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PREDICTING GLOBAL SOLAR RADIATION USING ARTIFICIAL NEURAL NETWORK BASED ON TWO PARAMETERS MODELFOR TECHNOLOGY FUTURE

S.G.Fashoto[1*], M., Ebea[2], O., FME, Uzoka[3], Owolabi[4] and EJ, Banda[2]
Department of Computer Science, University of Swaziland, Kwaluseni, Swaziland.
Department of Physics, Kampala International University, Kampala, Uganda.
Department of Computing and Mathematics, Mount Royal University, Calgary, Canada.
Department of Computer Science, University of Abuja, Nigeria.
Email: sgfashoto@uniswa.sz

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Abstract

Solar energy is one of the alternative energy sources for the technology future. A number of sub-Saharan African countries are blessed with a good quantum of solar radiation, which could jumpstart their clean energy needs of the 21st century and beyond. Empirical models are mostly linear, and are unable to effectively deal with empirical irregularities, resulting from the dynamism of the measurement process that is riddled with noise.In this study, we utilized the artificial neural network technology in training solar data, in order to achieve global solarradiation predictions, which have higher levels of accuracy than empirical models. The sunshine and temperature difference based on ANN model made use of data collected from one site in Zaria Nigeria. The results of this study shows that the ANN model predictions with correlation coefficient r= 0.9984, which is modestly superior to the best estimates from the empirical model r= 0.935. The results of this study will contributes to bridging of the gap between developed and developing countries, in the utilization of soft-computing models for increasing the accuracy of global solar radiation predictions.

Keywords: Activation Functions; Artificial Neural Network; Global Solar Radiation; Solar Energy

Introduction

Global solar radiation (GSR) data in Zaria, Kaduna state, Nigeria is currently provided through actual measurements by pyranometers. There is no doubt that measured data are the best source of information on solar radiation; however, the measurement of solar parameters is made only in meteorological stations[1]. In scenarios of absence of actual measured data due to instrument failure or lost data records, the alternative source of data is usually prediction models based on readily available weather data at the site.

Solar energy is one of the most important and efficient alternative sources of energy in the entire world, especially in tropical regions (e.g. Nigeria) with vast amounts of daily solar radiation[2]. Nigeria receives an annual average daily solar radiation of about 5250 $Whm^{-2}day^{-1}$ at the coastal areas, and 7000 $Whm^{-2}day^{-1}$ at the northern boundary. The average sunshine hours all over the country is about 6.5 h[3-4]. Thus, Nigeria has enormous solar energy potential which is essential for so many applications such as the provision of electricity and water supply in rural and semi-urban areas[5].

Some scientists and engineers rely on radiation information in order to design effective and efficient solar energy systems, crop growth models, and other agricultural systems[6]. The interest in solar energy-powered systems has increased in many parts of the world (including Nigeria), because of the need for more environmentally friendly power generation to secure both the future power demand and the survival of the planet[7]. [8]pointed to electricity as a fundamental support of a progressive economy; unstable power supply will surely hamper a nation's growth and economic development. Most electricity is generated using coal, natural gas, nuclear energy, and hydropower; however, a number of developed countries are fast exploring the utilization of alternate and safer sources of energy, such as geothermal energy, solar energy, wind power, biomass and fuel cell.

[9]posited that the design of a solar energy conversion system requires precise data of GSR at the location of interest, as the most critical input parameter; and accurate design of the conversion systems is based on accurate detailed long term data of measured GSR at the location. This data is best obtained through a network of ground-based measuring instruments, and also from satellites. However, measuring instruments can be costly to purchase, install and maintain while satellite measurements pose difficulties (such as overestimation) because atmospheric conditions at satellite overpass are assumed to be the same for a whole day[10]. Thus, when GSR data is missing or not available because of the aforementioned limitations, it must be estimated by scientifically developed models. Whereas it's a fact that estimated data is always of lesser accuracy than measured data, it is useful information in applications, which are not sensitive to solar radiation intensities.

