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Artificial Neural Network Estimation of Global Solar Radiation Using Meteorological Parameters in Gusau, Nigeria

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ABSTRACT

Three meteorological parameters namely sunshine duration, maximum ambient temperature and relative humidity were used to estimate monthly average global solar irradiation on a horizontal surface for Gusau, Nigeria. The study used artificial neural networks (ANN) for the estimation. Results have shown good agreement between the estimated and measured values of global solar irradiation. A correlation coefficient of 0.9996 was obtained with a maximum percentage error of 0.8512 and root mean square error of 0.0029. The comparison between the ANN and some existing empirical models has shown the advantage of the proposed ANN prediction model.

INTRODUCTION

Solar energy is the most ancient source of energy; it is the basic element for almost all fossil and renewable types. Solar energy is freely available and could be easily harnessed to reduce our reliance on hydrocarbon-based energy by both, passive and active designs. Precise solar radiation estimation tools are critical in the design of solar systems. Using solar energy necessitates an exact estimation of solar energy in proposed locations. This is usually possible through solar measurement equipments while these devices are not available in some of remote or rural locations that specially have potential of solar installation. Even locations with these devices, the maintenance and logistics are enormous. Using prediction tools such as solar models are one of the best methods to have a good estimation of solar potential (Srivasta *et al.*, 1993). We can categorize the solar prediction models in three distinct groups. First group in this classification are empirical models. These models usually consist of a few measurable meteorological parameters. Empirical methods to estimate global solar radiation requires the development of a set of equation that relate it to other meteorological parameters (Donatelli *et al.*, 2003). Second categories of solar prediction models are radiative transfer models which necessitates complex geographical and meteorological parameters. These mathematical models provide a considerable precision in their output results. Though, capability of these models has been limited because of tough required calculations and also numerous input parameters which are not available in most of the locations (Dogniaux, 1973). Artificial neural network (ANN) models are the third and latest type of solar prediction models. In these models, it has gathered the superiorities of two prior models in terms of simplicity and accuracy (Azadeh, *et al.*, 2006a, 2006b; Al-Alawi and Al-Hinai, 1998; Mohandes, *et al.*, 1998). In ANN models we can provide a prediction with a believable amount of error which is obtained with regard to more available input parameters. Also, using artificial neural network has proved its efficiency as an estimation tool for predicting factors through other input parameters which have no any specified relationship. So applying artificial neural networks can be valuable in determining the effects of meteorological parameters and finally prediction of solar radiation. There have been several articles that have used artificial neural networks for predicting solar radiation.

ANN models employ artificial intelligence techniques and are data-driven. Essentially, ANN are used to learn the behaviour of a system and subsequently used to simulate and predict this behaviour (Kalogirou, 2001). Apart from modelling solar radiation, ANN have been used in a broad range of applications including: pattern recognition and classification (Knutti et al., 2003), function approximation and prediction (Mohandes et al., 1998), identification and control (Slavisa et al., 2001), optimization and diagnostics (Reddy and Ranjan, 2003). Kalogirou (2004) has optimized a solar energy system with the purpose of maximizing the economic benefits of this system.

In this paper, Artificial Neural Network (ANN) will be used to analyse the monthly global solar radiation in Gusau which lies in the tropics between latitudes 12.167^{o} N and longitudes 6.700^{o} E and altitude of 464 m above the sea level in Zamfara State of Nigeria.

