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Global Solar Radiation Prediction for Makurdi, Nigeria Using Feed Forward Backward Propagation Neural Network

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ABSTRACT

The optimum design of solar energy systems strongly depends on the accuracy of solar radiation data. However, the availability of accurate solar radiation data is undermined by the high cost of measuring equipment or non-functional ones. This study developed a feed-forward backpropagation artificial neural network model for prediction of global solar radiation in Makurdi, Nigeria (7.7322° N long. 8.5391° E) using MATLAB 2010a Neural Network toolbox. The training and testing data were obtained from the Nigeria metrological station (NIMET), Makurdi. Five meteorological input parameters including maximum and temperature, mean relative humidity, wind speed, and sunshine hour were used, while global solar radiation was used as the output of the network. During training, the root mean square error, correlation coefficient and mean absolute percentage error (%) were 0.80442, 0.9797, and 3.9588, respectively; for testing, a root mean square value, correlation coefficient, and mean absolute percentage error (%) were 0.98831, 0.9784, and 5.561, respectively. These parameters suggest high reliability of the model for the prediction of solar radiation in locations where solar radiation data are not available.

1. INTRODUCTION

There is an ever-increasing interest in renewable energy; one of such interests is solar energy, because of its sustainability. One of the importance of renewable energy technologies is its growing role in the energy production field, which has found application in meeting the energy demands of residential and industrial uses [1]. The estimation or prediction of solar radiation has gained tremendous importance in the design, operation, and management of solar energy systems, because it helps determine its feasibility. Makurdi has great potential for solar energy utilization due to its high solar radiation for the most part of the year. Solar radiation data are not unavailable in most locations due to the high cost of measuring equipment or lack of maintenance of the existing ones leading to low accuracy of results. Empirical methods for the prediction of solar radiation are no longer attractive due to their limitation in scope, the complexity of energy systems, and non-linearity of available data for these calculations. Artificial intelligence and software packages, such as Design-builder, Energy plus, etc., are used. Historical and meteorological data are used for predicting solar radiation [2], [3], [4], [5]. Neto and Fiorelli [6] compared a detailed model simulation with the artificial neural network, which was used for forecasting energy consumption of a building. In their study, they used energy-plus software and compared the results with a simpler model based on artificial neural network (ANN), and concluded that both are suitable for auditing and predicting the energy consumption of a building.

Neelamegama and Amirtham [7] studied the “prediction of solar radiation for solar systems using ANN models with different back propagation algorithms”. Two ANN structures with four different algorithms considered 10 year weather data collected from a meteorological center in Makurdi, Nigeria were used. For training and testing of the network, five different locations were used. The model was validated for accuracy by the use of statistical parameters such as mean absolute error (MAE), root mean square error (RMSE), and maximum linear correlation coefficient (R^2). They confirmed that the ability of the ANN models to accurately forecast solar radiation was a function of the total set of parameters used for training the network for the intended application. Egeonu et al. [8] carried out a “comparative assessment of temperature- based ANN and angstrom type models for predicting global solar radiation”. The network inputs were based on location and weather data while the monthly global solar radiation served as the model target. The Angstrom equation relates global solar radiation to minimum and maximum ambient temperatures. The accuracy of the ANN and Angstrom models was assessed with statistical performance parameters. It was seen that the coefficient of determination (R2) was more than 99 % for all the chosen areas, while R2 for the empirical method was 89 %. They concluded that the temperature based ANN model provided a more reliable outcome than the empirical method did. Li et al. [9] suggested a cross between genetic algorithm and adaptive network-based

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fuzzy inference system, which makes use of the fuzzy "if-then" rules into the neural network-like structure for determining solar radiation. The computed outcomes showed better prediction accuracy than the ordinary ANN model did. Karatasou et al. [10] studied how neural networks used and applied to building energy consumption prediction could be improved, guided by statistical procedures. They collected potential relevant inputs and did away with the irrelevant inputs and useless hidden units through a subtractive phase. Yadav and Chandel [11] carried out a review of different artificial neural network models used for the prediction of energy consumption of the building. Edalati et. al. [12] estimated the monthly mean daily global solar radiation on horizontal surfaces using artificial neural networks models in the south east of Iran. Results showed that the correlation coefficients between the predictions and actual global solar radiation intensities for training and testing datasets were higher than 97 %, suggesting high reliability of the model. Yohana et al. [13] developed an empirical model for determining the monthly average daily global solar radiation on a horizontal surface for Makurdi, Nigeria, using the Angstrome-Page equation. The developed model had a correlation coefficient of 0.78. Jovanovic et al. [14] analyzed an ensemble of three neural networks: feed forward backpropagation neural network (FFNN), radial basis function network (RBFN), and adaptive neuro-fuzzy interference system (ANFIS) in order to improve prediction accuracy. During the analysis, the predicted target values of the feed forward backpropagation showed the best agreement with the measured target values.

