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Modelling of solar energy potential in Nigeria using an artificial neural network model

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ABSTRACT

In this study, an artificial neural network (ANN) based model for prediction of solar energy potential in Nigeria (lat. 4–14°N, log. 2–15°E) was developed. Standard multilayered, feed-forward, back-propagation neural networks with different architecture were designed using neural toolbox for MATLAB. Geographical and meteorological data of 195 cities in Nigeria for period of 10 years (1983–1993) from the NASA geo-satellite database were used for the training and testing the network. Meteorological and geographical data (latitude, longitude, altitude, month, mean sunshine duration, mean temperature, and relative humidity) were used as inputs to the network, while the solar radiation intensity was used as the output of the network. The results show that the correlation coefficients between the ANN predictions and actual mean monthly global solar radiation intensities for training and testing datasets were higher than 90%, thus suggesting a high reliability of the model for evaluation of solar radiation in locations where solar radiation data are not available. The predicted solar radiation values from the model were given in form of monthly maps. The monthly mean solar radiation potential in northern and southern regions ranged from 7.01–5.62 to 5.43–3.54 kW h/m^2 day, respectively. A graphical user interface (GUI) was developed for the application of the model. The model can be used easily for estimation of solar radiation for preliminary design of solar applications.

1. Introduction

The energy crisis in Nigeria has been a great concern for many decades. At present, the government is committed to finding a long-term solution to this crisis through the renewable energy master plan (REMP) with a target of increasing the present 5000 MW generation capacity to 16,000 MW through renewable energy resources by the year 2015 [1]. In pursuance of this goal, the exploration of solar energy potential is being given serious attention. Nigeria, located between 4°N and 14°N Latitudes, is endowed with sufficient solar radiation that can be effectively harnessed as renewable energy resource. The annual average sunshine duration of about 6.25 h/day and annual average solar radiation of 5.25 kW h/m^2 day has been reported by Bala et al. [2]. Solar resources are known to exhibit a high variability in space and time due to the influence of other climatic factors such as cloud cover. Therefore, solar resource modelling or mapping is one of the essential management tools for proper development, planning, maintenance scheduling and pricing of solar energy system. For efficient conversion and utilization of the solar resource, the solar engineer designing solar energy systems requires an accurate and detailed short-term and long-term knowledge of the solar radiation characteristics of the location in various forms such models or maps for proper sizing of the solar energy systems [3–6]. Solar radiation models or maps are therefore essential design-input parameter in the assessment of solar energy systems. Hence, the solar radiation data is one of the key parameters required to be monitored at any meteorological station. In Nigeria, the Nigerian Meteorological Services (NIMET) Oshodi, Lagos, is the national agent saddled with the task of measuring and archiving daily values of meteorological parameters. However, while NIMET measures other meteorological parameters for most Nigerian locations, there are no installed pyrometers for measuring solar radiation intensities. Only very few locations in Nigeria have solar radiation data such as those monitored by stations owned by research institutes like International Institute of Tropical Agriculture (IITA) and Universities. Hence, due to this lack of solar radiation data, many researchers [7–13] have developed different forms of empirical models for estimation of global solar radiation for different locations in Nigeria based on other available meteorological parameters. The developed empirical models are location specific and hence are limited in scope and application.

Artificial neural network (ANN) is a numerical modelling technique that has been applied for prediction of global solar radiation in different parts of the world. Sozen et al. [3] reported the application of ANN model for mapping of solar potential in Turkey. Mellit et al. [14] has developed an adaptive wavelet-network model for

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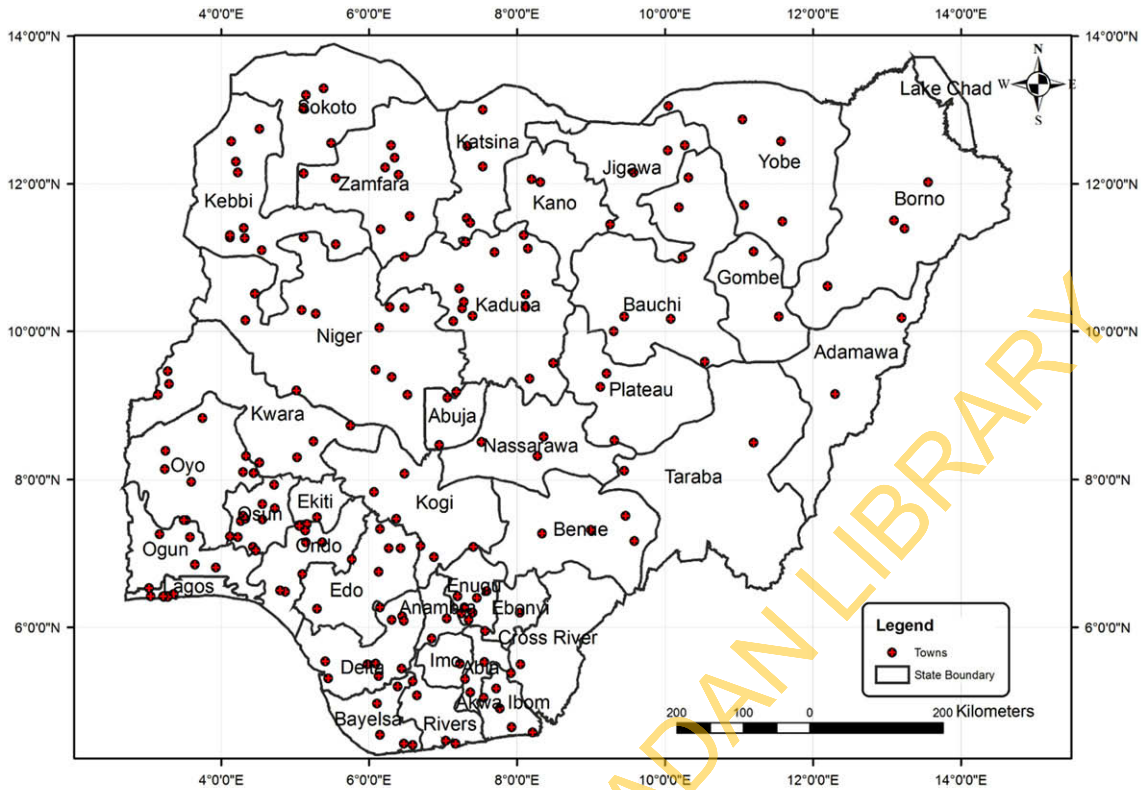

Fig. 1. Map of Nigeria showing the geographical locations of the cities used in training and testing the model.

forecasting daily total solar radiation in Algeria. A comprehensive review of ANN applications in renewable energy systems has been reported by Kalogirou [15]. Artificial neural network for modelling the starting-up of a solar steam generator has been developed by Kalogirou et al. [16].

In Nigeria, Alfa et al. [17] applied ANN for prediction of hourly time series global solar radiation for Bauchi city, while Jiya and Alfa [18] reported the application of ANN model for mapping of global solar radiation for the entire country. In the latter model, meteorological data from 31 ground stations for a period of 1 year was used for training and testing the network. The model used five geographical and meteorological parameters (latitude, longitude, altitude, sunshine duration, and month of the year) as input to predict the monthly global solar radiation. The limited number of sampling points and shortness in duration of the data used in this study are major limitations on accuracy of the developed model. In this present study, feed-forward, back-propagation, multilayer perceptron neural networks are developed to predict the mean monthly global solar radiation using the data of 195 cities spread over Nigeria for the period of 10 years (1983–1993). The model uses seven geographical and meteorological parameters (latitude, longitude, altitude, month, mean sunshine duration, mean temperature, and relative humidity) as input parameters for the model. The essence of this study was to investigate the feasibility of using ANN to model the non-linear relationship between solar radiation and other meteorological parameters. Hence, the model can be used to predict the monthly mean solar radiation potential for specific locations in Nigeria where there are no records of solar radiation such as meteorological ground stations. The predicted solar radiation values from the model were given in the form of monthly maps from January to December, which can be used easily for design and assessment of solar application systems.

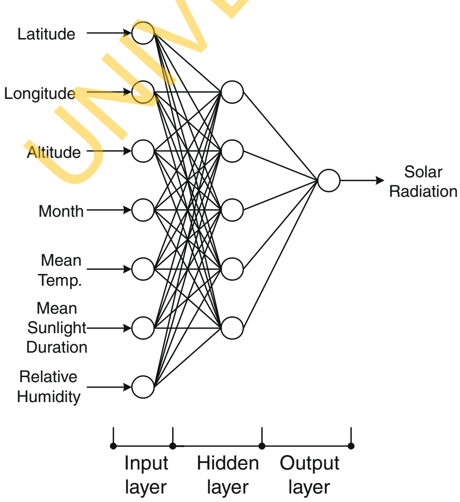

Fig. 2. Typical artificial neural network used for the prediction of solar radiation.