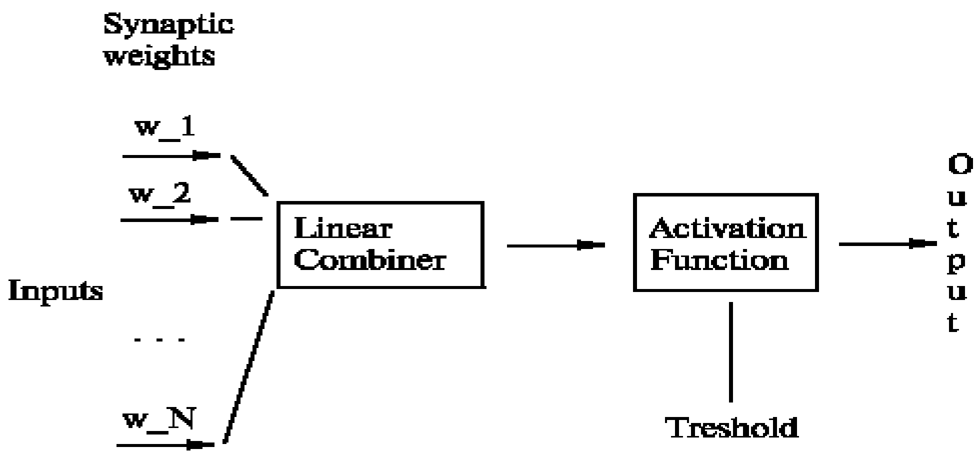

Fig.1: structure of a neuron

Artificial Neural Network

The area of Artificial Neural Networks (ANN) probably belongs to the borderline between the Artificial Intelligence and Approximation Algorithms. Think of it as of algorithms for "smart approximation". The NNs are used in (to name few) universal approximation (mapping input to the output), tools capable of learning from their environment, tools for finding non-evident dependencies between data and so on. The Neural Networking algorithms (at least some of them) are modelled after the brain (not necessarily - human brain) and how it processes the information. The brain is a very efficient tool. Having about 100,000 times slower response time than computer chips, it (so far) beats the computer in complex tasks, such as image and sound recognition, motion control and so on. It is also about 10,000,000,000 times more efficient than the computer chip in terms of energy consumption per operation. The brain is a multi layer structure (think 6-7 layers of neurons, if we are talking about human cortex) with 10^{11} neurons, structure, that works as a parallel computer capable of learning from the "feedback" it receives from the world and changing its design (think of the computer hardware changing while performing the task) by growing new neural links between neurons or altering activities of existing ones. To make picture a bit more complete, let us also mention, that a typical neuron is connected to 50-100 of the other neurons, sometimes, to itself, too. To put it simple, the brain is composed of neurons, interconnected (Kalogirou, 2000).

The neuron has set of nodes that connect it to inputs, output, or other neurons, these nodes are also called synapses. A Linear Combiner, which is a function that takes all inputs and produces a single value. After the neuron in the first layer received its input, it applies the Linear Combiner and the Activation Function to the inputs and produces the Output. This output will become the input (one of them) for the neurons in the next layer. So the next layer will feed forward the data, to the next layer. And so on, until the last layer is reached.

METHODOLOGY

The monthly mean values of the global solar radiation on horizontal surface, H, sunshine duration S, relative humidity, R, and maximum ambient temperature, T_m for a period of ten years (1994 – 2003) were obtained from Nigeria Meteorological Agency Oshodi, Lagos. The values of the extraterrestrial radiation, H_0 and the day length S_0 were calculated for the fifteenth day of the month (Klein, 1977). The data was subjected to quality checks before being used in the analysis. It was ensured only complete data set was used. The values of H/Ho and S/So are all less than one. The solar radiation values obtained using Gunn – Bellani radiation integrators were converted to MJ/m^2-day using the conversion 1 ml is equivalent to 1.216 MJ/m^2 – day (Ododo, 1994 and Abdulazeez, *et al.*, 2010). The values of the sunshine duration were obtained using Campbell- Stokes sunshine recorder.

