Transactions of the Nigerian Association of Mathematical Physics
Volume 12, (July – Sept., 2020 Issue), **pp179 – 186**

AN ARTIFICIAL NEURAL NETWORK ESTIMATION OF GLOBAL SOLAR RADIATION AT IBADAN, NIGERIA USING METEOROLOGICAL DATA.

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Abstract

This paper estimates global solar radiation (R_s) from routinely measured meteorological parameters in the city of Ibadan, Nigeria, using artificial neural network method. Six combinations were used to estimate R_s namely (i) daily mean air temperature (T) and day of the year as inputs and global solar radiation as output, ((ii) daily mean relative humidity (RH) and day of the year as inputs and R_s as output (iii) daily mean T, daily mean RH and day of the year as inputs and R_s as output (iv) daily mean minimum relative humidity (RH_{min}) and day of the year as inputs and R_s as output, (v) daily mean minimum temperature (T_{min}), daily RH_{min} and day of the year as inputs and R_s as output (vi) daily mean maximum temperature (T_{max}), daily mean T_{min}, daily mean RH_{min}, daily maximum relative humidity (RH_{max}) and day of the year as inputs and R_s as output. The neural network was trained with 3653 measured data between 1995 and 2004 and tested with data for 731 days between 2003 and 2004. The data for testing the neural network were not used for the training. The results obtained showed that the combination of RH_{min}, RH_{max} and day of the year gave the best estimate of R_s with MSE of 3.4124. This is followed by RH_{min} and day of the year with MSE of 3.4424. Daily mean air temperature and day of the year could not mimic the measured R_s; it gave MSE of 5.3345. It is concluded that R_s can be estimated for locations where only temperature and relative humidity data are available.

Keywords: Global solar radiation, Artificial neural network, Temperature, Relative humidity, Day of the year.

1.0 Introduction

The main concern of the world today is sustainable development. The contributing factors to sustainable development is energy supply that is fully sustainable to meet the needs of the population. The environmental consequences of energy conversion should be such that present and future generations are able to cope [1]. This goal is attained by harnessing renewable energy sources such as solar energy [2]. Since the petroil crises, the rapid depletion of the various energy sources and global warming and other environmental problems, the green energy sources are being encouraged [3,4]. Solar radiation studies have therefore become a very important issue for renewable energy.

Solar energy is a clean, pollution free, and an inexhaustible source of renewable energy. This energy is more abundant in the region of the earth between latitudes 40ºN and 40ºS generally referred to as the solar belt [5,6]. It is of particular interest within this region as one of the renewable energy source. Nigeria (4ºN – 14ºN) is located within this region and hence its geographical position favours the development and utilisation of solar energy. Other sources of energy that are fast replacing fossil fuels due to increasing cost and environmental pollution problems are the green sources such as solar photovoltaic, solar thermal, wind, biomass, small and big hydro, tidal, wave, ocean, etc [7]. The common ones in use are wind, solar and hydro. Solar energy is the primary energy source driving the physical and biological processes occuring at the earth's surface [8]. It is also an essential input in many models from crop growth models to land surface meteorological based models at regional scales and in global circulation models. Solar radiation energy influences photosynthesis, evapotranspiration, spreading of diseases and agricultural pests, and environmental comfort to animals. The variation of the mean climate of the earth, the thermal balance of the earth-atmosphere system and hence the atmospheric and Ocean circulation pattern is being influenced by the distrinution of radiative energy around the world.

To harness this abundant energy resource (solar energy), a detailed and continuous measurement of solar radiation in the location of interest should be carried out. However, as noted by many researchers [9 and the refereces therein], these measurements are relatively scarce, especially in developing countries because of the high cost of the sensors and their maintenance. An accurate knowledge of the

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availability and variability of solar radiation intensity for a particular location of interest both in time and spatial domain is very crutial for a proper, economical and efficient development and utilisation of solar energy [5,7]. Similarly, the design of solar energy conversion systems (e.g photovoltaic conversion system) require a precise knowledge of the availability of solar radiation and its components at the desired location [4]. This knowledge is very critical even before any capital investment is made [6].

