Evaluation of Geographical Information System and Intelligent Prediction of Solar Energy

HAYDER H. ABBAS[1], ADNAN KHASHMAN[2]
[1,2] European Centre for Research and Academic Affairs
Lefkosa, Mersin 10, Turkey
[1]Faculty of Engineering, Koya University, Koya City, KRG-IRAQ
[2]University of Kyrenia, Karakum, Kyrenia, via Mersin 10, Turkey
[1]hayder.hassan@koyauniversity.org, [2]adnan.khashman@ecraa.com

Abstract: - On-site data records of solar radiation are required for environmentalists and engineers to establish any project related to solar electric power generator systems. Often existing meteorological observing systems provide such required data, however, they suffer from limited coverage areas which hinders many geographical locations with no data. Therefore, a smart and accurate system is required to predict solar radiation. This paper presents a comparison between two solar energy prediction systems that use geographical information system and neural networks to determine daily global solar irradiation in Nicosia, Cyprus. The experimental results show that the use of GIS in prediction of solar radiation, can be successfully used in real life applications.

Key-Words: -; Geographical Information Systems (GIS), Solar Radiation Predication, Artificial Neural Network (ANN), Back Propagation Algorithm (BP).

1 Introduction

The The Global Demand for electricity is increased rapidly, due to many factors the most important are the rapid increase in population, rising standards of living, and used the electric energy in many new applications such as public transportation consequently, increasing the environmental degradation [1].
Generally, using artificial neural networks as an estimation tool has proved its efficiency in predicting different parameters using other indirectly related parameters; via estimating their non-linear relationship. An example of such parameters includes climatological and meteorological parameters which are important in indicating the amount of solar radiation in a selected region. Therefore, using an artificial neural network (ANN) can be invaluable in determining the effects of meteorological parameters and finally prediction of solar radiation [2].
The use of a Geographical Information System (GIS) in analyzing the feasibility of solar energy through solar radiation can be realized by using analysis tools such as the ArcGIS Spatial Analyst extension, which enables us to map and analyze the effects of the sun over a geographic area for specific time periods. The resultant outputs can be easily integrated with other GIS data and can help in modeling physical and biological processes [3].
The use of traditional prediction method and ANN of techniques in solar energy prediction has been addressed by few research works. For example, in [1] the authors used GIS output parameters as an input parameters for ANN prediction system, three schemes are used to validate the best schemes for solar energy prediction in Nicosia, Cyprus [4], ANNs were used to determine the theoretical potential of solar irradiation in Indonesia and visualize the solar irradiation by province as solar map for the entire of Indonesia. Their data, which was used for training and testing the ANN model, was based on geographical and meteorological data from 25 locations obtained from NASA database. In another recent work [5], the authors suggested the use of an ANN to predict the daily GSR under clear sky conditions at any location on a horizontal surface; based on meteorological variables. The various parameters such as earth skin temperature, relative humidity (simply humidity), date and month of the year were used to estimate the daily GSR. In [6], global solar irradiation was estimated from global horizontal irradiation using an ANN to realize this conversion. In [7], an ANN was used to provide a 24-hour prediction of solar energy irradiance. In [8], a feasibility study of using an

ANN model for the prediction of solar energy potential in Africa was presented. In [2], an ANN was used for predicting solar global radiation based on using climatological variables in the locations where no direct measurement equipment was available. In [9], ANN models were suggested for estimating and modeling daily global solar radiation, the input parameters used in this work included: the air temperature, relative humidity, sunlight duration and day of year. In [10], ANN models were also used for the estimation of solar radiation in Turkey. Meteorological and geographical data (latitude, longitude, altitude, month, mean diffuse radiation and mean beam radiation) were used as input parameters. The Authors were used in [11] the following ANN algorithms: Standard multilayer, feed-forward, and back-propagation neural networks for the 12 solar radiation models with different numbers of neurons, training functions and activation functions.

In [12] the researchers developed ANN models with artificial neural network fitting tool (nftool), Radial Basis Function Neural Network (RBFNN) and Generalized Regression Neural Network (GRNN) are compared. The Rapid Miner shows that clearness index, extraterrestrial radiation, latitude and longitude are least relevant input parameters and maximum temperature, minimum temperature, altitude, sunshine hour are found to be the most relevant input parameters for solar radiation prediction.

