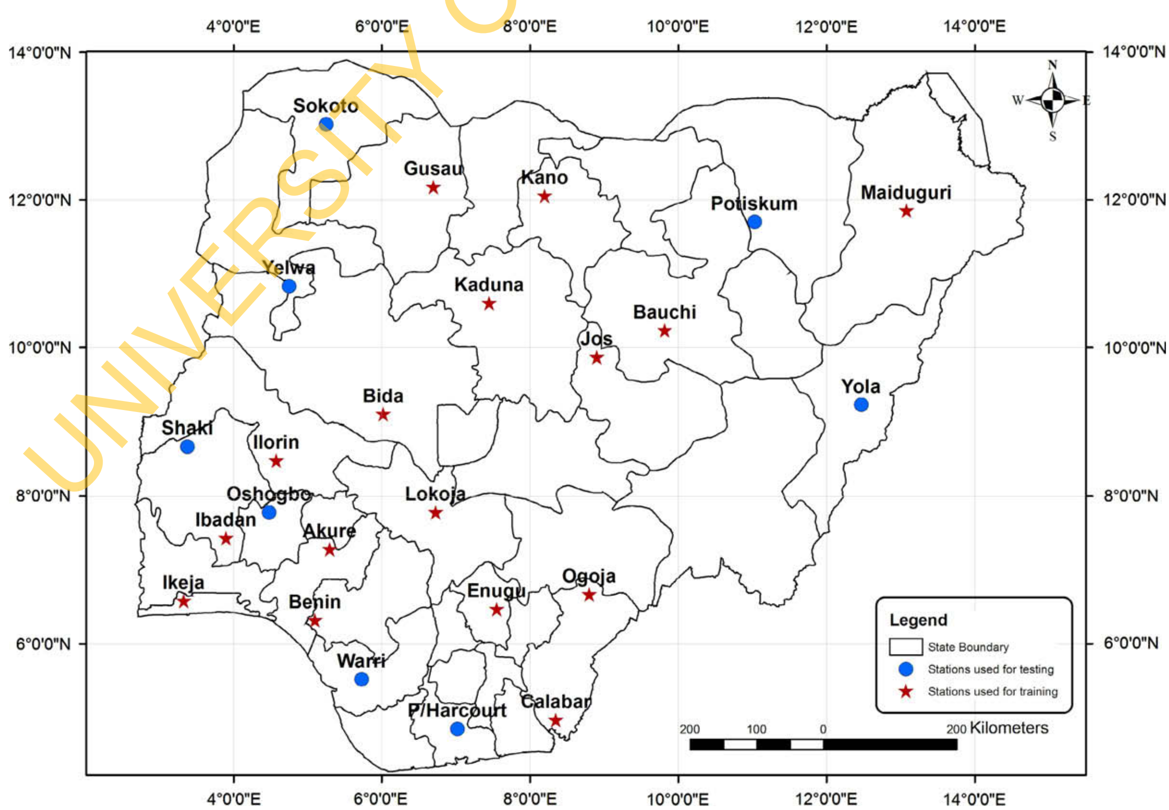

Fig. 1. Geographical location of the meteorological ground stations used for training and testing of the network.

The developed models are location specific and hence are limited in terms of accuracy due to non-linear variability of wind characteristics in space and time. However, for efficient exploration of the wind energy potentials of nation, a nationwide assessment is required.

Ojosu and Salawu [19] reported a nationwide study on wind energy availability and potential in Nigeria. In their study, wind data for 22 ground stations from 12 to 33 years (1951–1983) were used to create isovents based on the yearly average values of wind speed. The use of limited number (22) of sampling points and the yearly average values of wind speed underscores the high variability of wind speed in space and time and hence, limits the accuracy and the applicability of the proposed map. To improve the accuracy application of the map, more sampling points and smaller time frame interval (monthly) variability is required. Since there is limited number of ground stations in Nigeria, a modelling and prediction tool is required to provide additional sampling point data for the development of a more precise and high resolution wind speed variation map.

Artificial neural network (ANN) is a modelling and prediction tool, widely accepted as a technique offering an alternative way to tackle complex and ill-defined problems [26]. They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, to deal with non-linear problems and, once trained, can perform prediction and generalisation at high speed. They have been used in diverse applications in control, robotics, pattern recognition, forecasting, medicine, power systems, manufacturing, optimisation, signal processing and social/psychological sciences. They are particularly useful in system modelling such as in implementing complex mappings and system identification [27]. ANN has been applied to modelling of complex systems such as meteorological parameters [26]. Jiya and Alfa [28] and Fadare [29] have applied ANN model to predict solar radiation in Nigeria while Sozen et al. [30] used the technique for mapping solar potential in Turkey. ANN models are efficient and less time consuming in modelling of complex systems compared to other mathematical models such as regression [31]. ANN with different topologies has been developed for spatial prediction of wind speed in different parts of the world [11,32]. Comprehensive reviews on ANN applications in renewable energy systems and energy systems have been reported by Kalogirou [26,27]. Basic theory and application of ANN can be found in generic text like [33]. The aim of this paper is to apply artificial neural networks for modelling and prediction wind speed variation in Nigeria using the few available ground stations data to generate high resolution monthly isovent maps for energy applications.