$$S_0 = \frac{2}{15} \cos^{-1}(-\tan L \tan\delta) \qquad \ldots (1)$$

$$H_0 = \frac{24}{\pi} I_{0n} \left(1 + 0.033 \cos \frac{360}{365} n\right)\left(\cos L \; Cos\; \delta \; Sin\; \omega_s + \frac{2\pi}{360}\,\omega_s \; Sin\; L\; Sin\; \delta\right) ..(2)$$

where $\omega_s = \cos^{-1}(-\tan L \tan \delta)$

$$\delta = 23.45 \, \text{Sin}\left(\frac{360}{365}(284 + n)\right)$$

where n is the day of the year, L is the latitude of the location, δ is angle of declination and ω_s is the sunrise hour angle. I_{on} is a solar constant, having a value of 1367 W/m^2. The relative humidity is the average values of the measured data for 09:00 and 15:00 local time. The value of the relative humidity of a sample of atmosphere represents the degree of saturation of the water vapour present in the atmosphere. It will be 0.00 if there is no vapour present, and 1.00 if the vapour is saturated.

A feed-forward back-propagation neural network was used in this study, with three input variables. The following is an outline of the procedure used in the development of the ANN model:

i) Input and target values were normalized, in the range -1 to 1.
ii) Matrix size of the dataset was defined.
iii) Partition and create training and validation sub-datasets.
iv) Fed-forward neural network was created
v) The feed-forward neural network was trained
vi) Generate output values.
vii) Un-normalize the output values.
viii) The performance of the neural network was checked by comparing the output values with target values.

Table 1: Monthly mean values of H/Ho, S/So, T_m (^{0} C) and R for Gusau

MONTHS	H/Ho	S/So	T_m (^{o} C)	R
Jan	0.6263	0.5678	31.7	0.1159
Feb	0.6730	0.4479	33.6	0.0800
Mar	0.6241	0.6376	37.5	0.0800
Apr	0.5883	0.5705	38.9	0.2778
May	0.4911	0.5494	37.4	0.4172
Jun	0.5294	0.3855	33.6	0.5617
Jul	0.4506	0.4032	31.0	0.6661
Aug	0.4550	0.4194	29.5	0.7544
Sep	0.5493	0.5431	31.2	0.7133
Oct	0.6053	0.6399	33.5	0.5339
Nov	0.7413	0.7349	34.4	0.1944
Dec	0.7441	0.4694	32.4	0.1300

Data Analysis

The artificial neural network analysis was carried out using Neurosolution software version 5.0. Multiple regression analysis was employed for the empirical models (Angstrom-Prescott-Page, Igbal, Swartmann and Ogunlade, Bamiro, Burari and Sambo 2001 and 2003, Ododo *et al.*, and Ododo 1997). The utility of the models were obtained using;

i) the coefficient of determination, R^2

$$R^2 = 1 - \frac{\left(H - \hat{H}\right)^2}{\left(H - \overline{H}\right)^2}$$

ii) the root mean square error, RMSE

$$\text{RMSE} \left\{ \frac{\left(H - \hat{H}\right)^2}{n} \right\}^{1/2}$$

iii) the maximum percentage error, MPE

$$\text{MPE} = \max 100 \left| \frac{H - \hat{H}}{H_i} \right|$$

where H are the observed values, $\hat{H}$ are the fitted values, n is the number of data points and $\overline{H}$ is the mean of the measured values.

Table 2: Values for the goodness-of-fit index

Models	R^2	RMSE	MPE
Angstrom-Prescott-Page	0.2600	0.0820	22.3759
Igbal	0.2670	0.0816	21.6069
Swartmann- Ogunlade	0.6760	0.0543	16.3304
Bamiro	0.3500	0.0768	21.2233
Burari and Sambo 2001	0.7010	0.0521	16.1839
Burari and Sambo 2003	0.7710	0.0456	12.8941
Ododo *et al.,*	0.8140	0.0411	5.5612
Ododo1	0.9800	0.0134	1.3814
Ododo2	0.9870	0.0109	1.4327
Artificial Neural Network	0.9996	0.0029	0.8512