2. Materials and methods

2.1. Model description

ANN is a branch of artificial intelligence (AI), which belongs to the group of computational algorithms called connectionist models [19]. ANN models are inspired by the biological neural system, with capability to learn, store and recall information based on a given training dataset. They are 'black-box' modelling technique capable of performing non-linear mapping of a multidimensional input space onto another multidimensional output space without the knowledge of the dynamics of the relationship between the input and output spaces. ANNs have been successfully employed in solving complex problems in various fields of application including pattern recognition, identification, classification, speech, vision,

Table 1
The geographical description of the 195 cities.

No.	Town	LAT (°N)	LONG (°E)	ELEV (m)	No.	Town	LAT (°N)	LONG (°E)	ELEV (m)	No.	Town	LAT (°N)	LONG (°E)	ELEV (m)	No.	Town	LAT (°N)	LONG (°E)	ELEV (m)	No.	Town	LAT (°N)	LONG (°E)	ELEV (m)
1	Aba	5.12	7.37	176	41	Brass	4.32	6.24	83	81	Gwasero	9.29	3.30	303	121	Kabba	7.83	6.07	216	161	Ogbomosho	8.10	4.30	274
2	Abaji	8.47	6.95	257	42	Bununu Das	10.00	9.31	559	82	Hadejia	12.45	10.04	376	122	Kaduna	10.31	7.26	575	162	Ogunlogun	6.41	3.28	73
3	Abak	4.90	7.77	117	43	Burutu	5.21	5.31	71	83	Ibadan	7.22	3.58	183	123	Kafanchan	9.36	8.17	586	163	Oguta	5.44	6.44	127
4	Abakaliki	6.20	8.04	277	44	Bussa	10.15	4.33	267	84	Ibeto	10.29	5.09	309	124	kajuru	10.21	7.40	575	164	Ogwashi-uku	6.10	6.31	159
5	Abeokuta	7.15	5.15	233	45	Calabar	4.58	8.21	246	85	Ibi	8.12	9.45	357	125	kamba	11.53	3.36	252	165	Oke-igbo	7.09	4.43	223
6	Abonema	4.43	6.47	83	46	Chafe	11.56	6.55	456	86	Idah	7.07	6.43	216	126	Kano	12.02	8.32	456	166	Okene	7.33	6.15	216
7	Abuja	9.10	7.06	484	47	Damaturu	11.49	11.59	397	87	Idanre	6.72	5.10	135	127	Katsina	12.51	7.33	492	167	Okitipupa	6.50	4.80	104
8	Ado-ekiti	7.40	5.16	233	48	Dan-Gora	11.30	8.09	545	88	Ifon	6.92	5.77	135	128	Kaura-Namoda	12.35	6.35	415	168	Okrika	4.47	7.04	117
9	Ado-odo	6.36	2.56	64	49	Dan-Gulbi	11.38	6.16	456	89	Igbaja	8.23	4.52	274	129	Kauru	10.33	8.12	647	169	Okuta	9.14	3.15	303
10	Afikpo	5.53	7.56	176	50	Danja	11.21	7.31	559	90	Igboho	8.83	3.75	278	130	Keffi	8.51	7.52	325	170	Okwoga	7.01	7.50	218
11	Agbor	6.27	6.15	159	51	Dankama	13.20	7.44	437	91	Igbologun	6.25	3.20	73	131	Keffi-Hausa	12.15	9.58	411	171	Omoko	5.20	6.39	127
12	Agege	6.37	3.20	73	52	Darazo	11.00	10.24	422	92	Igbo-ora	7.26	3.17	183	132	Kende	11.30	4.12	269	172	Ondo	7.04	4.47	223
13	Agenebode	7.10	6.70	216	53	Dawaki	12.06	8.20	456	93	Igbor	7.27	8.34	249	133	Kenduga	11.39	13.24	377	173	Onitsha	6.09	6.47	159
14	Ahoada	5.08	6.65	127	54	Deba Haba	10.20	11.54	416	94	Igumole	6.49	7.59	183	134	Koko	11.26	4.32	269	174	Opobo	4.34	7.27	117
15	Akete-Oja	6.41	3.23	73	55	Dikwa	12.02	13.56	313	95	Ihiala	5.85	6.85	127	135	Kontagora	10.24	5.28	309	175	Opobo	4.30	7.30	117
16	Aku	6.42	7.20	183	56	Duku	11.10	4.55	269	96	Ijebu-Ode	6.81	3.93	73	136	Kotonkarifi	8.08	6.48	257	176	Oron	4.48	8.14	246
17	Akure	7.15	5.15	233	57	Dutsan Wal	10.50	8.12	647	97	Ikara	11.12	8.15	545	137	Kushaka	10.32	6.48	420	177	Oshogbo	7.47	4.33	223
18	Amagunze	6.20	7.40	183	58	Dutse	11.45	9.26	480	98	Ikare	6.42	3.23	73	138	Kusheriki	10.33	6.28	420	178	Otu	8.14	3.24	278
19	Amassama	4.97	6.11	83	59	Ede	7.44	4.27	223	99	Ikeja	6.40	3.45	73	139	Lafia	8.32	8.28	374	179	Otukpa	7.09	7.41	218
20	Anka	12.07	5.55	333	60	Eha-Amufu	6.40	7.46	183	100	Ikerre	7.31	5.14	233	140	Lafiagi	8.52	5.25	256	180	Otun	6.42	3.22	73
21	Apapa	6.45	3.36	73	61	Eket	4.65	7.93	117	101	Ikire	7.23	4.12	223	141	Lagos	6.27	3.24	73	181	Owerri	5.27	6.59	127
22	Argungu	12.74	4.52	270	62	Ekpoma	6.75	6.13	159	102	Ikole	7.49	5.30	233	142	Lema	12.57	4.14	270	182	Owo	7.15	5.37	233
23	Arochukwu	5.38	7.92	176	63	Elele	6.95	6.88	159	103	Ikot Ekpene	5.17	7.72	176	143	Lere	9.43	9.21	506	183	Oworonsoki	6.33	3.24	73
24	Asaba	6.15	6.45	159	64	Enugu	6.27	7.29	183	104	Ila	7.67	4.56	223	144	Lokoja	7.47	6.37	216	184	Oyo	7.22	4.23	223
25	Auchi	7.07	6.27	216	65	Epe	6.42	3.05	73	105	Ilaro	6.53	3.03	73	145	Maiduguri	11.50	13.10	808	185	Panyem	9.25	9.13	506
26	Awgu	5.51	7.23	176	66	Fiditi	7.45	3.53	183	106	Ilawe	7.37	5.06	233	146	Makurdi	7.45	13.10	377	186	Pategi	8.73	5.75	256
27	Awka	6.12	7.05	183	67	Fokko	11.40	4.31	269	107	Ile-Ife	7.46	4.56	223	147	Malumfashi	11.47	7.37	559	187	Pindiga	9.59	10.54	421
28	Azare	11.68	10.19	422	68	Funtua	11.53	7.32	559	108	Ilesa	7.61	4.73	223	148	Maru	12.22	6.22	415	188	Port Harcourt	4.41	6.59	83
29	Babana	10.26	3.50	281	69	Gamawa	12.08	10.32	376	109	Ilobu	7.51	4.30	223	149	Mashi	13.00	7.54	437	189	Potiskum	11.71	11.07	397
30	Badagri	6.27	2.55	64	70	Gandi	12.55	5.49	333	110	Ilora	7.45	3.50	183	150	Matsema	13.05	10.05	381	190	Rigachikun	10.40	7.28	575
31	Baro	8.37	6.25	257	71	Gashua	12.87	11.05	354	111	Ilorin	8.32	4.34	274	151	Mberubu	6.10	7.35	183	191	Sagamu	6.85	3.65	73
32	Bauchi	10.20	9.45	559	72	Gawu	9.14	6.52	319	112	Iree	7.93	4.72	223	152	Minna	9.38	6.31	319	192	Sapele	5.54	5.41	71
33	Bena	11.18	5.55	342	73	Gboko	7.32	9.00	353	113	Irele	6.48	4.87	104	153	Mokwa	9.20	5.02	254	193	Shaki	8.39	3.25	278
34	Benin-City	6.25	5.30	135	74	Geidam	12.57	11.57	354	114	Iseyin	7.97	3.60	183	154	Moriki	12.52	6.30	415	194	Shendam	8.53	9.32	357
35	Bida	10.58	7.22	575	75	Gombe	10.17	10.08	458	115	Ishiagu	5.95	7.57	176	155	Mubi	10.18	13.20	432	195	Sokoto	13.03	5.12	331
36	Birnin-Gwari	11.01	6.48	456	76	Goronyo	13.29	5.39	331	116	Iwo	8.30	5.03	256	156	Mushin	6.32	3.22	73					
37	Birnin-Kebbi	12.30	4.20	270	77	Gummi	12.14	5.12	333	117	Jalingo	8.50	11.20	476	157	Nafada	11.08	11.20	397					
38	Birnin-kudu	11.27	4.12	269	78	Gusau	12.12	6.40	415	118	Jega	12.15	4.23	270	158	Nguru	12.52	10.27	376					
39	Biu	10.61	12.20	434	79	Gwadabawa	13.20	5.15	331	119	Jibiya	13.05	7.12	437	159	Obiaruku	5.51	6.09	127					
40	Bonny	4.43	7.17	117	80	Gwagwada	10.14	7.14	575	120	Jos	9.57	8.49	586	160	Offa	8.09	4.44	274					

and control systems. In recent times, application of ANNs is becoming increasingly popular in modelling of complex engineering problems.

