Application of Artificial Neural Network for Estimatig Hourly Global Solar Radiation

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Abstract

In this work, we have considered the application of artificial neural network (ANN) for the estimation of hourly solar radiation. The inputs to the network are four instantaneous radiation values (irradiance) taken at 15 minutes interval. The cascade forward propagation network was used. Solar irradiance data taken at 15minutes interval between 09:00 – 12:00 hours universal time in the month of January, 2010 for our location, Akoka, Lagos (lat. 6.51^0N; lon. 3.40^0E) were used to train and simulate the network. The network was simulated with data that were not used for the training process. The MBE and RMSE obtained are 2.59kJ/m^2 , 1.88kJ/m^2 , 9.35kJ/m^2 and 8.37kJ/m^2 , 16.71kJ/$m^{2,}$ 19.95kJ/m^2 respectively for each hour during the period between 09:00 and 12:00 hours universal time.

Keywords: Artificial neural network (ANN), Normalized (digital) count, Cloud cover index, clearness index

1. Introduction

The estimation of solar radiation at the earth's surface is an important aspect of harnessing solar energy resources. Many approaches have been adopted in trying to estimate the amount of solar energy reaching the earth's surface. Artificial neural networks represent one of the recent methods researchers have adopted. Another important method is remote sensing – through satellite images. Artificial neural network (ANN) is a useful tool for predicting the amount of solar radiation reaching the earth surface. ANN have be used for forecasting [2] and estimating [3] available solar radiation. In the case of the latter, they used a combination of parameters for geographic location, time and meteorological data to train Feed-foward ANN. The results reported for locations in India had a maximum mean absolute relative deviation of predicted hourly global radiation to be 4.07% [3].

In this work, we have considered how a time varying quantity such as solar radiation can be estimated from instantaneous readings taken at definite interval through the use of artificial neural network (ANN).

The significance of this method lies in the fact that it can provide a means for estimating solar radiation from satellite images. A number of meteorological satellites produce images of the earth at specific intervals – such as those of EUMETSAT which scans the earth four periods in an hour. Researchers have proposed different methods of determining the amount of solar radiation reaching the earth surface from the images received from the satellites. The method adopted in this work will provide another means for harnessing the potentials of satellite derived data in the assessment of solar radiation reaching the earth surface.

2. Method

We have used a three layered network for this work. This is different from that reported by some authors. Dorvlo et al [7] reported the use of both the Multilayer perceptron (MLP) and Radial Basis Function (RBF) networks and commented on the suitability of these networks. We have decided to use the Cascade forward back – propagation network because its ease of use and less demand on computing time.

Our data comprise of hourly global radiation measured values between 9:00 and 12:00 hours universal time (UT) for the month of January, 2010. This was sepearted into two sets – one for training the ANN and the other for simulating the ANN.

2.1 Artificial neural network (ANN) model and training

Artificial neural networks (ANNs) are an important tool for predicting the amount of solar radiation reaching the earth [2 , 3]. ANNs are based on ideas on how biological neural networks function. They are non-linear, parallel processing systems that have the ability to learn through adaptation of its response to changes in its environment. The function of ANN is based on these properties. This gives them the power for exploring relationships between physical quantities.

We have used the Cascade-forward back propagation ANN, both of which are available in the Mathlab neural network tool box. The network consists of three layers; the first layer is the input layer and it contains 10 neurons. The second layer is a hidden layer containing 20 neurons while the third layer – the output layer – contains a neuron. The neurons in the first and second layers employ the logsigmoid transfer function while that for the output layer is purelin transfer function. We applied the resilient back propagation (trainrp) training function. This function has good converging properties and is quite fast.

2.2 Application to Solar Irradiance from Satellite Data

The principle underlining the extraction of information on ground-reaching solar radiation is the construction of a cloud index arising from the comparison of observation made by the satellite's sensor with what would be observed if the sky were clear [5]; each pixel of the image is associated with a digital count. The satellite counts are normalized to remove unwanted effects due to geometrical positions of the sun and satellite. The normalized count for an observed pixel is $C_N(i,j)$ and can be expressed as[5]:

$$C_N(i,j) = [C_N^*(i,j) - C_{N0}] / Io\ \varepsilon\ [Sin^{1.15}\gamma] \quad (1)$$

where $C_N^*(i,j)$ is the observed numerical count at that instant for pixel (I,j) C_{N0} is taken as the sensor's zero and $\sin^{1.15}\gamma$ is the clear sky transmittance model of Perrin de Brichambaut, Vauge (1982).

