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Estimation of monthly average daily global solar irradiation using artificial neural networks

J. Mubiru *, E.J.K.B. Banda

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

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Abstract

This study explores the possibility of developing a prediction model using artificial neural networks (ANN), which could be used to estimate monthly average daily global solar irradiation on a horizontal surface for locations in Uganda based on weather station data: sunshine duration, maximum temperature, cloud cover and location parameters: latitude, longitude, altitude. Results have shown good agreement between the estimated and measured values of global solar irradiation. A correlation coefficient of 0.974 was obtained with mean bias error of 0.059 MJ/m^2 and root mean square error of 0.385 MJ/m^2. The comparison between the ANN and empirical method emphasized the superiority of the proposed ANN prediction model.

Keywords: Artificial neural networks; Global solar irradiation; Sunshine hours; Cloud cover; Maximum temperature; Model

1. Introduction

Direct applications of solar energy include solar drying and solar water heating while indirect applications include generation of electricity using solar photovoltaic systems, among other applications. Assessing performance of these solar systems is necessary in order to optimize their layout and size (Hammer et al., 2003; Helwa et al., 2000; Lingamgunta and Veziroglu, 2004). Such a procedure requires a database of solar radiation for locations for which the systems are being assessed. Solar radiation data is also required in modeling a building's thermal performance (Williamson and Erell, 2001) and as input into ecological and crop models (Grant et al., 2004; Suzaki et al., 2003). Solar radiation data can be provided through measurements but it is difficult to have measurements from all locations of interest. Measuring instruments are expensive to purchase, install and maintain. An alternative to obtaining solar radiation data is to estimate it using an appropriate solar radiation model.

According to Mihalakakou et al. (2000) and Tymvios et al. (2005), the most popular estimation models are analytic, stochastic, empirical and of recent artificial neural networks models. Analytic models are based on knowledge of laws governing a phenomenon under study. Differential equations or parameterized expressions are employed. In solar radiation predictions, such models consider physical interactions between solar radiation and terrestrial atmosphere. Dagestad (2005) has used such a model to estimate global solar radiation at ground level. The development of such models is difficult taking into account that the information about the phenomenon is often incomplete, the initial and boundary conditions of the problem cannot always be clearly specified and sometimes requires a large number of unavailable input parameters.

Stochastic models such as autoregressive models are essentially linear models and are incapable of adequately

* Corresponding author. Tel.: +256 772413517; fax: +256 41321401.
E-mail address: jwm_mubiru@yahoo.com (J. Mubiru).

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simulating non-linear nature of dynamic processes. Zeroual et al. (1995) have used such a model in the prediction of solar radiation.

Empirical models exploit empirical relationships between solar radiation and existing climatic parameters. Angstrom (1924) pioneered this method. Sometimes, the relationships are masked by noise, which increases the uncertainty in the predictions. Much as the empirical method has been used quite widely, to estimate global solar radiation (by several authors, such as Mosalam Shalout et al., 2001; Paulescu and Schlett, 2004; Samuel, 1991; Srivasta et al., 1993), this method has not met the desirable accuracy required of a reliable prediction model because it does not wholly capture non-linearity characteristics exhibited by solar radiation. It is in this respect that several authors, such as Hontoria et al. (2002), Reddy and Ranjan (2003) and Mellit et al. (2005) have explored the use of artificial neural networks' (ANN), to estimate global solar radiation.

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

The present study explores the possibility of developing a model using artificial neural networks method, which could be used to estimate global solar irradiation on a horizontal surface, based on weather station data: sunshine duration, maximum temperature, cloud cover and location parameters: latitude, longitude, altitude. The weather station data is easily accessible. Four stations are chosen for the study and the data collected from these stations is split into two sets. The first dataset includes data from three stations which is used for building the model and the other set has data for one station to be used for validating the model. The simulated values are compared with measured pyranometer data.