2. Materials and methods

2.1. Data collection

Wind speed data of 28 ground stations for a period of 20 years (1983–2003) was obtained from NIMET, Oshodi, Lagos, Nigeria. The data are acquired using a cup-generator anemometer at a hub height of 10 m. The geographical parameters of the stations (latitude, longitude and altitude) and the month of the year were used as input data, while the monthly mean wind speed was em-

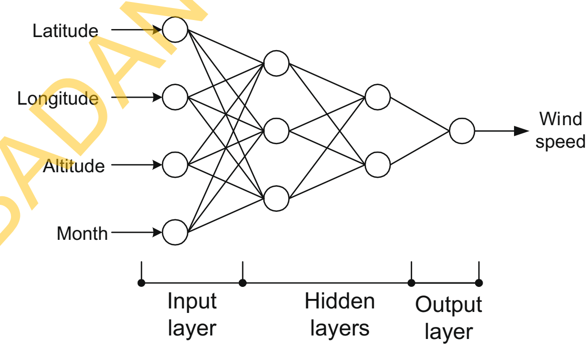

Fig. 2. Typical neural network architecture for prediction of wind speed.

Table 2
Monthly mean wind speed (m/s) observed at the stations for the period 1983–2003.

Station code	January	February	March	April	May	June	July	August	September	October	November	December	Yearly mean wind speed
65,001	3.30	3.27	4.25	5.37	5.64	4.95	3.88	3.44	3.55	3.12	2.85	2.94	3.88
65,010	8.59	8.22	7.21	6.76	8.17	9.07	8.00	6.07	5.39	4.92	6.45	7.69	7.21
65,015	7.70	7.04	7.26	6.86	7.34	7.00	5.93	5.03	4.09	3.77	5.06	7.02	6.17
65,019	6.83	6.40	5.67	5.22	5.16	5.26	4.96	4.41	3.58	3.27	4.72	6.03	5.13
65,046	9.28	9.93	9.40	9.55	10.18	10.81	9.54	8.36	7.97	7.27	7.34	13.10	9.39
65,055	4.56	5.08	4.93	4.66	4.55	4.02	4.19	3.90	3.74	2.82	2.36	2.71	3.96
65,073	5.17	5.59	6.00	5.54	6.15	5.93	5.91	4.92	3.96	4.33	4.84	4.58	5.25
65,082	4.86	5.86	5.90	5.68	5.78	6.16	5.87	4.64	4.35	4.04	4.40	5.16	5.22
65,101	3.95	4.40	5.93	6.70	6.06	5.47	5.98	5.99	4.63	4.11	3.92	3.37	5.04
65,108	4.69	4.65	4.78	4.64	4.82	4.30	4.55	4.44	3.91	4.05	4.21	4.94	4.50
65,112	2.18	2.49	2.97	3.45	3.18	2.58	2.21	2.21	2.27	1.98	1.83	2.20	2.46
65,123	7.12	7.42	6.09	6.03	5.21	5.04	4.36	4.33	4.24	3.51	4.34	6.58	5.36
65,125	3.36	3.74	3.95	4.36	4.29	3.95	3.83	3.81	3.70	3.67	3.28	3.28	3.77
65,134	10.29	10.23	9.67	10.23	9.82	9.28	9.17	8.68	7.95	8.45	9.71	10.14	9.47
65,167	2.48	2.86	3.53	3.94	3.96	3.57	3.24	2.87	2.53	2.47	2.20	2.15	2.98
65,200	3.76	4.10	5.20	4.43	4.17	3.92	4.33	3.78	3.68	3.59	3.58	3.55	4.01
65,201	4.29	5.01	6.00	5.43	4.47	4.44	5.16	4.98	4.38	4.02	3.50	3.60	4.61
65,203	4.06	4.95	5.12	5.56	5.15	4.70	4.94	5.23	4.90	4.08	4.00	3.64	4.69
65,208	3.71	3.88	4.30	4.27	3.84	3.91	4.54	4.58	4.02	3.27	2.85	3.15	3.86
65,210	3.64	4.58	4.37	4.10	3.61	3.59	3.76	3.61	3.53	2.80	2.65	3.16	3.62
65,215	3.06	3.62	4.30	4.36	3.58	3.52	4.01	4.06	3.09	2.35	1.89	2.15	3.33
65,222	1.18	1.78	2.26	2.09	1.75	1.81	2.48	2.83	2.01	1.47	0.78	0.80	1.77
65,229	3.30	3.58	3.88	3.70	3.41	3.55	3.77	3.78	3.55	2.96	2.52	2.61	3.38
65,243	2.44	3.00	4.18	4.33	3.30	2.78	2.66	2.61	2.49	2.54	2.38	2.28	2.92
65,250	3.20	3.70	3.77	3.70	3.41	3.33	3.36	3.75	3.47	2.88	2.54	2.54	3.30
65,257	6.28	6.12	6.72	6.63	5.71	5.60	5.80	5.76	5.25	4.81	4.47	5.58	5.73
65,264	4.39	4.89	4.82	4.57	4.61	4.58	4.58	4.74	4.83	4.70	4.17	4.30	4.60
65,275	3.94	4.09	4.48	4.10	3.72	3.60	3.54	3.52	3.35	3.37	2.97	3.44	3.68