The normalized counts for cloud free atmosphere Cg(i,j) and for complete cloud cover Cc(i,j) where determined using equation (1). The normalized count Cg(i,j) represents the condition for clear atmosphere; the radiation sensed by the satellite's sensor is due to reflection from the earth surface. The normalized count Cc(i,j) represents the condition where the sky is cloudy. For a given pixel (i,j), the cloud cover index n' is defined as follows from [5]:

$$n' = [C_N(i,j)-Cg(i,j)) / (Cc(i,j)-Cg(i,j)] \qquad (2)$$

The cloud index obtained is then related in a linear manner with the clearness index from [1] and expressed as

$$K_T = A\, n' + B \qquad (3)$$

where K_T is the clearness index, n' is the derived cloud cover index and constants A and B are empirically determined. We have used equation (3) to determine the clearness index for intantaneous radiation.

3. Results

The results from the training show that the ANNs were able to reproduce the target accurately. This is observed from the correlation coefficient returned from plots of the output during the training of the ANNs against ground measured readings as shown in figures 1(a), 2(a), and 3(a) for the hours 09:00 – 10:00 UT, 10:00 – 11:00 UT and 11:00 – 12:00 UT respectively. Figures 1(b), 2(b) and 3(b) show the result from the simulation of the ANNs for the corresponding periods.

The MBE obtained are 2.59kJ/m^2 , 1.88kJ/m^2 and 9.35kJ/m^2 for the hours 09:00 – 10:00 UT, 10:00 – 11:00 UT and 11:00 – 12:00 UT respectively while the corresponding RMSE are 8.37kJ/m^2 , 16.71kJ/m^2 and 19.95kJ/m^2 respectively. In relative terms, the MSE are 0.016, 0.009 and 0.043 respectively while the RMSE are 0.053, 0.081 and 0.093 respectively.