However, the daily and seasonal variations of many factors such as geographical conditions, typical weather related to cloud cover and clearness index, etc influence the detail investigation of solar radiation amount and variation and implementation of in any particular location [6]. Data on solar radiation amount, its variation under different weather conditions at any location of interest can be obtained by installing solar radiation measuring sensors and instruments of high resolution [5, 6]. Solar radiation are estimated by empirical models and other techniques where it is not possible to carry out direct measurements. Meteorological and climate parameters such as wet and dry bulb temperatures, relative humidity, wind speed, vapour pressure, sunshine hour, cloud cover, altitude, number of dusty days, etc, are being used in such models [10, 4]. These parameters are readily measured and are available at most locations due to their importance in many fields such as Agriculture, Aviation industry, etc. Solar radiation had been correlated with sunshine duration [11, 12, 13, 14]. Many correlation equations of different forms-linear, quadratic, third degree polynomials, logarithmic and exponential functions, have been developed since then [15, 4]. Cloudiness index and air temperature had also been used by [16, 17, 18, 19, 20] respectively. Models based both on sunshine duration and air temperature was proposed by [21]. An emperical model to estimate monthly daily global radiation using air temperature was proposed by [10] for Asturias, Spain, etc. The commonly used regression technique is the Linear Least Squares (LLS) method which treats all data points equally. Most of these studies are, however, limited in their accuracy and the number of parameters they handle effectively. Hence the need to explore other techniques that could measure or accurately predict solar radiation. One of such techniques is the use of artificial intelligence such as Artificial Neural Netweorks (ANN), fuzzy logic and Expert Systems (ES). These techniques become popular because they can handle effectively large number of input parameters and predict the contribution of these parameters to the output [22, 23]. The use of artificial intelligence technique became popular in the renewable energy domain especially for predicting meteorological data such as solar radiation [23]. Comparatively, ANNs provides nonlinear parametric models than conventional algorithms which are based on linear models [23]. The performance of ANNs to predict solar radiation using sunshine hours as compared to empirical models show that ANNs are better [24]. In this work, we estimated global solar radiation in Ibadan using air temperature and relative humidity (RH) using ANNs. The importance of using temperature and relative humidity to predict solar radiation had been earlier highlighted by [25] who used T_{max} and RH to predict solar radiation in south-east and north-east Nigeria by statistical methods. A lot of emperical prediction methods have been developed for the city of Ibadan but none have used ANNs. Section 2 describes the data used in this work while the ANNs is briefly described in section 3. The results are presented and discussed in section 4 and a summary is given in section 5.

2.0: DATA DESCRIPTION

The solar radiation and meteorological data used in this work were collected from the International Institute for Tropical Agriculture (IITA) Ibadan, Nigeria, from January 1995 to December 2004. Daily averages of solar radiation (R_s), maximum (T_{max}) and minimum (T_{min}) temperature, and daily mean relative humidity were collected from the meteorological department of the institute. From the data collected, the meteorological climate for Ibadan is as follows. For the period under study, the average daily T_{max} and T_{min} are 32.02°C and 22.44°C respectively while the monthly and daily rainfall are 108.95 mm and 3.63 mm also respectively. The monthly maximum relative humidity (RH_{max}) and minimum relative humidity (RH_{min}) are 98.25% and 54.45%. Generally, the temperature varied between 14.47°C and 32.43°C while the relative humidity varied between 14.5% and 99%. On the average, the city of Ibadan experiences 153.3 hrs of sunshine per month and 5.11 hrs per day. The daily global solar radiation varied between a minimum value of 1.8 MJ/m^2/day and a maximum value of 29.1 MJ/m^2/day respectively for the period of study. The general climate of Ibadan have been described elsewhere [26]. Fig 1 show the variation of T_{max} and T_{min} while Fig 2 show the variation of RH_{max} and RH_{min} for the period of study. Fig 3 show the variation of sunshine hour for the same period. The variation of global solar radiation between 1995 -2004 is shown in Fig 4. As shown from Fig4, the global solar radiation varied between 5 MJ/m^2/day and 19 MJ/m^2/day with some peacks reaching 23.00 MJ/m^2/day in 1983 and 1990.