RESULTS AND DISCUSSION

The values of the goodness-of-fit indices are shown in Table 2. The values of the coefficient of determination show poor correlation between the measured and the predicted values for Angstrom-Prescott-Page, Igbal and Bamiro models. These models could not be applied for prediction of global solar radiation in Gusau. Fair correlation was obtained using Swartmann-Ogunlade, Burari and Sambo 2001, Burari and Sambo 2003 and Ododo *et al.,* models. The Burari and Sambo 2001 and 2003 models and Ododo *et al.,* model could be used for short-term prediction of solar radiation in Gusau. The Burari and Sambo models give the values of root-mean –square errors for the 2001 and 2003 models as 0.0521 and 0.0456 respectively. These models could not be used for long-term prediction of global solar radiation in Gusau. The Ododo models 1 and 2 give a good correlation with values of the coefficient of determination of 0.9800 and 0.9870, root-mean-square errors of 0.01342 and 0.0109 and maximum percentage errors of 1.3814 and 1.4327 respectively. The graphs for the measured and predicted values of the clearness index for the various models are shown in figures 2 – 10. In the figures each model is compared with the ANN model. The best empirical model is the Ododo models 1 and 2 as can be seen in Table 2 and figures 9 and 10. The Ododo models 1 and 2 could be applied for both short- and long-term prediction of solar radiation in Gusau. Despite the successes of the Ododo models 1 and 2, it has problems of choosing the parameters for the regression analysis. The Ododo (1997) equation is

$$RTY_p = \frac{H}{H_0} = \sum_{i,j=0}^{p} a_{ij} R^i T_m^j$$

where p was recommended to take the maximum value of 3 for all Nigerian Stations and i, j are integers ranging between 0 and 3. It is obvious that the number of regression constants to be used from the above equation total to 16, but the recommended maximum to be used is 11 (Ododo, 1997). What is the criterion for choosing the best 11 regression constants? There will be 4, 368 models, out of which the best model will be chosen. Among these models are;

$$\frac{H}{H_0} = \sum_{i,j=0}^{2} a_{ij} R^i T_m^j + a_{03} T^3 + a_{30} R^3 \qquad Ododo1$$

$$\frac{H}{H_0} = \sum_{i,j=0}^{2} a_{ij} R^i T_m^j + a_{03} T^3 + a_{13} R T^3 \qquad Ododo\ 2$$

Ododo 1997 recommended model 1 for all Nigerian Stations for the prediction of global solar radiation. Another possible model is Ododo 2 where $a_{30}R^3$ in Ododo 1 was substituted with $a_{13}RT^3$, the result shows an improved correlation between measured and predicted values of the clearness index. In order to avoid this problem, ANN model was employed. When ANN is applied to the data from Gusau an improved coefficient of determination, root-mean-square error and maximum percentage error were obtained as shown in Table 2. The graph of predicted and measured values of the clearness index is shown in figures (2-10). This study has confirmed the results obtained by Al-Alawi and Al-Hinai, 1998, Mohandes et al., 1998 and Reddy and Ranjan 2003.