ployed as the output of the network. The stations used for training and testing the networks are listed in Table 1, while Fig. 1 shows their geographical locations. The monthly mean wind speed measured at the stations for the period 1983–2003 is shown in Table 2.

2.2. Design of artificial neural networks model

Multi-layer feed-forward back-propagation hierarchical networks with different architecture were designed using the 'Neural Network Toolbox' version 4.0.2 for MATLAB [34]. The networks consisted of three layers: input layer; hidden layer; and output layer (Fig. 2). There were four input parameters into the network, which consisted of the geographical parameters of the stations (latitude, longitude, and altitude), and month of the year and one output parameter corresponding to the monthly mean wind speed. Different networks with single or double hidden layer topologies were used and the number of neurons was varied from 5 to 15, at interval of five neurons to enhance the generalisation capability of the network. Neurons with tangent sigmoid (tansig) transfer function were used in the hidden layer(s), while linear transfer function (purelin) was exploited in the output layer.

2.3. Training and testing of the model

Prior to the training process, both input and target data sets were normalised to range -1 and $+1$. Scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM) learning algorithms were used in training the networks. A total number of 12 networks were designed and tested. In order to avoid 'overfitting' of the data and hence improve generalisation of the network the '*early stopping*' technique was used in conjunction with the training algorithms. The input/target datasets were divided randomly into three subsets: training; validation; and testing datasets. The training set, which consisted of data of randomly selected 18 stations (Table 1), was used for computing the gradient and updating the network weights and biases, while the testing dataset consisting of data of 10 stations was partitioned randomly into two, half of it was used for testing and the remaining half was used for validation. The maximum number of 100 iterations and minimum gradient of 10^{-10} was used in the training process. The performance of the different networks with different configurations and training algorithms were evaluated based on the correlation coefficient (r) between the predicted and the measured values in order to determine the network with optimum prediction capacity.

Table 3
Performance of the different networks based on the training and testing datasets.

Network no.	Training algorithm	No. of hidden layer	No. neurons in hidden layer	Number of iterations	Training dataset			Test dataset		
					MSE	MAPE (%)	*R*-value	MSE	MAPE (%)	*R*-value
1	LM		5	34	1.4862	18.0	0.7810	1.2873	16.4	0.7895
2		1	10	32	0.6919	12.3	0.9046	0.8058	13.3	0.8770
3			15	40	0.1873	6.7	0.9751	0.4241	9.7	0.9420
4			5	83	0.3836	9.3	0.9484	0.4467	10.3	0.9329
5		2	10	39	0.0997	4.1	0.9868	0.4669	10.1	0.9333
6			15	27	0.0205	1.5	0.9973	0.4508	8.9	0.9380
7	SCG		5	17	2.9919	27.7	0.4666	2.5828	25.3	0.4953
8		1	10	20	2.5133	25.6	0.5875	1.8560	21.4	0.8762
9			15	100	0.9566	15.2	0.8665	0.8960	14.9	0.8591
10			5	40	2.0158	22.4	0.6863	1.7413	21.3	0.6999
11		2	10	22	2.3863	24.4	0.6131	1.8613	22.1	0.6772
12			15	83	0.6931	13.1	0.9066	0.6514	11.8	0.9005

MSE = mean square error; MAPE = mean absolute percentage error; R = correlation coefficient; LM = Levenberg–Marquardt training algorithm; SCG = Scaled conjugate gradient training algorithm.

