

Research Article

Using Artificial Neural Networks to Predict Direct Solar Irradiation

James Mubiru

Department of Physics, Makerere University, P.O. Box 7062, Kampala, Uganda

Correspondence should be addressed to James Mubiru, jwm_mubiru@yahoo.com

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This paper explores the possibility of developing a prediction model using artificial neural networks (ANNs), which could be used to estimate monthly average daily direct solar radiation for locations in Uganda. Direct solar radiation is a component of the global solar radiation and is quite significant in the performance assessment of various solar energy applications. Results from the paper have shown good agreement between the estimated and measured values of direct solar irradiation. A correlation coefficient of 0.998 was obtained with mean bias error of 0.005 MJ/m² and root mean square error of 0.197 MJ/m². The comparison between the ANN and empirical model emphasized the superiority of the proposed ANN prediction model. The application of the proposed ANN model can be extended to other locations with similar climate and terrain.

1. Introduction

Much of the work of the prediction of solar radiation has been the estimation of global solar radiation, yet data of the two main components (direct and diffuse) of global solar radiation are equally important. These components are required in a variety of applications such as in thermal analyses and crop models. There is need to estimate these components in the absence of measured values. Some authors such as Davies and McKay [1] and Gueymard [2] have used radiative transfer models in the estimation of direct solar irradiance. Such models take into account interactions between the direct solar irradiance and terrestrial atmosphere. The problem with the use of such models is the unavailability of some of the atmospheric information needed. Simpler models that relate direct solar irradiance with global irradiance have been developed by Vignola and McDaniels [3] and Louche et al. [4]. Other empirical models have been used to predict solar radiation by Majumdar et al. [5] in relation to surface humidity and absolute air mass; accuracy of prediction has been found to be $\pm 10\%$ with 95% confidence limits. Al-Mohamad [6] has calculated empirically direct solar radiation as one of the solar radiation components giving a relative percentage error in the range of $\pm 3\%$ between the calculated and actual

values. Benson et al. [7] have derived daily and monthly regressions for direct solar radiation as one of the solar radiation components, which relate to sunshine duration. However, the empirical approach has tended to assume linearity in the prediction process.

The uncertain nature of solar radiation and the modeling abilities of artificial neural networks (ANNs) have inspired the application of ANN techniques to predict solar radiation [8]. ANN is an intelligent system that has the capacity to learn, memorize, and create relationships among data [9]. They simulate a human brain and are ideal for modeling nonlinear, dynamic, noise-ridden, and complex systems. According to Haykin [10], an ANN is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. ANNs have been used by Tymvios et al. [11] and Sözen et al. [12] to predict global solar radiation.

Generally, neural networks have been applied successfully in a number of application areas such as mathematics, engineering, medicine, economics, meteorology, psychology, and neurology. In particular, they have been used in a broad range of applications including pattern recognition and classification, function approximation and prediction, optimization, automatic control, constraint satisfaction, associative memory, data compression, diagnostics, multisensor data

fusion, identification, fault detection, signal processing, and tracking [8, 13–15].

Neural networks have been used in climate modeling by Krasnopolsky and Fox-Rabinovitz [16] and Dibike and Coulibaly [17], and forecasting sea surface temperature by Wu et al. [18]. ANNs have also been used in generating “loss of load probability” curves for sizing PV standalone systems [19] and prediction of performance parameters of flat-plate solar collectors [20].

This study explores the application of artificial neural networks in predicting monthly average daily direct solar radiation. The developed ANN prediction model is compared with an empirical model.

2. Literature Review of Estimation of Direct Solar Radiation

Using measured data from three Canadian stations, Iqbal [21] developed an empirical model represented by the following equation, which correlates monthly average daily beam transmittance \bar{H}_b/\bar{H}_0 with relative sunshine duration (\bar{S}/\bar{S}_0) :

$$\frac{\bar{H}_b}{\bar{H}_0} = a_1 + b_1 \left(\frac{\bar{S}}{\bar{S}_0} \right) + c_1 \left(\frac{\bar{S}}{\bar{S}_0} \right)^2, \quad (1)$$

where \bar{H}_b is the monthly average daily direct solar radiation, \bar{H}_0 is the monthly average daily extraterrestrial solar radiation, \bar{S} monthly average daily sunshine hours, and \bar{S}_0 is the average day length. The corresponding empirical coefficients a_1 , b_1 , and c_1 were -0.18 , 1.45 , and -1.12 , respectively. A standard error of estimate of 0.025 was obtained.