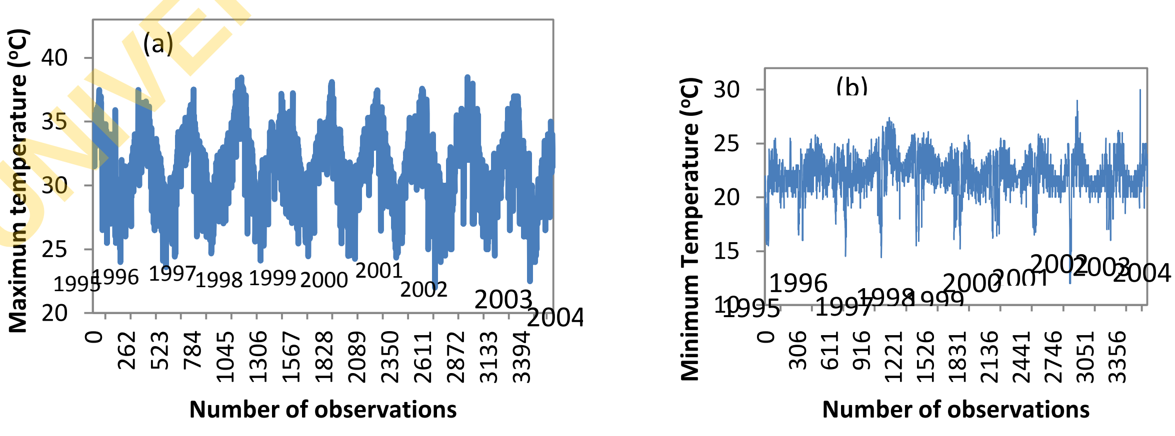

Fig. 1: Variation of (a) T_{max} and (b) T_{min} with respect number of observations for the period 1995-2004

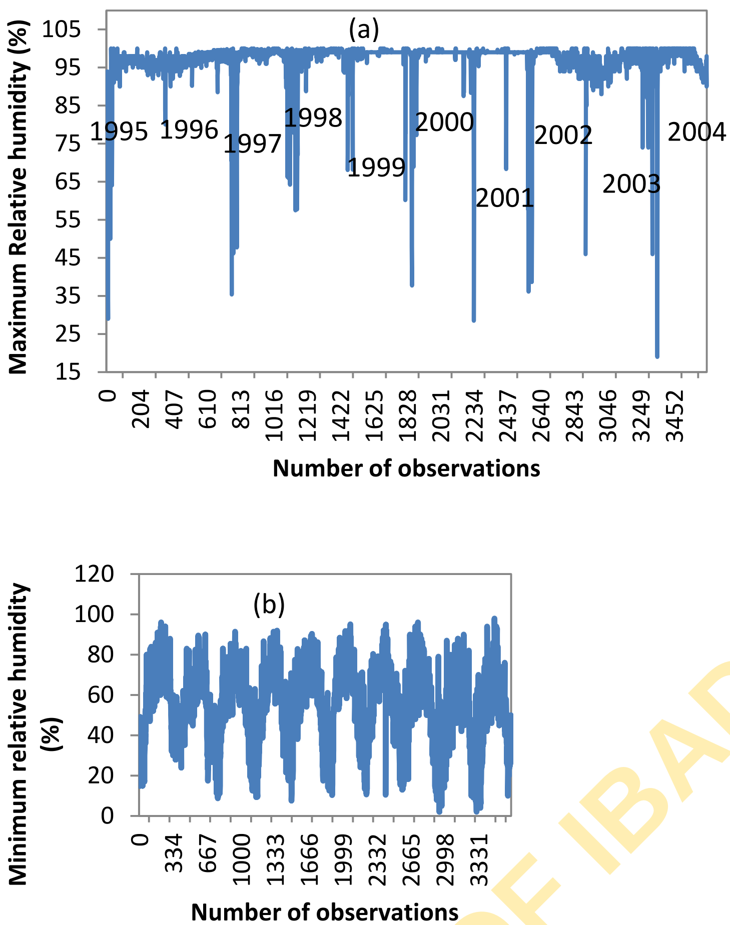

Fig.2: Variation of maximum relative humidity (a) and minimum relative humidity (b) with respect to number of observations for the period 1995-2004.