Basically, ANN models consist of multiple connected processing elements (PE), which are called nodes or neurons. They consist generally of five basic components: (1) input, (2) weight and biases, (3) summing junction, (4) transfer function, and (5) output. The neurons are arranged in three multiple layers known as input, hidden, and output layer. In neural networks, knowledge is acquired during the training or learning process by updating or adjusting the weights in the network through different algorithms. The network weights are upgraded literarily until the network reproduces the desired output or target from a given set of input. The network is trained with either supervised learning (when both input and the desired targets are presented to the network) or unsupervised learning (when the expected targets are not used in the training). The back-propagation algorithm is a supervised training rule with multiple-layer networks, in which the network weights are moved along the negative of the gradient of the mean squared error (MSE) so as to minimize the difference between the

Table 2
Statistics of the *R*-values of network performance for the training and entire dataset.

Training algorithm[a]	No. of hidden layer	No. neurons in hidden layer	Correlation coefficient (*R*-value)							
			Training dataset				Entire dataset			
			Mean	Max	Min	Standard deviation	Mean	Max	Min	Standard deviation
LM	1	5	0.9783	0.9911	0.8683	0.0270	0.9567	0.9526	0.8136	0.0271
		10	0.9738	0.9944	0.8444	0.0340	0.9438	0.9613	0.8656	0.0225
		15	0.9748	0.9938	0.8736	0.0261	0.9411	0.9567	0.8864	0.0195
	2	5	0.9540	0.9941	0.5634	0.0864	0.9207	0.9569	0.5090	0.0868
		10	0.9724	0.9968	0.8935	0.0275	0.9349	0.9617	0.8376	0.0295
		15	0.9768	0.9970	0.8895	0.0210	0.9394	0.9575	0.8474	0.0222
SCG	1	5	0.9368	0.9815	0.7876	0.0448	0.9110	0.9520	0.8410	0.0306
		10	0.9535	0.9889	0.8735	0.0307	0.9210	0.9488	0.8802	0.0227
		15	0.9417	0.9889	0.8071	0.0434	0.9115	0.9490	0.7856	0.0367
	2	5	0.9161	0.9800	0.3704	0.1104	0.8909	0.9483	0.3274	0.1109
		10	0.9607	0.9899	0.9211	0.0212	0.9270	0.9517	0.8869	0.0183
		15	0.9373	0.9897	0.6590	0.0641	0.9087	0.9514	0.7024	0.0507

[a] SCG = Scaled conjugate gradient; LM = Levenberg–Marquardt.

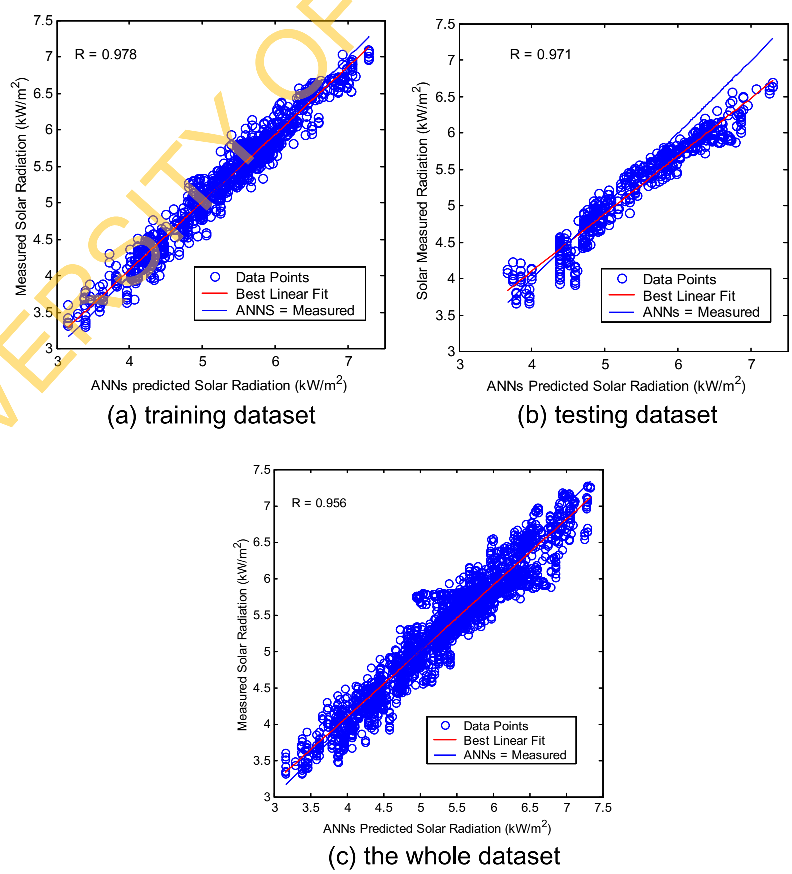

Fig. 3. Performance of the artificial neural network model for prediction of solar radiation potential in Nigeria.

network's output and the desired target. There are generally four steps in the training process: (1) assembling the training data, (2) designing the network object, (3) training the network, and (4) simulating the network response with new input data sets. After a sufficient training session, which may require considerable computational resources such as memory and time of the computer, the trained network has adequate capabilities to perform non-linear pattern association between input and output variables and can easily predict the output when a new input data set that is not used in the training is presented to the network. ANN models are known to be efficient and less time-consuming in modelling of complex systems compared to other mathematical models such as regression [15,20]. Basic theories and applications of ANN can be found in generic texts such as in Ref. [21].

Table 3
Geographical of the location of the 24 ground stations.

Station index no.	Station name (State)	WMO code	Latitude (°)N	Longitude (°)E	Altitude (m)
1	Akure (Ondo)	65232	7.28	5.30	375.0
2	Bauchi (Bauchi)	65055	10.23	9.82	609.7
3	Benin (Edo)	65229	6.32	5.10	77.8
4	Bida (Niger)	65112	9.10	6.02	144.3
5	Calabar (Cross River)	65264	4.97	8.35	61.9
6	Enugu (Enugu)	65257	6.47	7.55	141.8
7	Gusau (Zamfara)	65015	12.17	6.70	463.9
8	Ibadan (Oyo)	65208	7.43	3.90	227.2
9	Ikeja (Lagos)	65201	6.58	3.33	39.4
10	Ilorin (Kwara)	65101	8.48	4.58	307.4
11	Jos (Plateau)	65134	9.87	8.90	586.0
12	Kaduna (Kaduna)	65019	10.60	7.45	645.4
13	Kano (Kano)	65046	12.05	8.20	472.5
14	Lokoja (Kogi)	65243	7.78	6.73	62.5
15	Maiduguri (Borno)	65082	11.85	13.08	353.8
16	Ogoja (Cross River)	65275	6.67	8.80	117.0
17	Oshogbo (Osun)	65215	7.78	4.48	302.0
18	P/Harcourt (Rivers)	65250	4.85	7.02	19.5
19	Potiskum (Borno)	65073	11.7	11.03	414.8
20	Shaki (Oyo)	65108	8.67	3.38	278.0
21	Sokoto (Sokoto)	65010	13.02	5.25	350.8
22	Warri (Delta)	65236	5.52	5.73	6.1
23	Yelwa (Kebbi)	65001	10.83	4.75	244.0
24	Yola (Adamawa)	65167	9.23	12.47	186.1