2. A review of estimation of global solar radiation

Mubiru et al. (2007) assessed the performance of 13 old and new global solar radiation empirical formulations (Aksoy, 1997; Almorox et al., 2005; Angstrom, 1924; Elagib and Mansell, 2000; Gopinathan, 1988; Jain and Jain, 1985; Newland, 1989; Ogelman et al., 1984; Oturanc et al., 2003; Togrul and Togrul, 2002), in Kampala, Uganda. Results showed that the quadratic formulation relating clearness index $\overline{H}/\overline{H}_0$ to relative sunshine duration $\overline{S}/\overline{S}_0$ was the most appropriate for the estimation of monthly average daily global solar irradiation. The corresponding mean bias error (MBE) was 0.004 MJ/m^2 and root mean square error (RMSE) as 1.670 MJ/m^2.

Due to the very nature of solar radiation, many parameters can influence both its intensity and availability and such an influence can be quite complex (Tymvios et al., 2005). It follows that Alawi and Hinai (1998) have used ANN to predict solar radiation. The input data to the network included: location parameters, month, averages of pressure, temperature, vapor pressure, relative humidity, wind speed and sunshine duration. The corresponding ANN model predicted with an accuracy of 7.3% as the mean absolute percentage error.

Mohandes et al. (1998) used data from 41 stations in Saudi Arabia of which data from 31 stations was used in training the network and data from the other 10 stations for testing. Input variables to the network included: latitude, longitude, altitude and sunshine duration. The results were within 16.4% accuracy.

Tymvios et al. (2005) has trained seven ANN models using daily values of measured sunshine duration, theoretical sunshine duration, maximum temperature and the month number. The period of data collection was 1986–1992 at a location at Athalassa, Cyprus situated at latitude 35°08′N, longitude 33°23′E, altitude 161 m. Back-propagation method was used with tangent sigmoid as the transfer function. Two-hidden layers with neurons varying between 23 and 46 were investigated. The best performing ANN model was one with all inputs except the month number and its result showed a MBE and RMSE of 0.12% and 5.67%, respectively. Tymvios et al. (2005) also illustrated the use of a one-layer architecture ANN model.

Sozen et al. (2004) created two datasets, using measured data from seventeen stations in Turkey collected between 2000 and 2002. One set with data for 11 stations was used for training a neural network and the other dataset from six stations was used for testing. The back-propagation method was used with one- and two-hidden layers. The other settings were conjugate gradient and Levenberg–Marquardt as training algorithms, sigmoid as transfer function and the number of neurons varied between 4 and 9. The inputs to the network were: latitude, longitude, altitude, month, averages of sunshine duration and temperature. The output was solar radiation and results showed a maximum mean absolute percentage error of less than 6.7%.

Mihalakakou et al. (2000) split data into two sets collected from a location in Athens situated at latitude 37.967°N, longitude 23.717°E and altitude 107 m. The portion measured from 1984 to 1992 was used in training a neural network and that measured between 1993 and 1995 was used for testing. A multi-layer feed-forward network based on back-propagation algorithm was designed to predict time series of global solar radiation. The selected ANN architecture consisted of one-hidden layer with 16 log sigmoid neurons and an output layer with one linear neuron. Results showed that the differences between the predicted and measured values of global solar radiation were less than 0.2%.

Elminir et al. (2005) used data collected between 2001 and 2002 at an urban area in Helwan, Egypt (latitude 29°52′N, longitude 31°20′E) to determine solar radiation in different spectrum bands using an ANN model. Inputs to the ANN model included daily values of wind direction, wind velocity, ambient temperature, relative humidity and cloud cover. The back-propagation algorithm was used with one-hidden layer and a sigmoid transfer function. The corresponding prediction accuracy was approximately 94.5%.

Kemmoku et al. (1999) used multi-stage neural network to forecast daily insolation in Omaezaki Japan, resulting into a mean error of about 20% while that of a single-stage neural network was about 30%. Input data included atmospheric pressure (in various formats) and temperature running from 1988 to1993. The number of neurons in the hidden layer varied between 8 and 18.

From the above review, it has been observed that much of the utilization of ANN in the prediction of global solar radiation has been confined in Europe, USA, Far East, Middle East and Northern Africa. There is limited or no usage of ANN to develop models for solar radiation prediction in eastern, central and southern Africa. This paper explores the development and subsequent usage of the ANN model in such locations.

3. Test area and data

Table 1 shows four locations that have been selected and used for the study. The same table shows some of the climate parameters for these locations. It is observed that Kampala and Mbarara stations exhibit wetter and more humid conditions than the other two stations. Lira and Tororo stations register longer sunshine durations. The wetter stations are located at higher altitudes than the other study stations. However, all the four stations are generally characterized by scattered bushes and short grass.

