APPLICATION OF ARTIFICIAL NEURAL NETWORK IN ESTIMATING HOURLY GLOBAL SOLAR RADIATION FROM SATELLITE IMAGES

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Abstract

The assessment of Earth-reaching solar radiation continues to be relevant in the utilization of this form of energy. In this work, we have used satellite images of the Earth in the visible spectrum obtained from EUMETSAT and Artificial Neural Network to estimate the solar radiation at our location, Akoka (lat. 6.51^{0}N; lon 3.40^{0}E), for the months of January, February and March, 2010. The estimates were obtained for the hours between 10:00hours UT and 13:00hours UT. The reflectance of the Earth was determined for each image and from this, cloud index were estimated. The cloud index obtained for each hour for half the total number of days in the months, were used to train a Feed-forward back propagation Artificial Neural Network. Clear-sky index for the hours of the days used for the training served as target for the network. For the three months considered in their usual order, the relative values of RMSE obtained for the hours ending at 11:00, 12:00 and 13:00 were 0.0349, 0.0276, and 0.0356 while the corresponding relative MBE values were -0.120, -0.040 and 0.013.

Keywords: Artificial neural network (ANN), Satellite images, Normalized (digital) count, Cloud index, Clear-sky index , Reflectance

1. Introduction

The assessment of the amount of solar radiation reaching the Earth surface continues to play an import role in the utilization of this form of energy. Some of the early works on the use of satellite images to estimate solar irradiation reaching the Earth's surface include those of Tarpley (1979), Gautier *et al.* (1980) (from Cano (1986)) and Cano *et al.* (1986). Earlier methods involved the defining of a cloud index with respect to the properties of image pixels (digital counts). This was achieved by first normalizing the counts and then considering possible extreme cases as references on which the definition of cloud index was based. Linear regression method was used to obtain a correlation between the cloud index and a well-known parameter – the clearness index. Further developments of this approach incorporate some elements of this first methods.

Following the success of the these authors, efforts were made towards improving on this method of assessing Earth-reaching solar radiation, by some authors. Efforts, such as those by Rigollier *et al*. (2004) and Mueller *et al.* (2004) - reported by Badescu (2008)- have provided significant improvements on earlier works. While Rigollier *et al*. (2004) adopted the approach that eliminated the need for tuning satellite data with ground data, Mueller *et al.* (2004) adopted an approach that depended greatly on integrating atmospheric effects – in particular, aerosols – through the use of Radiative Transfer Code.

Artificial Neural Network (ANN) has been shown to be a useful tool for predicting the amount of solar radiation reaching the earth surface. ANN have been used for forecasting (Sfetsos and Coonick (2000)) and estimating (Reddy, Ranjan (2003)) 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-forward ANN. The results reported for locations in India had maximum mean absolute relative deviation of predicted hourly global radiation as 4.07%.

In this work, we have considered the possibility of an approach which involves combining remote sensing with artificial intelligence. This is to harness the potentials these two techniques provide – the geo-spatial coverage of satellites and the power of ANN as a modelling tool for relating data from different sources. This, it is hoped, will contribute to the efforts being made towards developing accurate methods of assessing the amount of solar radiation reaching the surface of the Earth.

2. Methods

2.1 Solar Radiation in the Atmosphere

Solar radiation is depleted in a very clear atmosphere by three distinct processes; these are

- selective absorption by water vapour, molecular oxygen, ozone and CO^2 in certain wavelengths

– Rayleigh scattering by molecules of different gases and dust particles in the atmosphere
– Mie scattering

In a clear atmosphere, the scattering of solar radiation by gas molecules and particles of much smaller dimension compared with the wavelength of the radiation takes place in accordance with Rayleigh's theory which indicates that the scattering coefficient is of the order of λ^{-a} where λ is wavelength of the radiation. Solar radiation experiences scattering and absorption in the atmosphere. About half of the scattered radiation returns to space while the rest is directed downwards to the surface of the Earth. The scattering of radiation by particles of larger dimensions compared with the wavelength of the radiation constitute Mie scattering. The radiation in this case experiences real scattering and absorption. The scattered radiation is directed downwards towards the Earth surface in form of diffuse radiation. The total solar radiation reaching the earth surface comprises of both diffuse radiation and the portion of solar radiation that is not scattered – direct radiation.

