

Artificial Neural Network based Solar Radiation Estimation: A Case Study of Indian Cities

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ABSTRACT: Estimation of Solar radiation is the integral part of optimization of solar energy applications. Solar energy equipments perform better if the radiation to be received is estimated well in advance. Due to the limited availability of meteorological stations (equipped with solar measuring devices), various solar radiation estimation models are developed. This paper presents the development of a solar radiation estimation model using Artificial Neural Network with a case study of five Indian stations (Sri Nagar, Calcutta, Trivandrum, Dwarka, and Bhopal) comprising different climatic zones. Latitude, longitude, altitude, months of a year, maximum temperature, minimum temperature, relative humidity, wind velocity, and sunshine hour are considered for input and solar radiation is obtained at output. Climatic conditions, geographical profile, model complexity are the major challenges behind solar radiation estimation. Present study addresses them. Simulation is carried out with MATLAB 2016a. Multilayer perceptron with feed-forward back-propagation architecture is used with the Levenberg-Marquardt algorithm for training. The data are downloaded from CLIMWAT 2.0 and CROPWAT 8.0, which is developed by the Food and Agriculture Organization (FAO) of the United Nations. The developed model has an overall regression value of 0.99 (approx.), RMSE of 0.1700, 0.35551, and 0.2645 for Training, Validation, and Testing respectively. The simulation results advocate the justification of the developed model. The proposed model may be used at other stations of interest also, where the meteorological stations equipped are scarce.

Keywords: Artificial Intelligence, Artificial Neural Network, Solar Radiation, Renewable Energy, Sustainable Energy, Machine Learning.

I. INTRODUCTION

Solar energy has great lead over other types of renewable energy with large scope of applications [1]. Sun radiates about 1,20,000 TW of energy per hour which is more than sufficient to meet the demand of energy requirement of the world [2, 3]. Solar energy equipment takes solar radiation as input and provide electrical energy. Solar radiation depends on climatic conditions. This means the performance of solar energy devices can be optimized only when solar radiation is estimated well in advance. Solar radiation is measured by devices like pyranometer, pyrhelimeter, solarimeter, radiometer, etc. installed at various meteorological stations. Due to cost constraints, installation, and maintenance issues, the availability of these devices are limited [4]. These shortcomings are addressed by developing the solar radiation estimation models which receive various geographical and location parameters as input and provides solar radiation as output. These models may be applied to estimate solar radiation at the location of interest where measuring devices are scarce. Potency and current status of India in usages of solar energy are well explained [5]. Several researchers have studied and developed solar radiation estimation models for Indian stations based on ANN [6-8].

In the present study, an ANN-based solar radiation model is developed with a case of Indian cities which may be used to estimate solar radiation at the other locations of interest.

II. ARTIFICIAL NEURAL NETWORK IN ESTIMATION OF SOLAR RADIATION

This ANN is a good tool for estimation related issues. It provides a computationally efficient way of determining nonlinear relationships between multiple inputs and multiple outputs. A mathematical representation of ANN is shown in Fig. 1.

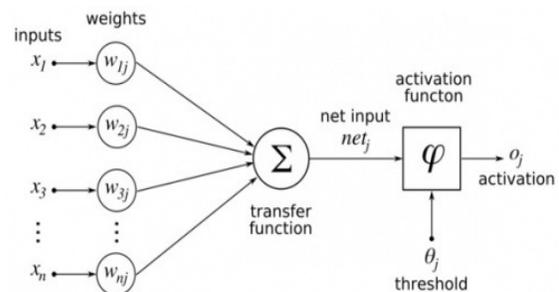


Fig. 1. Mathematical representation of the artificial neural network.

Table 1: Geographical Characteristics of selected stations along with solar radiation data.

