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Research Article

Application of Artificial Neural Networks to Predict Daily Solar Radiation in Sokoto

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Abstract

This paper presents an application of Artificial Neural Networks (ANNs) to predict daily solar radiation in Sokoto (lat. 13° 03'N, log. 5° 14'E). The mean daily data for sunshine hours, air temperature, and relative humidity data, along with day number and month number for period of 3years were selected as the input variables to the ANN models. The ANN models and regression models based on Hargreaves-Samani and Angstrom Prescott approaches were tested for the study area. The ANN model indicated a reasonably strong predictive power, where mean bias error (MBE), root mean square error (RMSE), mean percentage error (MPE), and R^2 values were found to be 0.063, 0.164, -2.489%, and 0.965 respectively for the training, and 0.103, 0.288, -4.177% and 0.959 respectively for the testing. These results showed that artificial neural network could give reasonably good estimation of global solar radiation in the study area and other locations with similar climatic factors.

Keywords: *ANN, Solar Radiations*

Introduction

Global solar irradiation data provide information on how much of the sun's energy strikes a surface at a location on earth during particular time period. The amount of solar irradiation potential in the particular location is important for solar energy system design, such as stand-alone PV and hybrid system. The global solar radiation data is considered the most important parameter for the sizing of PV system. Nevertheless, in most locations this parameter is non-existent or even where available, their quality is very poor (Gansler et al., 1994).

In order to solve this problem, many researchers have demonstrated that it is possible to replace real series of solar radiation by synthetic ones. There are two main approaches which can be used for this purpose. One may be called the classical approach that is based on traditional methods, which apply statistical properties of solar radiation series. The other one, called the neural network approach, is based on the use of artificial neural networks. The most widely used and the simplest equation relating radiation to sunshine duration is the Angström-Prescott relationship (Angström 1924; Prescott 1940). Medugu and Yakubu (2011) applied Angstrom model to estimate the global solar radiation based on the available climatic parameters of sunshine hour at Yola, Nigeria. From the results obtained, the value of the radiation varies from the range of 13.75 $MJm^{-2}day^{-1}$ to 25.16 $MJm^{-2}day^{-1}$ with the mean value of 21.54±0.46 $MJm^{-2}day^{-1}$.

Hargreaves and Samani (1982) correlated solar radiation (Rs) with temperature and extraterrestrial radiation. Okundamiya and Nzeako (2010) proposed a temperature-based model of monthly mean daily global solar radiation on horizontal surfaces for selected cities, representing the six geopolitical zones in Nigeria. The modelling was based on linear regression theory and was computed using monthly mean daily data set for minimum and maximum ambient temperatures. The results of three statistical indicators: Mean Bias Error (MBE), Root Mean Square Error (RMSE) and t-statistic (TS); performed on the model along with practical comparison of the estimated and observed data validated the excellent performance accuracy of the proposed model.

Artificial neural network (ANN) modeling technique offers a better solution for developing a more generalized model for prediction of solar radiation data using climatological parameters. ANN is a modeling and prediction tool, widely accepted as a technique offering an alternative way to tackle complex and ill-defined problems (Kalogirou, 2001). This novel modeling approach has been conducted to predict the solar radiation in different parts of the world.

AbdulAzeez (2011) developed artificial neural networks (ANN) for estimation of global solar radiation on a horizontal surface for Gusau, Nigeria. He obtained a correlation coefficient of 0.9996 with a maximum

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percentage error of 0.8512 and root mean square error of 0.0029. The comparison between the ANN and some existing empirical models was carried out. He discovered that the proposed ANN prediction model performed better than the empirical models.