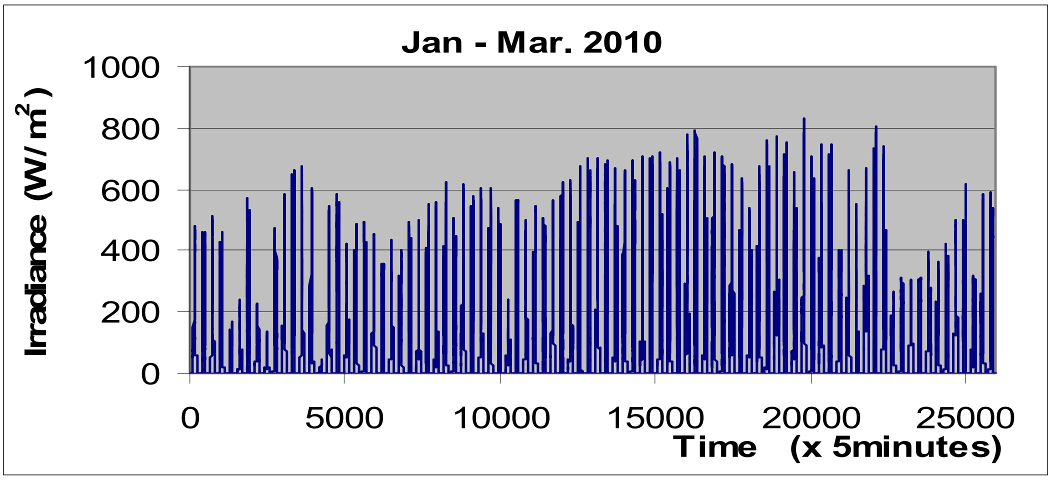

Figure 1 Solar irradiance pattern for the months of January, February and March, 2010.

Solar radiation experiences a greater degree of scattering in a cloudy atmosphere; a large portion of the radiation from the sun is reflected back to space while some of the scattered radiation is directed towards the earth surface as diffuse radiation. The sensing of the radiation reflected back to space from the atmosphere as well as the Earth's albedo form the basis for the assessment of ground – reaching solar radiation from satellite images.

The networks were trained and simulated to assess their performance. The MSE returhed from the training was of the order of 10^{-26} indicating that the networks had learnt to relate the inputs with the targets. The deviation from measurements range from as high as about 22% down to less than 2%. The relative MBE and RMSE obtained from simulating the network were 0.037MJ/m^2 and 0.183MJ/m^2 respectively; the relative values are 0.0268 and 0.1308 respectively. The results obtained show that ANN can be a viable option as a tool for assessing solar energy reaching the earth surface from satellite images.

2.2 Normalized Digital Counts and Cloud Cover Index

The principle governing the extraction of information on ground-reaching solar radiation is based on the construction of a cloud cover index arising from a comparison of the observations made by the satellite's sensor with what would be observed if the sky were clear (Rigollier *et al.* (2001)); each pixel of the image is associated with a digital count.. The normalized count, $C_N(i,j)$, for an observed pixel is expressed as :

$$C_N(i,j) = \frac{\left(C_N^*(i,j) - C_{NO}\right)}{I_O.\varepsilon.\sin^{1.15}\gamma} \tag{1}$$

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, I_o is the extra-terrestrial irradiance while $sin^{1.15}\gamma$ is the clear sky model of Perrin de Brichambaut, Vauge (1982) which is dependent on solar altitude. The essence of normalizing the counts is to obtain count values that can be related with ground-reaching solar radiation; this is achieved by eliminating or drastically reducing the effects associated with sun-earth-satellite geometry. Therefore, the model used must be sensitive only to the quantity of interest. As mentioned earlier in the introduction, the approach adopted by earlier researchers involves obtaining the cloud index and relating it, in a linear manner, with the clearness index as follows (Cano *et al.*(1986)):

$$K_T = An + B \quad (2)$$

where K_T is the clearness index, n is the derived cloud cover index while constants A and B are empirically determined.

In this work, we estimated the Earth's reflectance for each image from digital counts. This was done by converting the counts into radiance, L, and then using equation (3) to obtain reflectance.

$$\rho(i,j) = \frac{\pi L}{I_O \varepsilon . \sin \alpha \exp(-\tau)} \quad (3)$$

Equation (3) was used to generate values for reflectance. The reflectance for cloud free atmosphere $\rho_g(i,j)$ and that for complete cloud cover (overcast) $\rho_c(i,j)$ where determined from the images for the period considered in this work. The reflectance $\rho_g(i,j)$ represents the condition for clear atmosphere; in this case, the radiation sensed by the satellite's sensor is due mainly to reflections from the Earth surface. For a given pixel *(i,j)*, the cloud cover index *n* is defined as follows from Rigollier *et al.* (2001, 2004):

$$n = \frac{\rho(i,j) - \rho_g(i,j)}{\rho_C(i,j) - \rho_g(i,j)} \quad (4)$$

Equation 4 was used to generate cloud index values that were used to train and simulate artificial neural networks.