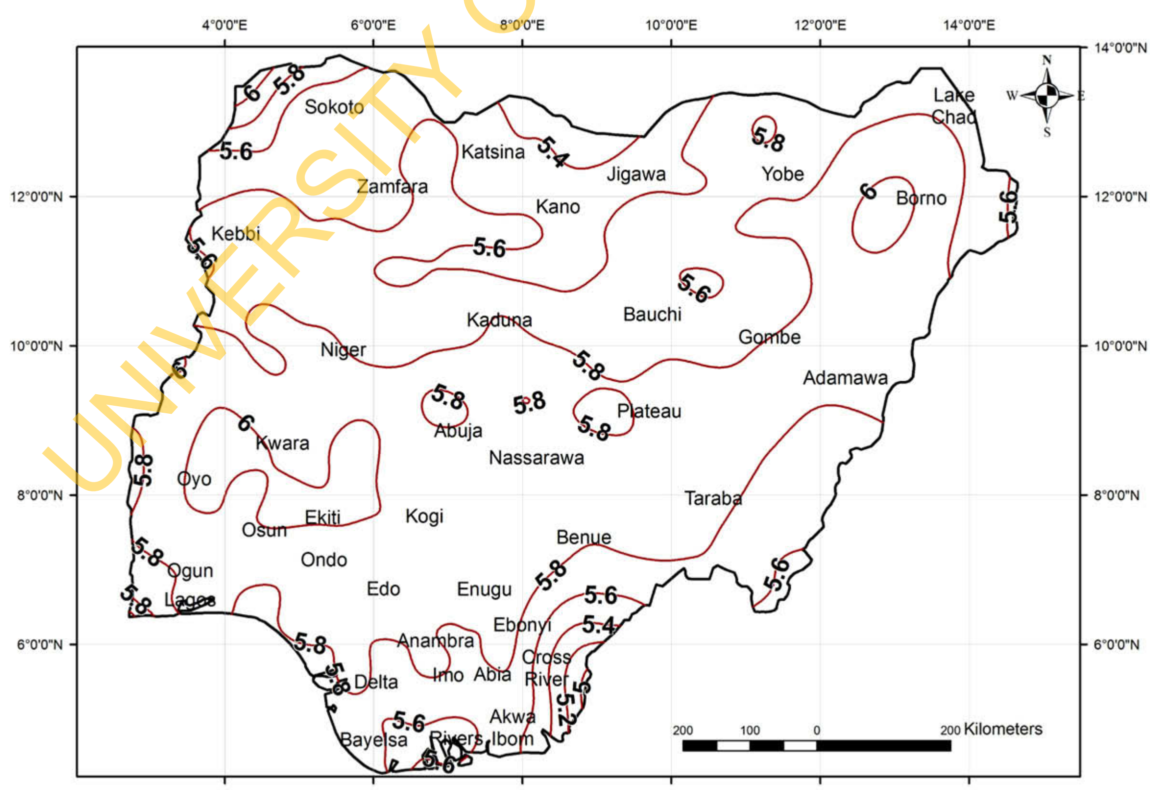

Fig. 4. Predicted solar energy potential (kW h/m^2 day) for the month of January in Nigeria.

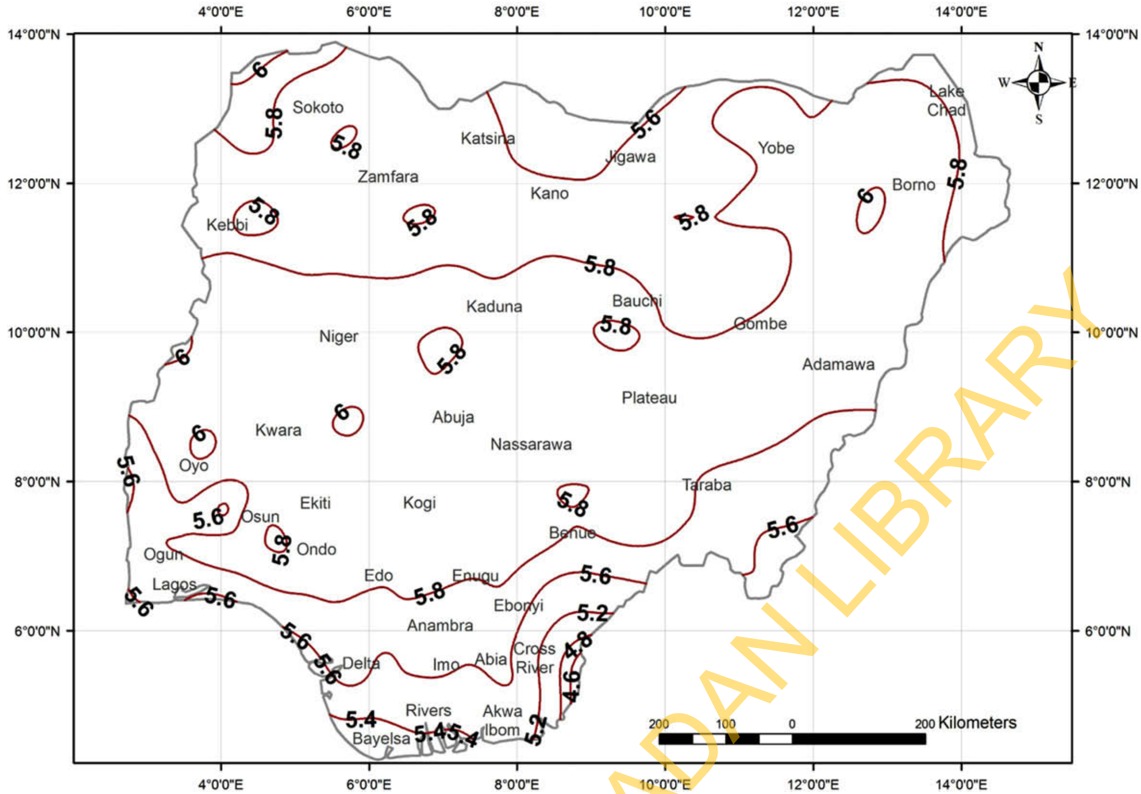

Fig. 5. Predicted solar energy potential (kW h/m^2 day) for the month of February in Nigeria.

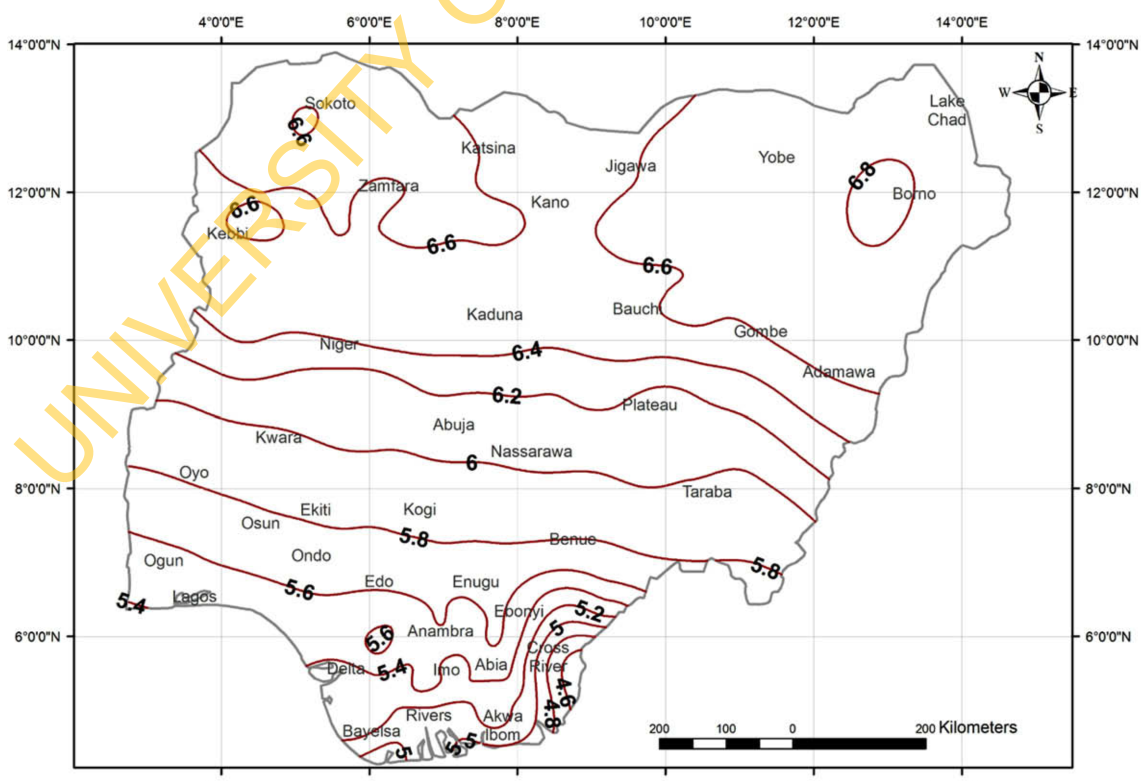

Fig. 6. Predicted solar energy potential (kW h/m^2 day) for the month of March in Nigeria.