Having summarized some of the recent research works on combining solar energy prediction and artificial neural network models; it is, evident that the use of ANN models for solar energy prediction is feasible.

Therefore, we propose, in this paper, the use of a neural network model with and without GIS measured parameters together in order to validate the role of GIS in predict and estimate the solar irradiation. Our novel prediction system uses six input parameters obtained from a GIS and has one output indicating the amount of solar irradiation. As a real life implementation the proposed system is applied the solar irradiation in Nicosia the capital city of Cyprus.

2 GIS Spatial Analyst Tool and ANN

The best definition of a practical ANN is that it is a set of interconnected neurons that incrementally learn from given set of data to mimic the human brain in linear and nonlinear trends in complex data; so that it has capability to predict and adapt to new situations containing partial information. The basic computing units are neurons which perform processing the data in a neural model [13],[14]. ANNs have been used successfully for a variety of tasks; for example in, pattern recognition pattern classification, clustering, and prediction [15]-[22]. ANNs have also been implemented in various fields of mathematics, engineering, medicine, economics, meteorology, psychology, neurology, and many others [9]. The most commonly used neural model in ANN applications is the back propagation learning algorithm (BPNN) due to its implementation simplicity and proven learning and generalization capability. The BPNN algorithm was created by generalizing the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. The neural model system is usually trained until it approximates a function associating input vectors with specific output vectors [13]. The solar analyst tool in GIS can be used to provide useful information to calculate the solar energy in a region or an area where the potential of solar energy is to be evaluated [3]. The solar energy tool which we used at a location in the north of Nicosia in Cyprus is the Digital Elevation Model (DEM), with resolution of (3-ARC) downloaded from USGS. The DEM is a digital model or 3-D representation of a terrain's surface used by a GIS program in spatial analysis processing. The GIS solar analyst tool can perform solar radiation analysis for any region or specific location using two methods [3]: Area solar radiation analysis and Point solar radiation analysis the differences between these methods are the first is calculate the amount of radiant energy for a given area, and the second is calculate the amount of radiant energy for a given Locations can be stored as point features or as (x,y) coordinates.

3 Proposed Systems Design

3.1 ANN Architecture

For the simulation and implementation of our proposed prediction models, two software package were used GIS spatial analyst tool and MATLAB software. The inputs for the each system are difference, the firs model used six inputs and the second model used seven input as shown in Figure 1 and Figure 2 respectively. Package data was used to train and validate the neural model predictor which was simulated using MATLAB software tool. The 3-layer neural network comprised input, hidden, and output layers. The input layer, which has six and seven neurons for model one and model respectively, is fed with climatological indicators such as the Month Number (**M.N**) and averaged values of each of the following parameters: Air Temperature (**A.T**), Air Pressure (**A.P**), Wind Speed (**W.S**), Sunlight Duration (**S.D**), Global Solar Radiation (**G.S.R**) and GIS program output (**GISO)**. The hidden and output layers have 25 neurons and one neuron, respectively. The output of the prediction system represented the solar Irradiation (**S.IR**) in (kwh/m^2/day). The transfer function used in the hidden and output layer was the sigmoid function, and the parameters of the system were altered in several experiments in order to achieve better error convergence for the neural prediction model. The topology of the solar energy prediction neural models is shown below in Figure 1 and Figure 2**.**

3.2 Input Database

The averages of air temperature, air pressure, and wind speed were taken from recorded data from Ercan Airport, north of Nicosia. The averages of sunlight, and global solar radiation were taken from the NASA database [23], The GIS data were taken from running a spatial analyst tool with DEM accuracy 1m. Table.1 shows a sample of climatological and solar energy data were used in this paper. The input data values require normalization prior to presenting them to the input layer of the neural network. All neural model inputs should have values between '0' to '1'. Therefore, a simple normalization procedure was applied by automatically finding the maximum value for each input attribute set, and then dividing all values within that attribute by the obtained maximum value. Table. 2 shows the obtained maximum input attributes values, whereas, Table 3 displayed examples of normalized input values. Also, the output and desired out normalize by dividing on the greater number.