The Fadare et al. (2010) investigated the feasibility of an artificial neural network (ANN) based model for the prediction of solar energy potential in Africa. They designed Standard multilayered, feed-forward, backpropagation neural networks with different architecture using NeuroSolutions. Geographical and meteorological data of 172 locations in Africa for the period of 22 years (1983-2005) were obtained from NASA geo-satellite database. The input data (geographical and meteorological parameters) to the network includes: latitude, longitude, altitude, month, mean sunshine duration, mean temperature, and relative humidity while the solar radiation intensity was used as the output of the network. The results showed that after sufficient training sessions, the predicted and the actual values of solar energy potential had Mean Square Errors (MSE) that ranged between 0.002 - 0.004, thus suggesting a high reliability of the model for evaluation of solar radiation in locations where solar radiation data are not available in Africa. The solar radiation potential (actual and ANN predicted) in northern Africa (region above the equator) and the southern Africa (region below the equator) for the period of April – September ranged respectively from 5.0 - 7.5 and 3.5 - 5.5 kW h/m2/day while for the period of October – March ranged respectively from 2.5 – 5.5 and 5.5 - 7.5 kW h/m2/day. This study has shown that ANN based model can accurately predict solar radiation potential in Africa.

Behrang et al. (2010) applied multi-layer perceptron (MLP) and radial basis function (RBF) neural networks for daily GSR modeling based on six proposed combinations. The measured data between 2002 and 2005 were used to train the neural networks while the data for 214 days from 2006 were used as testing data. The comparison of obtained results from ANNs and different conventional GSR prediction (CGSRP) models showed very good improvements (i.e. the predicted values of best ANN model (MLP-V) has a mean absolute percentage error (MAPE) about 5.21% versus 10.02% for best CGSRP model (CGSRP 5)).

The aim of this study is to develop suitable models for global solar radiation in Sokoto, Nigeria.

Methodology

Data of global solar radiation, sunshine duration, air temperature and relative humidity for the study areas for a period of the years 2004 - 2007 were obtained from the Nigerian Meteorological Agency (NIMET). The data was used to develop global solar radiation models using the regression techniques and artificial neural networks.

The two – parameter Angstrom – Prescott linear regression equation (Angstrom, 1924 and Prescott, 1940) was employed to correlate the daily clearness index, K_t ($= \frac{H}{H_o}$) and the ratio of measured sunshine hours to the daily maximum possible sunshine duration, with the equation defined as follows:

$$\frac{H}{H_o} = a + b\frac{S}{S_o} \quad (1)$$

S = measured daily sunshine duration (hour)
S_o = daily maximum possible sunshine duration, day-length (hour)
Mathematically, S_o is defined as follows:

$$S_o = \frac{2}{15}\cos^{-1}(-\tan\emptyset\tan\delta) \quad (2)$$

where $\emptyset$ = latitude
δ is the solar declination angle which is given as

$$\delta = 23.45\sin\left(360\,\frac{248+J}{365}\right) \quad (3)$$

Extraterrestrial radiation (H_o) which is the maximum amount of solar radiation available to the earth at the top of the atmosphere was calculated by the following equations (Duffie et al., 1994).

$$H_o = \frac{24\times3.6\times10^{-3}\times I_{SC}}{\pi}\left(1 + 0.033\cos\left(360\,\frac{J}{365}\right)\right)\cos\emptyset\cos\delta\sin\omega + \omega\sin\emptyset\sin\delta \quad (4)$$

where I_{sc} is the solar constant (1367Wm^{-2}), J is the Julian day number, Ø is the latitude of the location, ω is the sunset hour angle given as

$$\omega = \cos^{-1}(-\tan\emptyset\tan\delta) \quad (5)$$

Hargreaves and Samani were the first to suggest that global radiation could be evaluated from the difference between daily maximum and daily minimum temperature. The equation form introduced by Hargreaves and Samani (1982) is

$$H = H_o k_t (T_{max} - T_{min})^{0.5} \quad (6)$$

Initially, k_t was set to 0.17 for arid and semiarid regions. Hargreaves (1994) later recommended using k_t = 0.16 for interior regions and k_t = 0.17 for coastal regions.

Development of the ANNs for solar radiation models

The neural network employed was a multi-layer feedforward perceptron (MLP) which was one of the most commonly used neural networks that learn from examples (Rumelhart et al., 1986). In the ANN architecture adopted, there were 3 layers – the input, hidden and output layers. Each layer was fully interconnected together by the connection strengths called weights. The activation function adopted for the neural network was the well-known logistic sigmoid function. As a first approach, in order to evaluate the quality of a generated series, the dataset were grouped into training dataset, validation

dataset and testing dataset. The training dataset is used to adjust the neural network so that a best fitting of the nonlinear function representing the phenomenon under investigation, is reached. The validation dataset is used to evaluate the generalization of the neural network (Elminir et al., 2005).