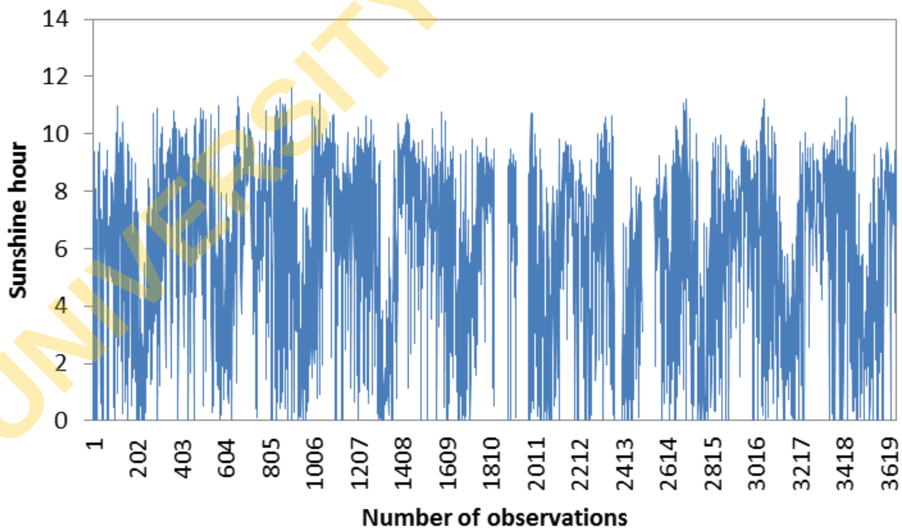

Fig.3: Sunshine duration for the period 1995-2004

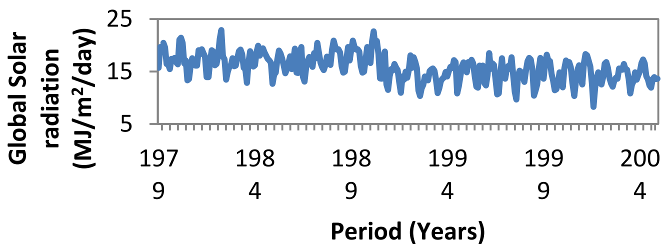

Fig. 4: Variation of solar radiation for the period under investigation.

The rate of evaporation is about 112.30 mm/month and 3.74 mm/day while the average windspeed is 33.14 km/hr per month and 2.77 km/day. Also for the same period, the monthly and daily solar radiation received is 441.12 MJ/m^2/day/month and 14.70 MJ/m^2/day per day respectively. These values are not surprising particularly considering the fact that Ibadan is located in a tropical humid region. It is only about 160 km from the Atlantic Ocean. These values were obtained after subjecting the data to quality check by removing all outliers. The data is then used for further analysis using artficial neural network method as described below.

3.0: THE ARTIFICIAL NEURAL NETWORK

For over two decades now artificial neural networks are being employed extensively in many fields of science and technology. Termed as universal function estimators, ANNs are used in solving complex practical problems [27, 28, 29]. Artificial neural networks are non linear mapping structures based on the function of the human brain. They are non-algorithmic, non-digital and extensively parallel. They can approximate any continuous nonlinear functions to arbitrary precision [30, 31, 32, 33, 34, 35, 29, 36]. Basically, ANNs are computing algorithms that mimic the basic biological neural networks of the human brain. An ANN consist of an interconnected structure of simple processing units that resemble the biological processing elements called neurons [3, 5, 35, 29, 37, 6] and an input and an output, and one or more hiden layers, hiden neurons [35, 28, 36]. The processing units are organised in such a way that makes the structure of the network to adapt itself to the problem being solved [37]. They are characterised by their architecture, training or learning algorithm and activation function. On the other hand, the connection between the layers is known as the architecture of the network.