2.3 Clear-sky index

The clear-sky index, k_c, for our location, were determined for the period covered in this work. We estimated the transmittance for the combined direct and diffuse irradiation and applied computed the k_c from radiation measurements taken at our location.

2.4 Artificial neural network (ANN) model and training

Next, we consider 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).
Artificial neural networks (ANNs) are based on ideas about how biological neural networks function. They are usually non-linear, parallel processing systems that have the ability to learn through adaptation of its response to changes in its environment.

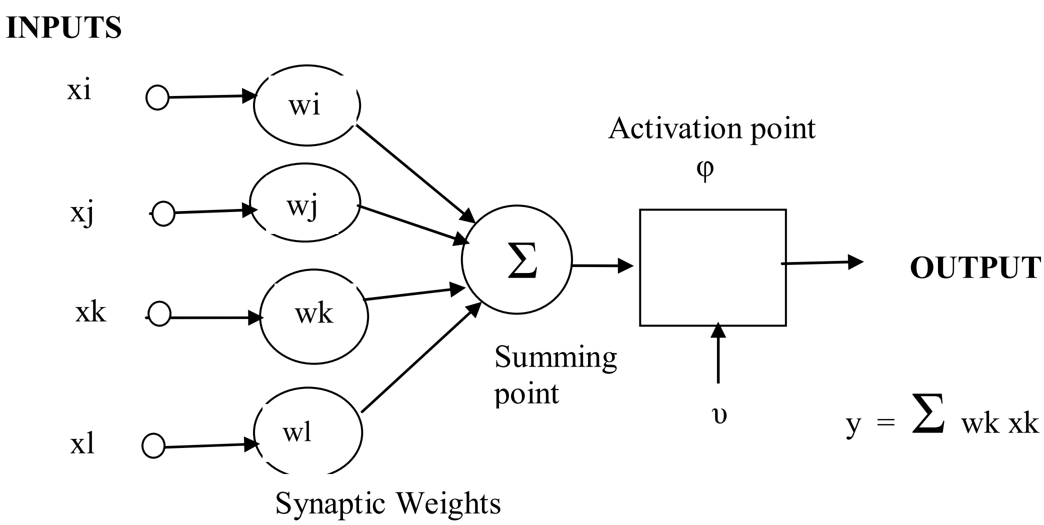

Figure 2 Basic features of Artificial Neural Network

The function of ANN is based on these properties. This gives them the power for exploring relationships between physical quantities. Reddy and Ranjan (2003) used multilayer feed forward ANN to estimate solar radiation for two locations in India; data from eleven other locations were used to train the network. Jacyra et.al. (2004) and Dorvlo et. al. (2002) have carried out similar works for locations in Brazil and Oman respectively.

We have used the Feed-forward Back-propagation ANN in this work. The cloud index for 15 days from each month consider were used as inputs. The weights were set before each training session. The epoch was set at 10000 to ensure that the network properly computes the targets. The cloud index for other days that were not used for the training of the network were then used to simulate it.

2.5 Approach adopted

The approach adopted involves first, investigating the suitability of ANN through the use of time series solar radiation data (Erusiafe *et al.* (2010)). Hourly solar radiation values were calculated from this data. This was for the periods 9:00 to 10:00UT and 10:00 to 11:00UT for the month of January 2010. Irradiance reading logged at five minutes were taken at fifteen minutes interval in the hour to represent periods when the satellite scans the Earth; this was used to train the network. The purpose was to ascertain the possibility of reproducing the hourly radiation values given four readings at fifteen minutes interval within an hour.

3. Results and Conclusion

The results from the training show that the ANNs were able to reproduce the target fairly accurately. This is observed from the mean- squared – error values (of the order of 10^{-10}) returned at the end of each training session.

The results from simulation of the network indicates that the network was able to estimate the desired parameter. This is seen from the correlation coefficients (R^2 values) returned from plots of the output of the network against ground measured readings. This is as shown in figures 3, 4 and 5 for the hours 10:00 – 11:00 UT, 11:00-12:00 UT and 12:00 – 13:00 UT respectively.

The MBE for the hours 10:00 – 11:00 UT, 11:00-12:00 UT and 12:00 – 13:00 UT are expressed (in relatively terms) as -0.1202, -0.0405 and 0.0128 respectively while the RMSE for the same period are expressed (also relatively) as 0.0349, 0.0276 and 0.0356 respectively.