The most common scientific estimation models are stochastic models, analytic models, and empirical models. Stochastic models include autoregressive models, which are essentially linear models. They are simple and understandable, but incapable of simulating the nonlinear nature of various dynamic real world processes[11]. The analytical models are considered one of the most powerful and accurate approaches of predicting global solar radiation[11]. However, their development is often a very difficult task. The empirical models are regarded less powerful approaches, and based on the principle of linearity. Their limitation arises from the fact that empirical regularities in a dynamic process are not always evident as they are masked by noise[12].

This study utilizes existing methods for creating both empirical and neural network models for predicting mean monthly global solar radiation, utilizing data from Zaria, Nigeria. The essence is to provide further impetus to the development and utilization of solar based applications in Nigeria and other developing countries. A number of previous works in the utilization of ANN for the prediction of global solar radiation have focused on developed countries[13-15]**.** A few studies have also been conducted in East Africa[16]and southern Africa[17]on the use of ANN in GSR prediction; but not much has been done in western Africa, especially Nigeria. Thus, this paper also attempts to fill the literature gap.

The rest of the paper is organized as follows: review of related works is presented in section 2. In section 3, we discuss our research methodology (the study design, methods for evaluating the performance of the Empirical model and ANN models and the development model for the ANN); the results are presented and discussed in Section 4, while some conclusions are drawn in Section 5.

Review of related works

The estimation of global solar radiation (GSR) based on empirical models has been extensively presented. The first empirical correlation for the estimation of GSR was proposed by Angstrom (1924) using the sunshine hours data as input parameter. Angstrom-regression equation (1) has been found to accurately predict global solar radiation in several locations[18].

The Angstrom-regression has been severally modified, using the values of extraterrestrial radiation on a horizontal surface rather than that of clear day radiation[19]. [20]modified the Angstrom-Prescott regression as in equation (2).

Several other empirical formulae have been developed to predict the global solar radiation using various meteorological variables such as sunshine hours, cloud cover, relative humidity, maximum temperature, and water vapour pressure[21]. A handful of researchers have employed hours of bright sunshine to estimate solar radiation[22]. [14] and [23] derived their equations using other climatological parameters, such as relative humidity, temperature and latitudes of the locations they studied. [24]suggested the use of the number of rainy days, sunshine hours and a factor which depends on the geographical location of the area of interest along with the latitude.

[14]evaluated empirical models for the correlation of global solar radiation with meteorological data for Iseyin, Nigeria. They observed that the monthly global solar radiation, duration of sunshine, mean of temperature, ratio of minimum and maximum temperature as well as relative humidity could be partially combined to develop several correlations equation.

Methodology

A. Study Design

The global solar radiation and climatological data was obtained from the Nigerian Meteorological Agency (NIMET), Zaria, Nigeria for the period of forty-two (42) months (January, 2012 to June, 2015). Zaria is situated in the Northern Guinea Savannah. It lies between latitudes 11º 3’ N -11º 15’ N and longitude 7º 30’ E-7º 45’E of Greenwich meridian, at an elevation of 646 m above sea level. The mean annual rainfall in the area is 1100 mm, lasting from May to October. It has an area of 300km^2 and population of 804,198 (as at 2006 census). Mean daily temperatures during the wet season is 25^{o}C, while mean relative humidity is 72%. The dry season lasts from November to April, during which the daily temperatures range from 14 to 36^{o}C, and the relative humidity from 20 to 30%.

Various climatic parameters namely; minimum and maximum temperature, relative humidity, sunshine hours, and GSR were used in developing the empirical correlation and ANN model for predicting the monthly average global solar radiation[25]. Besides, for comparison purposes, empirical models based on four weather parameters namely; maximum and minimum temperature, relative humidity, sunshine hours, and global solar radiation on a horizontal surface were also developed.

