

Artificial Neural Network based Prediction of Solar Radiation for Indian Stations

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ABSTRACT

The Artificial Neural Network (ANN) fitting tool is used for the prediction of solar radiation. Solar radiation data from 12 Indian stations with different climatic conditions are used for training and testing the ANN. The Levenberg-Marquard (LM) algorithm is used in this analysis. The results of ANN model are compared with measured data on the basis of root mean square error (RMSE) and mean bias error (MBE). It is found that RMSE in the ANN model varies 0.0486–3.562 for Indian region.

Keywords

Solar radiation, Levenberg-Marquard (LM) algorithm, Artificial neural network.

1. INTRODUCTION

Solar radiation data are required for a number of solar thermal and Solar photovoltaic applications like solar power generation, solar heating, cooking, drying and solar passive design of buildings [1–4]. The measured solar radiation data are not available for most of the sites due to high cost, maintenance of the measuring instruments. As such, various empirical models have been used to predict monthly mean daily solar radiation all over the world [5–9].

The Artificial neural networks (ANNs) are used to solve a number of scientific problems. It has the capability to approximate any continuous non-linear function to arbitrary accuracy [10]. A multi-layer feed-forward neural network can approximate a continuous function due to its robustness, parallel architecture and fault tolerance capability. In past years, ANN models are used by a number of researchers to estimate solar radiation [11–15] and concluded that ANN model are proven to be superior to other empirical regression models.

Reddy [11] used Radial Basis Functions (RBF) and Multilayer Perceptron (MLP) models to predict solar radiation using data from eight stations in Oman. So'zen [12] determined the solar-energy potential in Turkey using artificial neural networks. A Rehman and Mohandes [15] estimated daily global solar radiation for Abha city in Saudi Arabia by taking air temperature, number of day and relative humidity as inputs to neural networks. The results obtained indicate that the mean absolute percentage error (MAPE) is 4.49%. M.A. Behrang et. al [17] predicted daily global solar radiation for Dezful city in Iran by using different ANN techniques based on different combination of meteorological variables (day of the year, daily mean air temperature, relative humidity, sunshine hours, evaporation and wind speed). The MAPE for the Multilayer Perceptron (MLP) network is 5.21% while this value is 5.56% for Radial Basis Function (RBF) network. Mohandes et al. [16] has used RBF network for modeling solar radiation and compares its performance with MLP model by using latitude, longitude, altitude and sunshine duration as input parameters.

The average MAPE for the MLP network is 12.6 and the average MAPE for RBF networks is 10.1.

In the present study, an ANN model is developed which can be used to predict solar radiation at any given location in India.

2. ANNS FOR SOLAR RADIATION PREDICTION

According to Haykin [18], a neural network is a massively parallel-distributed processor that has the capability for storing experiential knowledge and making it available for use. It works like human brain in two respects: the network through a learning process acquire the knowledge, and inter-neuron connection strengths known as synaptic weights are used to store the knowledge. ANN has the ability to handle large and complex systems with many inter-related parameters. It ignores insignificant excess data and concentrates on the more important inputs (Kalogirou [19]). The most popular and powerful learning algorithms in neural network, are the back propagation. This algorithm is based on the error-correction learning rule. The error back-propagation process consists of a forward pass and a backward pass. In the forward pass, input vectors are applied to the input layer of the network and its effect propagates through the network via connection weights and layer by layer. Finally, a set of outputs is produced as the actual response of network. During the forward pass, the synaptic weights of the network are fixed whereas during the backward pass, the synaptic weights of the network are all adjusted in accordance with the error-correction rule. The actual response of the network is subtracted from the desired (target) response to produce an error signal. This error signal is then propagated backward through the network (Haykin [18]).

This network consists of an input layer, an output layer and usually one or more hidden layers. The architecture used in this work, has an input layer of four inputs, one hidden layer with a tan-sigmoid activation function, f , defined by the logistic

function as
$$\phi = \frac{1}{1+e^{-n}}$$
 where n is the corresponding input [Fig.1].

For the output layer, a linear activation function 'Purelin' is used. The MATLAB Neural Network Fitting Toolbox (nftool), is used for the implementation. The algorithm 'TRAINLM' is used for the training of network.

3. METEOROLOGICAL DATA AND METHODOLOGY

In the present analysis 12 Indian locations, Ahmedabad, Mangalore, Mumbai, Kolkata, Chandigarh, Dehradun, Jodhpur, Lucknow, Nagpur, New Delhi, Shillong, Vishakapatnam are selected [Table 1]. The measured meteorological data by India Meteorological Department (IMD), and compiled by A.Mani [20] viz. monthly mean solar radiation on horizontal surface; mean duration sunshine per hour, height above sea level for these stations, are used.

