International Journal of Engineering & Technology, 7 (3.34) (2018) 692-696

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Prediction of Global Solar Radiation Using Artificial Neural Network Model for Coastal District of Karnataka

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Abstract

Solar energy has enormous direct and indirect applications. The direct ones are solar water heating, crop drying and the indirect ones are probably electricity generation using photovoltaic technology, heliostatic powerplants, hydrogen generation using solar power electrolyser are the few among many other applications. The prediction of daily global solar radiation (GSR) data is important for many of these solar applications, and other applications on renewable energy that can be found in meteorological studies, for small to long range of data accumulation. This work aims at Prediction of global solar radiation for a particular place in India which bases itself on several input parameters using Artificial Neural Networks (ANN). The study is carried out in Nitte, Udupi which is a village in Karkala taluk of Udupi district, in the coastal district state of Karnataka having latitude 13.100N and longitude 74.930E and is at an altitude of about 265 feet above sea level. The empirical models available to estimate global solar radiation for dedicated places the accuracies have been found to be low which in fact is the requirement for a dedicated model to be provable in the later stages when there is variation within the parameters. Artificial neural networks it has been found in many cases to give better prediction accuracies. The neural network model made in this work has been built using the neural network toolbox in Mat lab version 7.13. Artificial Neural Network modelling will be done using Multilayer Perceptron Neural Network model.
MLP model has been considered for the creating the ANN model which is done using the measured data, where the input parameters are decided to be air temperature, relative humidity, time of the day, wind velocity, wet bulb temperature, atmospheric pressure, sunshine hours, solar angle, clearance index, declination angle and the global solar radiation has been the output parameter. The collected data from measurements has been divided into two parts, the first part will used for training and the latter part will be used for testing the created neural network model. Training data set, which contains 85% of the data and test data set, which contains 15 % of the data, selected randomly. The suitable number of hidden layer has been selected, such that the overall accuracy is maximized. In order to select the best training algorithm, the MLP model has been trained using different training algorithms like trainscg, trainrp, trainlm, trainbfg and trainoss. The evolved MLP model from the entire training and testing has been able to predict the estimated and experimental values of global solar irradiation with an accuracy of 86.69% for the test data. From the overall results it has been found there is good agreement between the predicated using ANN and experimental values of global solar irradiation.

Keywords: *Global solar radiation, Prediction Accuracy, Multi-layer perception, Artificial Neural networks.*

1. Introduction

Solar radiation coming from the sun which has not been absorbed or scattered due or undergone diffraction and reaches the ground directly from the sun is called direct radiation sometimes also called beam radiation. If the Beam radiation suffers diffraction or scattering by atmosphere clouds or dust particles such as smog this is considered as Diffuse radiation. The total solar radiation received at any point on the earth’s surface can be found out as the sum of the direct radiation and diffuse radiation which is totally called as Global solar radiation. In specific, the GSR can be defined as the total solar radiation received by a horizontal surface of unit area on the surface in unit time.
Solar radiation data on the surface of the earth is required for solar engineers, in meteorological studies like study of performance parameter of solar collector, photovoltaic cell etc., agriculturists and hydrologists in many applications.
The general prediction techniques used for estimating solar radiation involve analytic-empirical methods, artificial neural networks (ANN) & stochastic methods. The Angstrom correlation has served as a basic approach to estimate global radiation for a long time.

$$\frac{H}{Ho} = a + b\frac{S}{So}$$

Where,
H= Global solar radiation in w/m^2
H_0= Extraterrestrial radiation in w/m
a,b= Constants obtained by fitting data
S= Sunshine hours per day (h)
S_0= Maximum possible Sunshine hours per day (h)

The study by Tymvios et al. [1] who made ANN model based on on six years’ data for GSR, the model had two-hidden layers with neurons between 23 and 46. The MBE and RMSE values were found to be 0.12% and 5.67%, respectively. Alawi and Hinai [2]