Based on the available literature, only Itodo et al. [15] developed an empirical model for predicting the monthly average daily global radiation for Makurdi location using the Angstrom equation. Angström models ignore some important factors such as elevation, relative humidity, and temperature. This study intends to develop an artificial neural network model for predicting the monthly average daily global radiation for Makurdi location using feed-forward backpropagation neural network.

2. ARTIFICIAL NEURAL NETWORKS

Artificial neural network (ANN) is one of the artificial intelligence branches, and it is a reliable tool for solving numerous problems of nonlinear function, data classification, pattern recognition, optimization, clustering, and simulation. ANN models operate in two steps: the models are first trained, then they are applied to the problem, in this case, prediction of ground solar radiation. During network training, weights are altered in order to reduce the error function by reducing the difference between the predicted output and target output of the network model. The networks learn by running a full set of training data through the network model, each run is called an epoch and trained using a set of learning rules. There are four ways to train a network: supervised, unsupervised, reinforcement, and evolutionary learning. The weights and biases are altered by merging training pattern set and the respective errors between the target output and the predicted network response [16]. The model deviation in comparison with the actual (measured) solar ground radiation in Makurdi, Nigeria is based on some statistical indicators: mean absolute percentage error (MAPE), root mean squared error (RMSE), mean absolute error (MAE), and goodness of fit (R^2). They are given by the following relationships [14]:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{[y'_i - y_i]}{y_i} \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[y_i - y'_i]^2} \tag{2}$$

$$\mathrm{MAE} = \sum_{i=1}^{n}\frac{1}{n}[y_i - y'_i] \tag{3}$$

$$R^2 = \frac{\sum_{i=1}^{n}(y'_i - y")^2}{\sum_{i=1}^{n}(y_i - y")^2} \tag{4}$$

where n is the cardinality of dataset involved in the analysis, y_i is the variable to estimate, y" is the mean value of y_i, and y' is the value calculated by the model. MAPE is a measure of prediction accuracy of a forecasting method in statistics and RMSE is used to measure the differences between values (sample or population values) predicted by a model or an estimator and the values observed. MAE measures the difference between two continuous variables, the predicted values and measured values, while R^2 calculates the ratio between the variation evaluated by a regression model and the sample data variation; R^2 is an important parameter since it evaluates the general accuracy of a regression model [15, 16].

2.1. Feedforward backward-propagation neural network (FFNN)

This is an ANN architecture that caters for learning of non-linear functions, and Figure 1 shows the diagrammatic representation of its architecture. The FFNN networks are typically trained with the Back Propagation (BP) algorithm, which is a supervised learning method that maps the process inputs to the desired outputs by minimizing the errors between the desired outputs and the calculated outputs [17]. The feedforward backward propagation neural network architecture is made up of three layers of neurons: input, hidden, and output. Each layer is made up of neurons and each neuron is fully coupled with adjustable weighted links to neurons in the subsequent layer. The pattern of activation arriving at the output layer is then compared with the correct output pattern to calculate an error function. In the hidden layer of neurons, the non-linear activation function enables the neural network to be a universal approximator. A network is trained by altering the weights, so that the network can produce the target output using the training data set as inputs. To minimize the error function, different training algorithms could be applied. The typical training algorithms are the backpropagation algorithm and the algorithms derived from it. The error function is minimized by the gradient descent technique, and the error function is the mean square of the difference between the desired and the actual network outputs.

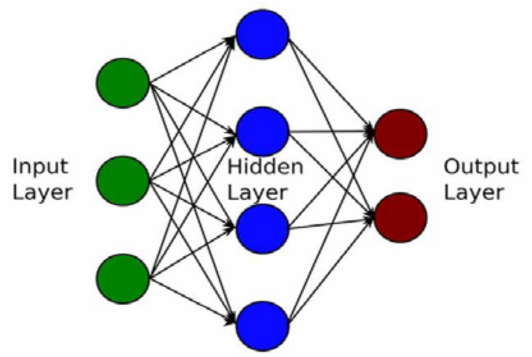

Figure 1. FFNN Architecture.