Global irradiation data was measured on an hourly basis and a daily value recorded at the end of the day. The measurements were carried out from April 2003 to December 2005, on a horizontal surface, using Kipp and Zonen CM6B Pyranometers installed at the four locations. The measured global irradiation data was validated using a service at the website: http://www.helioclim.net (Geiger et al., 2002). A CM6B Pyranometer complies with the specification for first class of World Meteorological Organization classification of pyranometers. Its response time is less than 30 s and is characterized by a non-linearity deviation of ±1.2%. Just like any other pyranometer, the sensitivity of the CM6B pyranometer is determined in the manufacturer's laboratory, by comparison with a standard pyranometer. Sensitivity of a pyranometer changes with time and with exposure to radiation. In this respect, a re-calibration is performed once every 2 years, as recommended by Kipp & Zonen, the manufacturer.

Sunshine duration (h) were measured using Kipp and Zonen CSD 1 sunshine duration sensors and covers the same period as the global irradiation data. The maximum temperature (°C) and cloud cover (oktas) data was obtained from the Uganda Meteorological Department and covers a period between 1993 and 2005. Monthly average daily values of these parameters were computed and used in this study. The extraterrestrial solar irradiation $\overline{H}_0$ and maximum possible sunshine hours $\overline{S}_0$ were calculated from expressions defined by Duffie and Beckmann (1980). Daily extraterrestrial solar radiation H_0 incident on a horizontal surface (in J) is given by the following equation:

$$H_0 = (86,400G_{sc}/\pi)(1 + 0.033\cos(360n/365)) \times (\cos\phi\cos\delta\sin\omega_s + (2\pi\omega_s/360)\sin\phi\sin\delta) \quad (1)$$

where δ is the solar declination, ϕ is the latitude of location in the range $-90° \leqslant \phi \leqslant +90°$, ω_s is the sunset hour angle represented by the following equation:

$$\omega_s = \arccos(-\tan\delta\tan\phi) \quad (2)$$

The sunset hour angle ω_s is also utilized in the computation of maximum possible sunshine hours S_0 from the following equation:

$$S_0 = (2/15)\omega_s \quad (3)$$

4. An overview of artificial neural networks

Artificial neural networks (ANN) are intelligent systems that have the capacity to learn, memorize and create relationships among data. ANN are able to learn key information patterns within a multidimensional information domain (Kalogirou, 2001). In a way, ANN mimic the learning process of a human brain and therefore do not

Table 1
The four study sites with their location and climate parameters

Station	Latitude	Longitude (°E)	Altitude (m)	Annual average sunshine (h)	Annual average cloud (oktas)	Annual average relative humidity	Annual average rainfall (mm)
Mbarara	−0.62	30.65	1413	5.5	5.9	70.8	1438
Lira	2.28	32.93	1189	7.6	4.2	61.2	1250
Tororo	0.68	34.17	1170	6.7	5.5	65.5	1125
Kampala	0.32	32.58	1220	6.0	6.0	69.8	1375

Positive north latitude.

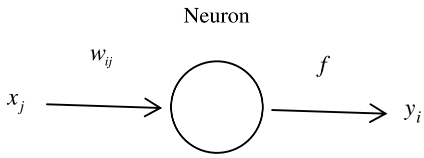

Fig. 1. Typical neuron in a two-layer feedforward neural network.

need characteristic information about the system; instead, they learn the relationship between input parameters and the output variables by studying previously recorded data (Kalogirou, 2000).

A typical neural network consists of an input, a hidden (or intermediate) and output layer. Other components include a neuron, weight and a transfer function. Fig. 1 shows a typical neuron in a neural network. An input x_j is transmitted through a connection which multiplies its strength by a weight w_{ij} to give a product $x_j w_{ij}$. This product is an argument to a transfer function f which yields an output y_i represented by Eq. (4). Such iterative makes up the *training* process:

$$y_i = f\left(\sum_{j=1}^{n} x_j w_{ij}\right) \tag{4}$$

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

Training is the process of modifying the connection weights in some orderly fashion using a suitable learning method or training algorithm. A neural network uses a learning mode, in which an input is presented to the network along with a desired output and the weights are adjusted so that the neural network attempts to produce the desired output. The weights after training contain meaningful information pertaining to the phenomenon being trained (Kalogirou, 1999).