Ideriah [22] developed a model for computing two solar radiation components, one of which was direct solar radiation, at Ibadan, Nigeria. Deviations were within 15%, when the estimates were compared with the experimental data. Hussain [23] obtained a prediction relation by correlating monthly average daily direct solar irradiation with bright sunshine hours using data from seven locations in north and central India. Monthly estimates of direct solar irradiation were calculated and compared with measured values. Root mean square errors were within 3% and 6%, for the seven locations and other sites in India.

Nonnormalized measured data from two sites with dissimilar radiation climate was fitted by regression. The quadratic form of the regression gave the lowest standard error of estimate, 10.6% of the mean value of the direct solar irradiance. The two sites were Valentia, in Ireland ($51^\circ 56' \text{N}$, $10^\circ 15' \text{W}$) and Bet Dagan, in Israel ($32^\circ 00' \text{N}$, $34^\circ 49' \text{E}$) [24]. Mubiru et al. [25] correlated monthly average daily beam transmittance \bar{H}_b/\bar{H}_0 with monthly average daily clearness index (\bar{H}/\bar{H}_0) on a horizontal surface at a site in Kampala, Uganda (0.32°N , 32.58°E), giving a correlation coefficient of 0.967 . The correlation is represented by the following equation

$$\frac{\bar{H}_b}{\bar{H}_0} = a_2 + b_2 \left(\frac{\bar{H}}{\bar{H}_0} \right), \quad (2)$$

TABLE 1: The four study sites with their location parameters.

Station	Latitude	Longitude (degree east)	Altitude (m)
Mbarara	-0.62	30.65	1413
Lira	2.28	32.93	1189
Tororo	0.68	34.17	1170
Kampala	0.32	32.58	1220

Positive north latitude

where \bar{H} is the monthly average daily global solar radiation and a_2 , b_2 are empirical coefficients. The estimates from the resulting empirical model were compared with measured values giving a root mean square error of 0.359 and a mean bias error of -0.010 .

Zhandire [26] attempted to predict hourly direct solar radiation using artificial neural networks at a location in South Africa. A feedforward neural network was used where inputs to the network included the clearness index and the ratio $1/\cos \theta_z$ where θ_z is the zenith angle. The experimental data used was for a period from March to May. The error analysis showed the mean bias error varied between -21 and 89 W/m^2 and root mean square error between 21 and 147 W/m^2 . A small time series was used in this study and therefore the results may not be quite conclusive.

3. Test Area and Data

Table 1 shows four locations that have been selected and used for the study. The direct solar radiation was measured as an additional parameter from a Kipp and Zonen CSD-1 sensor with an accuracy of $\pm 50 \text{ W/m}^2$. Global solar irradiation data was measured using a Kipp and Zonen CM6B Pyranometer. The direct and global solar irradiation was measured from 2003 to 2005. Sunshine hours' were obtained using a Kipp and Zonen CSD 1 sunshine duration sensors and covers the same period as the solar irradiation data. The maximum temperature data was obtained from the Uganda Meteorological Department and covers a period from 1993 to 2005. Monthly average daily values of these parameters were computed and used in this study. The monthly average daily extraterrestrial solar irradiation \bar{H}_0 and average day length \bar{S}_0 were calculated from expressions defined by Duffie and Beckmann [27].

4. Feedforward Neural Network

This study employed a feedforward neural network. A typical neural network consists of an input, a hidden, and output layer. Other components include a neuron, weight, and a transfer function. Figure 1 shows a typical neuron in a feedforward network. An input x_j is transmitted through a connection that multiplies its strength by a weight $w_{i,j}$ to give a product $x_j w_{i,j}$. This product is an argument to a transfer function f which yields an output y_i represented by the

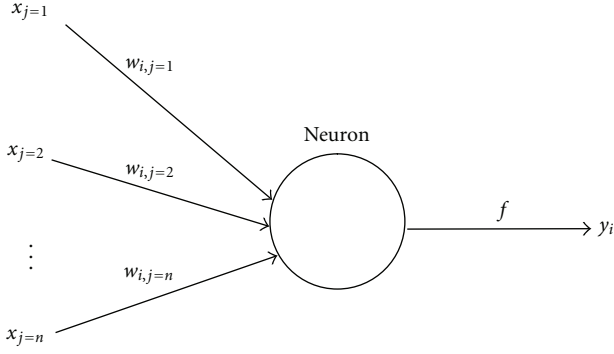


FIGURE 1: Typical neuron in a feedforward network.

following equation this kind of interaction is reflected in a process referred to as training:

$$y_i = f\left(\sum_{j=1}^n x_j w_{i,j}\right), \quad (3)$$

where i is an index of neuron in hidden layer and j is an index of an input to the network.