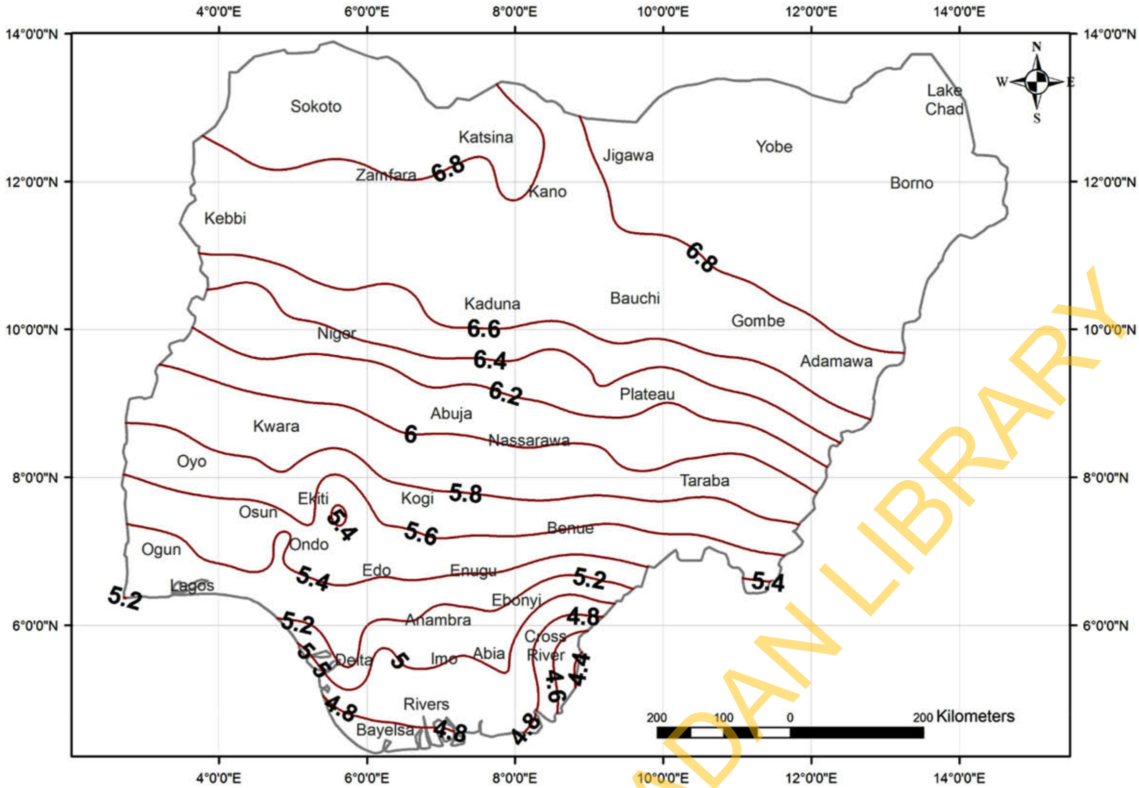

Fig. 7. Predicted solar energy potential (kW h/m² day) for the month of April in Nigeria.

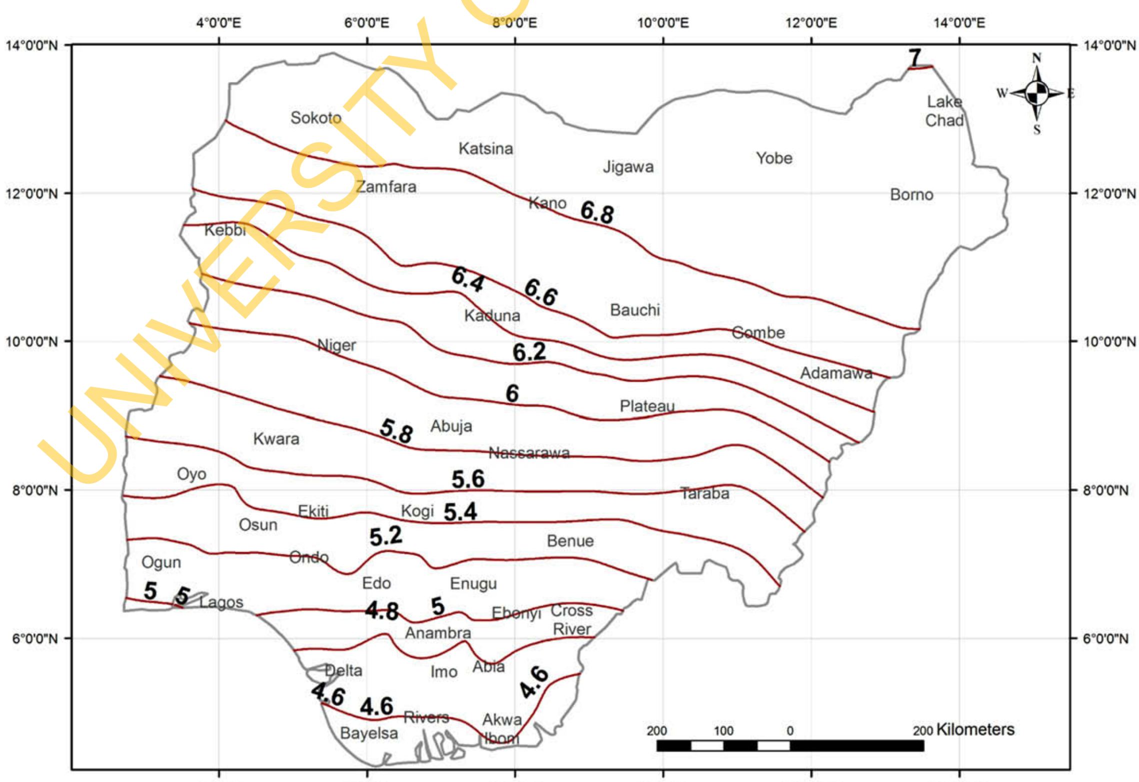

Fig. 8. Predicted solar energy potential (kW h/m² day) for the month of May in Nigeria.

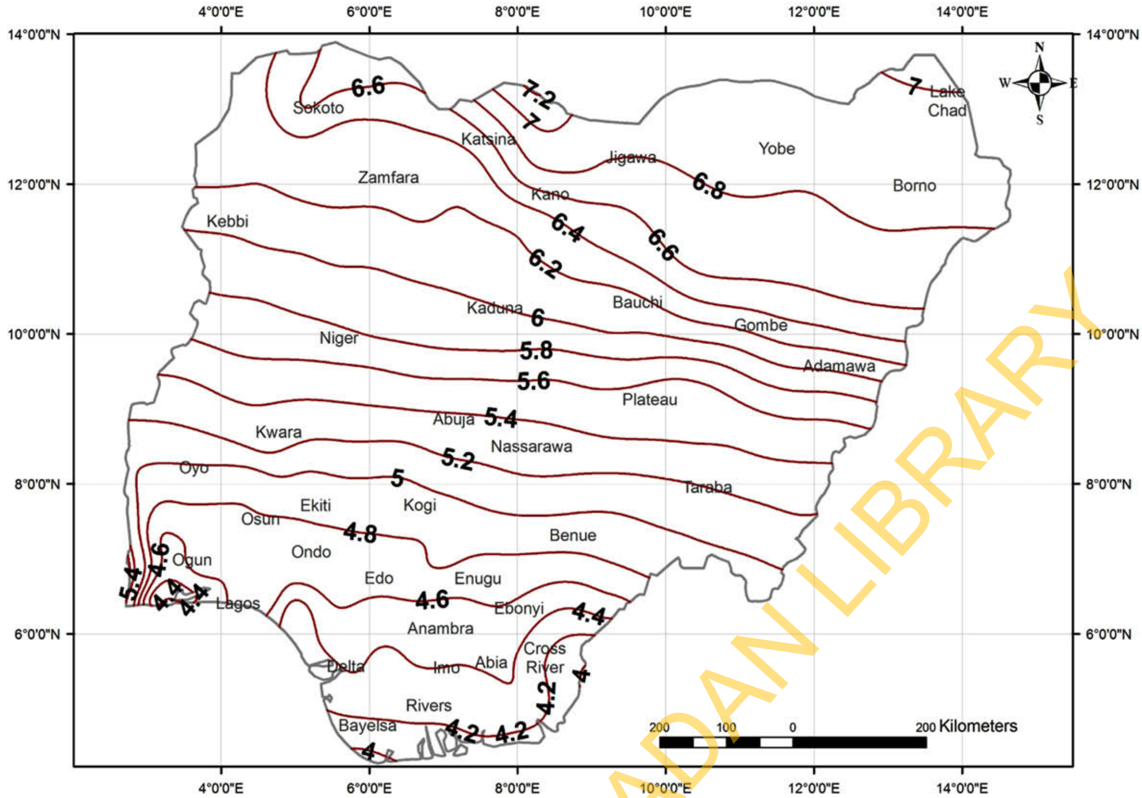

Fig. 9. Predicted solar energy potential (kW h/m^2 day) for the month of June in Nigeria.