For over two decades now, ANNs have been shown to be excellent tools for research because of their capability to handle non-linear interrelations, separate data, locate hidden relations in data groups or model natural systems [28, 37]. Simulation studies have shown that ANNs out performs the autoregressive modelling technique and ARMA models in predicting windspeed [38, 28]. They are also used in estimating solar radiation e.g. [22, 3, 5, 35, 37], modelling solar radiation [39, 36], and so on. The ANNs have the ability to study previously recorded data via the interconnected neurons and then establish the relationship between the input and output variables [3, 5, 35, 36]. Each neuron receives inputs from its n input signals x_j for $j = 1, 2, 3, ... n$ from its incoming connections, combines these inputs and performs a non-linear operation on them and produce an output signal y given as

$$y = \varphi\left(\sum_{j=1}^{n} \omega_i x_j\right) \quad (1)$$

where ω_i is the weight associated with the jth input, $\varphi(.)$ is a unit step function at O [3, 36]. A major advantage of ANNs is that they have the ability to learn to perform specific tasks by adjusting the weights of the connections between neurons. The weights between the connections is learned by the network from the available representative training data. A typical non-linear sigmoid function for weighted sum of inputs, x, is defined as [3, 36],

$$\Phi(x) = \frac{1}{1 + \exp(-x)} \quad (2)$$

The desired input and output mapping is attained by adjusting the weights of the interconnections between neurons during the training process. In this study, we used the Multi-Layer Perceptron (MLP) because of its precision in the usage of homogeneous Transfer Functions (TFs), especially with complex or large data set. It is also the only known ANN type that allows for statistical inference. The feed-forward MLP is the most commonly used ANN in hydrological applications. The structure of a three-layer MLP consists of three layers; an input layer, a hidden layer, and an output layer [40]. A typical simple MLP is shown in Fig. 5 which consists of m inputs, l hidden layers having n hidden neurons and n outputs.

The Statistical Neural Network (SNN) model structurally is composed of two parts namely the predictive and the residual given as

$$y = f(X, w) + e_i \quad (3)$$

Udomboso and Amahia [41] proposed a simple time series neural network model for predicting rainfall using SNN given as

$$y_t = \alpha x_t + \sum_{h=1}^{H} \beta_h g\left(\sum_{i=0}^{I} \gamma_{hi} x_{ti}\right) + e_t, \qquad t = 1, 2, \dots, n \quad (4)$$

where $x_t = \left(x_o,\ x_1,\ x_2,\ .....,\ x_l\right)$ is the vector of the input variable, $g(.)$ is the transfer function, α, β and γ are the weights associated with the input vector, hiden neuron and transfer function respectively and e the error associated with the network. Taylor's first order approximation method was used to estimate the weights as

$$y_t = y_t^0 + \frac{\partial f(x_t,w)}{\partial w}\Big|_{w=w^0}^{(w-w^0)} + e_t \quad (5)$$

The first term on the right hand side of equation (5) is the first order of Taylor approximation.
In this paper, we used the Hyperbolic Tangent Sigmoid function (TANSIG), defined as