3.3 Methodology and Evaluation Method

The approach adopted in this work to train our neural system, was based on implementing two neural models which are validated in order to discover the role of GIS on performance of ANN in predication of solar irradiance. The performance evaluation of the prediction system was based on using an error analysis method in order to compare the predicated solar irradiation values with actual measured values. The three evaluation measurements comprised root mean square error (RMSE), mean absolute percentage error (MAPE), and a correlation coefficient (R^2). These empirical measurements, i.e. RMSE, MAPE, and R^2 are defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} SR_{i(estimated)} - SR_{i(actual)}}{n}} \tag{1}$$

$$MAPE = e = \frac{1}{n}\sum_{i=1}^{n} \frac{\left|SR_{i(estimated)} - SR_{i(actual)}\right|}{SR_{i(actual)}} \tag{2}$$

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n}\left(\left|SR_{i(estimated)} - SR_{i(actual)}\right|\right)^2}{\sum_{i=1}^{n}(SR_{i(actual)})^2}\right] \tag{3}$$

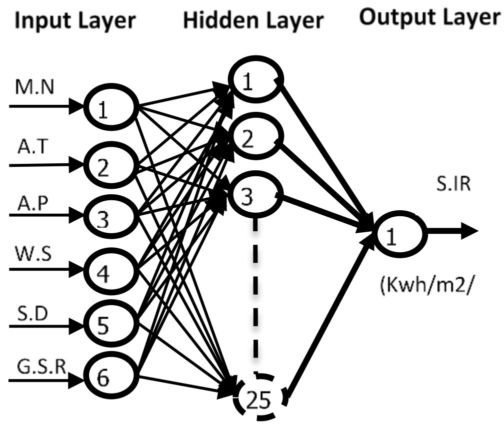

Figure 1. The topology of the proposed neural prediction model I.

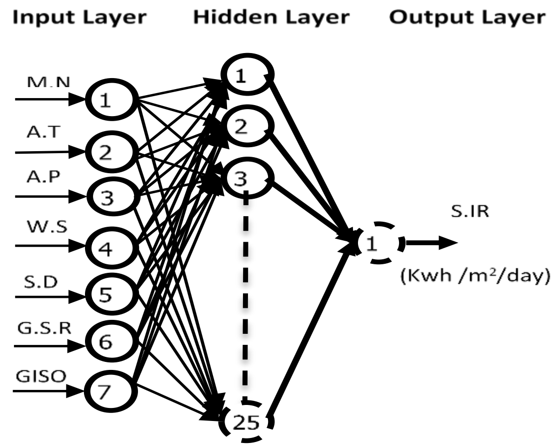

Figure 2. The topology of the proposed neural prediction model II.

Table 1. A sample of climatological and solar energy database for the year 2014. (M.N: Month Number, Av: Average value, A.T: Air Temperature, A.P: Air Pressure, W.S: Wind Speed, S.D: Sunlight Duration, G.I.S.O: GIS Output)

Solar Prediction System Input Data							
M.N		Av A.T (C)	Av A.P (Kpa)	Av W.S (m/s)	Av S.D (H)	G.S.R (kh/m^2/d)	GISO (kh/m^2/d)
Jan	1	14	1.016	10	10.15	2.49	1.6
Feb	2	17	1.013	12	10.98	3.44	2.30
Mar	3	18	1.015	13	11.98	4.83	3.40
Apr	4	22	1.013	14	13.08	5.98	4.45
May	5	30	1.006	12	13.36	7.24	5.86
Jun	6	32	1.008	14	14.43	8.11	6.54
Jul	7	30	1.006	12	14.20	7.93	5.75
Aug	8	36	1.006	12	13.42	7.08	5.00
Sep	9	29	1.010	13	12.36	5.88	3.95
Oct	10	27	1.013	8	11.23	4.26	2.50
Nov	11	21	1.017	11	10.36	2.87	1.70
Dec	12	18	1.015	11	9.76	2.2	1.55

Table 2. The maximum value in each numerical input of the 46 month; these values are used to normalize the input data to values between 0 and 1.

Input	1	2	3	4	5	6
Max. Value	12	36	1.019	21	14.43	8.11

Table 3. A sample of normalized input data values.

Input	1	2	3	4	5	6
Jan	0.0833	0.388	0.997	0.476	0.703	0.307
Feb	0.166	0.472	0.994	0.571	0.76	0.424
Mar	0.25	0.5	0.996	0.829	0.829	0.595

Table 4. The Final parameters of the trained BPNN prediction models.