Stations	Latitude (°N)	Longitude (°E)	Altitude (m)	Radiation (MJ/m ² /day)
SRINAGAR	34.08	74.83	1587	20.5-5.9
CALCUTTA (DUM-DUM)	22.06	88.45	6	21.8-14.8
TRIVANDRUM	8.48	76.95	64	21.5-15.1
DWARKA	22.36	69.08	11	23.4-14.8
BHOPAL (BAIRAGARH)	22.28	77.35	523	24.8-15.0

It contains inputs, weights, transfer function, threshold/bias, and activation function.

$$O_j = \sum_{i=1}^n x_i \cdot w_i + \phi \cdot \theta_j(1)$$

Here, O_j is the output of ANN, x_i is the input to the ANN, w_i is the weights of ANN, θ_j is the bias/threshold, and ϕ is activation function.

Several researchers have developed/studied a number of Artificial Neural Network-based solar radiation models [9-14].

III. DEVELOPMENT OF SOLAR RADIATION ESTIMATION MODEL USING ARTIFICIAL NEURAL NETWORK

Various steps involved in this section are detailed as under:

A. Geographical and Meteorological data and Methodology

In the present analysis, five cities (Sri Nagar, Kolkata, Trivandrum, Dwarka, and Bhopal) of India of different climatic zones belonging to northern, eastern, southern, western, and central parts respectively, are selected for study. The selected stations are shown in Fig. 2. Table 1 shows the geographical properties of selected stations along with the range of solar radiation received. The stations are selected from CLIMWAT 2.0 tool and CLI (.cli), PEN (.pen) files are downloaded, with the help of this software. This application was developed by Jiirgen Grieser in July 2006 based on CLIMWAT.

The downloaded files are then imported to CROPWAT 8.0 software for geographical and meteorological data download for the stations. These applications are developed by Food and Agriculture Organization (FAO) of UN which is an agency of UN that leads efforts to defeat hunger by providing a long term (fifteen years approx.) mean monthly observed agriculture-climatic information (latitude, longitude, altitude, months of a year, maximum temperature, minimum temperature, humidity, wind velocity, sunshine duration, and solar radiation) of various locations worldwide.

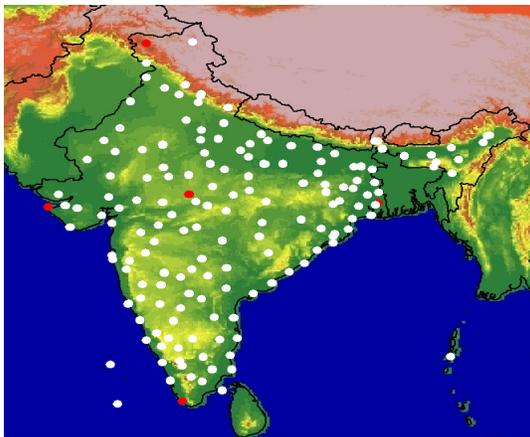


Fig. 2. Selected stations (shown by red dots) of India for study.

Climatic plots are also observed/downloaded for study from CROPWAT 8.0, shown in Fig. 3(a)-(e) for Sri Nagar, Calcutta (Dum-Dum), Trivandrum, Dwarka and Bhopal (Bairagarh) respectively. These are 3D plots between minimum temperature, maximum temperature, humidity, wind velocity, sunshine hour, and solar radiation. Simple observation of all plots reveals that wind velocity and humidity are less correlated with radiation as compared to others.

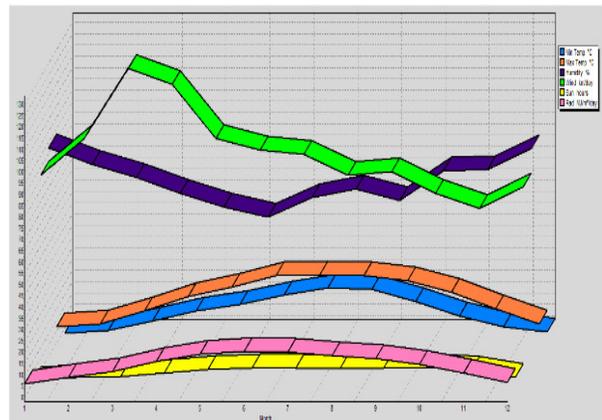


Fig. 3 (a) Climatic Plot of Sri Nagar.