In order to consider the effect of each input variable on GSR prediction, four following combinations of input variables (MLP-1, MLP-2, MLP-3 and MLP-3) were developed for Sokoto

- Day-number, month-number and daily mean air temperature as inputs and daily GSR as output
- Day-number, month-number and daily relative humidity as inputs and daily GSR as output
- Day-number, month-number, daily mean air temperature and daily relative humidity as inputs and daily GSR as output.
- Day-number, month-number, daily sunshine duration and daily GSR as output

Model testing and assessment

The testing process involved generating estimated values of global solar irradiation from the proposed model. The estimated values were compared with actual values through error analysis. Three comparison tests, namely Mean Bias Error (MBE), Root Mean Square Error (RMSE) and Mean Percentage Error (MPE) were used in evaluating performance of the models. These error terms are calculated using the following equations

$$MBE = \frac{\sum_{i=1}^{n}(y_i - x_i)}{n} \quad (7)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - x_i)^2}{n}} \quad (8)$$

$$MPE = \frac{\sum_{i=1}^{n}\left(\frac{x_i - y_i}{x_i} \times 100\right)}{n} \quad (9)$$

where i is an index, y_i is the ith estimated value , x_i is the ith actual value and n is the number of observations.

The MBE test provides information on the long term performance of a given correlation. A positive MBE signifies an overestimation in the calculated value while a negative MBE stands for an underestimation. A low MBE indicates good estimation. The RMSE test provides information on the short term performance of a correlation. It allows term by term comparison of the actual deviation between the calculated and the actual values. The smaller the RMSE value the better the performance of the model (Togrul and Togrul, 2002). MPE gives long term performance of the examined regression equations, a positive MPE values provides the averages amount of overestimation in the calculated values, while the negatives value gives underestimation. A low value of MPE is desirable.

Results and discussion

The daily average clearness index was correlated with daily average relative sunshine duration, transforming Eq. (1) into Eq. (10).

$$\frac{H}{H_o} = 0.237\frac{S}{S_o} + 0.102 \quad (10)$$

Estimates of daily average global solar irradiation were computed using Eq. (10) and then compared with the measured values. Results showed R^2, MBE, RMSE and MPE of 0.109, -0.244, 4.655 and -35.49% respectively. Plot of estimated versus observed values is given in Figure 1. The values of the coefficient of determination showed poor correlation between the measured and the predicted values for Angstrom-Prescott model. This model could not be applied for prediction of daily global solar radiation in the area of the study. The previous models based on Angstrom-Prescott approach (Medugu and Yakubu, 2011; Falayi et al. 2008) could only be used to predict monthly global solar radiation.

The daily average clearness index was correlated was correlated with the square root of difference between maximum and minimum temperature, transforming Eq. (6) into Eq. (11)

$$\frac{H}{H_o} = 0.11\sqrt{T_d} \quad (11)$$

Estimates of daily average global solar irradiation were computed using Eq. (11) and then compared with the measured values. Results showed R^2, MBE, RMSE and MPE equaled 0.146, -0.022, 0.119, and -19.75% respectively. The Figure 2 showed poor correlation between the measured and estimated values of daily global solar radiation based on equation 11. The coefficient of determination using this model showed very poor agreement between the measured and estimated values. This model could not be applied for prediction of daily global solar radiation in the area of the study.