Back-propagation is one of the available forms of neural networks and there are different training algorithms associated with it, such as Gradient descent and Levenberg–Marquardt. Back-propagation algorithms are ideal for multi-layer feedforward neural networks. A back-propagation training algorithm minimizes the mean square difference between the network output and the desired output. The associated error function is expressed as Eq. (5); minimizing this error function results in an updating rule to adjust the weights of the connections between neurons:

$$E = (1/P)\sum_{p}\sum_{k}(d_{pk} - o_{pk})^2 \tag{5}$$

where p is a pattern index, k is an index of elements in the output vector, d_{pk} is the kth element in the target vector in the pth pattern, o_{pk} is the kth element in the output vector in the pth 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 pre-specified value or the weights no longer change. At this point the training process stops, then testing and operation of the new network is pursued (Mohandes et al., 2000; Ghiassi et al., 2005).

The nature and complexity of the phenomenon to be trained will detect the structure of the neural network in terms of the number of hidden layers, number of neurons in these layers, training algorithm and the transfer function used. In retrospect, artificial neural networks are ideal for modeling non-linear, dynamic, noise-ridden and complex systems. In particular, ANN are good for tasks involving incomplete data sets, fuzzy or incomplete information and for highly complex and ill-defined problems (Kalogirou, 2000).

5. Experimental procedure

The data from the four sites were split into two such that the dataset from three stations, that is, Mbarara, Lira and Tororo, was used for *training* a neural network and formulating an empirical model. The dataset from the Kampala station was reserved for *validating* both the ANN and empirical models.

A feedforward back-propagation neural network was used in this study, with six input variables, which included: sunshine hours, cloud cover and maximum temperature, together with latitude, longitude and altitude. Three transfer functions were investigated including the tangent sigmoid, log sigmoid and linear functions. Further, both a one-hidden and two-hidden layer architecture were tested in which the number of neurons was varied. Twelve back-propagation training algorithms were tested in order to obtain the most appropriate for the training process. The algorithms included: Gradient descent, Gradient descent with momentum, Adaptive learning rate, Resilient back-propagation, Fletcher–Reeves conjugate gradient, Polak–Ribiere conjugate gradient, Powell–Beale conjugate gradient, Scaled conjugate gradient, BFGS quasi-Newton, One step secant method, Levenberg–Marquardt and Bayesian regularization. A description of these algorithms can be found in the MathLab manual by Demuth and Beale (1998). The MathLab version 6.5 program was utilized in this study. The following is an outline of the procedure used in the development of the ANN model:

(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) Un-normalize the output values.
(viii) Check performance of the neural network by comparing the output values with target values.

This study required a comparison between the ANN model and an empirical model. It followed that clearness index, $\overline{H}/\overline{H}_0$ was correlated with relative sunshine duration, $\overline{S}/\overline{S}_0$. Empirical coefficients of the quadratic expression were obtained and used to build the empirical model suggested by Mubiru et al. (2007) for a location in Uganda.

Simulated 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:

$$\mathrm{MBE} = \left(\sum_{i=1}^{N}(y_i - x_i)\right)\Big/N \tag{6}$$

$$\mathrm{RMSE} = \sqrt{\left(\sum_{i=1}^{N}(y_i - x_i)^2\right)\Big/N} \tag{7}$$

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

6. Results and discussion

6.1. Modeling using artificial neural networks

The linear transfer function was fixed at the output layer while the tangent sigmoid and log sigmoid functions were tested in the hidden layer. Results from using either sigmoid transfer functions in the hidden layer did not show significant difference. Nevertheless, the tangent sigmoid transfer function was chosen. Similarly, there was no significant difference between the use of a two-hidden layer and one-hidden layer. One-hidden layer was used in order to minimize on the complexity of the proposed ANN model. Among the 12 training algorithms investigated, the Levenberg–Marquardt gave a correlation coefficient of over 0.96 when the measured values were correlated with the simulated values. After several trials, 15 neurons were found to be appropriate for the training process.