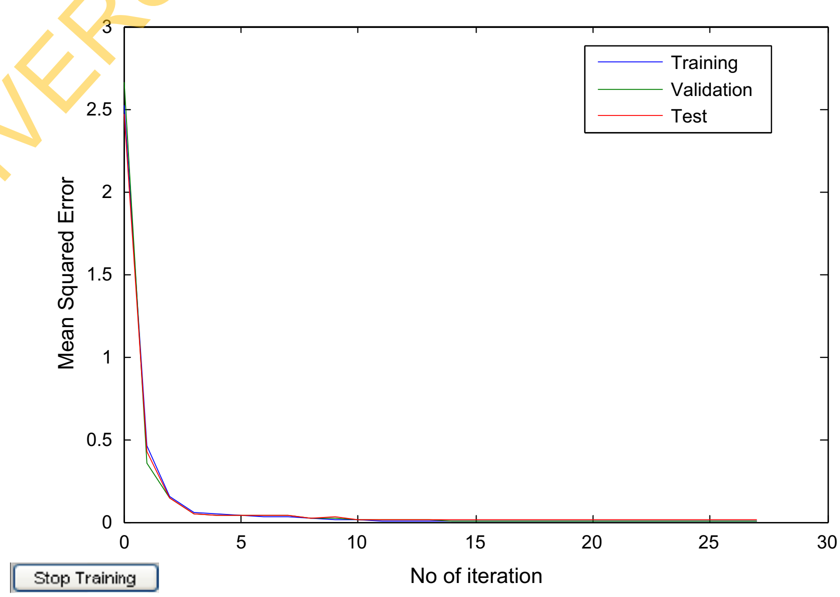

Fig. 3. Reduction in MSE during the training process for the network with 4-15-15-1 configuration.

3. Results and discussion

The training process for all the networks investigated except network No. 9 was terminated based on '*early stopping*' validation criteria. Only network No. 9 was terminated based on reaching the prescribed maximum no of 100 iterations. The network performances in terms of the Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE) and correlation coefficient (r) between the predicted and the measured values of monthly mean wind speed for training and testing datasets using 12 different configurations are shown in Table 3. Based on the training dataset, the MSE, MAPE and coefficient (r) ranged from 0.0205–2.9919, 1.5–27.7% and 0.467–0.997, respectively, while corresponding ranges of 0.451–1.861, 8.9–22.1% and 0.495–0.942, respectively were obtained based on the testing dataset. Network No. 6, with two hidden layers having 15 neurons in each (4-15-15-1), trained with the LM algorithm with the lowest value of MAPE of 8.9% based on the testing dataset was selected as the optimum network used for the model. A lower MAPE value of 6.8% has been reported by Sozen et al. [30], while higher value of 19.1% have been reported by Mohandes et al. [35] for prediction of solar radiation using similar ANN models. The reduction in MSE during the training process is shown in Fig. 3. The optimum network has correlation of coefficient (r) values of 0.997, 0.938 and 0.976 for the training, testing and the whole datasets, respectively (see Fig. 4). This showed that the ANN predicted wind speed values were very close to the measured values for the all datasets. The number of iteration during the training process for the optimum network was 27. The comparison between the predictions of the optimum network and the measured wind speed for the city of Ogoja, one of the stations used as testing dataset is shown in Fig. 5. The minimum, maximum, mean and standard deviation of the mean absolute percentage error for the prediction of wind speed for city of Ogoja are 0.6, 12.6, 4.9 and 4.6%, respectively. These ranges of error are normally considered as acceptable in weather data prediction [30].