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they have used ANN to predict the global solar radiation. In this model the inputs considered were location, month, and pressures, temperatures, vapor pressures, relative humidity's, wind speeds and sunshine duration. The mean absolute percentage error for this model was found to be of 7.3% a good correlation. In the study by Reddy and Ranjan [5] on solar radiation estimation using ANN and comparison along their correlation models. GSR data from thirteen stations in India were collected and training and testing the ANN. Mean absolute relative deviation of predicted values of hourly GSR was found to be4.07% maximum. According to the research by Karoro Angela et al. [8] five years solar radiation data has been collected and ANN model created for average daily global solar radiation and obtained a correlation coefficient of 0.963 and the mean bias error of 0.0550 MJ/m2 and root mean square Error of 0.52 MJ/m2. In their study by Marquardt et al. [18] as training algorithms, sigmoid as transfer function and the number of neurons varied between 4 and 9. The GSR prediction value showed a maximum mean absolute percentage error of much less than 6.70%. There have been many different ANN models for places in India and Karnataka however for the costal area of Karnataka where the humidity is high and the beam radiation decreases in the month of peak summer due to heavy clouds in the area. There has been no mathematical or other model available for this place; hence an attempt is made here to create one such model.

2. Artificial Neural Networks

Artificial neural network generally referred to as "neural network" is a massively is made of processing units and possesses brain like capabilities to adjust values or biases/weights within itself while in brain it's the chemical structurally transformation.

The Multilayer Perceptron (MLP) model of Neural network is an example of an ANN that is used extensively for types of solution which needs different problem-solving technique such as pattern recognition and interpolation.

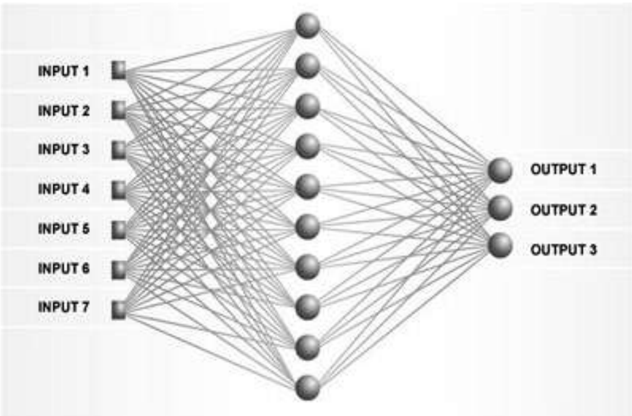

Figure 1: Multi-layer Perceptron Architecture

Algorithm

a. Initialize the weights and biases to small random values as possible.
b. An Input patter is chose in the form $\{\xi^\mu_i, \zeta^\mu_k\}$ from the training set and present ξ^μ_i to the input layer, where μ = 1,20,….n are the number of patterns and i =1,20,..p, are the features.
c. The activation in the neurons is computed in the hidden layer $V_j^\mu = 1 / (1 + e^{-(\Sigma w_{ji} \xi_i)})$.
d. The output of each neuron is computed in the output layer $O^\mu_k = 1/ (1 + e^{-(\Sigma w_{kj} V_j)})$.
e. Mean Square Error is computed $E^\mu = 1 / 2 \sum_\mu (\zeta^\mu_i - O^\mu_k)^2$.
f. If $E^\mu < E_{min}$ go to step m.
g. Compute $\delta^\mu_k = (\zeta^\mu_k - O^\mu_k) O^\mu_k(1- O^\mu_k)$
h. The weight are updated between the output and hidden layers $w^{new}_{kj} = w^{old}_{kj} + \Delta w_{kj}$
i. Where $\Delta w_{kj} = \eta\sum_\mu \delta^\mu_k V_j^\mu$ the momentum coefficient α and η is to be the learning rate and $\Delta w_{kj} = \eta\alpha\sum_\mu \delta^\mu_k V_j^\mu$
j. Compute $\delta^\mu_j = V_j (1-V_j) \sum^m_{k=1} \delta_k w_{kj}$
k. The weights are updated between the hidden and input layers $w^{new}_{ji} = w^{old}_{ji} + \Delta w_{ji}$ where $\Delta w_{ji} = \eta\sum_\mu \delta^\mu_j \xi^\mu_I$, and with momentum coefficient $\Delta w_{ji} = \eta\alpha\sum_\mu \delta^\mu_j \xi^\mu_{i,}$
l. Go to step b.
m. Save all weights and bias and exit.