A training process requires an algorithm which directs learning within an artificial neural network. Backpropagation is one of the existing training algorithms. The former minimizes the mean square difference between the network output and the desired output. The associated error function is expressed as follows; minimizing this error function results in an updating rule to adjust the weights of the connections between neurons:

$$E = \left(\frac{1}{P}\right) \sum_p \sum_k (d_{pk} - o_{pk})^2, \quad (4)$$

where p is a pattern index, k is an index of elements in the output vector, d_{pk} is the k th element in the target vector in the p th pattern, o_{pk} is the k th element in the output vector in the p th pattern, and P is the total number of training patterns.

The process of presenting an input-output pair, computing the error function and updating the weights continues until the error function reaches a prespecified value or the weights no longer change. At this point the training process stops, then testing and operation of the new network is pursued [28, 29].

5. Experimental Procedure

The data from the four study sites was split into two such that the dataset (36 sets) from three stations, that is, Mbarara, Lira and Tororo, was used for *training* the ANN and building the empirical model. The dataset (12 sets) from the Kampala station was reserved for *validating* both the ANN and empirical models. 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 [30].

Figure 2 shows a proposed artificial neural network model. It is a feedforward backpropagation network with the following six input variables: latitude Lat, longitude Lon, altitude Alt, monthly average daily values of global solar irradiation \bar{H} , sunshine hours \bar{S} , and maximum temperature T_{\max} . The output variable is monthly average daily direct solar irradiation \bar{H}_b . Three transfer functions were investigated, which included the tangent sigmoid, log sigmoid, and linear functions. One-hidden and two-hidden layer architectures were tested in which the number of neurons was varied. Twelve backpropagation training algorithms were tested in order to obtain the most suitable for the training process. A description of these algorithms can be found in the MATLAB manual by Demuth and Beale [31]. Overall, the following is an outline of the procedure used in the development of the ANN model [32].

- (i) Normalize input and target values, in the range 1 to -1.
- (ii) Define matrix size of the dataset.
- (iii) Partition and create training and validation sub-datasets.
- (iv) Create a feedforward neural network.
- (v) Train the feedforward neural network.
- (vi) Generate output values.
- (vii) Unnormalize the output values.
- (viii) Check performance of the neural network by comparing the output values with target values.

The MATLAB version 6.5 program was utilized in this study.

Estimated values were compared with measured values through correlation and error analysis. The latter was carried out through computation of mean bias error (MBE) and root mean square error (RMSE), represented by the following equations

$$\begin{aligned} \text{MBE} &= \frac{\left(\sum_{i=1}^N (y_i - x_i)\right)}{N}, \\ \text{RMSE} &= \sqrt{\frac{\left(\sum_{i=1}^N (y_i - x_i)^2\right)}{N}}, \end{aligned} \quad (5)$$

where y_i is an estimated value, x_i is a measured value, and N is equal to the number of observations.

6. Results and Discussions

6.1. Modeling Using Artificial Neural Networks. The linear transfer function was fixed at the output layer while the sigmoid tangent and log sigmoid functions were tested in the hidden layer. Results in usage of either sigmoid transfer functions in the hidden layer did not show a significant difference. The tangent sigmoid transfer function was chosen, though. Similarly, there was no significant difference when two hidden layers were used as compared to one hidden layer. One-hidden layer was used in order to minimize the