$$f(x) = \frac{2}{1-e^{-2n}} - 1 \quad (6)$$

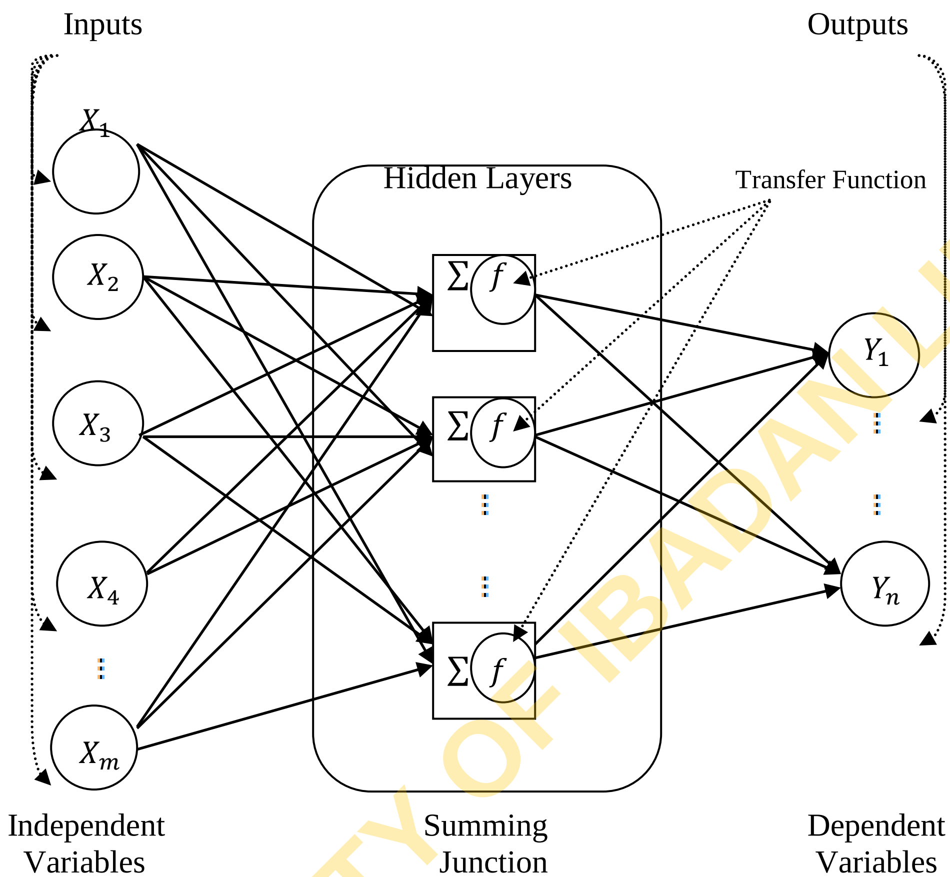

Fig. 5: A Simple Multilayer Perceptron of an Artificial Neural Network

In order to avoid the application of extremely small weighting factors in the case of large input values, all the input variables were standardized and converted to the range (0, 1) before feeding them into the network. Similarly, the output values are "destandardized" to provide meaningful results since all values leaving the network are automatically output in a standardized format. This is done by simply reversing the standardization algorithm used on the input nodes. A neural code was written for the analysis of the $TSNN$ using MATLAB R2009a, and the results obtained are presented and discussed in section 4.

4.0: RESULTS AND DISCUSSION

Global solar radition was estimated from daily temperature and day of the year by first training the ANN using the feedforward method. A network with 2 inputs and 50 hidden neurons in one layer and one output unit was found to be sufficient after several experiments. We used data for 3653 days during the period 1995-2004 for the training purpose and 20% of this data, making 731 days from the period 2003-2004 was used to test the performance. The maximum number of iterations allowed was 1000. Fig 6 show the values of the estimated global solar radiation (R_s) as compared to the measured for the period of the testing. The predicted and actual values of R_s are 15.22823529 and 14.28241313 respectively with a MSE of 5.3345.

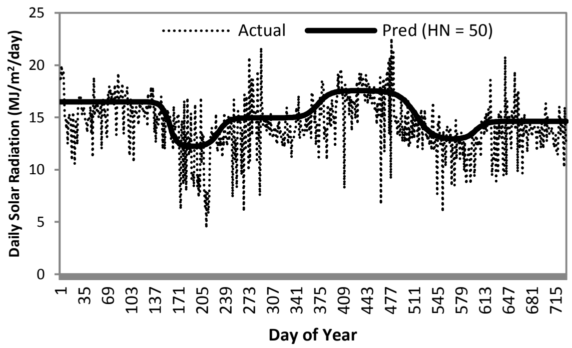

Fig 6: Estimated and measured solar radiation using daily mean temperature and day of the year as inputs with 50 hidden neurons.

Next we used the feed forward to train the ANN to estimate R_s based on daily mean relative humidty and days of the year. A network of 2 inputs and 7 hidden neurons in 1 layer and one output was found to perform very well for this case. Using the same data division as above, the MSE was found to be 3.5867. The predicted and the actual values of R_s are 14.49659959 and 14.28241313 respectively. Fig 7 show the measured and estimated R_s for this case.

Finally, we used a neural network with three inputs and 6 hidden neurons in 1 layer and 1 output unit to train the ANN on day of the year, daily mean air temperature and daily mean RH to predic R_s. The same number of data (3653 days), was used for the training and 731 days for the testing. For this case, the MSE on the data was 3.7460. The measured and estimated R_s is shown in Fig 8.