3. Experimental Set Up and Methodology

Nitte in Udupi district which is having latitude of 13.100N and longitude of 74.930E and is at an altitude of about 265 feet above sea level has been selected for the experimental work and also the collected data has been used for making the proposed ANN model.

Figure 2: The selected region for using ANN model

The prediction of solar radiation involves selection of the location for recording the meteorological parameters and the various instruments used to measure these parameters and tabulate them.

The meteorological parameters considered for creating the proposed ANN model are, air temperatures, relative humidity wet and dry, atmospheric pressures, wind speeds, time of the day, sunshine duration, wet bulb temperature and clearance index these readings were measured using appropriate instruments, the other parameters such as solar angle and declination angle has been calculated using empirical formulas.

3.1 Details of Measurements and Sensors

a. Global solar radiation: The instantaneous values of global solar radiation in W/m2 has been measured on daily basis at the time interval of 10 minutes using the Global Radiation sensor KDS-051

b. Wind speed: The wind speed in m/sec has been measured at a distance 2 meters above the ground level from using a digital anemometer MASTECH MS6250. The data has been measured on daily basis at the time interval of 10 minutes.

c. Air temperatures, Relative humidity's and Atmospheric pressures. The air temperature, relative humidity and atmospheric pressure has been measured using an instrument called GAIA wireless whether station. The data has been measured on daily basis at the time interval of 10 minutes.

d. Sunshine duration: The parameter sunshine duration is measured using an instrument sunshine recorder. The data has been measured on daily basis.

e. Wet bulb temperature: The wet bulb temperatures has been measured using the instrument called Wet bulb dry bulb thermometer. The data has been measured on daily basis at the time interval of 10 minutes.

3.2 Methodology:

The experiment has been carried out from January 1st to March 30th. The various parameters like air temperature, relative humidity, time of the day, wind velocity, wet bulb temperature, atmospheric pressure has been measured for every ten-minute interval. And the other parameters like sunshine hours, solar angle, clearance index, declination angle is measured and calculated on daily basis. The instantaneous values of Global solar radiation have been measured and recorded for every ten minutes interval to more accurately note the variation in solar energy input and also to keep accurate track of the overcast period. Therefore, for a period of two months a total of 2548 set of readings of each parameter are obtained. These recorded values have been used for the proposed ANN model its prediction qualities have been found out.
The experimental maximum and minimum values of the input parameters which are measured using above said sensors are given in the table below. This gives the simple weather prediction of the site under consideration.

Figure 3: Pyranometer KDS-051 & Sunshine recorder for measurement of solar radiation and sunshine hours

Figure 4: Data Cards showing maximum sunshine duration hours which is the burnt card length

Figure 5: Data cards showing minimum sunshine duration hours

Table I: Recorded Maximum And Minimum Values Of The Measured Value

Parameters	Maximum recorded value	Minimum recorded value
Air Temperature	40^0 C	24.7^0 C
Relative Humidity [RH]	77%	39%
Wind Velocity	2.7 m/sec	0.1 m/sec
Atmospheric Pressure	1018 Pascal	1007 Pascal
Wet bulb Temperature	31.1^0C	24^0C

4. Ann Model -Global Solar Radiation

MLP model has been created by using the measured data, the input parameters are air temperature, relative humidity, time of the day, wind velocity, wet bulb temperature, atmospheric pressure, sunshine hours, solar angle, clearance index, declination angle and the target output parameter is global solar radiation.
The measured data has been divided into two parts; the first part has been used for training and the latter used for testing the neural network. Training data set, which contains 85% of the data and test data set, which contains 15 % of the data, selected randomly. The network has one hidden layer and different activation functions like log-sigmoid and tan-sigmoid have been studied. Mat lab 7.13 version has been used for developing the MLP model.