3. MATERIALS AND METHODS

Makurdi, Nigeria is located on latitude 7.7322° N and longitude of. 8.5391° E and is 111m above sea level (Fig. 2). The Neural Network Toolbox in MATLAB™ software provides a framework for designing, implementing, visualizing, and simulating proposed neural network.

3.1. Data collection

The input and output data were acquired from NIMET Makurdi station data base in a period of 15 years (2001-2014). For training the models, the data ranging from 2000-2010 were used and, for testing, the data ranging from 2011-2014 were used. Inputs include monthly averages, daily maximum temperature [Tmax (°C)], daily minimum temperature [Tmin (°C)], daily relative humidity(high/low) RH (%), daily sunshine duration [SH (hr)], and wind speed [WS (m/s)], while the monthly average daily global solar radiation GSR measured in ml (1ml = 1.216MJ/m^2-day) using Gunn Bellani solar integrator was the output. In order to achieve structured access to the dataset, a database was created in Excel to store the acquired meteorological data. After collecting the data, data pre-processing was conducted to train the ANN more efficiently. The procedure is set as follows:

•Solving the problem of missing data: The missing data are replaced by the average of neighboring values during the same year.
•Normalizing data: These are necessary so that the neural network (NN) will not be caught in a local minimum or overestimate the data points.
•Division training and testing data: The data are divided into 70 % for training and 30 % for testing. The data are then converted to row vectors.

3.2. Feedforward backpropagation neural network (FFNN) model

The Feed Forward backpropagation neural network is made up of three layers of neurons: an input layer, at least one intermediate hidden layer, and an output layer. Matlab built-in transfer functions were used: linear (purelin) for the output layer and hyperbolic tangent sigmoid (tansig) for the hidden layers. The appropriate parameters and best configuration that will eventually guarantee optimal performance for the FFNN are as follows:

- Determination of appropriate backpropagation training algorithm.
- Determination of optimal number of epochs.
- Determination of the type of transfer functions to use both in the hidden and output layers.
- Determination of the number of hidden layers.
- Determination of the number of hidden layers' neurons.

Figure 2. Location of Makurd in Benue State, Nigeria.

The earlier results then established the architecture of the ANN, as shown in Table 1.

Table 1. Summary of the configurations of the ANN classification platform for the prediction system.

S/N	Parameters	Results
1	Backpropagation training algorithm	Scaled conjugate gradient
2	Maximum number of epochs	1000
3	Hidden layer transfer function	Tansig
4	Output layer transfer function	Linear
5	Number of hidden layers	3
6	Number of hidden layers' neurons	14

The appropriate number of neurons in the hidden layer is selected based on the results obtained for mean square error (MSE) and linear correlation coefficient (R). The optimum number of neurons in the hidden layer was chosen as the number of hidden neurons with the combined value of minimum RMSE and maximum R2.

After obtaining the optimal parameters for training and testing the FFNN, the FFNN model was first trained by importing both input and target data sets saved in an Excel.

Subsequently, the selected input parameters and output parameter were trained and tested.

For training the model, measured samples for eleven years (2000-2010) were used for training the ANN model (a total of 132 samples points), and measured samples for the four years of 2010-2014 were used for testing (48 sample points). To ensure that no special factor is dominant over the others, both input and output data sets were normalized to between -1 and+1 by a linear scaling function.

4. RESULTS AND DISCUSSION

The accuracy of the trained ANN model is determined by the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute percentage error (MAPE). Table 2 presents the ANN performance in terms of R^2, RMSE, and MAPE; under the column "network structure", the figure on the left represents the number of neurons in the input layer; the figure on the right indicates the number of neurons in the output layer, and the figure in the middle indicates the number of neuron in the hidden layers.

Table 2 indicates that all studied network structures can forecast ground solar radiation within acceptable error margins. The statistical error parameter for training and testing the model is presented in Table 3. For training the model, R^2 = 0.9797, RMSE =0. 80442, and MAPE (%) = 3.9588, while that of the testing model is: R^2 = 0.9784, RMSE = 0.9883, and MAPE (%) = 5.5561. These results are in agreement with those of Neelamegam and Amirtham [7]; they found out that the best results for training and testing of the Levenberg–Marquardt (LM) algorithm were obtained in terms of minimum MAPE values of 0.8278, 3.4979 and minimum RMSE values of 1.08819, 4.5497, respectively.