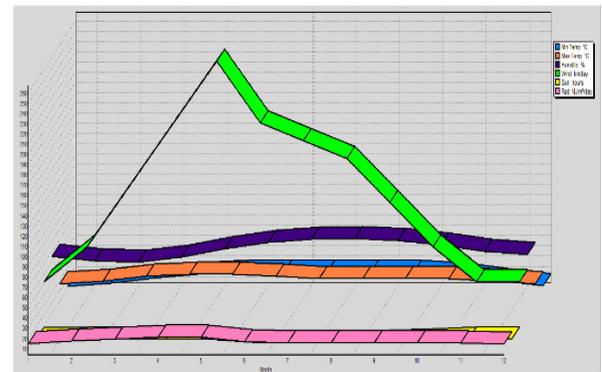


Fig. 3 (b) Climatic Plot of Calcutta Dum-Dum.

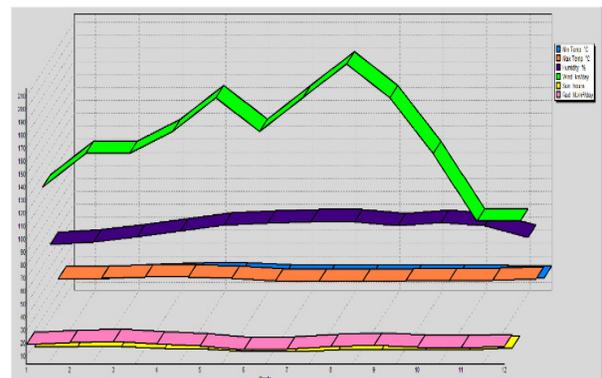


Fig. 3 (c) Climatic Plot of Trivandrum.

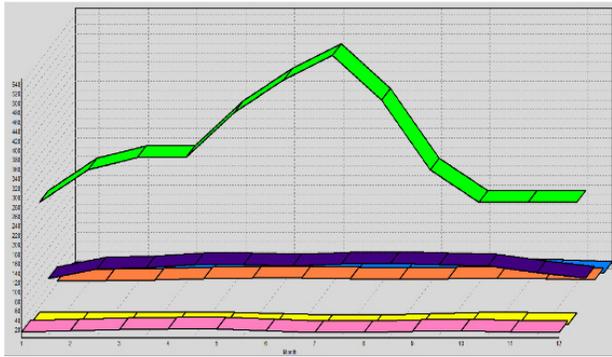


Fig. 3(d) Climatic Plot of Dwarka.

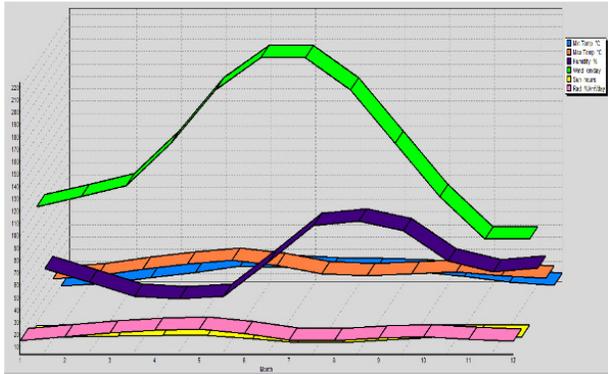


Fig. 3(e) Climatic Plot of Bhopal (Bairagarh).

As, downloaded data are in different units and scales. So, normalization of data is required to be carried out. There are three types of popular normalization techniques: Max-Min Normalization, Decimal Scale Normalization and Z score normalization/ Mean Normalization.

To maintain the simplicity, max-min normalization (within the range 0-1) was performed hereon the downloaded data by equation (2):

$$v'_i = \left[\left(\frac{v_i - B}{A - B} \right) \cdot (M - N) \right] + N \quad (2)$$

Here v'_i is normalized value of variables, v_i is downloaded value variables, A is Maximum value, B is minimum value, M is new maximum value, and N is new minimum value.

B. Methodology

A computer program is performed under MATLAB-R2016a using Neural Fitting Tool (NF Tool), configured as detailed in Table 2.