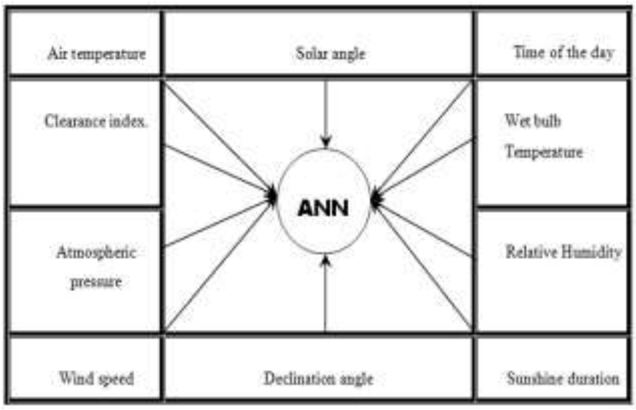

Figure 6: Block Diagram for the proposed ANN model

4.1 Error Analysis:

The estimated have been compared with actual values of GSR through error analysis. An error signal which has originated at output layers of network and propagates backward (layer by layer) adjusting the weights and biases until the error set has been met through the network.

4.2. Mean Square Error:

The mean square error is defined as Average Square of the difference between desired response and actual system output. The MSE is defined by below equation.

$$MSE= (y_i – x_i)^2 / N$$

Where i is an index, yi is the ith estimated value, xi is the ith actual value and N number of observations to be made.

4.3. Mean Relative Error:

The mean relative error is defined as ratio of difference between desired response and actual system output to the desired response. The MRE is defined by below equation

$$MRE= (y_i – x_i) / y_i$$

Where i - index, yi- ith value estimated, xi is the ith actual value.

4.4. Modelling of an Artificial Neural Network

To begin with the modelling one important parameter considered is the selection of number of neurons in the hidden layer which has a significant effect on the prediction accuracy.
Different training functions like trainglm, triangbfg, trainscg, trainrp and trainoss are available which can implement these algorithms. These were studied, in order to select the best training algorithm.
The Variation of mean square error which is the type of error selected for backpropagation, and variation of neurons in the hidden layer has been shown in below Figure. The number of neurons in the hidden layer has been varied between 10 to 50 neurons. Trainrp algorithm was used for training, since it this algorithm had showed better prediction accuracy for both training

and test data. Table 2 shows training accuracy & testing accuracy for different algorithms, it can be seen that trainrp has the maximum value of accuracy which is the reason it has been selected for all modelling purpose.

The least value of MSE was found to be 6477.2053 for 34 neurons and corresponding prediction accuracy is 84.41% & after this there was an increase in the error. Considering all these factors it was decided to fix the number of neurons in the hidden layers 34 neurons. The below graph shows variation of MSE with the no of neurons in the hidden layer, the error decreases to a certain value after which it remains constant.

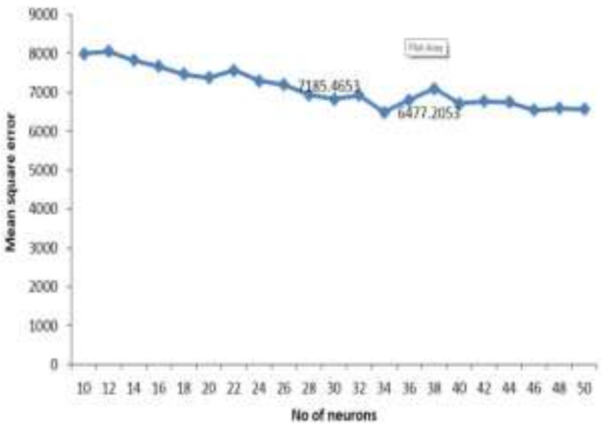

Figure 7: Variation of MSE with the no of neurons in the hidden layer

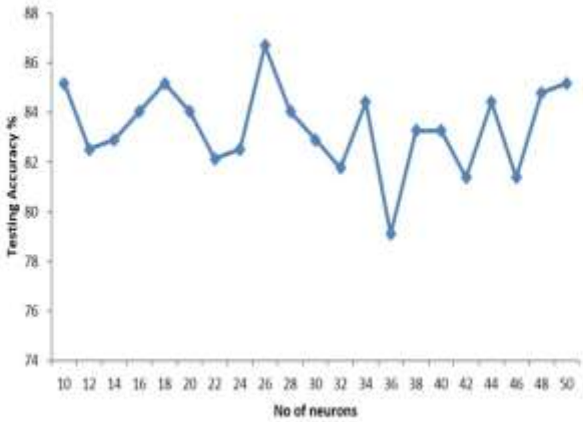

Figure 8: Variation of testing accuracy in % with the no of neurons in the hidden layer

Table II: Performance Of Mlp For Various Training Algorithm

TYPES	MSE	TRAINING ACCURACY	TESTING ACCURACY
Trainlm	4306.4541	89.37%	80.61%
Trainbfg	8971.3389	86.42%	82.89%
Trainrp	7185.4653	88.89%	86.69%
Trainscg	6066.0383	87.87%	82.51%
Trainoss	6568.2462	89.68%	82.89%

5. Results and Discussion

Performance Prediction, Once the artificial neural network model is trained and set, that is all weights and bias in it are set, it is now ready for testing. A comparison of Experimental values and by the artificial neural network predicted global solar radiation is presented point by point in Figure 9.