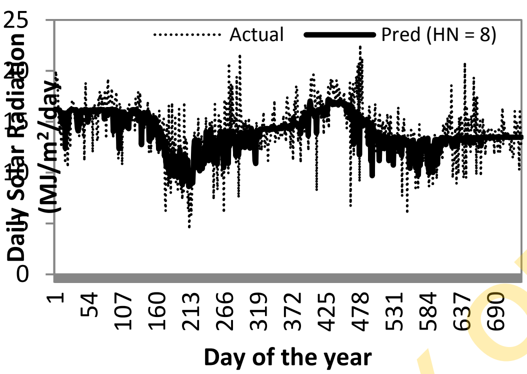

Fig 7: Estimated and measured solar radiation on testing data using relative humidity and day of the year as inputs with 8 hidden neurons.

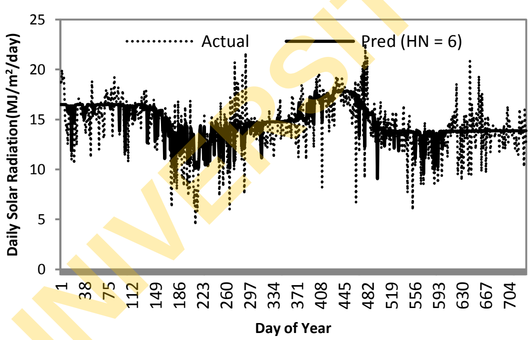

Fig. 8: Estimated and measured solar radiation on testing data using daily temperature, relative humidity and day of the year as inputs with six hidden neurons.

We also carried out the same procedure using the daily maximum and minimum values of temperature and relative humidity, and day of the year as inputs respectively to estimate R_s. Furthermore, we use a combination of these with day of the year also as inputs to predict R_s. Our aim is to determine if the separate values of T_{max}, T_{min}, RH_{max} and RH_{min} or a combination of them could give a better prediction of R_s rather than their daily average values. The results showed that T_{max} and T_{min} with 50 hidden neurons each and combined with day of the year as inputs gave estimate of R_s with MSE of 5.2042 and 4.6435 respectively while a combination of T_{max}, T_{min} and day of the year as inputs also with 50 hidden neurons, gave a higher MSE of 8.3207, thereby making it less reliable. None of these could mimic the measured R_s. Similarly, when RH_{max} , and RH_{max} and T_{max}, were each used with day of the year as inputs could not mimic the measured solar radiation. They gave MSE of 4.7505 and 4.7453 respectively.

However, when daily RH_{min} and day of the year was used as inputs with 7 hidden neurons, the estimated R_s mimic the measured R_s very well (Fig. 9) with low value of MSE of 3.4424. Similarly, when three parameters (daily RH_{min}, RH_{max} and day of the year) were used as inputs with 7 hidden neurons, the predicted R_s also mimiced the measured R_s giving a MSE of 3.4125. The actual and predicted solar radiation for this case is shown in Fig.10. A combination of daily T_{min}, RH_{min} and day of the year as inputs with 6 hidden neurons also gave similar results like in Figs 9 & 10.

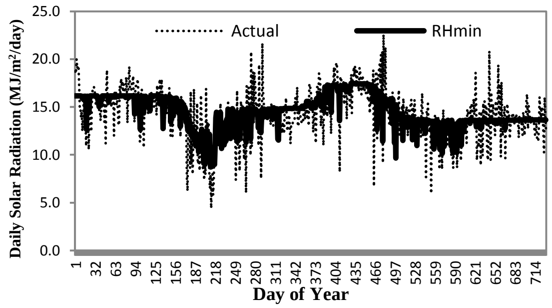

Fig. 9: Estimated and measured global solar radiation using daily RH_{min} and day of the year as inputs with 7 hidden neurons.

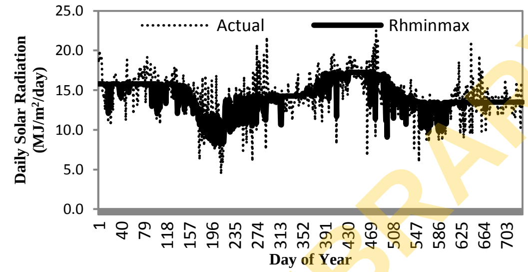

Fig. 10: Estimated and measured solar radiation on testing data using daily RH_{min} and RH_{max} and day of the year as inputs.