In backpropagation, the count of neurons determines, how good a problem may be solved. If excess neurons are used then the network will attempt to memorize the problem and thus got generalized well later. However, If less neurons are used then the network will generalize good but may not have enough capacity to learn from the patterns properly. Therefore finalizing the correct number of neurons is a trial and error approach. In this paper, the following empirical formula (Equation 3) is used to determine the critical number of neurons for proper learning and memorizing as well.

$$\begin{aligned} &\text{Number of Neurons} \\ &= \left\lceil \left[\left(\frac{\text{Input} + \text{Output}}{2} \right) \cdot (\text{Sample})^{1/2} \right] \right\rceil \quad (3) \end{aligned}$$

Table 2: Customization detail of Neural Fitting Tool.

S. No.	Particulars	Configuration Details
1.	Network Type	Feed Forward Back Propagation
2.	Training Algorithm	TRAINLM
3.	Adaptation Learning Function	LEANGDM
4.	Error Function	MSE
5.	Number of Hidden Layers	02
6.	Properties for Layer-1	Transfer Function: TANSIG, No. of Neurons: 13
7.	Properties of Layer-2	Transfer Function: TANSIG
8.	Training Info	Input and Output
9.	Training Parameters	Epochs: 1000, max_fail: 6
10.	Data Division	Random (dividerand)
11.	Training	Levenberg-Marquardt (trainlm)
12.	Performance	Mean Squared Error (MSE)
13.	Calculation	MEX
14.	Plot Interval	1 Epochs

In the present study there are nine input parameters namely: latitude, longitude, altitude, months of a year, maximum temperature, minimum temperature, relative humidity, wind velocity and sunshine hour, and one output parameter: solar radiation. The total number of samples are 60. As per Equation 3, the number of neurons required become $12.77 \approx 13$.

C. Statistical Error Test

In the present study, due to simplicity and availability with Neural Fitting Tool, Root Mean Square Error (RMSE) is used for error calculation and evaluation of the model.

$$RMSE = \left[\left(\frac{1}{n} \sum_{i=1}^n (SR_{i(\text{predicted})} - SR_{i(\text{actual})})^2 \right)^{1/2} \right] \quad (4)$$

Here n is number of input, $SR_{i(ANN)}$ is predicted solar radiation, $SR_{i(\text{actual})}$ is actual solar radiation.

IV. RESULTS AND DISCUSSION

As per Table 2 and Equation 3, Neural Network Fitting Tool is customized. Normalized input and output are provided to network for training, validation, and testing. Training environment is shown in Fig. 4.

After training and retraining of the network, maximum validation checks are achieved with 10 iterations. Consequently, various plots like Performance, Training State, Error Histogram, and Regression are obtained, shown in Fig. 5, 6, 7 and 8 respectively.

Performance Plot represents Epochs Vs Mean Squared Error (MSE). In this, the best validation performance of 0.002533 is received at epoch 4. The plot depicts that mean squared error is becoming smaller as the number of epochs increases. This signifies good result.

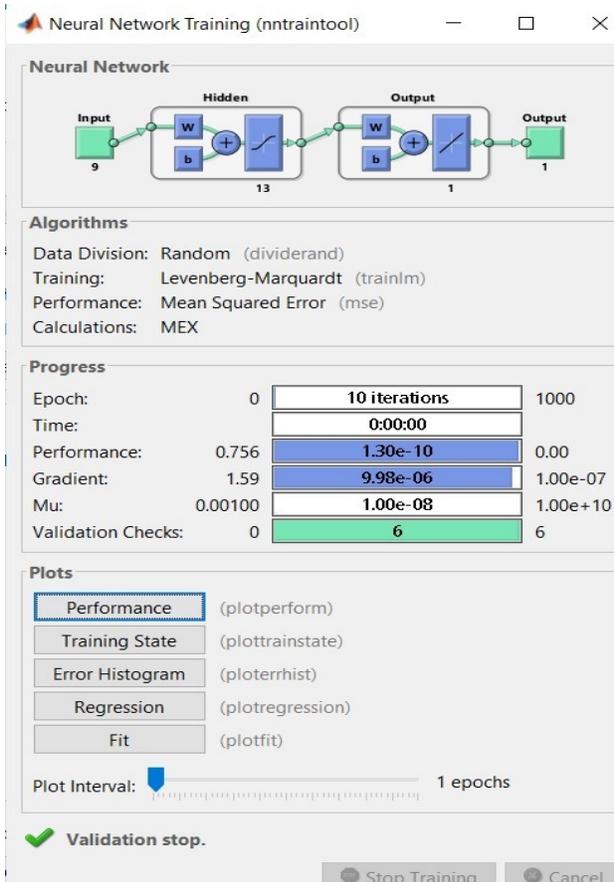


Fig. 4. Training environment.