The comparison of the experimental and predicted values shows that these values are aligned along the straight trend line. Higher agreements of points presented with respect to straight trend line shows better agreement between experimental and predicted values.

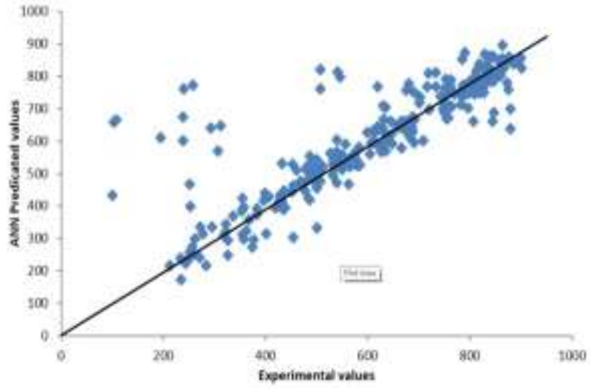

Figure 9: Experimental Vs ANN Predicted Values for solar global radiation in W/m^2

The Bar graph representation of Experimental and ANN Predicted Values for solar global radiation in W/m^2 for selected test data set is shown in Figure 10. From the study it is consider that the algorithm trainrp which gave better test prediction performance and the accuracy has been 86.69% for test data. The vertical bar values in respective colours either to each other shows little variation which shows good agreement experimental and ANN predicted values.

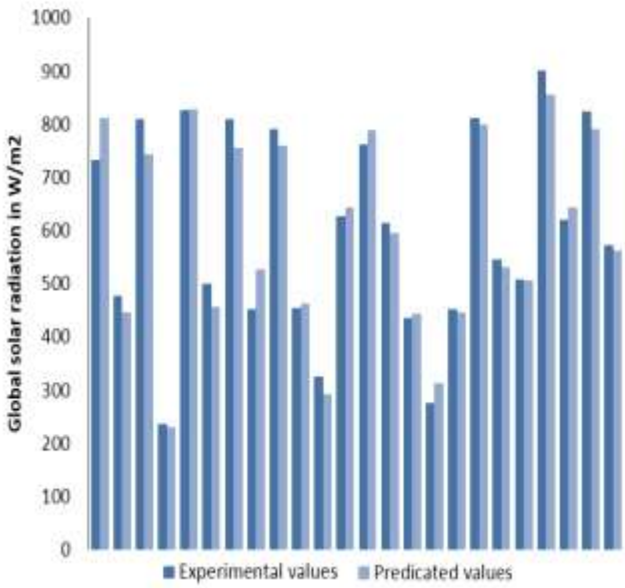

Figure 10: Bar graph representation of Experimental Vs ANN Predicted Values for solar global radiation in W/m^2 for selected test data set

6. Conclusion

Global solar radiation for Nitte a costal district of Karnataka is predicted with the help of artificial neural network. The developed model is an MLP in nature and has been able to predict the global solar radiation with a prediction accuracy of 86.69%.

MLP trained using trainrp algorithm gave the best possible prediction accuracy when compared to other training algorithms like trainlm, trainscg, trainbfg, and trainoss.

However, some more work is needed to improve predicted daily distribution of global solar radiation for cloudy days and the model probably more data's if the accuracies have to be improved.

From the studies carried out it has been found that ANN model can do much better predictions compared to other methods. The model developed for the place Nitte can be used for all solar and thermal application where global solar radiation is the main concern factor.

Acknowledgment

This work was supported with the help of Ms. Rashmi G. Dr. Sudesh Bekal & Dr.Srinivasa Pai P from the department of Mechanical Engineering, NMAM Institute of Technology.

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