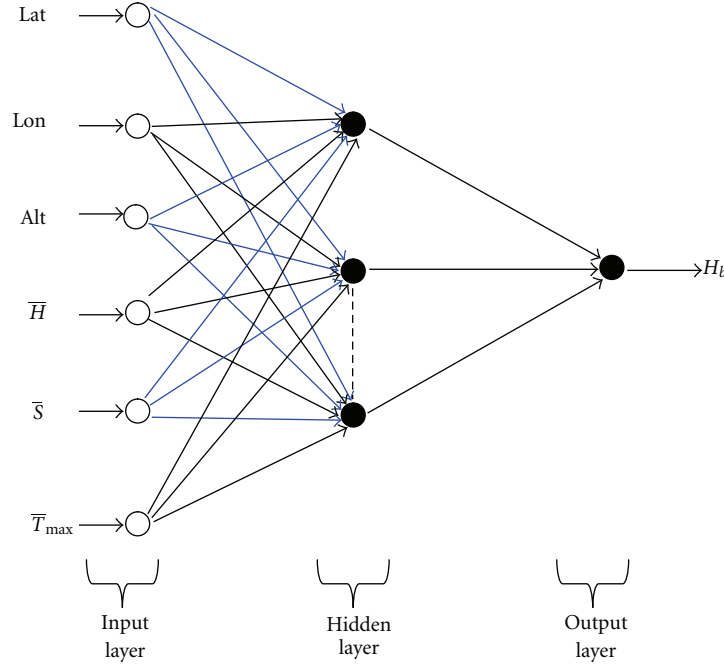


FIGURE 2: Artificial neural network structure.

complexity of the proposed ANN model. Among the twelve training algorithms investigated, the Levenberg-Marquardt gave a correlation coefficient r of over 0.96 when the measured values were correlated with the estimated values. After several trials, six neurons were found to be the most appropriate for the training process.

The estimates obtained from the proposed ANN model were correlated with the measured values, giving a correlation coefficient r of 0.998. The corresponding MBE was 0.005 MJ/m^2 and the RMSE was 0.197 MJ/m^2 . These results indicate a good fitting between the estimated and measured monthly average daily direct solar irradiation values.

6.2. Modeling Using Empirical Method. The monthly average daily beam transmittance was correlated with monthly average daily relative sunshine duration and with monthly average daily clearness index, transforming (1) and (2), respectively, into

$$\frac{\bar{H}_b}{\bar{H}_0} = -0.370 + 1.741 \left(\frac{\bar{S}}{\bar{S}_0} \right) - 0.900 \left(\frac{\bar{S}}{\bar{S}_0} \right)^2, \quad (6)$$

$$\frac{\bar{H}_b}{\bar{H}_0} = -0.232 + 0.964 \left(\frac{\bar{H}}{\bar{H}_0} \right). \quad (7)$$

Estimates of monthly average daily direct solar irradiation were computed using both (6) and (7) and then compared with the measured values. Results showed correlation coefficient r equal to 0.892 and 0.907, respectively; the MBE was 0.088 and -0.177 , respectively, and RMSE was equal to 1.275 and 1.196, respectively. Overall results showed (7) as a better empirical formulation than (6).

TABLE 2: Results of correlation and error analysis.

Model	r	MBE (MJ/m^2)	RMSE (MJ/m^2)
ANN	0.998	0.005	0.197
Equation (6)	0.892	0.088	1.275
Equation (7)	0.907	-0.177	1.196

6.3. Comparison between the ANN and Empirical Model. Table 2 shows results of correlation and error analysis for the ANN and empirical models. The estimates from (7) were compared with those from the proposed ANN model and the results showed the superiority of the ANN model. Further still, Figures 3, 4, 5, and 6 show a similar trend for the measured, neural network (NN) and empirically estimated values of direct solar irradiation, at all the four stations. However, the empirical model overestimates the direct solar irradiation in Mbarara and Lira and underestimates in Tororo and Kampala stations, throughout the year. The over- and underestimation tendencies of the empirical model are due to the fact that such a model does not ably capture all the radiative complexities typical of direct solar radiation. The ANN model does this more appropriately.

7. Conclusions

An artificial neural network model has been developed, which could be used to estimate monthly average daily direct solar radiation at four locations in Uganda, and at locations with similar climate. The ANN architecture designed is a feedforward backpropagation with one hidden layer containing six neurons with tangent sigmoid as the transfer

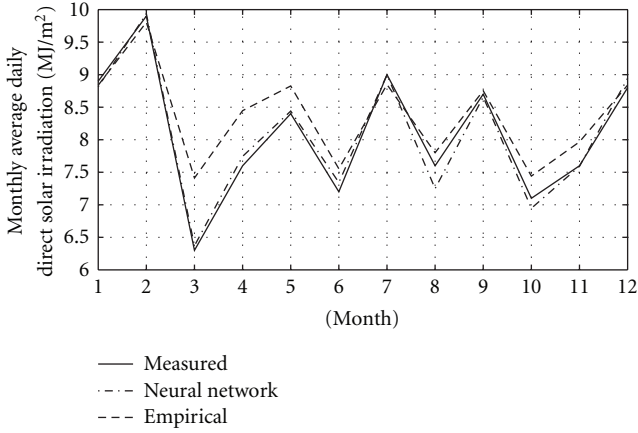


FIGURE 3: Comparison of neural networks and empirical models for Mbarara site.