Estimates obtained for the validation site (Kampala), from the proposed ANN model were correlated with the measured values giving a correlation coefficient of 0.974. The corresponding MBE was 0.059 MJ/m^2 and the RMSE was 0.385 MJ/m^2. These results indicate an acceptable fitting between the estimated and measured global solar irradiation values.

6.2. Modeling using empirical method

Correlating $\overline{H}/\overline{H}_0$ with $\overline{S}/\overline{S}_0$ using data from the three training sites, gave Eq. (8). Estimates of global solar irradiation were computed using Eq. (8) for the validation site and then compared with the measured values through correlation and calculation of MBE and RMSE. Results gave a correlation coefficient of 0.958, a MBE and RMSE as equal to 1.280 and 1.522 MJ/m^2, respectively. These results are inferior to those obtained with the proposed ANN model:

$$\overline{H}/\overline{H}_0 = 0.019 + 1.295(\overline{S}/\overline{S}_0) - 0.548(\overline{S}/\overline{S}_0)^2 \tag{8}$$

6.3. Comparison tests

Fig. 2 shows a comparison between estimates from ANN and empirical models and measured values for the validation station (Kampala). The graphical comparison between the ANN estimates and the measured values show a marked, though small, combination of under-estimation and over-estimation of the global solar irradiation during the last half of the year, at the validation station. On the other hand, there is a general over-estimation of global solar irradiation by the empirical model. The empirical model exhibits linear tendencies, contrary to the nature and availability of solar radiation. Further, the number of independent parameters that can be used by the empirical model is limited. The ANN model can take on more processed or unprocessed input parameters, in pursuit of an appropriate model. In retrospect, Fig. 2 shows a few instances where the predictions of the ANN model deviates from the measured values. This can be attributed to the fact that the input variables fed into the proposed ANN model may not have, entirely, described the non-linearity nature of global solar radiation. However, the neural network model is able to explore, learn and simulate the uncertain nature of global solar radiation to an acceptable level of accuracy.

Table 2 shows comparison between the mean absolute percentage error (normalized MBE) of the proposed ANN model and the mean absolute percentage errors of five selected ANN models, cited in Section 2. The proposed ANN model gives a smaller mean absolute percentage error than three out of the five selected ANN models.

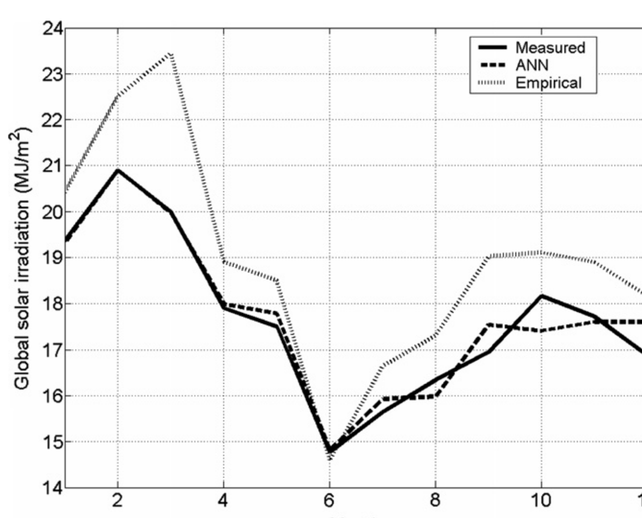

Fig. 2. Comparison between estimates from ANN and empirical models and measured values for the validation station (Kampala).

Table 2
Comparison between the mean absolute percentage error of the proposed ANN model and that of five selected ANN models

Model by author	Mean absolute percentage error
Proposed ANN model	0.3
Alawi and Hinai (1998)	7.3
Mohandes et al. (1998)	16.4
Tymvios et al. (2005)	0.12
Sozen et al. (2004)	6.7
Mihalakakou et al. (2000)	0.2

ANN models attributed to Tymvios et al. (2005) and Mihalakakou et al. (2000) give the least mean absolute percentage error values. This can be attributed to the fact that, data running for a longer period was used in the development of these two ANN models and this data was obtained from a single site, for each case.