B. Methods Used in Evaluating the Performance of Models

The statistical tests used in evaluating the models include correlation coefficients and error analysis, namely root mean square error (RMSE), mean bias error (MBE),mean absolute error (MAE) and mean absolute bias error (MABE)[26]. Besides, the ranking method was used to single out the best model among many.

However, in this study MAE, RMSE and correlation coefficient were used for evaluating the performance of the ANN models.

C. Empirical and Artificial Neural Network (ANN) Model

The monthly average values of extraterrestrial solar radiation $H_o$in (MJ/m^2) for Zaria were computed using a latitude 11.111^o N, which is the location of the site, and is presented in Table 1. The highest and lowest values were observed in the months of April and December, respectively.

Table-1: Monthly-average daily extraterrestrial global radiation in W/m^2 for Zaria.

MONTH	H_o (MJ/m^2)
JANUARY	31.35
FEBRUARY	34.20
MARCH	37.70
APRIL	37.96
MAY	37.79
JUNE	37.32
JULY	37.37
AUGUST	37.67
SEPTEMBER	36.97
OCTOBER	34.77
NOVEMBER	32.00
DECEMBER	30.54

1) Estimation of Global Solar Radiation Using Empirical Model

Five empirical correlation models were developed to predict global solar radiation data in table 3 from climatologically recorded parameters of sunshine duration, temperature, relative humidity and global solar radiation. The models were Angstrom-type regression equation, relating the monthly average daily global radiation to select climatological parameters.The five models are presented in equations 1 to 5.

$\frac{H}{H_o} = a + b\,[\frac{S}{S_o}]$..................1

$\frac{H}{H_o} = a + b\,(T_{max}/65$.............2

where T_{max} is the average daily maximum temperature.

$\frac{H}{H_o} = a + b\,[\frac{\Delta T}{Nh}]$ …...........3

where $\Delta T = T_{max} - T_{min}$ i.e difference between maximum and minimum average daily maximum temperature and N_h is the monthly average daily maximum number of hours of possible sunshine (or day length).

$\frac{H}{H_o} = a + bR$…………..... 4

Where

R is the monthly average daily relative humidity

$\frac{H}{H_o} = a + b\,(\frac{S}{S_O}) + c\,\frac{\Delta T}{Nh}$……...5

Where **S** is the monthly average daily number of hours of bright sunshine, S_o is the monthly average daily maximum number of hours of possible sunshine (or day length),

$\Delta T = T_{max} - T_{min}$ i.e difference between maximum and minimum average daily maximum temperature and N_h is the monthly average daily maximum number of hours of possible sunshine (or day length) and *a; b and c* are regression constants to be determined using multiple linear regression.

The performance of the five different models was evaluated using correlation and error analysis from which the best model was deduced.

Table-2: Comparison of the different empirical models used in estimating global solar radiationin Zaria by correlation coefficient.

	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5
R	0.807	0.484	0.934	0.913	0.935
RANK	4	5	2	3	1

Similarly, regression coefficient values indicated that Model 5 (r= 0.935) is the best in predicting global solar radiation (H_e) while the worst model is Model 2 (r= 0.484).

The monthly mean of daily measured global solar radiation (H_m), sunshine duration, S, monthly average daily maximum number of hours of possible sunshine (or day length) (S_o) and estimated global solar radiation (H_e) obtained using Empirical Model for Zaria for the period 2012 to 2014 are shown in Table 3. The highest measured global solar radiation (H_m) was obtained in March (24.32 MJ/m^2) while the lowest value was obtained in August (17.63 MJ/m^2) as shown in Table 3.

Table-3: Measured (H_m) and estimated (H_e) monthly-average values of daily global solar radiation for Zaria using Empirical model.