Figures 3 – 6 showed the training stages of the ANN models (MPL-1, MPL-2, MPL-3, and MPL-4). The performances of the models at the training stage are presented in Table 1. MPL-1 has coefficient of determination (R^2) of 0.949, mean bias error (MBE) of 0.092, root mean square error (RMSE) of 0.239, and mean percentage error (MPE) of -3.647%. MPL-2 has R^2 of 0.965, MBE of 0.063, RMSE of 0.164, and MPE of -2.489%. MPL-3 has R^2 of 0.636, MBE of 0.512, RMSE of 1.358, and MPE of -20.596%. MPL-4 has R^2 of 0.766, MBE of 0.138, RMSE of 0.668, and MPE of -6.414%.
From Figures 3 – 6, ANN models (MPL-1 and MPL-2) had good performances at the training stages. There were good agreement between output of the ANN models and the target data. Surely this could be due to the nonlinearity of the relationship of daily global solar radiation with any of the considered variables, and as noted by Verger et al. (2008) artificial neural networks allow good estimates for complex and nonlinear problems. From Table 1, MPL-2

gave the best result for training stage with mean square error (MSE) and R^2 values of 0.027 and 0.965 respectively. The performances of the four ANN models at the testing stages showed good agreements between measurements and predictions value of daily global solar radiation for MPL-1, MPL-2 and MPL-4 models. This shows the potential of the ANN models to predict daily global solar radiation in reasonable accuracy.

Comparison between measured and estimated values of daily global solar radiation for testing data based on the four ANN models have been shown in Figures 7 - 10. The statistical performances of the models at the testing stage are presented in Table 2. MPL-1 has R^2 of 0.950, MBE of 0.167, RMSE of 0.295, and MPE of -7.724%. The values of 0.959, 0.103, 0.288, and -4.177% were found for R^2, MBE, RMSE, and MPE respectively for MPL-2. MPL-3 has R^2 of 0.545, MBE of 0.856, RMSE of 2.117, and MPE of -39.526%. The values of 0.931, 0.248, 0.901, and -11.948% were found for R^2, MBE, RMSE, and MPE respectively for MPL-4. At the testing stage, MPL-2 has superior performance with MBE, RMSE, MPE and R^2 values of 0.103, 0.288, -4.177% and 0.959 respectively. The estimates from equations (10) and (11) were compared with those from the proposed ANN models, and the results showed the superiority of the ANN models. From the results, smaller values of MBE, MPE and RMSE were observed for all the ANN models. This study has confirmed the results obtained by Al-Alawi and Al-Hinai, (1998), and Reddy and Ranjan (2003).

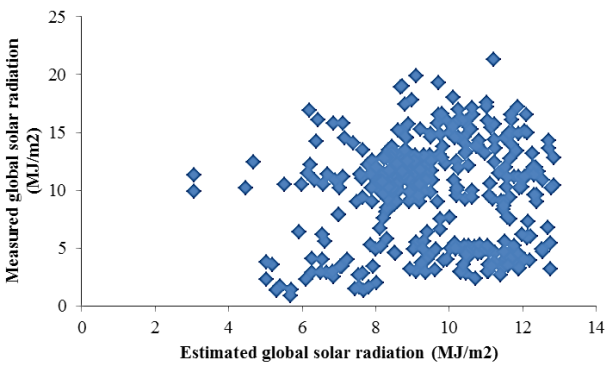

Figure 1: The measured and estimated (by Angstrom-Prescott model) values of daily global solar radiation

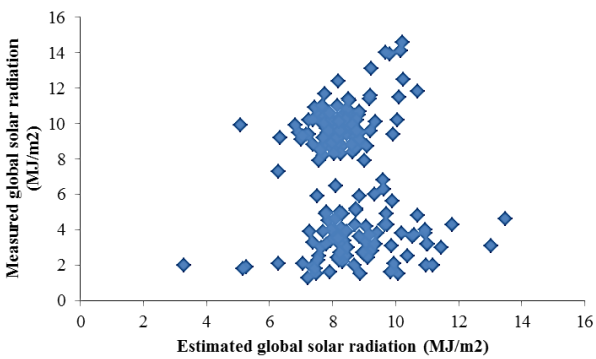

Figure 2: The measured and estimated (by Hargreaves model) values of daily global solar radiation