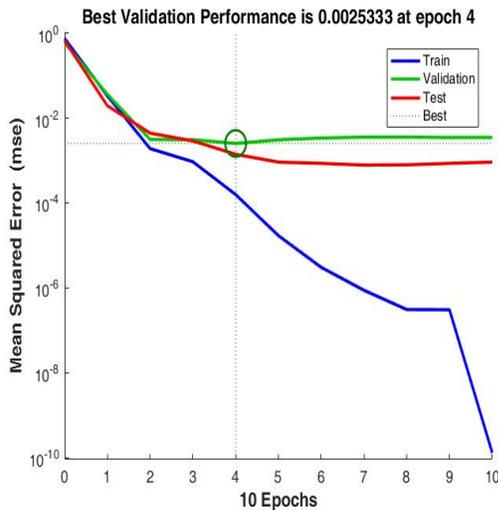


Fig. 5. Performance Plot.

Training State plot consists of three subplots, between Epochs vs Gradient, Epochs vs mu (training gain), and Epochs vs Val Fail. Best Gradient of 0.0247, best mu of 0.0003546, and best Validation Checks of 6 is obtained at Epochs 10. The result justify the good training of the network.

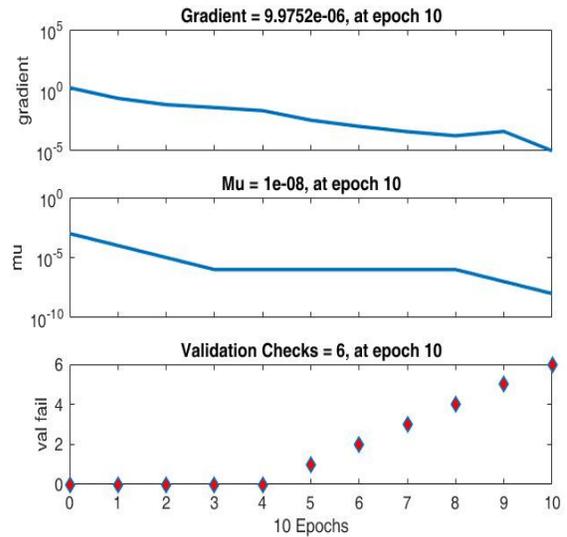


Fig. 6. Training State Plot.

The Error Histogram is the graphical representation of Training data, shown above. It is a plot between Errors and Instances which is essential for additional verification of network performance. Out of 20 number of errors, 12 are above the axis and 08 are not present, this signifies that 08 data are completely different from others. The Histogram is overall in support of the network performance especially test performance.

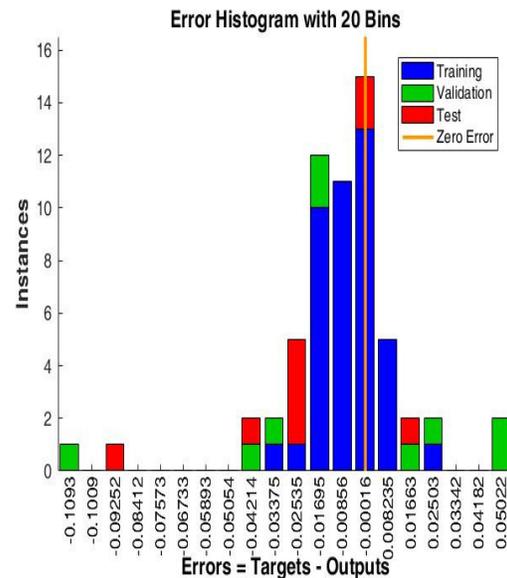


Fig. 7. Error Histogram.