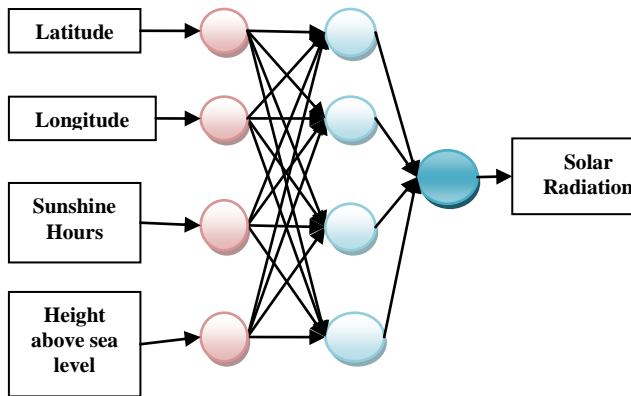


Fig 1: ANN architecture used for prediction in this present work

A computer program, has been performed under MATLAB 7.12.0.635 (R2011b) using Neural Network Fitting Tool (nftool). The geographical and sunshine hour data for cities Ahmedabad, Mangalore, Mumbai, Kolkata, Chandigarh, Dehradun, Jodhpur, Lucknow, are used for training data and the geographical and sunshine hour data for cities Nagpur, New Delhi, Shillong, Vishakapatnam, are used for testing.

Table.1. Geographical features of Stations in India

Stations	Latitude (°N)	Longitude (°E)	Height above sea level (m)
Ahmedabad	23.07	72.63	169
Mangalore	12.95	77.63	897
Mumbai	19.12	72.85	14
Kolkata	22.65	88.45	6
Chandigarh	30.73	76.88	347
Dehradun	30.31	78.03	683
Jodhpur	26.3	73.02	224
Lucknow	26.75	80.88	128
Nagpur	21.15	79.12	311
New Delhi	28.58	77.2	216
Shillong	25.57	91.88	1598
Vishakapatnam	17.72	83.23	3

The statistical tests like mean absolute percentage error (MAPE), sum of square error (SSE), mean square error (MSE), absolute fraction of variance (V^2) are

$$\left(\frac{1}{n} \sum_{i=1}^n \left| \frac{SR_{i(ANN)} - SR_{i(actual)}}{SR_{i(actual)}} \right| \right) \times 100$$

$$\frac{\sum_{i=1}^n (SR_{i(ANN)} - SR_{i(actual)})^2}{\sum_{i=1}^n SR_{i(actual)}^2} \times 100$$

respectively where n is number of inputs patterns, $SR_{i(ANN)}$ is predicted solar radiation by ANN, $SR_{i(actual)}$ is actual solar radiation.

4. RESULTS AND DISCUSSION

The performance curve is shown in Fig. 2. In this figure mean squared error have become small by increasing the number of epoch. The test set error and the validation set error has similar characteristics and no significant over fitting has occurred by epoch 6 (where best validation performance has occurred).