Parameters Name	Model I	Model II
Input layer Neurons	6	7
Hidden layer Neurons	25	25
Output layer Neurons	1	1
Random initial weight range	-0.3 to 0.3	-0.3 to 0.3
Learning Rate	0.07	0.07
Momentum Factor	0.25	0.25
Minimum required error	0.002	0.002
Max permitted iterations	10000	10000

4 Experimental Results

After the Two models for solar energy prediction systems were implemented using the MATLAB software tool. The finalized design and parameters of the neural network for the two models are shown in Table 4. These neural model parameters were obtained after several experiments which aimed to find an ideal neural model design for the task of solar prediction.

The training and validation or testing of the prediction neural model, was carried out following the Two models learning and validation. Table 5, shows the obtained evaluation measurements for each models. Figures 3-4 show the obtained root mean square error, whereas Figures 5-6 show the validation data scatter graphs and correlation coefficient (R^2), for the two models. Upon inspecting the values of the evaluation measurements in Table 5, we could in general conclude the suitability of using a neural network model for solar energy prediction tasks. The obtained values for the three measurements (RMSE, MAPE and R^2) under the two models reflect the efficient capability of neural predictors.

When inspecting the obtained results closely, it can be noticed that model II, provided the best results according to the values of R^2 ,MAPE, and RMS; which were, respectively, 99.7%, 0.05%, and 1.6% in training, and 99.5%, 0.12%, and 2.9% in validation. The least efficient results were obtained when using Model II. Here the evaluation measurements reflected higher error in prediction; this of course is due to the divergence of the output of the Neural Network from the actual value. Figure 7 shows the relationships between the actual value and the output of the model I and Model II, it’s clear the model I gives values very close to actual values therefore, we deduce that a proposed neural network models in this paper, could be successfully used for predicting of solar energy radiation based on variable input climatological parameters and the quantity of solar irradiance at a chosen location. Model II can be considered the better architecture for predication of solar energy according to the highest correct prediction accuracy value was 99.5%, when using model I, therefore, it could be efficiently used for real life solar energy prediction.

Table 5. The obtained solar energy prediction system evaluation measurements under the two models.

	Neural Models	**Model I**	**Model II**
	Training months	30	30
	Validation months	16	16
Training indicators	Processing time (s)	300	350
	R^2 (%)	99.18	99.7
	RMS (%)	2.36	1.6
	MAPE (%)	0.12	0.05
Validation indicators	Processing time (s)	0.02	0.04
	R^2 (%)	98.4	99.5
	RMS (%)	3.04	2.9
	MAPE (%)	0.15	0.12

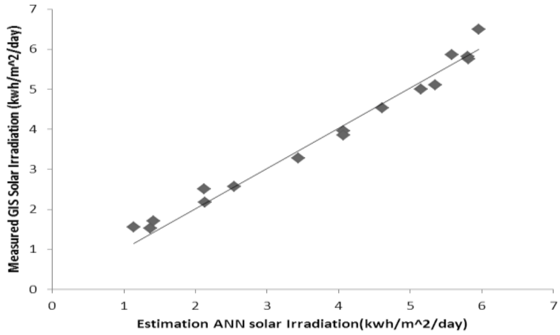

Figure 5. Validation data scattering and R^2 (98.4) for model I.

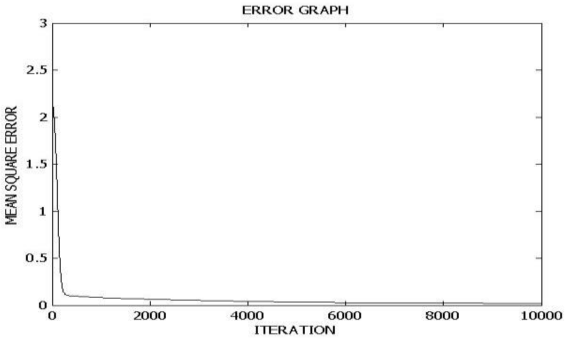

Figure 3. RMSE vs. Iteration learning curve in Model I

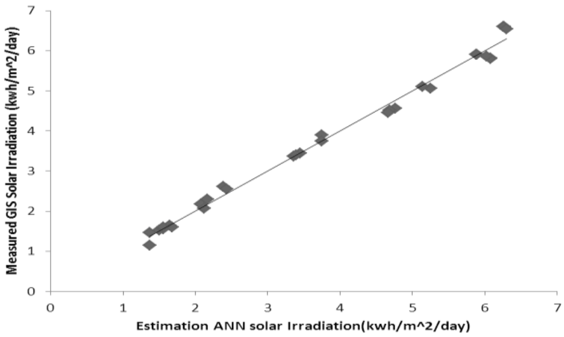

Figure 6. Validation data scattering and R^2 (99.5) for model II.