Table 2. Error Indicators of developed FFNN model of different network structures.

Model	Network Structure	R^2	RMSE	MAE
1	5-10-1	0.92	0.349	-0.00571
2	5-13-1	0.91	0.370	-0.00754
3	5-7-1	0.84	0.495	-0.01611
4	5-5-5-5-1	0.92	0.356	-0.02271
5	5-5-5-4-1	0.95	0.351	-0.07429
6	5-14-1	0.83	0.518	-0.05402
7	5-8-1	0.91	0.384	0.00376
8	5-15-1	0.89	0.485	0.06900
9	5-11-1	0.91	0.519	-0.03544
10	5-8-1	0.91	9.576	-0.02722
11	5-6-1	0.84	0.735	-0.00193

Table 3. Statistical error parameters for model testing and training.

	R^2	RMSE	MAPE
Training	0.9797	0.8044	3.9588
Testing	0.9784	0.9883	5.5561

Figure 3 shows the statistical regression coefficient R^2 for the measured and predicted values for the test period covering the years 2011-2014 is 0.974.

Figure 4 presents the plot of measured and predicted values. Results shows that, at different data points, the network shows good accuracy; for example, in the 5th month, the measured solar radiation is 17MJ/m^2/day, while the predicted value is 16.17158MJ/m^2/day.

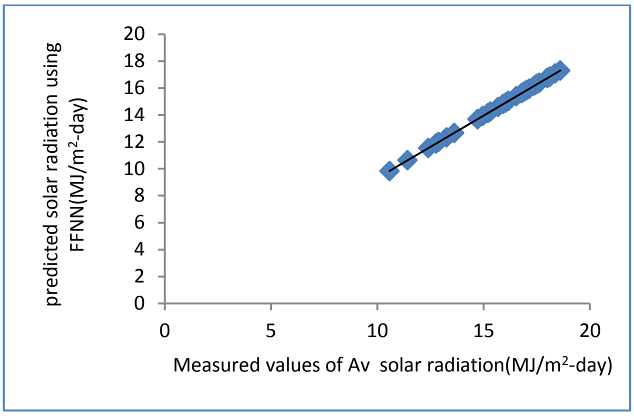

Figure 3. Comparison of the measured and predicted values using FFNN.

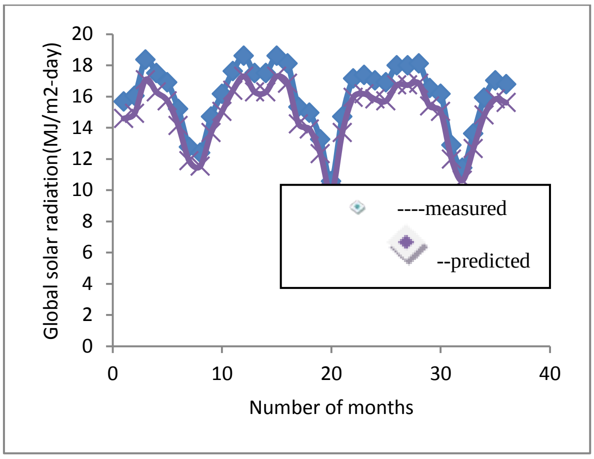

Figure 4: Graph of Measured and predicted results using FFNN.

From the analysis of the results, the predicted values are in good agreement with measured values in Levenberg Marquardt (LM) algorithm. The results further confirm the ability of feedforward backpropagation neural network model to accurately forecast global solar radiation.

5. CONCLUSIONS

The artificial neural network FFNN model was used for predicting solar radiation for Makurdi, Nigeria. Investigation shows that predictions by ANN feed forward backpropagation neural network model were in very good agreement with the measured results using available historical weather data. The application of this method for ground solar radiation prediction in locations, where solar measurement devices are down or non-existent, can save time and resources in selecting the best locations for investing in solar energy exploitation. The present study has been successful in estimating the global solar radiation rate. Results show that the FFNN model is a reliable tool for evaluating the solar potential in places where there are no monitoring stations.