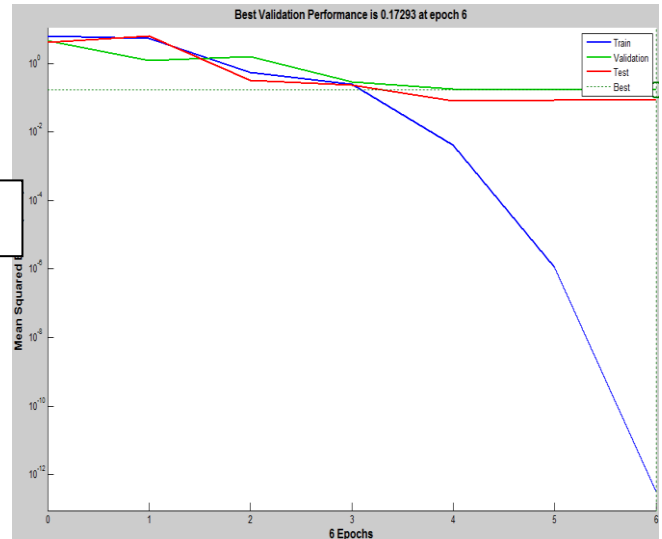


Fig 2: Performance Plot

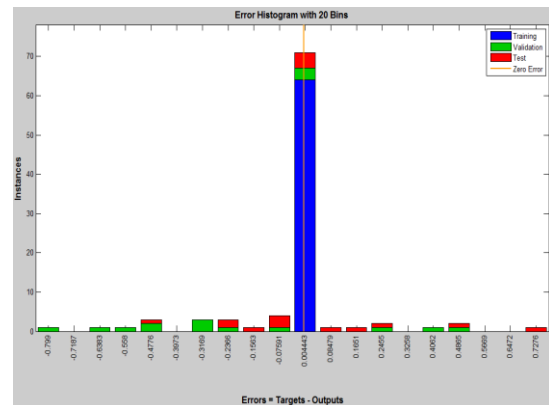


Fig 3: Error Histogram plot for Training data

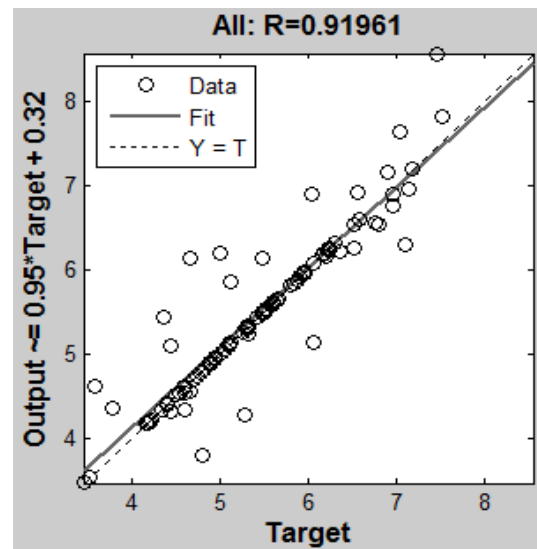


Fig 4: Regression Plot

Table.2. Error values analysis of ANN during training

Stations	MSE(%)	RMS	MAPE(%)	SSE	V^2 (%)
Ahmedabad	0.0277	0.1664	1.2803	0.3322	99.52
Mangalore	0.0531	0.2304	2.1462	0.6371	99
Mumbai	0.0024	0.0486	0.2783	0.0283	99.95
Kolkata	0.0337	0.1836	1.9896	0.4047	99.32

Chandigarh	0.015	0.118	0.887	0.1567	99
Dehradun	0.0132	0.1149	0.8998	0.1584	99.75
Jodhpur	0.066	0.2581	1.8822	0.7994	98.69
Lucknow	0.0502	0.2240	1.5699	0.6018	99.17

The Error Histogram plot for Training data is shown in Fig 3. for additional verification of network performance. Most of the data falls on zero error line which provides an idea to check the outliers to determine if the data is bad, or if those data points are different than the rest of the data.

The regression(R value) between the outputs and targets is a measure of how well the variation in the outputs is explained by the targets. The slope (m) and intercept (b) values in Fig 4 are 0.95, 0.32 respectively which predict the fit is good. The R-value is 91.96 % for the total response as shown in Fig 4. The gradient plot shown in Fig 6 indicates about optimization techniques procedures to achieve global solutions.

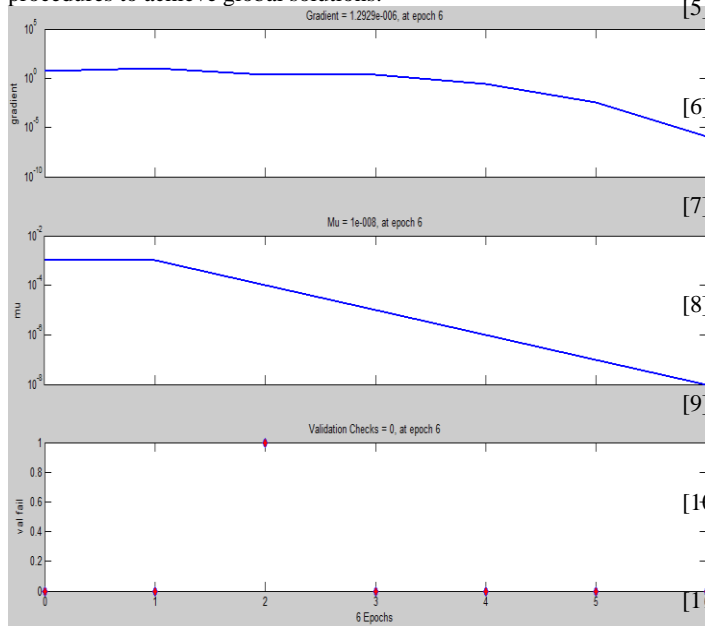


Fig 6: Gradient Plot

The predicted solar radiation values are close to the actual values for all months. A small deviation is observed for the calculated values. The maximum and minimum MAPE are 2.1462% and 0.2783% for Mangalore and Mumbai respectively. The best value of V^2 is 99.95% for Mumbai. The minimum value of V^2 is 98.69% for Jodhpur.

Table.3. Error values analysis of ANN during testing

Stations	RMSE
Nagpur	3.562
New Delhi	1.4610
Shillong	2.5469
Vishakapatnam	1.7123

5. CONCLUSION

The use of ANN technique in modeling solar radiation, is reported. The study indicates that selected ANN model has lower RMSE. This model is developed by including latitude, longitude, sunshine hours and height above sea level of different states in India. A comparison of the model with the measured data revealed that the predictions of solar radiation using this model are in good agreement with the IMD measured data. As such the model developed, is suitable for predicting solar radiation for locations in India for which solar radiation is

required for site specific solar energy applications especially for solar power generation.

6. REFERENCES

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