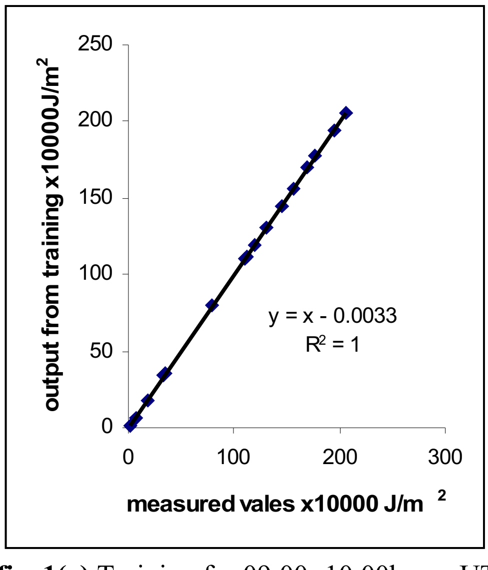

fig. 1(a) Training for 09:00- 10:00hours UT

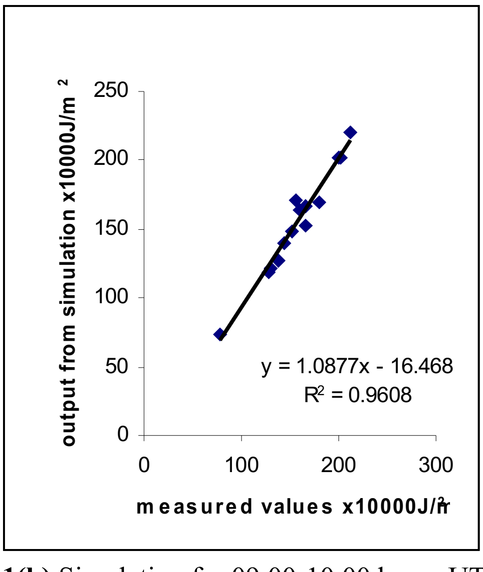

fig.1(b) Simulation for 09:00-10:00 hours UT

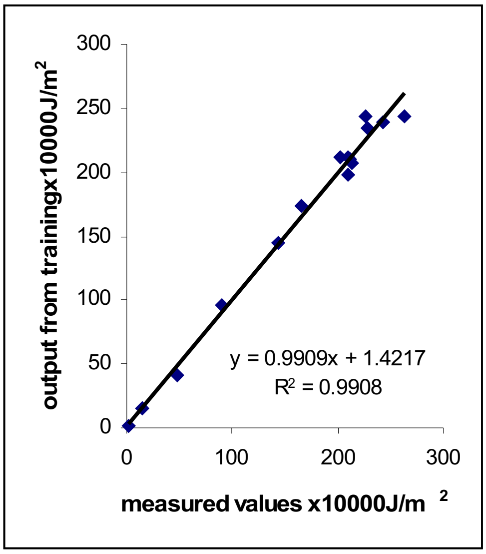

fig. 2(a) Training for 10:00- 11:00hours UT

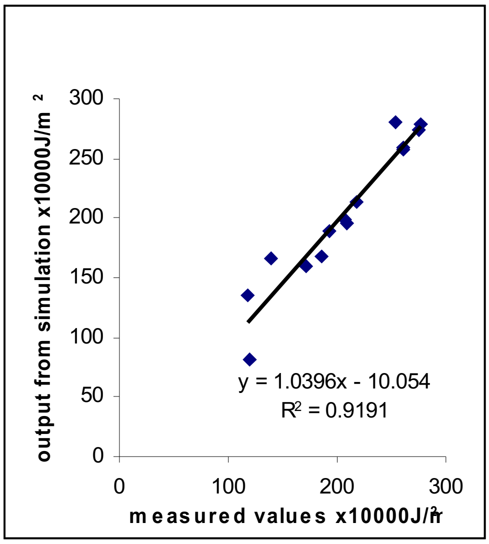

fig.2(b) Simulation for 10:00-11:00 hours UT

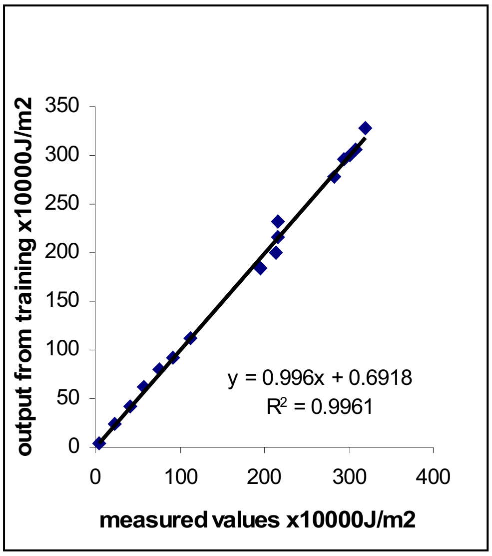

fig. 3(a) Training for 11:00- 12:00hours UT

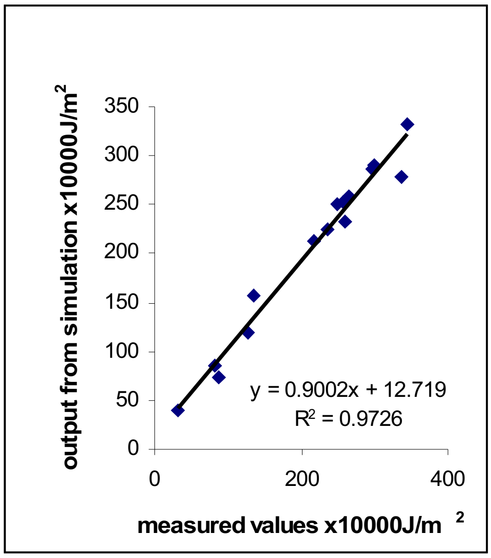

fig.3(b) Simulation for 11:00-12:00 hours UT

We next considered the possible application of this method in the derivation of solar radiation from satellite images; we adopted the method proposed by [1, 5] as have be mentioned in sub-section 2.2 and we obtained figure 4 (plotting for radiation rather than K_T). The correlation coefficient does not indicate a strong relationship between radiation and cloud cover index – this is the same situation that we observed with instantaneous radiation (irradiance) values with cloud cover index. We estimate that this could lead to large errors based on the correlation obtained for equation 3 as shown in figure 4.

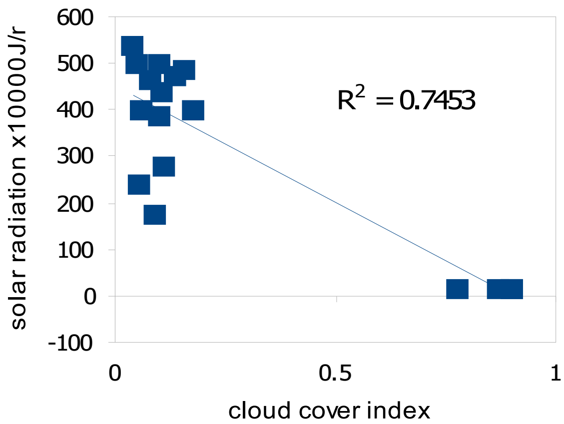

figure 4 Plot of solar radiation against cloud index from satellite data

4. Conclusion

We have considered the use of ANN for the determination of hourly global solar radiation. The results obtained show that ANN can be used to estimate the amount of hourly solar radiation reaching the earth surface from four instantaneous radiation readings taken at fifteen minutes interval. However, the potential of this method for direct determination of hourly solar radiation from satellite images is limited by the error inherent in the instantaneous radiation values that would be obtained from satellite data. An approach that utilizes a basic parameter such an image digital count or derived parameters such as satellite sensor radiance or cloud cover index would be more appropriate.

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