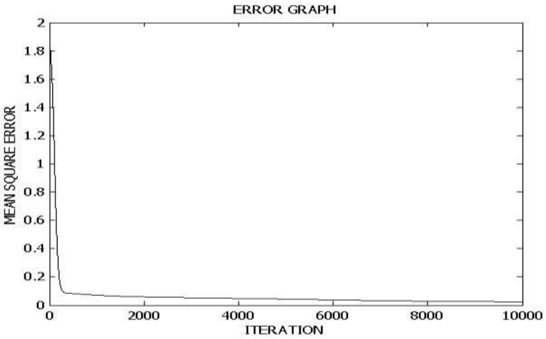

Figure 4. RMSE vs. Iteration learning curve in Model II.

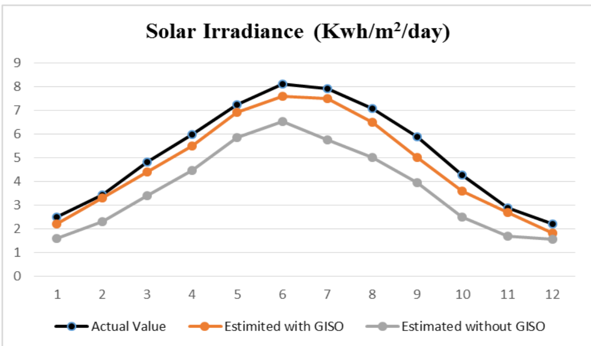

Figure 7. Actual value comparison with & without GISO.

5 Conclusion

This paper presented a novel system for predicting solar energy radiation. The novelty of this work is not only in using a neural model as a predictor, but also the choice of varying climatological parameters and the implementation. The application which is presented in this paper predicts the solar radiation in the northern region of Nicosia city in Cyprus. However, our system can be equally successfully applied in different locations. The climatological parameters were obtained using a digital elevation model (DEM), with resolution of (3-ARC) downloaded from USGS. The specific parameters used in this work were the month number and averaged values of each of the following parameters: air temperature, air pressure, wind speed, sunlight duration, and global solar radiation. These parameters are fed into the neural model during the learning and validation processes. The output is the solar irradiation measured in (kwh/m^2/day). The experiments used a database which spanned 46 months; this we consider as sufficient data for this task. The evaluation of the experimental results was based on three empirical measurements: the root mean square error (RMSE) of the predictor, the mean absolute percentage error (MAPE), and a correlation coefficient (R^2). The highest correct prediction accuracy (98.4%) was obtained when using learning Scheme I. Under this scheme, 65.3% of the entire data was using for training the neural model, while the remaining 34.7% was used for testing or validation. This means that such a prediction system requires more climatological data during training, which is conceivable, and thus can be used successfully in real life applications. Future work will focus on predicting solar radiation in other locations of this Mediterranean island.

References

[1] A. KKhashman,, H.H. Abbas, Solar Energy Prediction Using Geographical Information System and Neural Networks, *Proceedings of the 7th International Symposium on Electrical & Electronics Engineering and Computer Systems (EEECS'12*), European University of Lefka, Cyprus, 29-30 November 2012.

[2] A. Azadeh, A. Maghsoudi and S. Sohrab , Using an Integrated Artificial Neural Networks Model for Predicting Global Radiation: The Case Study of Iran. IEEE *Transactions on Power Systems*,2010, Vol. 8, No. 3, pp. 1195-1203

[3] GIS Spatial analyst tool, *ESRI Arc view 9.2 DVD.WA*, DC, 8615 Westwood Center Drive Vienna, 2013, VA 22182-2218703-506-9515.