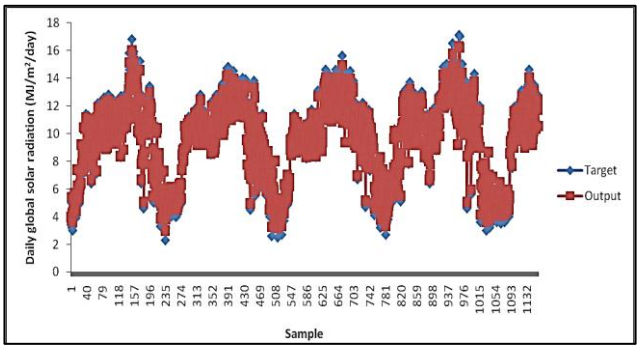

Figure 3: Comparison of target and output values of MPL-1 during training

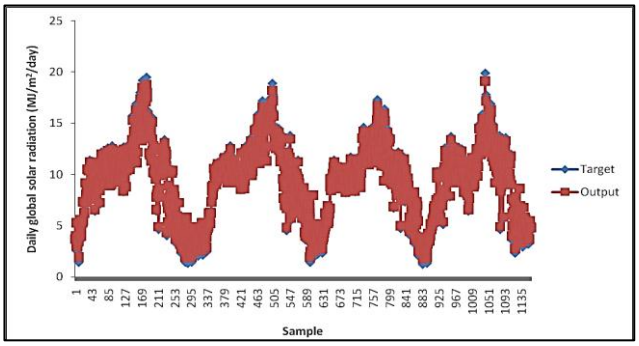

Figure 4: Comparison of target and output values of MPL-2 during training

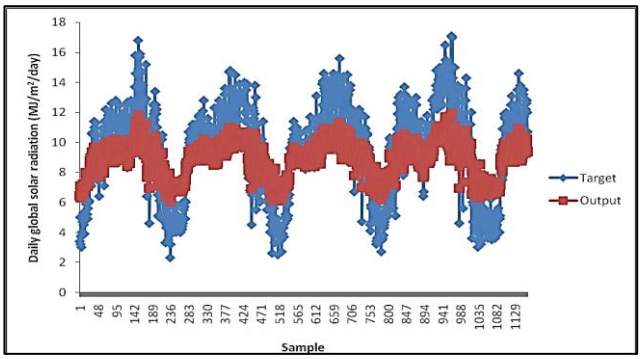

Figure 5: Comparison of target and output values of MPL-3 during training

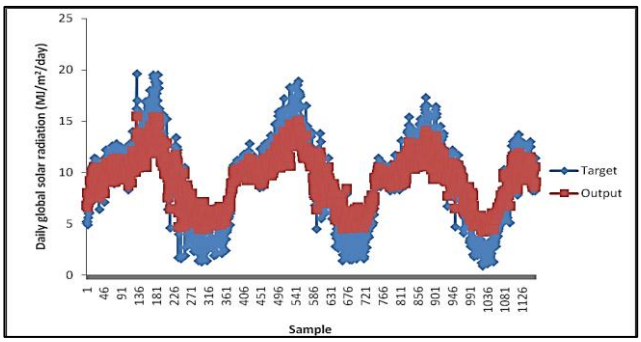

Figure 6: Comparison of target and output values of MPL-4 during training

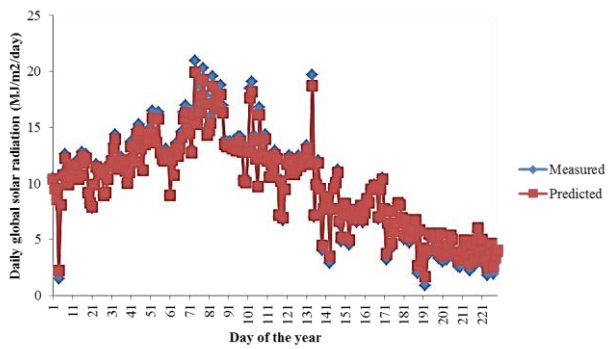

Figure 7: Measured and estimated values comparison based on MPL-1

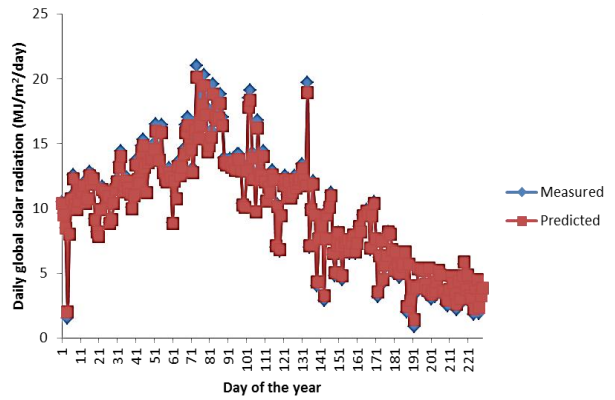

Figure 8: Measured and estimated values comparison based on MPL-2

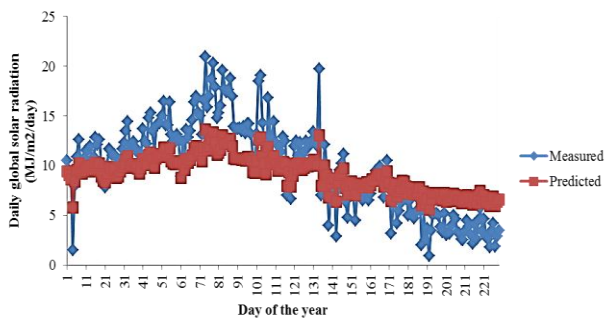

Figure 9: Measured and estimated values comparison based on MPL-3

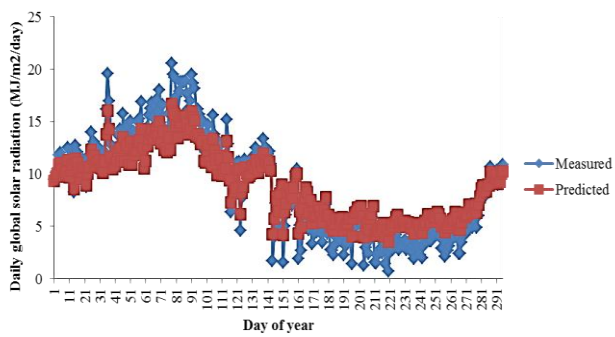

Figure 10: Measured and estimated values comparison based on MPL-4

Table 4.1. MSE and R^2 values of the training results

Combination model	MSE	R^2
MPL-1	0.057	0.949
MPL-2	0.027	0.965
MPL-3	1.844	0.636
MPL-4	0.446	0.766

Table 4.2. MBE, RMSE, MPE and R^2 values of the testing results

Combination model	MBE (Wh/m^2)	RMSE MBE (Wh/m^2)	MPE (%)	R^2
MPL-1	0.167	0.295	-7.724	0.950
MPL-2	0.103	0.288	-4.177	0.959
MPL-3	0.856	2.117	-39.526	0.545
MPL-4	0.248	0.901	-11.948	0.931

Conclusions

The development of daily global solar radiation prediction models was based on two approaches – regression techniques and artificial neural networks. Two-parameter regression techniques and artificial neural networks were employed to estimate the global solar radiation in Sokoto. Two