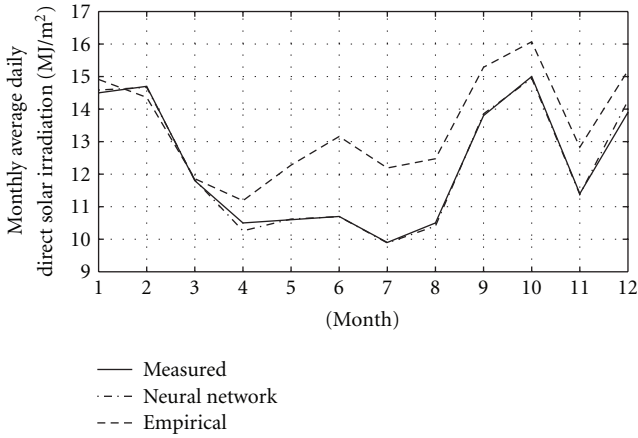


FIGURE 4: Comparison of neural networks and empirical models for Lira site.

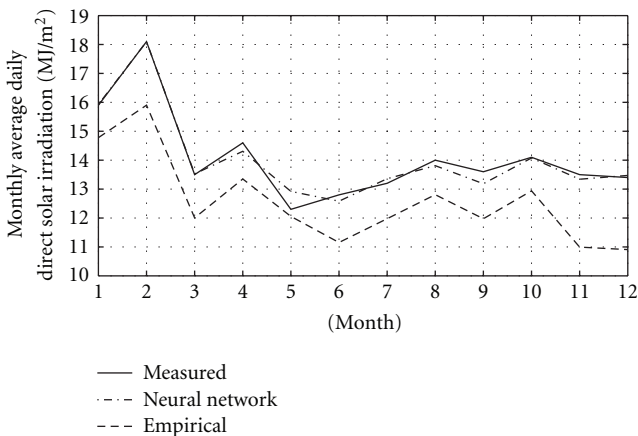


FIGURE 5: Comparison of neural networks and empirical models for Tororo site.

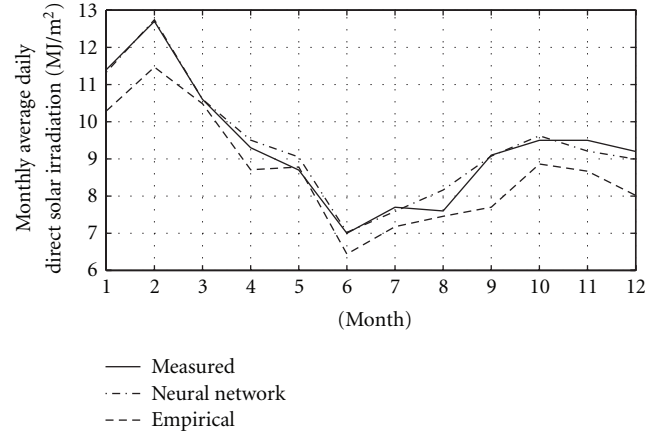


FIGURE 6: Comparison of neural networks and empirical models for Kampala site.

function. The output layer utilized a linear transfer function. The training algorithm used was the Levenverg-Marquardt. The input variables to the ANN model are monthly average daily values of global solar irradiation, sunshine hours, and maximum temperature together with latitude, longitude, and altitude of the location. The proposed ANN model proved to be superior over the empirical model in the prediction process. The ANN model is capable of capturing the nonlinear nature of solar radiation more reliably.

Nomenclature

- \bar{H}_b : Monthly average daily direct solar radiation
- \bar{H}_0 : Monthly average daily extraterrestrial solar radiation
- \bar{S} : Monthly average daily sunshine hours
- \bar{S}_0 : Average day length
- \bar{H} : Monthly average daily global solar radiation
- \bar{T}_{max} : Monthly average daily maximum temperature
- ANN: Artificial neural networks
- NN: Neural networks
- Lat: Latitude
- Lon: Longitude
- Alt: Altitude
- r : Correlation coefficient
- MBE: Mean bias error
- RMSE: Root mean square error.

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