It however gave a slightly higher MSE of 3.6286 as compared to that of Fig 10. The actual and predicted solar radiation is shown in Fig. 11. When we used five parameters (T_{max}, T_{min}, RH_{max}, RH_{min}, and day of the year) as inputs with 6 hidden meurons, the result is similar to that in Fig. 8 but have a lower MSE of 3.5054. The predicted and actual R_s is shown in Fig 12. It will be observed from Figures 6-12 that the ANN adequately estimated the global solar radiation using temperature, relative humidity and day of the year. In particular, the ANN performs optimally when daily average relative humidity, and day of the year are used as inputs compared to when daily temperature is used (cf Fig.6 and Fig.7). The ANN also performs better when air temperature in combination with relative humidity and days of the year are used as input to predict global solar radiation rather than air temperature and days of the year alone (Fig. 5). The results obtained here compare well with those of [7]

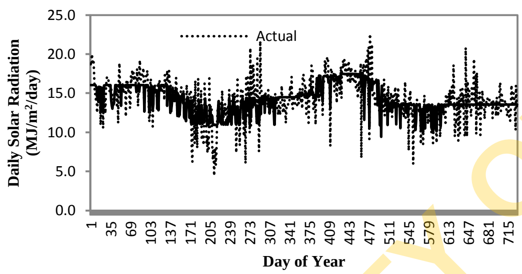

Fig. 11: Estimated and measured solar radiation using daily T_{min}, RH_{min} and day of the year as inputs with 6 hidden neurons.

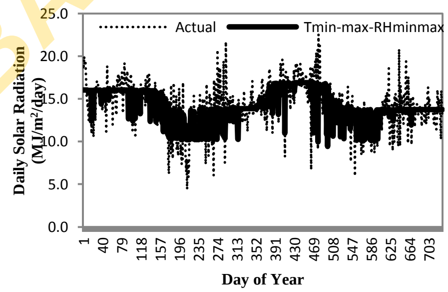

Fig. 12: Estimated and measured solar radiation on testing data using daily T_{min}, T_{max}, RH_{min}, RH_{max} and day of the year as inputs with 6 hidden neurons.

CONCLUSION

This paper presents the results of an attempt to predict global solar radiation using measured daily mean meteorological parameters namely temperature and relative humidity. The importance of this lies in the fact that these parameters are readily measured and are available in most meteorological stations where solar radiation data are scarce or not measured due to the high cost of the equipment and the requirement of continuous attention of skilled manpopwer. Data between 1995 and 2004 for Ibadan was used for training the feedforward ANN using backpropagation. The performance of the ANN system was tested using data for 731 days between the years 2003 and 2004. In the first case, the day of the year and daily mean temperature were used as imputs and R_s as the output. Secondly, relative humidity and day of the year were used as inputs and global solar radiation as output.

Lastly, daily mean temperature, daily mean relative humidity and day of the year were used as inputs to predict global solar radiation. The results showed that when we use daily mean values of temperature, relative humidity each with day of the year as inputs to predict R_s, the former did not mimic the measured R_s very well. It gave a high value of MSE of 5. 3345 compared to MSE of 3.5867 for the later. A combination of temperature, relative humidity and day of the year as inputs with 6 hidden neurons also gave similar result, with a MSE of 3.7460 (compare Fig.6 and Figs. 7 & 8). The other two cases mimic the measured R_s very well as shown in Figs 7 & 8.

When daily minimum and maximum values of temperature and relatively humidity respectively were used with day of the year as inputs, the results showed that only a combination of RH_{min} and day of the year, at 7 hidden neurons, as inputs; $RH_{min,max}$ + day of the year at 7 hidden neurons; T_{min} + RH_{min} at 6 hidden neurons; $T_{min,max}$, + $RH_{min,max}$ + day of the year also at 6 hidden neurons gave the best estimates of R_s with MSE of 3.4424, 3.4125, 3.6286 and 3.5054 respectively. This is followed with the combination of T_{max} + RH_{max} and day of the year at 6 hidden neurons which gave a MSE of 4.7453. Further work is underway to expand the scope of this work to cover most parts of the country, to predict both diffused and normal incident solar radiation on horizontal surfaces using meteorological parameters with ANN.

Acknowledgment

The authors are grateful to the International Institute for Tropical Agriculture (IITA) for making available the data used in this work.

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