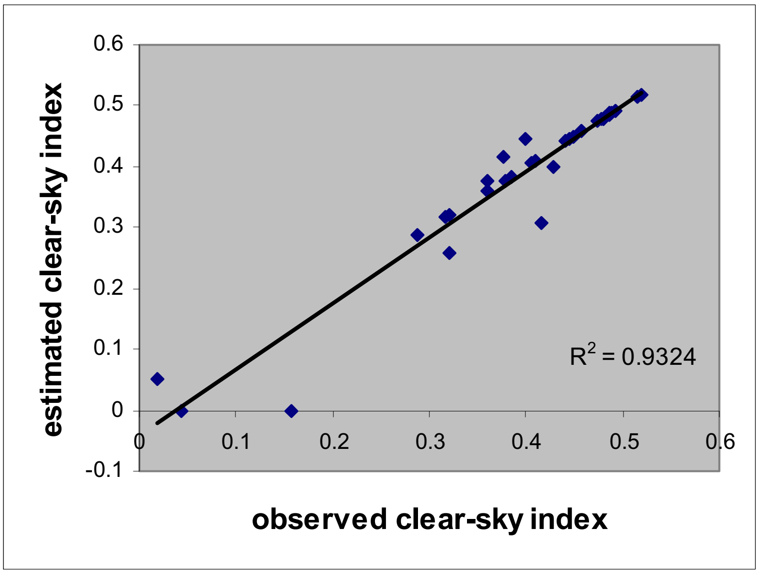

Fig. 3 Plot of estimated clear-sky index against observed values for 10:00 to 11:00UT

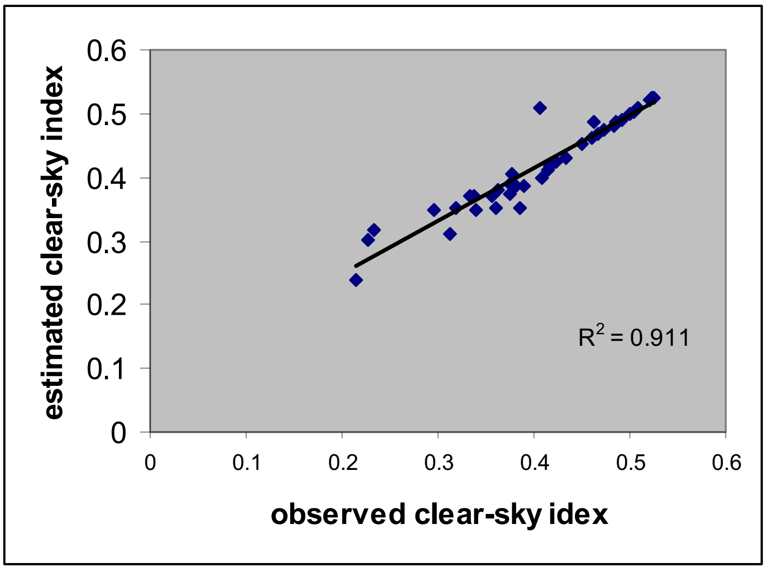

Fig. 4 Plot of estimated clear-sky index against observed values for 11:00 to 12:00UT

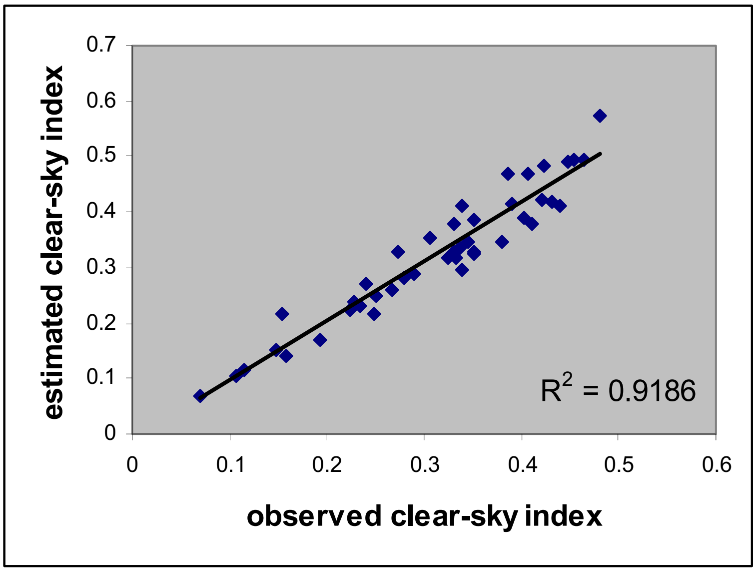

Fig. 5 Plot of estimated clear-sky index against observed values for 12:00 to 13:00UT

Considering sky conditions for our location for the period considered in this work (ranging from cloudy to partly cloudy), the results obtained appear to be satisfactory. The error in estimation gives an indication of the limitations that are expected with this approach.

This work has focussed on only one location; conparism with the results obtained by other authors would be of little or no significance for this reason. We intend to apply the method used in this work to other locations within our region and possibly beyond for its validation.

Appreciation:- We wish to express our appreciation to EUMETSAT for satellite images and software used in this work.

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