7. Conclusions

An artificial neural network model has been developed that could be used to estimate monthly average daily global solar radiation on a horizontal surface for locations in Uganda and others with similar climate and terrain. The ANN architecture designed is a feedforward back-propagation with one-hidden layer containing 15 neurons with tangent sigmoid as the transfer function. The output layer utilized a linear transfer function. The training algorithm used was the Levenberg–Marquardt and the input variables to the ANN model are sunshine hours, cloud cover, maximum temperature together with latitude, longitude and altitude of location. The proposed ANN model proved to be superior over the empirical model because it is capable of reliably capturing the non-linearity nature of solar radiation. The empirical method is based on the principle of linearity.

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References

Aksoy, B., 1997. Estimated monthly average global radiation for Turkey and its comparison with observations. Renewable Energy 10, 625–633.

Alawi, S., Hinai, H., 1998. An ANN based approach for predicting global solar radiation in locations with no direct measurement instrumentation. Renewable Energy 14, 199–204.

Almorox, J., Benito, M., Hontoria, C., 2005. Estimation of monthly Angstrom–Prescott equation coefficients from measured daily data. Renewable Energy 30, 931–936.

Angstrom, A., 1924. Solar and terrestrial radiation. Quarterly Journal of the Royal Meteorological Society 50, 121–125.

Dagestad, K., 2005. Estimating global radiation at ground level from satellite images. Ph.D. Thesis, Department of Meteorology, University of Bergen, Norway.

Demuth, H., Beale, M., 1998. Neural Network Toolbox: User's Guide Version 3.0. MathWorks Inc.

Duffie, J.A., Beckmann, W.A., 1980. Solar Engineering of Thermal Processes. Wiley–Interscience Publication, New York (Chapter 1–3).

Elagib, N.A., Mansell, M.G., 2000. New approaches for estimating global solar radiation across Sudan. Energy Conversion and Management 41, 419–434.

Elminir, H.K., Areed, F.F., Elsayed, T.S., 2005. Estimation of solar radiation components incident on Helwan site using neural networks. Solar Energy 79, 270–279.

Geiger, M., Diabate, L., Menard, L., Wald, L., 2002. A web service for controlling the quality of measurements of global solar irradiation. Solar Energy 73 (6), 475–480.

Ghiassi, M., Saidane, H., Zimbra, D.K., 2005. A dynamic artificial neural network model for forecasting time series events. International Journal of Forecasting 21, 341–362.

Gopinathan, K.K., 1988. A new model for estimating total solar radiation. Solar and Wind Technology 5 (1), 107–109.

Grant, R.H., Hollinger, S.E., Hubbard, K.G., Hoogenboom, G., Vanderlip, R.L., 2004. Ability to predict daily solar radiation values from interpolated climate records for use in crop simulation models. Agricultural and Forestry Meteorology 127, 65–75.

Hammer, A., Heinemann, D., Hoyer, C., Kuhlemann, R., Lorenz, E., Muller, R., Beyer, H.G., 2003. Solar energy assessment using remote sensing technologies. Remote Sensing Environment 86, 423–432.

Helwa, N.H., Bahgat, A.B.G., El Shafee, A.M.R., El Shenawy, E.T., 2000. Computation of the solar energy captured by different solar tracking systems. Energy Sources 22, 35–44.

Hontoria, L., Aguilera, J., Zufiria, P., 2002. Generation of hourly irradiation synthetic series using the neural network multilayer perceptron. Solar Energy 72 (5), 441–446.

Jain, S., Jain, P.C., 1985. A comparison of the Angstrom-type correlations and the estimation of monthly average daily global irradiation. ICIP Internal Report No. IC/85/264.

Kalogirou, S.A., 1999. Applications of artificial neural networks for energy systems. A review. Energy Conversion and Management 40, 1073–1087.

Kalogirou, S.A., 2000. Applications of artificial neural-networks for energy systems. Applied Energy 67, 17–35.

Kalogirou, S.A., 2001. Artificial neural networks in renewable energy systems applications: a review. Renewable and Sustainable Energy Reviews 5, 373–401.

Kalogirou, S.A., 2004. Optimization of solar systems using artificial neural-networks and genetic algorithms. Applied Energy 77, 383–405.

Kemmoku, Y., Orita, S., Nakagawa, S., Sakakibara, T., 1999. Daily insolation forecasting using a multi-stage neural network. Solar Energy 66 (3), 193–199.