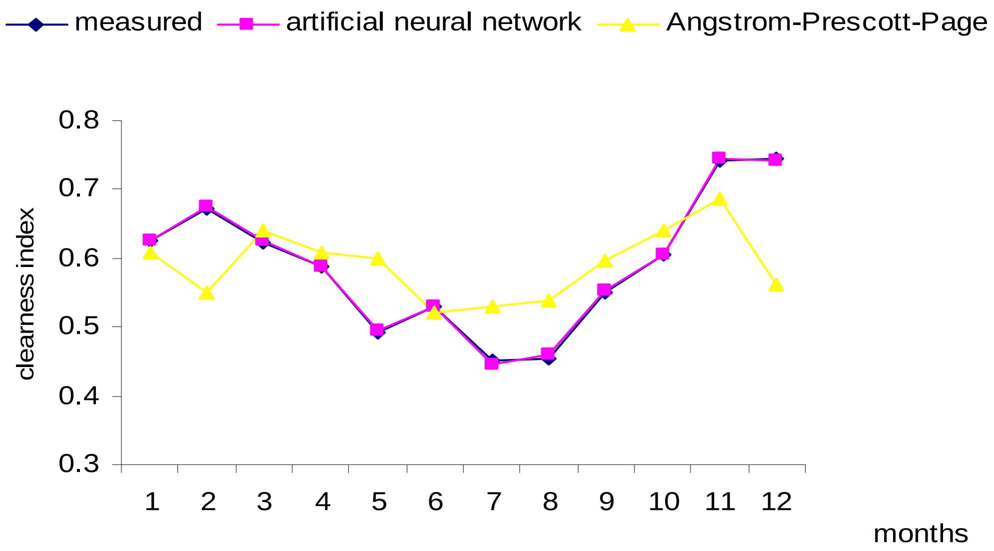

Fig. 2: A graph of measured and predicted values for clearness index

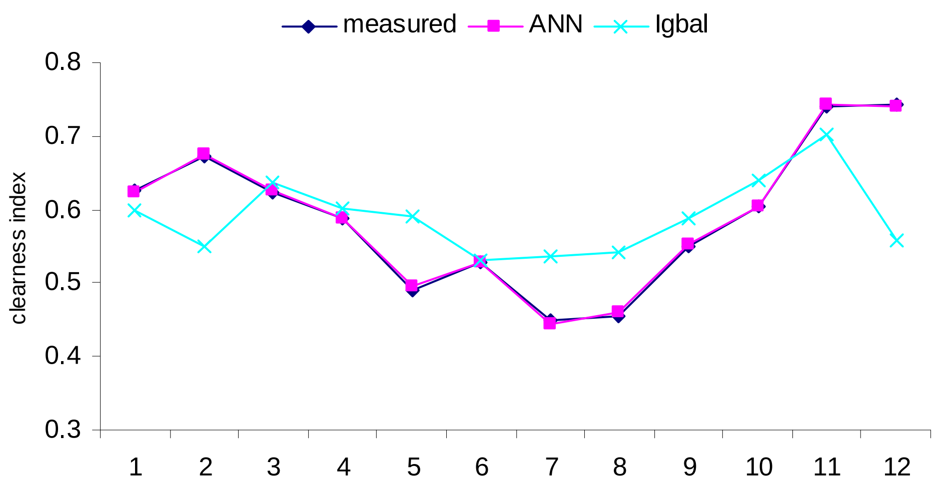

Fig 3: A graph of measured and predicted values for clearness index

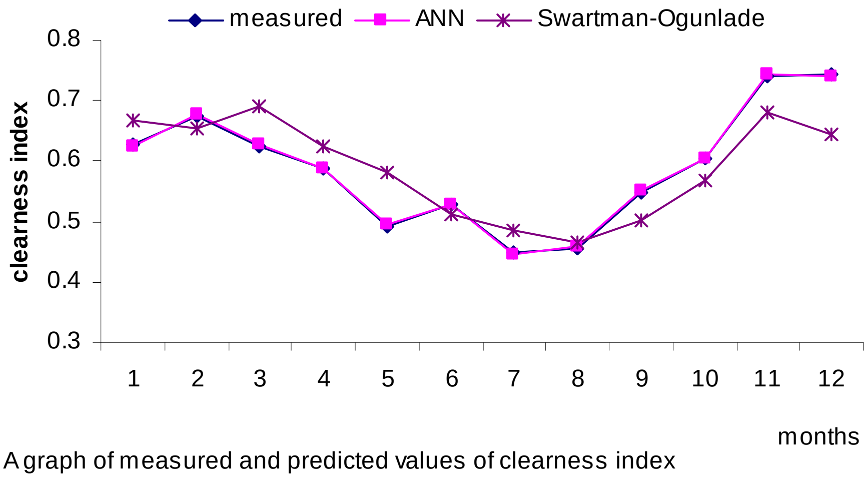

Fig. 4: A graph of measured and predicted values of clearness index

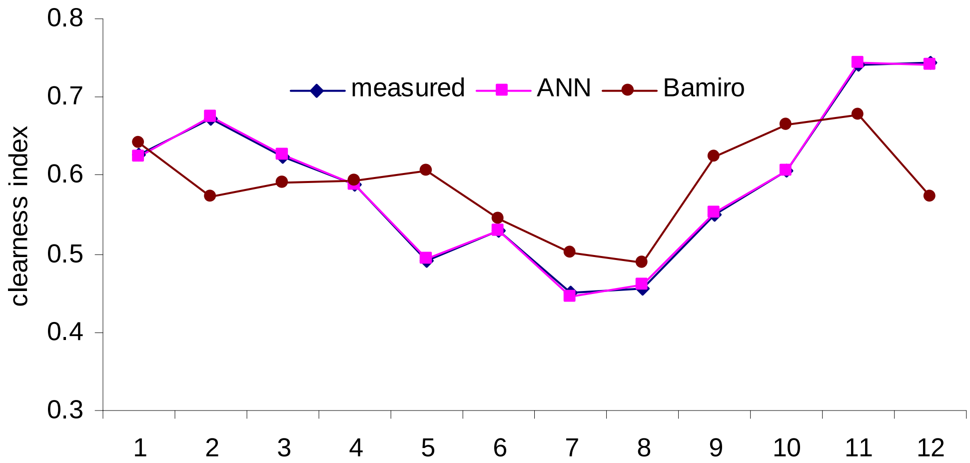

Fig. 5: A graph of measured and predicted values of clearness index months