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REFERENCES

1. Sueyoshi, T. and Goto, M., "Photovoltaic power stations in Germany and the United States: A comparative study by data envelopment analysis", ***Energy Economics***, Vol. 42, (2014), 271-288. (DOI: 10.1016/j.eneco.2014.01.004).
2. Zhao, H.-X. and Magoulès, F., "A review on the prediction of building energy consumption", ***Renewable and Sustainable Energy Reviews***, Vol. 16, No. 6, (2012), 3586-3592. (DOI :10.1016/j.rser.2012.02.049).
3. Islam, S.M., Kabir, M.M. and Kabir, N., "Artificial neural networks based prediction of insolation on horizontal surfaces for Bangladesh", ***CIMTA: Procedia Technology***, Vol. 10, (2013),482-4914. (DOI:10.1016/j.protcy.2013.12.386).
4. Kalogirou, S. and Sencan, A., Artificial intelligence techniques in solar energy applications, solar collectors and panels, theory and applications, Dr. Reccab Manyala Ed., ISBN: 978-953-307-142-8, InTech, (2010). (DOI: 10.5772/10343).
5. Tymvios, F.S., Jacovides, C.P., Michaelides, S.C. and Scouteli, C., "Comparative study of Angström's and artificial neural networks' methodologies in estimating global solar radiation", ***Solar Energy***, Vol. 78, (2005), 752–762. (DOI: 10.1016/j.solener.2004.09.007).
6. Hernandez Neto, A. and Sanzovo Fiorelli, F.A., "Comparison between detailed model simulation and artificial neural network for forcasting building energy comsuption", ***Energy and Buildings***, Vol. 40, (2008), 2169-2176. (DOI:10.1016 /j.enbuild.2008.06.013).
7. Neelamegama, P. and Amirtham, V.A., "Prediction of solar radiation for solar systems by using ANN models with different back propagation algorithms", ***Journal of Applied Research and Technology***, Vol. 14 ,(2016), 206–214. (DOI:10.1016/ j.jart.2016.05.001).
8. Egeonu, D.I., Njoku, H.O., Okolo, P.N. and Enibe, S.O., "Comparative assessment of temperature based ANN and angstrom type models for predicting global solar radiation", ***Proceedings of Afro-European Conf. for Ind. Advancement, Advances in Intelligent Systems and Computing***, (2015), 334. (DOI: 10.1007/978-3-319-13572-4_9. DOI:10.1007/978-3-319-13572-4_9).
9. Li, K., Su, H. and Chu, J., "Forecasting building energy consumption using neural network and hybrid neuro-fuzzy system: A comperative study", ***Energy and Buildings***, Vol. 43, No. 10, (2011), 2893-2899. (DOI:10.1016/j.enbuild. 2011.07.010).
10. Karatasou, S., Santamouris, M. and Geros, V., "Modeling and predicting building's energy use with artificial neural networks: Methods and results", ***Energy and Buildings***, Vol. 38, No. 8, (2006), 949–958. (DOI: 10.1016/j.enbuild.2005.11.005).
11. Kumar, A.Y. and Chandel, S.S., "Solar radiation prediction using artificial neural network tecniques: A review", ***Renewable and Sustainable Energy Review***, Vol. 33, (2014), 772-781. (DOI;10.1016/j.rser.2013.08.055).
12. Edalati, S., Ameri, M. and Iranmanesh, M., "Estimating and modeling monthly mean daily global solar radiation on horizontal surfaces using artificial neural networks in south east of Iran", ***Journal of Renewable Energy and Environment (JREE)***, Vol. 2, No. 1, (Winter 2015), 36-42.
13. Jovanovic, R.Z., Sretenovic, A.A. and Zivkovic, B.D., "Ensemble of various neural networks for prediction of heating energy consumption", ***Energy and Buildings***, Vol. 94, (2015) 189-199. (DOI:10.1016/j.enbuild.2015.02.052).
14. Yohanna, J.K., Itodo, I.N. and Umogbai, V.I., "A model for determining the global solar radiation for Makurdi, Nigeria", ***Renewable Energy***, Vol. 36, (2011), 1989-1992.
15. Yadav, A.K. and Hasmat, M., "Comparison of different artificial neural network techniques in prediction of solar radiation for power generation using different combinations of meterological variables", ***Proceedings of IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES)***, (2014). (DOI: 10.1109/PEDES.2014.7042063).
16. Renno, C., Petito, F. and Gatto, A., "Artificial neural network models for predicting the solar radiation", ***Energy Conversion and Management***, Vol. 106, (2015), 999-1012. (DOI:10.1016/ j.enconman.2015.10.033).
17. Huang, Y., "Advances in artificial neural networks: Methodological development and application", ***Algorithms***, Vol. 2, (2009), 973-1007. (DOI:10.3390/algor2030973).