Knutti, R., Stocker, T.F., Joos, F., Plattner, G.K., 2003. Probabilistic climate change projections using neural networks. Climate Dynamics 21, 257–272.

Lingamgunta, C., Veziroglu, T.N., 2004. A universal relationship for estimating clear sky insolation. Energy Conversion and Management 45, 27–52.

Mellit, A., Benghanem, M., Arab, A.H., Guessoum, A., 2005. A simplified model for generating sequences of global solar radiation data for isolated sites: using artificial neural network and library of Markov transition matrices approach. Solar Energy 79, 469–482.

Mihalakakou, G., Santamouris, M., Asimakopoulos, D.N., 2000. The total solar radiation time series simulation in Athens using neural networks. Theoretical and Applied Climatology 66, 185–197.

Mohandes, M., Rehman, S., Halawani, T.O., 1998. Estimation of global solar radiation using artificial neural networks. Renewable Energy 14 (1–4), 179–184.

Mohandes, M., Balghonaim, A., Kassas, M., Rehman, S., Halawani, T.O., 2000. Use of radial basis functions for estimating monthly mean daily solar radiation. Solar Energy 68 (2), 161–168.

Mosalam Shalout, M.A., Hassan, A.H., Fathy, A.M., 2001. Study of the solar radiation over Menia. Renewable Energy 23, 621–639.

Mubiru, J., Banda, E.J.K.B., D'Ujanga, F., Senyonga, T., 2007. Assessing the performance of global solar radiation empirical formulations in Kampala, Uganda. Theoretical and Applied Climatology 87 (1–4), 179–184.

Newland, F.J., 1989. A study of solar radiation models for the coastal region of South China. Solar Energy 43 (4), 227–235.

Ogelman, H., Ecevit, A., Tasdemiroglu, E., 1984. A new method for estimating solar radiation from bright sunshine data. Solar Energy 33 (6), 619–625.

Oturanc, G., Hepbasli, A., Genc, A., 2003. Statistical analysis of solar radiation data. Energy Sources 25, 1089–1097.

Paulescu, M., Schlett, Z., 2004. Performance assessment of global solar irradiation models under Romanian climate. Renewable Energy 29, 767–777.

Reddy, K.S., Ranjan, M., 2003. Solar resource estimation using artificial neural networks and comparison with other correlation models. Energy Conversion and Management 44, 2519–2530.

Samuel, T.D.M.A., 1991. Estimation of solar radiation for Srilanka. Solar Energy 47 (5), 333–337.

Slavisa, Trajkovic, Branimir, Todorovic, Miomir, Stankovic, 2001. Estimation of FAO Penman C factor by RBF networks. Facta Universitatis Series: Architecture and Civil Engineering 2 (3), 185–191.

Sozen, A., Arcaklioglu, E., Ozalp, M., 2004. Estimation of solar potential in Turkey by artificial neural networks using meteorological and geographical data. Energy Conversion and Management 45, 3033–3052.

Srivasta, S.K., Singh, O.P., Pandey, G.N., 1993. Estimation of global solar radiation in Uttar Pradesh (India) and comparison of some existing correlations. Solar Energy 51, 27–29.

Suzaki, T., Kume, A., Ino, Y., 2003. Evaluation of direct and diffuse radiation densities under forest canopies and validation of the light diffusion effect. Journal of Forestry Research 8, 283–290.

Togrul, I.T., Togrul, H., 2002. Global solar radiation over Turkey: comparison of predicted and measured data. Renewable Energy 25, 55–67.

Tymvios, F.S., Jacovides, C.P., Michaelides, S.C., Scouteli, C., 2005. Comparative study of Angstrom's and artificial networks' methodologies in estimating global solar radiation. Solar Energy 78, 752–762.

Williamson, T.J., Erell, E., 2001. The thermal performance simulation and the urban microclimate: measurements and prediction. In: Proceedings of the Seventh International IBPSA Conference, Rio de Janeiro, Brazil, August 13–15.

Zeroual, A., Ankrim, M., Wilkinson, A.S., 1995. Stochastic modeling of daily global solar radiation measured in Marrakesh Morocco. Renewable Energy 6 (7), 787–793.