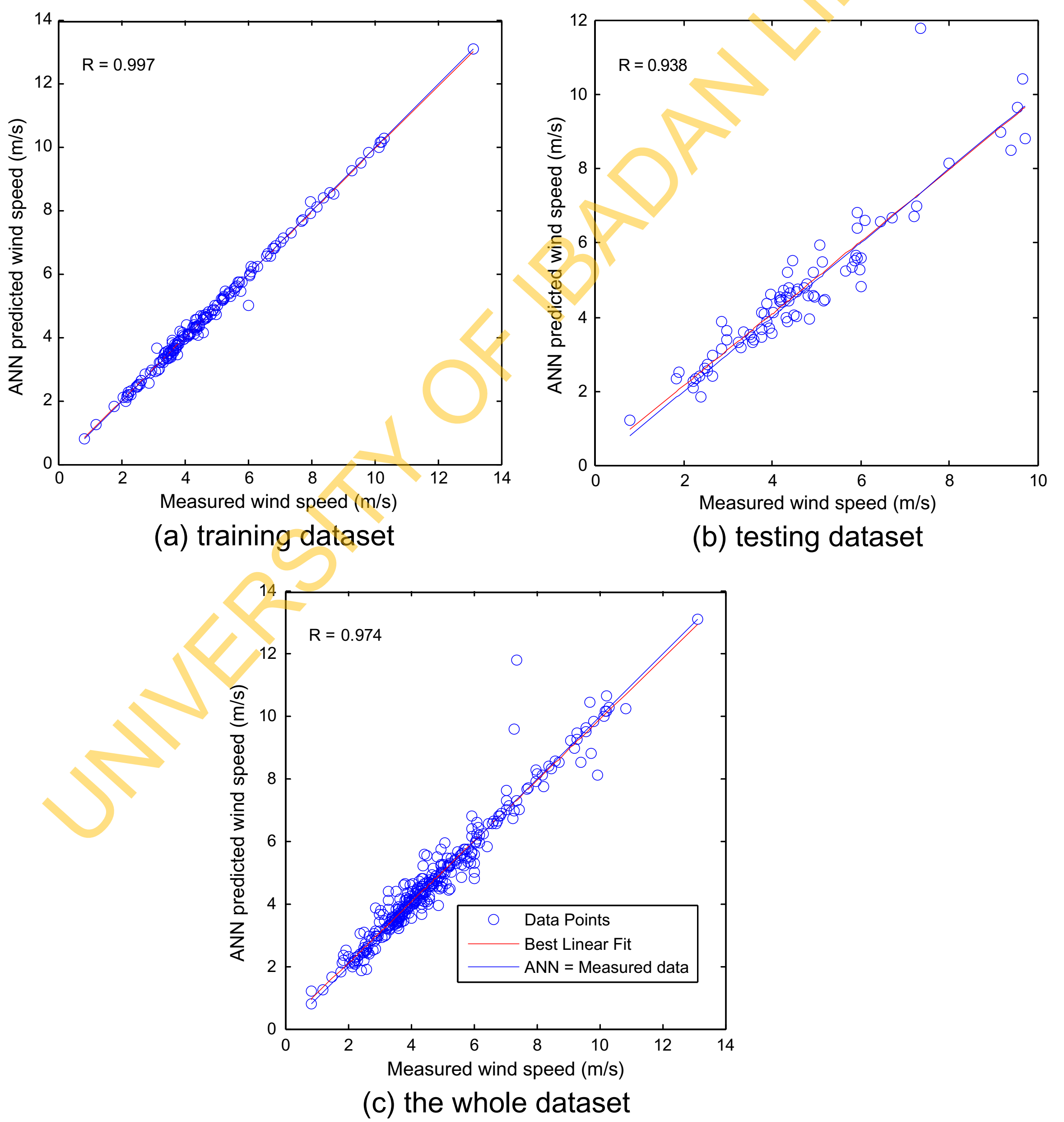

Fig. 4. Correlation between ANN predicted and measured wind speed for training (a); testing (b) and whole (c) datasets for network with 4-15-15-1 configuration.

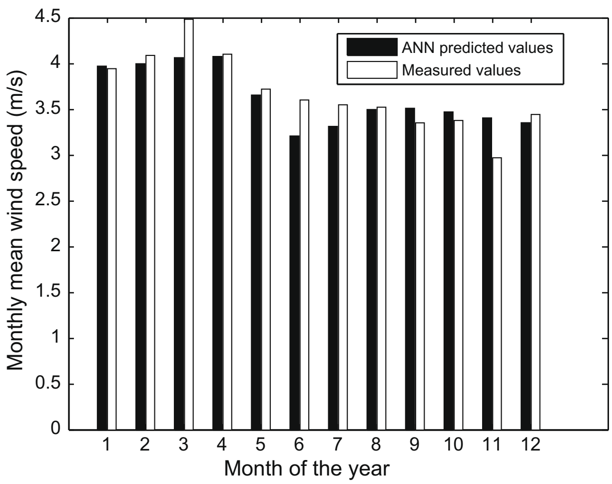

Fig. 5. Comparison between ANN predicted and measured monthly mean wind speed for the city of Ogoja, Nigeria.

3.1. Application of the ANN model for prediction of wind speed

The geographical parameters (latitude, longitude, and altitude), and month of the year were used as input for the developed model to predict the monthly mean wind speed from January to December for 195 locations within Nigeria consisting of the 28 ground stations and additional 167 locations where there are no meteorological ground stations. The ANN predicted monthly mean wind speed for the 195 geographical locations are presented in form of monthly maps using the Geographical Information System (GIS) software ArcVeiw® 3.2. Samples of the monthly isovents for March, June, September and December are shown in Figs. 6–9. The monthly mean wind speed varied increasingly from the costal region in the south to savannah region in the north. The monthly mean wind speed in northern region ranges from 7.0–13.1 m/s, while in the southern region the monthly mean wind speed ranges from 0.9–5.5 m/s. Similar trend in wind speed variation in Nigeria has been reported by Iloeje [36]. Two distinct wind belts are recognisable on the maps from January to December. The high wind belt in the north (wind speed >7.0 m/s) and the low wind belt in the south (wind speed <5.0 m/s). Summary of the monthly wind speed variation is presented in Table 4. The monthly wind speed ranged from 0.9–13.1 m/s with an annual mean of 4.7 m/s. The wind speed variation obtained in this study is higher than 3.0–7.0 m/s reported by Iloeje [36]. The maximum wind speed of 13.1 m/s occurs in December in the northern region, while a corresponding minimum value of 0.9 m/s occurs in same month in southern region (Table 4).

3.2. Estimation of wind power

The maps can be used to estimate the monthly mean available wind energy for a given wind rotor blade with sweep area A at any given site with a mean wind speed v_m as [6,12,18]:

$$P(v) = \frac{1}{2}\rho A v_m^3 \quad (1)$$

where $P(v)$ is the monthly mean wind energy (W), ρ is the air density at the site, A is the swept area of the rotor blades (m^2), v_m is the monthly mean wind speed at that location (m/s).

The monthly mean wind energy obtainable from a typical 25 m diameter wind turbine with an efficiency of 30% at given site (Ogoja) with air density, ρ = 1.21 kg/m^3 [18] are given in Table 5.