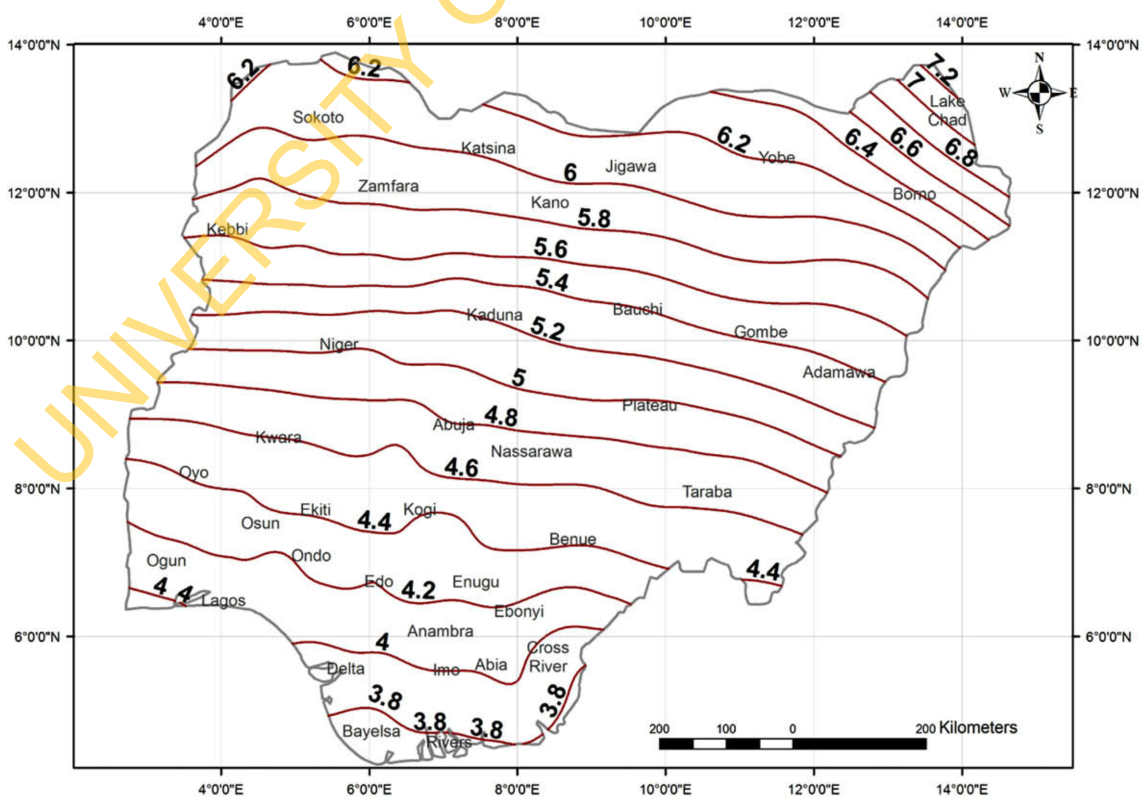

Fig. 10. Predicted solar energy potential (kW h/m^2 day) for the month of July in Nigeria.

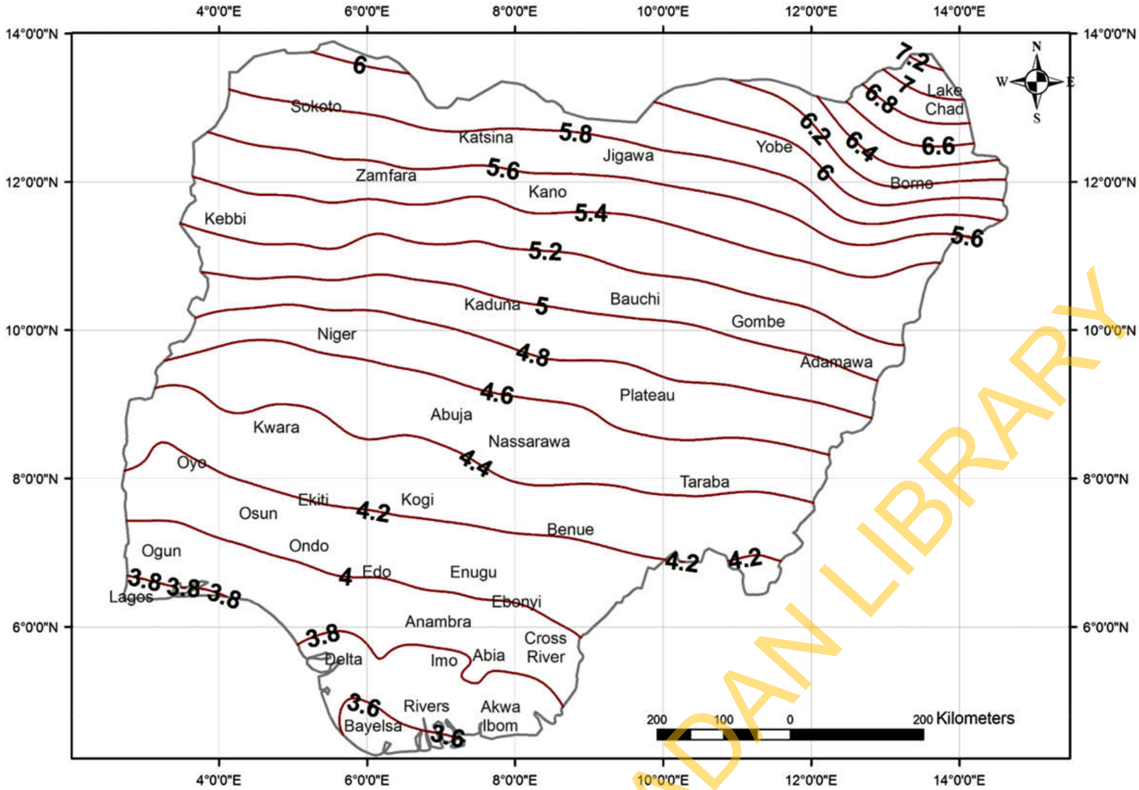

Fig. 11. Predicted solar energy potential (kW h/m^2 day) for the month of August in Nigeria.

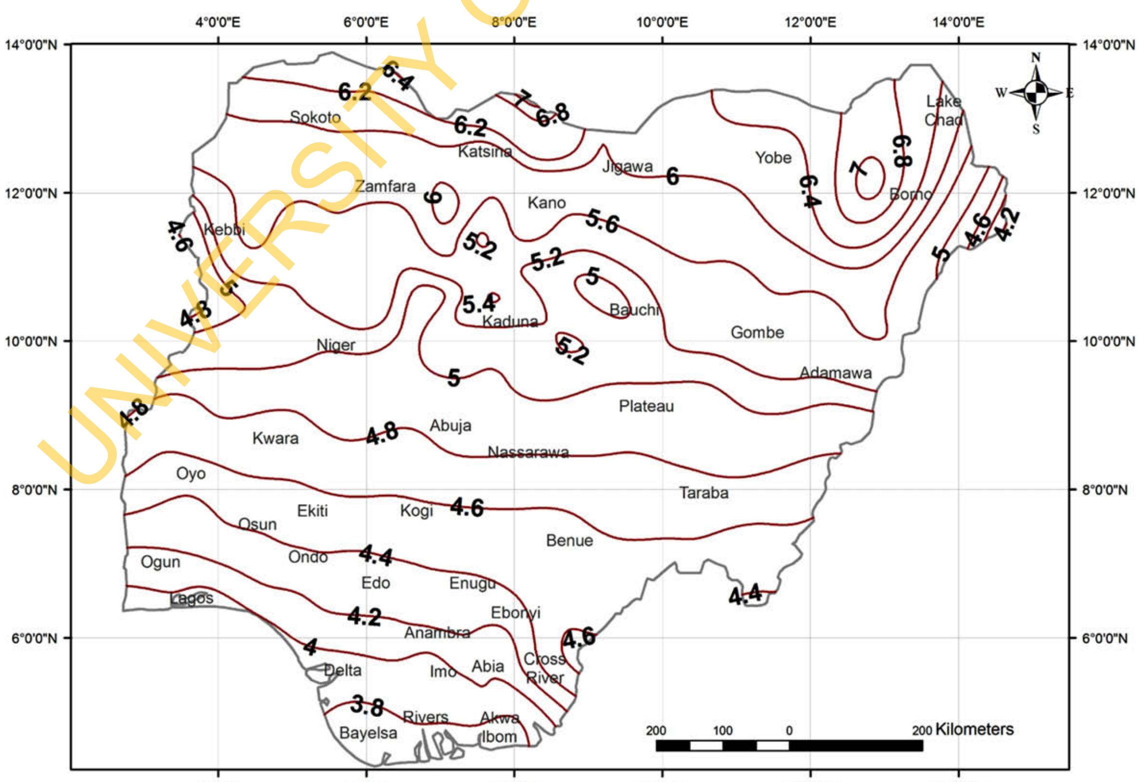

Fig. 12. Predicted solar energy potential (kW h/m^2 day) for the month of September in Nigeria.