sets of GSR models were developed for the site. Conventional two-parameter Angstrom-Prescott and Hargreaves-Samani linear regression equations were developed for the study area. The coefficient of determination (R^2), mean bias error (MBE), root mean square error (RMSE) and mean percentage error (MPE) were determined and compared. Through this research, it was found that the simple two-parameter regression technique could not give a good estimation of daily global solar radiation based on Angstrom-Prescott equation and Hargreaves-Samani equation in the study area.

Artificial neural network (ANN) was used to estimate the global solar radiation in Sokoto. The adopted neural network was a typical 3 layer multi-layer feed-forward perceptron (MLP) with back-propagation training algorithm. A total of 5 geographical and climatic variables were selected as the input variables for the study area to estimate the single output daily GSR. The MBE, RMSE and MPE were determined and compared. , the best result was obtained for ANN combination model 2 (MLP-2). The ANN model indicated a reasonably strong predictive power, where MBE, RMSE, MPE and R^2 values were found to be 0.063, 0.164, -2.489 % and 0.965 for training, and 0.103, 0.288, -4.177 % and R^2 0.959 for testing. This research showed that artificial neural network could give reasonably good estimation of global solar radiation in the station. A great significant improvement in GSR predictions was found using this novel modeling approach compared with the conventional linear regression.

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