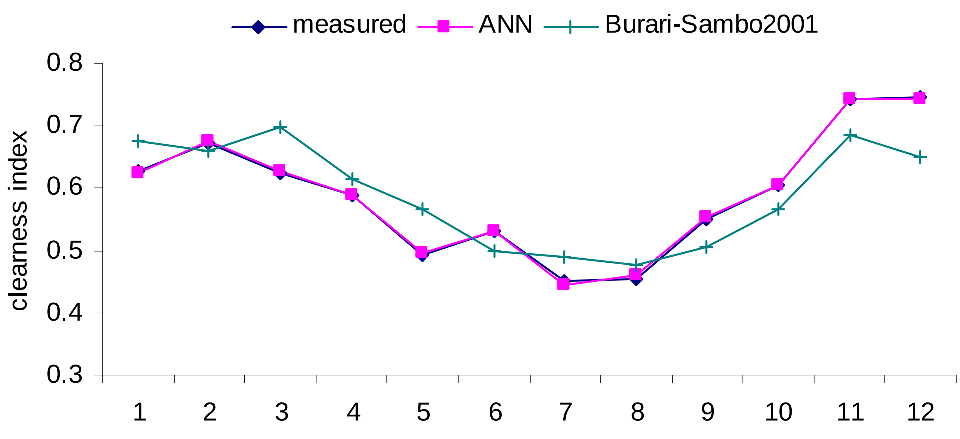

Fig. 6: A graph of measured and predicted values of clearness index months

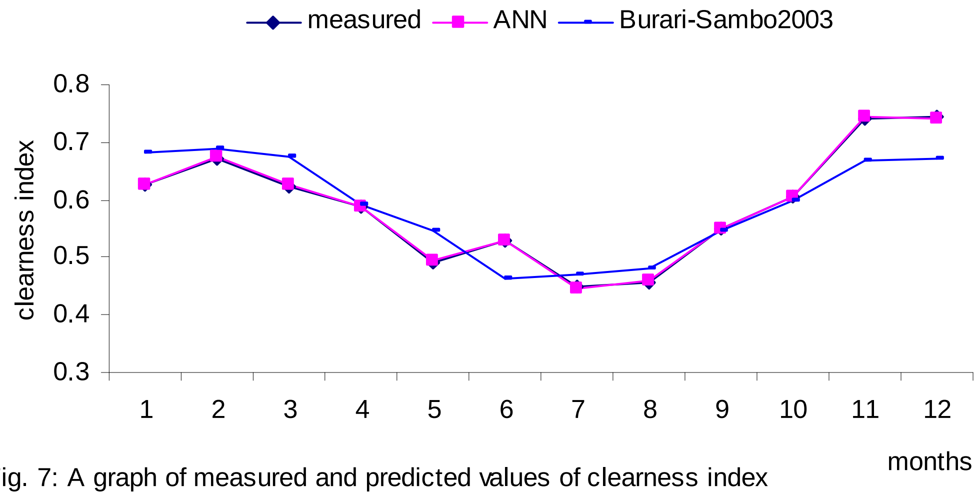

Fig. 7: A graph of measured and predicted values of clearness index

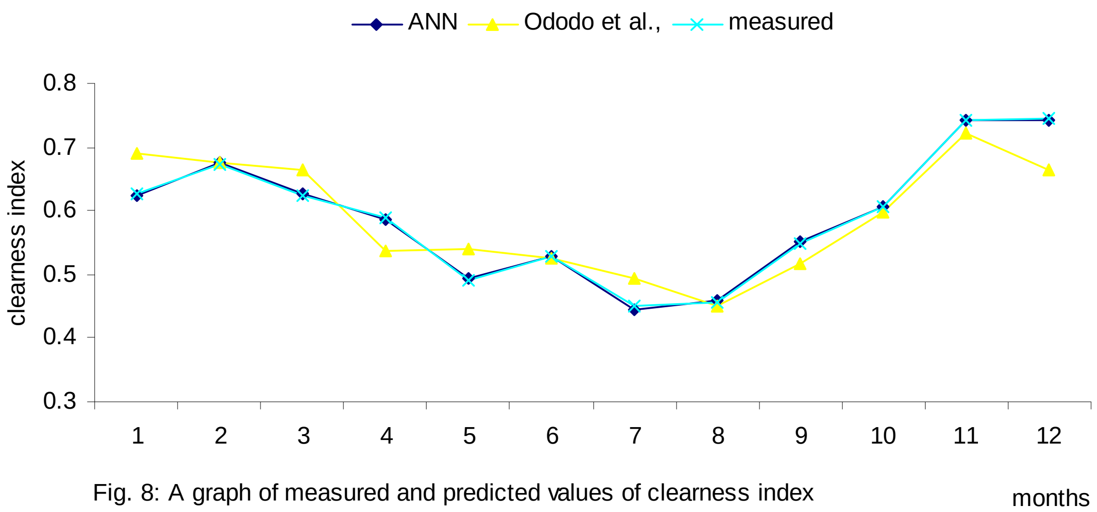

Fig. 8: A graph of measured and predicted values of clearness index

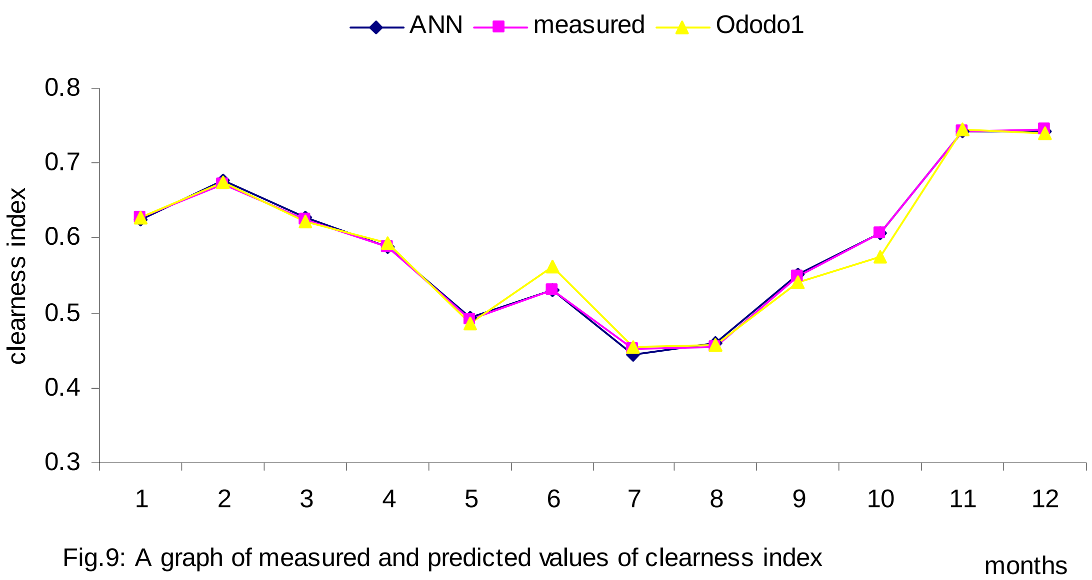