MONTH	H_m (MJ/m^2)	H_o (MJ/m^2)	S (h)	So (h)	H/H_o	S/S_o	H_e (MJ/m^2)
JAN	21.44	31.35	9.13	11.43	0.6840	0.7991	19.21
FEB	23.11	34.20	8.37	11.65	0.6758	0.7182	20.78
MAR	24.32	37.70	7.13	11.94	0.6451	0.5974	22.15
APR	23.39	37.96	7.97	12.25	0.6161	0.6503	21.59
MAY	22.29	37.79	7.20	12.51	0.5899	0.5755	20.85
JUN	20.68	37.32	7.63	12.64	0.5540	0.6039	19.73
JUL	18.28	37.37	7.40	12.58	0.4892	0.5882	18.18
AUG	17.63	37.67	6.07	12.36	0.4681	0.4908	17.81
SEP	19.74	36.97	7.17	12.01	0.5339	0.5967	19.06
OCT	18.16	34.77	8.37	11.75	0.5223	0.7121	17.66
NOV	23.18	32.00	9.73	11.49	0.7245	0.8471	20.45
DEC	21.60	30.54	9.10	11.46	0.7074	0.7941	19.18

The low values of measured global solar radiation (H_m) obtained during the raining season is due to minimal sunshine hours arising from attenuation of solar radiation caused by clouds. However, the H_m increased to a maximum value in November, when the sunshine hours had increased. Subsequently, the H_m decreased steadily from December to February. Although, there was little or no rain during this period, the Harmattan season, which is occasioned by dust, could have obscured the sunshine, causing a decrease in the sunshine duration (S). In addition, the onset of rain in May could have contributed to further reduction in S, thereby causing further decrease in H_m. March and April had the highest values of $H_m$due to high values of sunshine hour during those months.

2) Global Solar Radiation Using ANN Model

The forty two months data (January 2012 to June 2015), comprising of temperature difference, sunshine hours and GSR, from NIMET- Zaria Station (Kaduna State) was split into two. Thirty six months' (January 2012 to December 2014) dataset was used for training the neural network and six months' (January to June 2015) data set was used for testing the ANN model.

The ANN model was developed using Waikato environment for knowledge analysis (WEKA) version 3.6.10 data analysis software. The selected ANN structure has 8 hidden nodes. While the input to the model and the transfer function (logsig) was fixed, learning rate, momentum, epoch, and the number of hidden layers were varied to identify the most appropriate architecture for the ANN design. The training data was saved in an Attribute relation file format (Arff) code. The multilayer perceptron (MLP) under classified tab was selected for the WEKA application using two input parameters (S_0 and ΔT).

Multilayer perceptron in WEKA is a feed forward artificial neural network that maps sets of input data onto a set of appropriate outputs. It is a modification of the standard linear perceptron in that it uses three or more layers of neurons (nodes) with nonlinear activation functions, and is more powerful than the perceptron in that it can distinguish data that is not linearly separable by a linear hyper-plane. In order to determine the optimal performance, 2000 runs were made on the training data while varying the hidden layer, learning rate, epoch and momentum as shown in table 3.

Table-3: Specifications for obtaining optimal value.

Parameter	Range
Epoch runs	100 – 1000
Hidden layers	1 – 10
Learning rates	0.1 – 1.0
Momentum	0.1 – 1.0

Results and Discussion

The 2000 trial runs were done in groups of two (table 4); one group where learning rate was kept constant while momentum, epoch, and hidden layer were varied, and the other where momentum was fixed while hidden layer, epoch and learning rate were varied. This method was successfully adopted in[27]. The performance of the 2000 runs was based on computation of mean absolute error (MAE) and root mean square error (RMSE). The overall results of the training run with the least MAE and RMSE from the training session comprising of both groups were obtained as shown in table 4. To test the model, optimal values were extracted from the training runs with the least value.

Table-4: Momentum and Learning Rate.