[4] M. Rumbayan, A. Abudureyimu, K. Nagasaka, Mapping of solar energy potential in Indonesia using artificial neural network and geographical information system. *Renewable and Sustainable Energy Reviews*, 2012, Vol. 16, pp. 1437– 1449.

[5] K.D.V.S. Rao, B.I. Rani, G.S. Iango, Estimation of daily global solar radiation using temperature, relative humidity and seasons with ANN for Indian stations, *Power, Signals, Controls and Computation (EPSCICON)*, 2012 International Conference .

[6] G. Notton , C. Paoli , S. Vasileva , M. Nivet , J. Canalett a, C. Cristofari, Estimation of hourly global solar irradiation on tilted planes from horizontal one using ANN. *Energy*, 2012, Vol. 39, pp. 166-179.

[7] A. Mellit, & A.M. Pavan, A 24-h forecast of solar irradiance using artificial neural network: Application for performance prediction of a grid-connected PV plant at Trieste, Italy, *Solar Energy*, 2010, Vol. 84, No. 5, pp. 807-821.

[8] D. Fadare, I. Irimisose, A. Oni & A. Falana, Modelling of solar energy potential in Africa using an artificial neural network. Am. J. Sci. *Ind. Res*., 2010, Vol. 1, No. 2, pp. 144-157.

[9] M. Benghanem, A. Mellti, S.N. Alamri, ANN-Based Modelling and Estimation of Daily Global Solar Radiation Data. *Energy Conversion and Management*, 2009, Vol. 50, pp. 1644-1655.

[10] O. Senkal, T. Kuleli, Estimation of solar radiation over Turkey using artificial neural network and satellite data. *Applied Energy*, 2009, Vol. 86, pp. 1222–1228

[11] W. Al-Fatlawi, A. Rahim, N. A., Saidur, R., and T. A. Ward, Improving solar energy prediction in complex topography using artificial neural networks: Case study Peninsular Malaysia. *Environ. Prog. Sustainable Energy*, 2015, 34: 1528–1535.

[12] A. Yadav, H. Malik, S.S. Chandel, Application of rapid miner in ANN based prediction of solar radiation for assessment of solar energy resource potential of 76 sites in Northwestern

India, *Renewable and Sustainable Energy Reviews*, 2015, Volume 52, Pages 1093-1106.

[13] A. Khashman, Modeling cognitive and emotional processes: A novel neural network architecture, *Neural Networks, Elsevier*, 2010, Vol. 23, No. 10, pp.1155-1163.

[14] A. Khashman, IBCIS: Intelligent blood cell identification system, *Progress in Natural Science*, 2008, Vol. 18, No. 10, pp. 1309-1314.

[15] A. Khashman, A Modified Backpropagation Learning Algorithm With Added Emotional Coefficients. *IEEE Transactions on Neural Networks*, 2008, Vol. 19, No. 11, pp. 1896-1909

[16] A. Khashman, K. Dimililer, Neural networks arbitration for optimum DCT image compression, *EUROCON, 2007. The IEEE International Conference on 'Computer as a Tool', Warsaw, Poland*, 9-12 September 2007.

[17] A. Khashman, Face recognition using neural networks and pattern averaging, *Advances in Neural Networks*, ISNN 2006, 2006, pp. 98-103.

[18] A. Khashman, N.I. Nwulu, Support vector machines versus back propagation algorithm for oil price prediction, *Advances in Neural Networks*, ISNN 2011, 2011, pp.530-538.

[19] A. Khashman, Application of an emotional neural network to facial recognition, *Neural Computing and Applications*, 2009, Vol. 18, No. 4, pp. 309-320.

[20] Khashman A., Dimililer K. Comparison criteria for optimum image compression. *EUROCON, 2005*. The International Conference on 'Computer as a Tool' EUROCON 2005.

[21] Khashman A. Blood Cell Identification using Emotional Neural Networks. *J. Inf. Sci. Eng.* 2009, 25 (6), 1737-1751.

[22] Khashman A., Investigation of Different Neural Models for Blood Cell Type Identification, *Neural Computing and Applications*, Springer, New York, USA, vol. 21 (6), 2012, pp. 1177.

[23] NASA Atmospheric Science Data Center, Surface Meteorology and Solar Energy, Online Database: http://eosweb.larc.nasa.gov/sse/