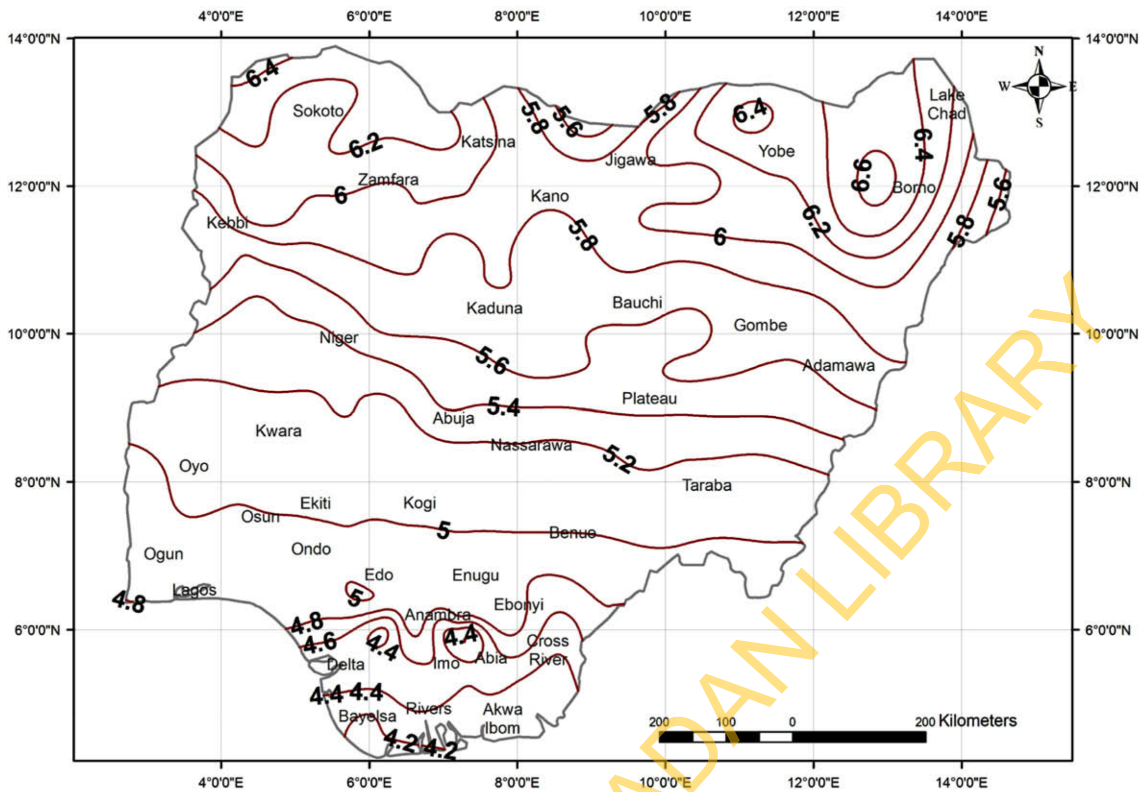

Fig. 13. Predicted solar energy potential (kW h/m^2 day) for the month of October in Nigeria.

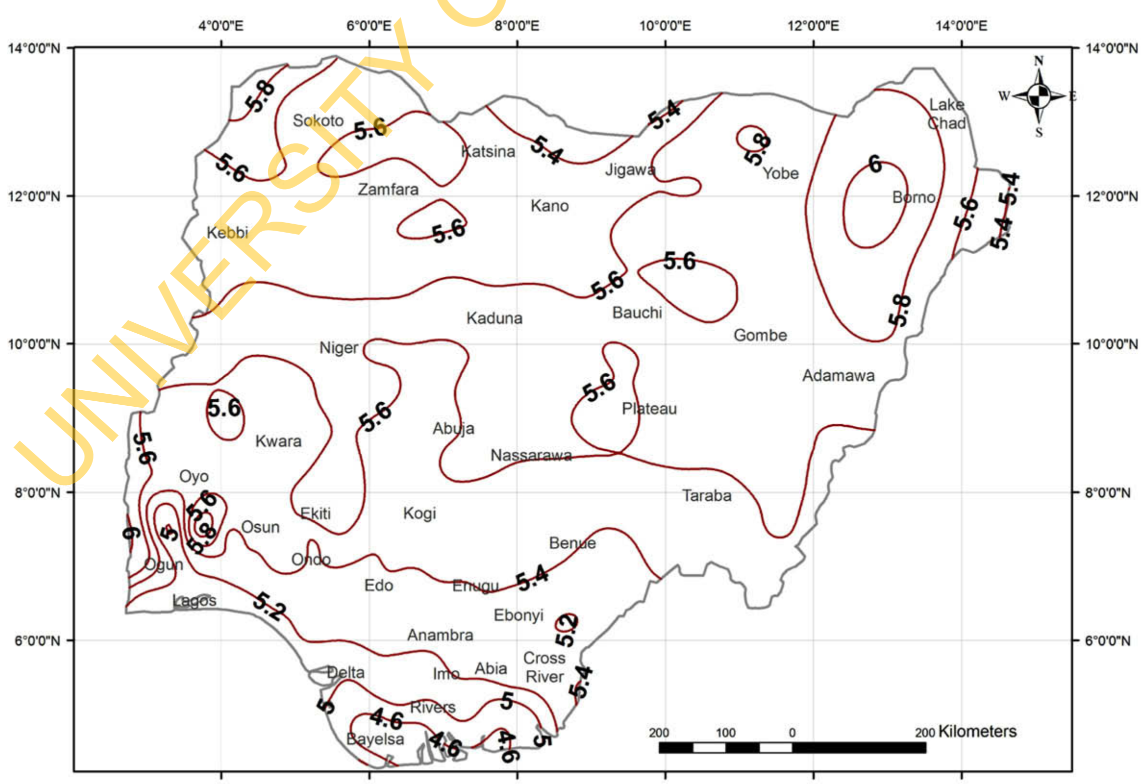

Fig. 14. Predicted solar energy potential (kW h/m^2 day) for the month of November in Nigeria.

2.2. Data collection

Geographical and meteorological data of 195 cities for the period of 10 years (1983–1993) were obtained from NASA geo-satellite database. The data includes geographical parameters such as: latitude, longitude, altitude, month of the year, and mean monthly meteorological parameters; mean sunshine duration, mean temperature, and relative humidity, and solar radiation intensity. The geographical location of the 195 cities used in this study for training and testing of the model is shown in Fig. 1.

2.3. Design of the artificial neural network 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 [22]. The networks consist of three layers: input layer; hidden layer; and output layer (Fig. 2). There are seven input parameters into the network, which consist of the geographical and meteorological parameters of the stations (mentioned above) and one output parameter corresponding to the global solar radiation intensity. 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. No transfer function was used in the neurons in the input layer, while neurons with tangent sigmoid (tansig) and linear (purelin) transfer functions were used in the hidden layer(s) and output layer, respectively.

2.4. Training and testing of the model

Prior to the training process, both input and target data sets were normalised to range between −1 and +1. Scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM) learning algorithms were used for the training of 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 consists of half (11,700) of the dataset, was used for computing the gradient and updating the network weights and biases, while one-quarter (5850) of the dataset was used as validation and test dataset, respectively. The maximum number of 100 iterations and minimum gradient of 10^{-10} were used in the training process. Each network was tested 30 times using different randomly selected weights and biases. The performance of the different networks with different configurations and training algorithms are evaluated based on the correlation coefficient (*R*-value) between the predicted and the actual values in order to determine the network with optimum prediction capacity.

3. Results and discussion

3.1. Network optimization

Table 2 shows the results of the optimization of the networks. The network with single hidden layer having five neurons trained with the LM algorithm gave the best performance. The correlation coefficient (*R*-value) between the predicted and the actual values of monthly mean global solar radiation are shown in Fig. 3 for training, testing and the whole datasets. *R-values* of 0.978, 0.971, and 0.956 were obtained for the training, testing and the whole dataset, respectively. This shows that the ANN predicted solar radiation values are very close to the actual values for all the datasets.