Varying momentum

HIDDEN LAYERS	LEARNING RATE	MOMENTUM	EPOCH	MAE	RMSE
10	0.3	0.1	900	0.2964	0.3529
10	0.3	0.2	700	0.3111	0.3677
10	0.3	0.3	1000	0.317	0.3893
9	0.3	0.5	1000	0.1675	0.202
9	0.3	0.6	900	0.1383	0.1645
8	**0.3**	**0.7**	**700**	**0.1274**	**0.1458**
9	0.3	0.7	1000	0.1663	0.2021
6	0.3	0.8	900	0.1798	0.2103
Varying learning rate					
7	0.2	0.2	1000	0.2986	0.3631
4	0.3	0.2	1000	0.3048	0.3737
10	0.3	0.2	800	0.3111	0.3677
8	0.7	0.2	1000	0.2542	0.367

Having attained an optimal value, we tested the model with the six-month data (saved in the ARFF code). The results showed MAE of 0.1274, RMSE of 0.1458, and a correlation coefficient of 0.9984.

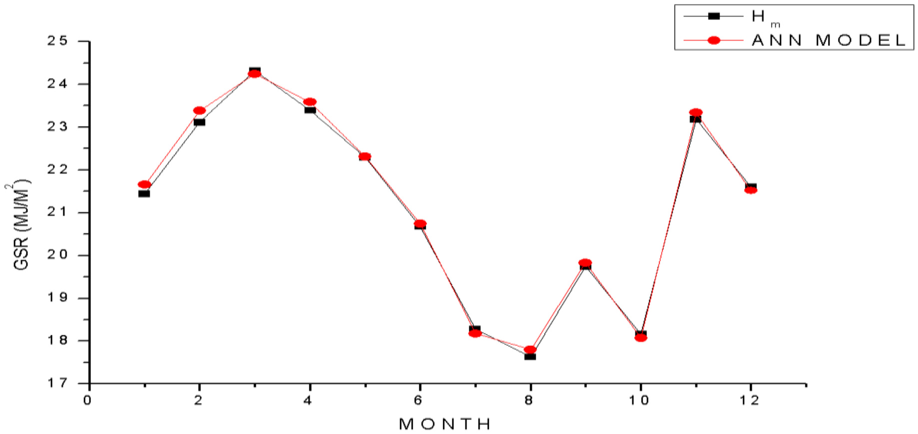

Figure 6: shows a graphical comparison between the performance of ANN and measured GSR.

From the graph above, it is very evident that the ANN model (r=0.9984) performed better than the best empirical model(r= 0.935) in terms of the measured GSR values across the months.

Table-5: Comparison of ANN model performance with the best empirical model.

Model	Correlation Coefficient	RMSE
Empirical(Best)	0.935	0.234
Proposed ANN	0.9984	0.146

The proposed model with two input parameters, gives a lower RMSE of 0.146 and a better correlation coefficient of 0.9984, compared to the best empirical model as shown in Table 5.

Conclusion

The artificial neural network designed has two input parameters, sunshine hours and temperature difference. The ANN optimal performance was attained with eight (8) hidden nodes, momentum at 0.7, 700 epochs, and a learning rate of 0.3. The ANN model made predictions with correlation coefficient r= 0.9984, which is modestly superior to the best estimates from the empirical model r= 0.935. The study has contributed to the field of prediction of global solar radiation. A reliable ANN model that is a lot easier to use, can be built from minimal parameters using Waikato environment for knowledge analysis (WEKA) which is user friendly.

The sunshine and temperature difference based on ANN model made use of data collected from one site in Zaria Nigeria. Data from other meteorological stations around Nigeria can be used to make a more universal ANN model. The accuracy of the artificial neural network models depends on the long term measurements of the data used; therefore, global solar radiation data, covering a longer period of time than the one used in the present study could be implored in future studies. In future studies, the estimation of monthly average daily global solar radiation can be investigated with both hourly and daily values of the same parameters.

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Corresponding Author:

S. G.Fashoto*,

Email: sgfashoto@uniswa.sz