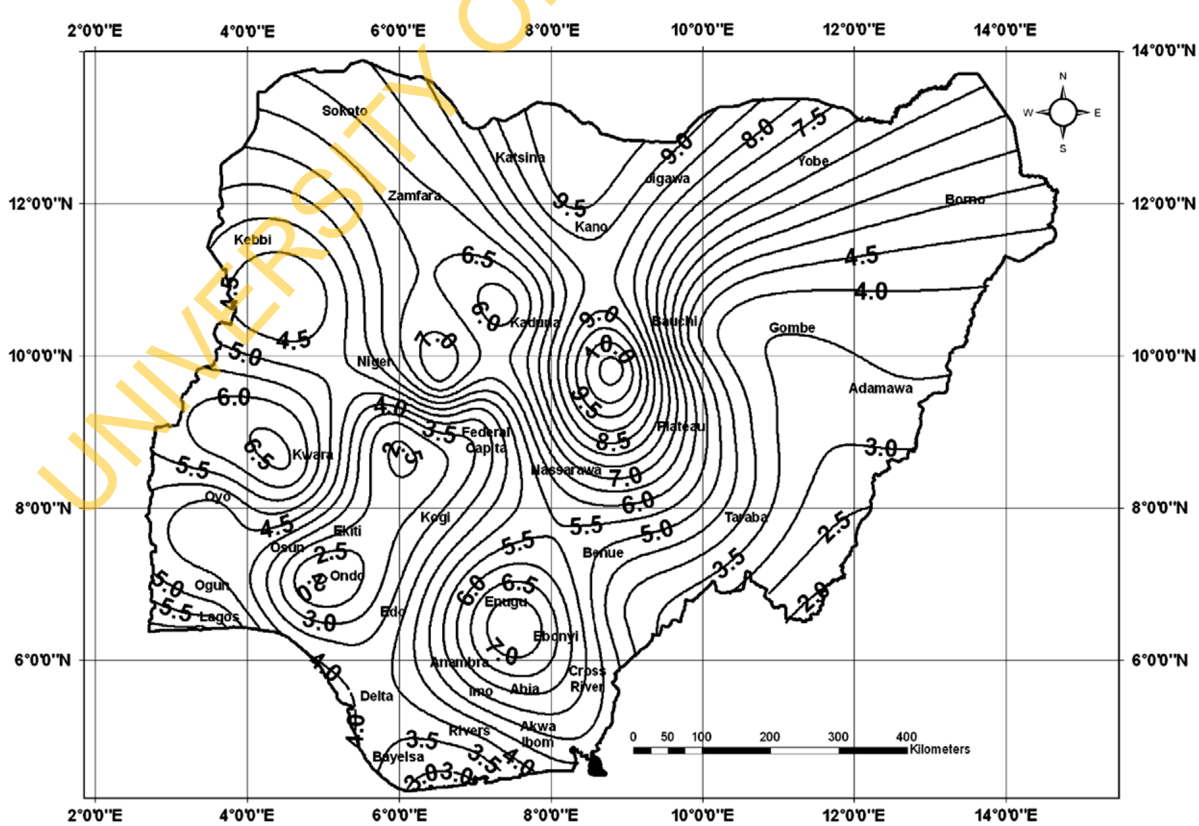

Fig. 6. Predicted monthly mean wind speed (m/s) for the month of March.