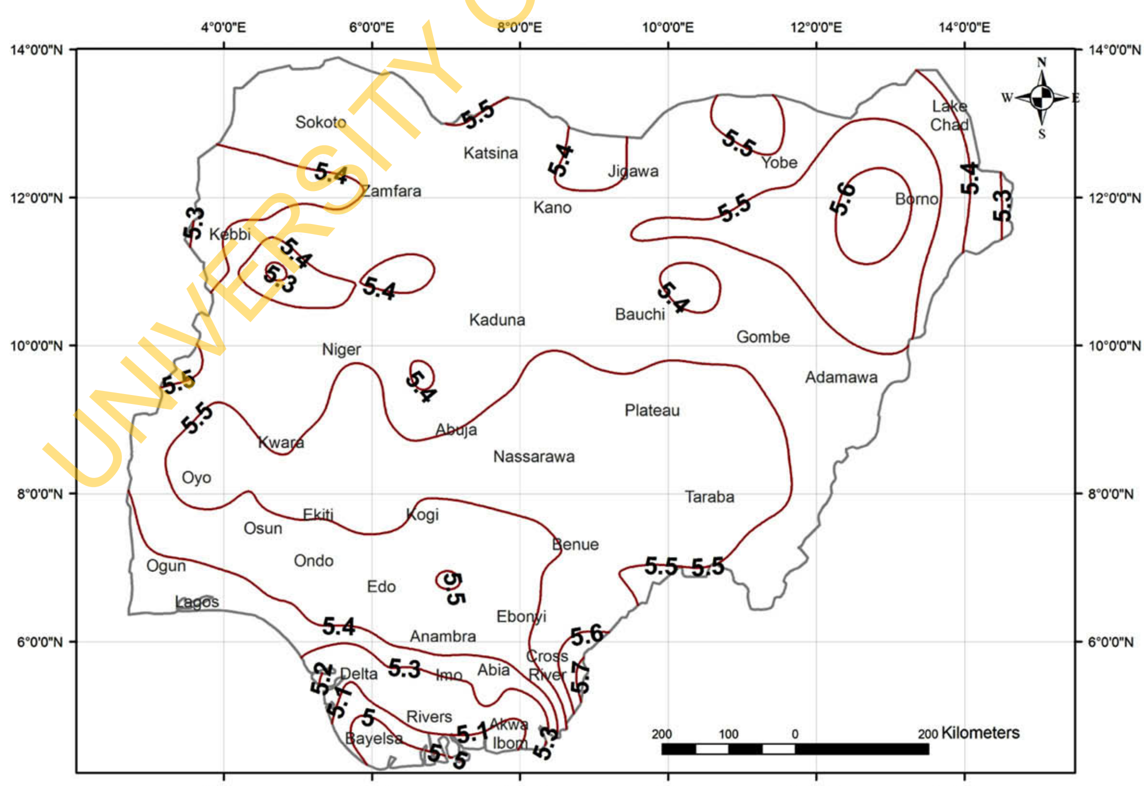

Fig. 15. Predicted solar energy potential (kW h/m^2 day) for the month of December in Nigeria.

Table 4
Maximum, minimum, average, and standard deviation of monthly mean solar radiation potential in Nigeria.

Month	Solar radiation potential (kW h/m^2 day)			
	Max	Min	Mean	Std
January	6.07	5.43	5.77	0.15
February	6.01	5.18	5.75	0.15
March	6.80	4.90	5.98	0.53
April	6.92	4.71	5.91	0.72
May	6.95	4.47	5.71	0.80
June	7.01	4.03	5.29	0.87
July	6.47	3.69	4.78	0.79
August	6.25	3.54	4.52	0.73
September	6.39	3.68	4.78	0.75
October	6.43	4.16	5.24	0.58
November	5.99	4.47	5.41	0.29
December	5.62	4.93	5.41	0.13

3.2. Prediction of solar radiation potential in Nigeria

After the network has been trained with sufficient accuracy, the model was used to predict the monthly mean daily solar energy potential for locations in Nigeria where there are no records of solar radiation particularly for 24 meteorological ground stations (Table 3). The essence of this study was to investigate the feasibility of using ANN to model the non-linear relationship between solar radiation and other meteorological parameters. The ground station and the satellite data were used as input for the model and the predicted solar radiation values were plotted as monthly solar maps for Nigeria. The results of the ANN predicted monthly mean solar radiation potential for the months of January–December are presented in form of monthly maps (see Figs. 4–15) using the geographical information system (GIS) software ArcVeiw 3.2. As shown in the maps (Figs. 4–15), the monthly mean daily solar radiation potential varied widely on monthly basis and increasingly from the coastal region in the south to savannah region in the north. Table 4 shows the maximum values obtained in the northern region, minimum values obtained in the southern region, average monthly values, and standard deviation of monthly mean daily solar radiation potential in Nigeria. The monthly mean daily solar radiation potential in northern region ranged from 7.01 to 5.62 kW h/m^2 day, while in the southern region the monthly mean solar radiation potential ranged between 5.43 and 3.54 kW/m^2 day. The maximum daily solar radiation occurred in the month of June in the northern region, while the minimum value occurred in the month of August (from Table 4).

3.3. Graphical user interface

Based on the developed ANN model, a graphical user interface (GUI) was designed for easy application of the model. The GUI (Fig. 16) was designed using the GUI toolbox for MATLAB. On input of the geographical and meteorological parameters of the location (latitude, longitude, altitude, mean sunshine duration, mean temperature, relative humidity, and month of the year), the monthly mean daily solar radiation potential for the given month is predicted for the location by clicking the 'predict solar radiation' button. The monthly mean solar radiation potentials for the location from January to December are predicted and plotted by using the 'plot monthly radiation' button. In this way, the user can very easily obtain a monthly mean solar radiation chart for the location. The GUI also allows easy comparison of radiation charts for two or more locations by plotting them together using the 'Hold on'

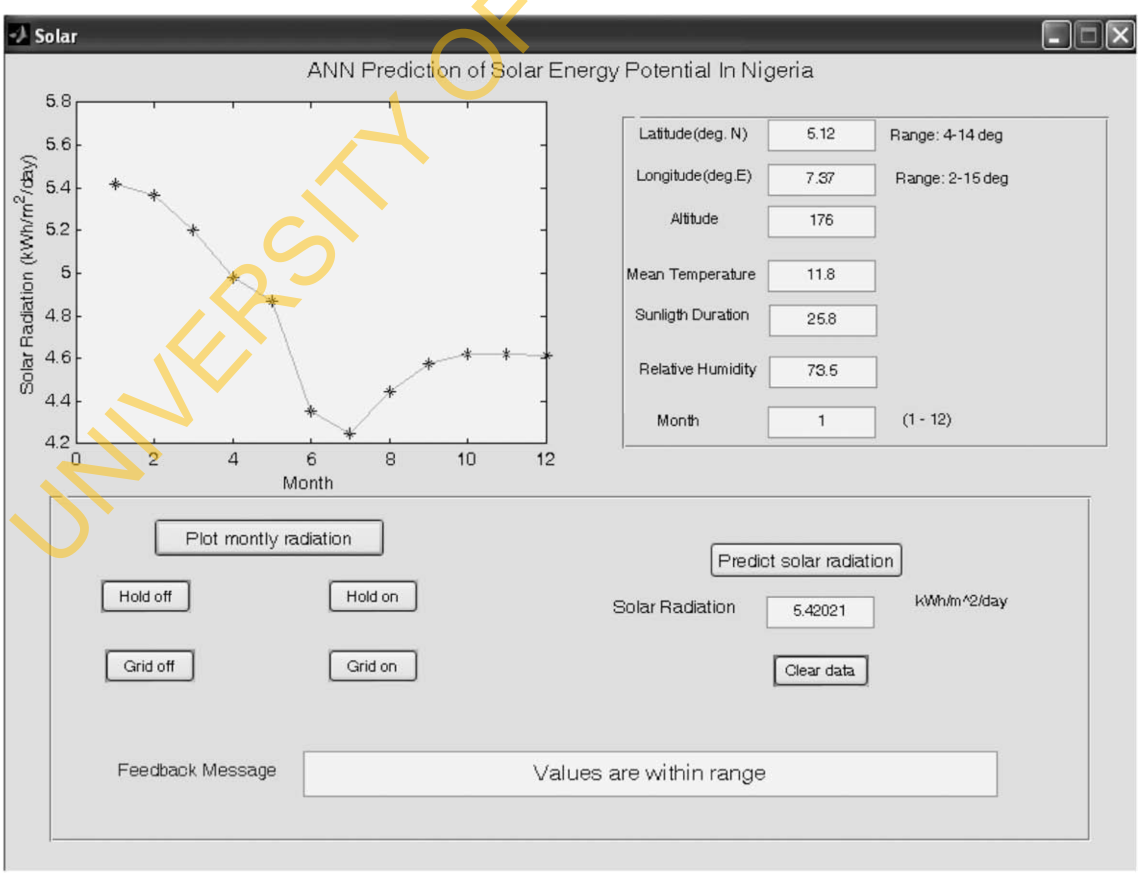

Fig. 16. Graphical user interface for prediction of solar energy potential in Nigeria.

button. It should be noted here that the program will work with appropriate accuracy within the range of the geographical and meteorological dataset used in this study. A warning message is displaced as feedback when data set inputted is out of range. Since the dataset used in this model were strictly for Nigeria with latitude ranging between 4°N and 14°N and longitude 2°E and 16°E, the acceptable range for the GUI was fixed within this range. The GUI (Fig. 16) shows a typical simulation for the city of Aba with geographical location as shown in Table 1.

4. Conclusions

The results of this study indicate that the ANN based model for solar radiation is accurate for prediction of solar radiation in Nigeria. The ANN model is promising and can be used to predict solar radiation for any region provided that comprehensive meteorological and geographical parameters such as: latitude, longitude, altitude, month of the year, mean sunshine duration, mean temperature, and relative humidity are available. The results indicate that the ANN model seems promising for evaluating the solar resource potential in places where there are no monitoring stations in Nigeria.

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