Fig.9: A graph of measured and predicted values of clearness index

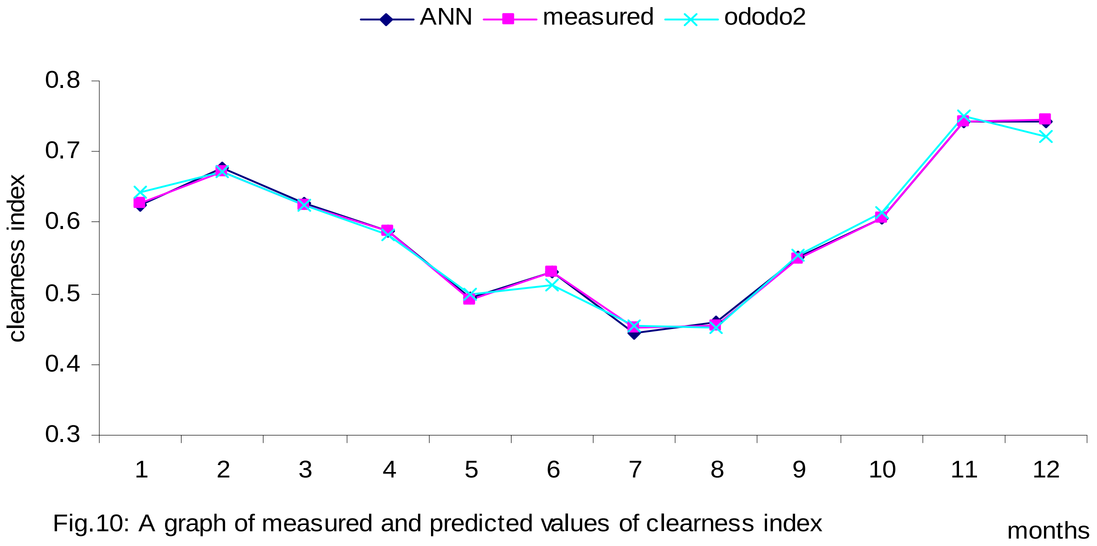

Fig.10: A graph of measured and predicted values of clearness index

CONCLUSION

Three meteorological parameters were used for the analysis of solar irradiation in Gusau, Zamfara State of Nigeria. Artificial Neural Network was employed to obtained the predicted values of the average monthly solar radiation. The result shows an excellent agreement between measured and predicted values with coefficient of determination of 0.9996, maximum percentage error of 0.8512 and root-mean-square error of 0.0028. The comparison between the ANN model and some existing empirical models has shown the superiority of the ANN model. The result has confirmed the results from similar application of the ANN model in the prediction of solar radiation.

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