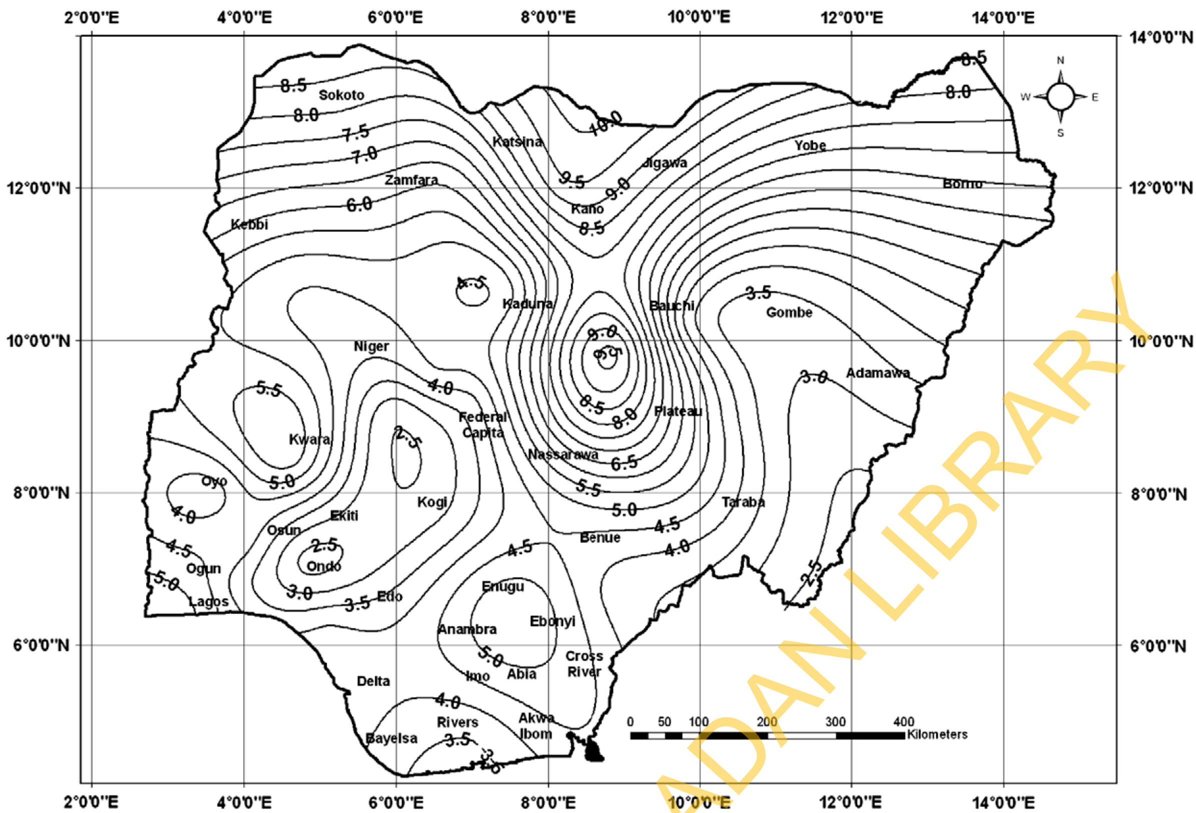

Fig. 7. Predicted monthly mean wind speed (m/s) for the month of June.

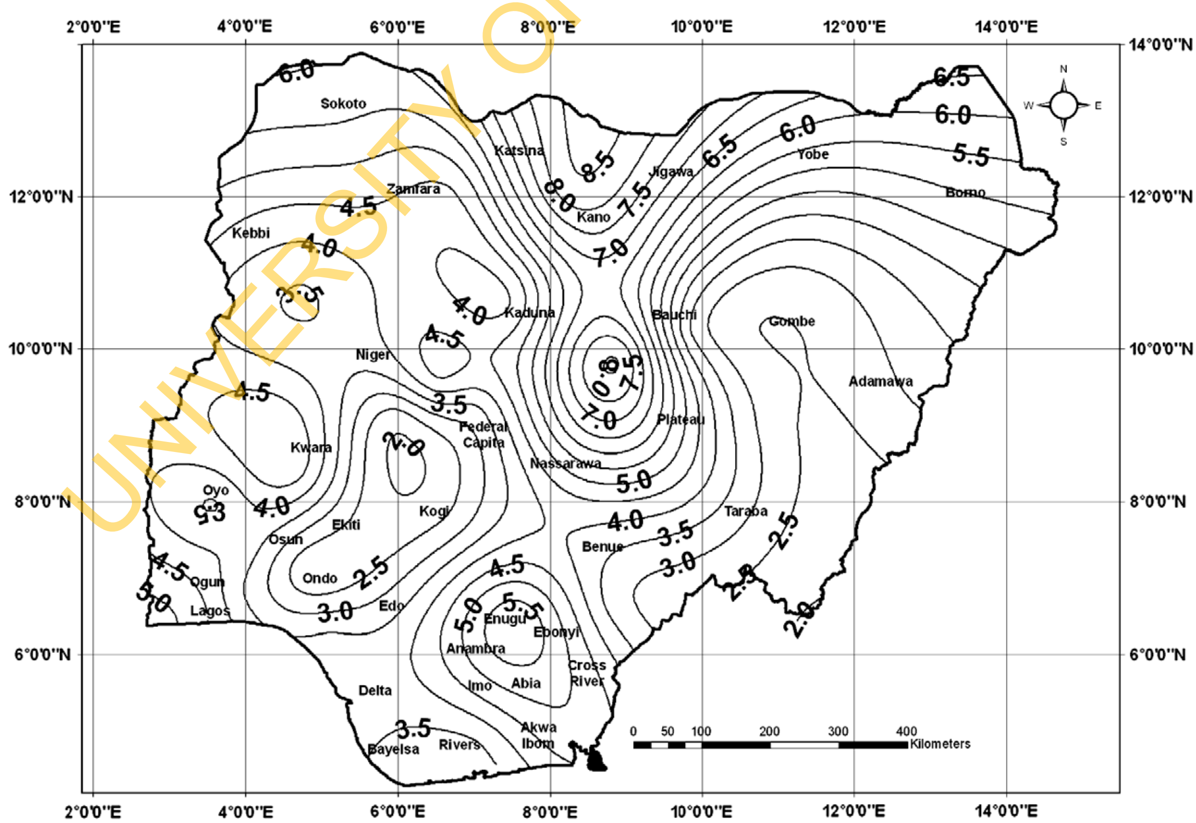

Fig. 8. Predicted monthly mean wind speed (m/s) for the month of September.

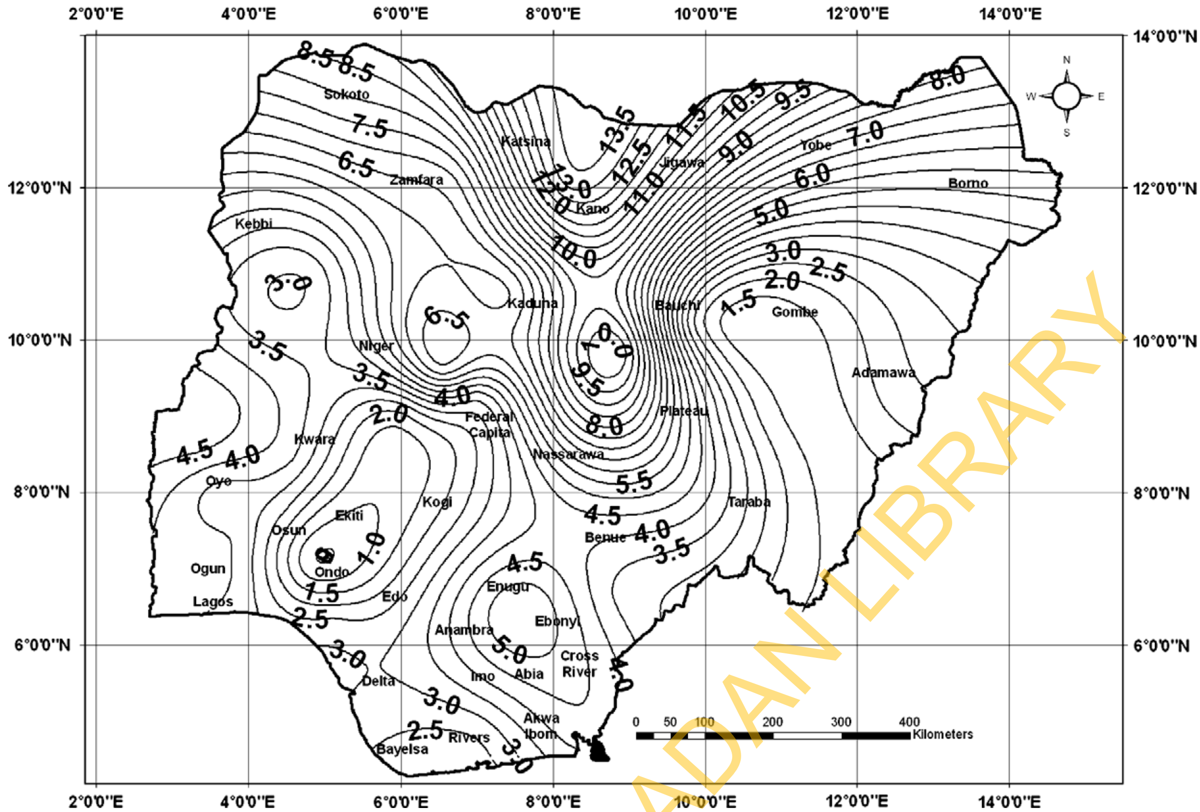

Fig. 9. Predicted monthly mean wind speed (m/s) for the month of December.

Table 4
Statistics of predicted monthly mean wind speed variation in Nigeria.

Month	Monthly mean wind speed (m/s)			
	Max.	Min.	Mean	Std.
January	10.3	1.3	4.7	2.2
February	10.7	2.1	5.1	1.8
March	10.4	2.3	5.2	1.6
April	10.2	2.0	5.2	1.7
May	10.2	1.8	5.1	1.9
June	10.2	2.2	4.9	2.1
July	9.7	2.3	4.8	1.8
August	8.5	2.3	4.4	1.4
September	8.3	2.1	4.2	1.4
October	9.6	1.6	4.0	1.7
November	11.8	1.2	4.1	2.2
December	13.1	0.8	4.6	2.6
Yearly	13.1	0.8	4.7	1.9

Table 5
Estimated available monthly mean wind energy for the city of Ogoja.

Month	Estimated available wind energy (W)
January	5579.0
February	5656.1
March	5982.1
April	6027.7
May	4359.5
June	2923.1
July	3224.1
August	3788.8
September	3862.5
October	3698.9
November	3500.7
December	3365.6
Yearly average	430.7

4. Conclusion

The study has shown that the ANN based model has an acceptable accuracy with Mean Absolute Percentage Error (MAPE) of 8.9% and correlation coefficient (r-value) of 0.9380 was attainted for prediction of wind speed profile in Nigeria. The predicted monthly wind speed ranged from a minimum of 0.9 m/s in the southern region to a maximum figure of 13.1 m/s in the northern region. The annual mean wind speed of 4.7 m/s was obtained for Nigeria. The model is promising and can be used to predict wind speed for locations where there are no monitoring stations.

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