Fig. 8 is a Regression plot with four subplots for Training, Validation, Testing, and All. The plots are between target and output. These plots signifies, how well the variations in the output are explained by the targets. For Training, Validation, Testing, and All, the values of R is 0.09983, 0.098456, 0.97671, and 0.9916 are obtained respectively with overall R-value of 0.9916 (99.16%) for the total response.

The slope (m) and intercept (b) values for overall are 0.98 and 0.32 respectively which predict that the fit is satisfactory.

After obtaining these plots/results, the RMSE value of Training, Validation, and Testing are recorded which is shown in Table 3.

Table 3: Obtained RMSE.

Results	Samples	RMSE
Training	42	0.1700
Validation	9	0.3551
Testing	9	0.2645

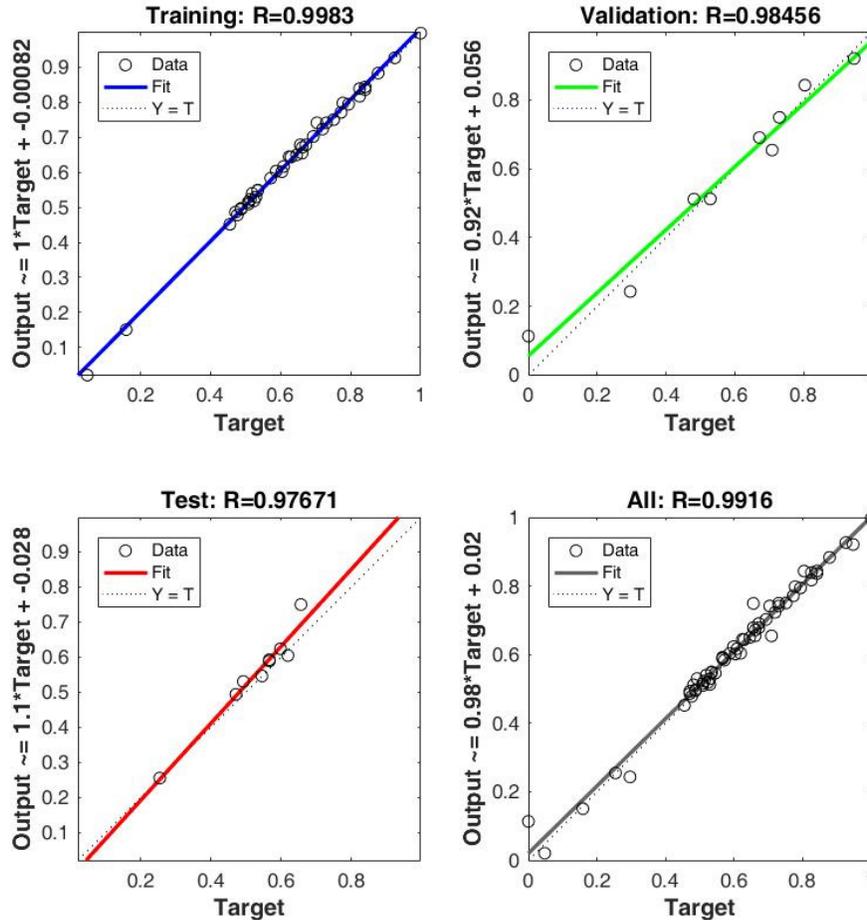


Fig. 8. Regression Plot.

Comparing with current standard methods, it is evident that the proposed model well out performs than [15], which attains a estimation error mentioned in Table 3. Moreover, the proposed model attains better estimation accuracy as compared to general techniques such as FCWN and CWN etc. [15].

V. CONCLUSION AND FUTURE SCOPE

The study gives the ANN-based method of solar radiation estimation using Levenberg-Marquardt feed-forward back-propagation algorithm with a case study of Indian cities. This proposed model is based on different geographical and meteorological parameters as input and solar radiation is estimated. The overall regression is 0.99 (approx.) and RMSE for Training, Validation, and Testing is 0.1700, 0.35551, and 0.2645 respectively. These results advocate the suitability of the proposed model. It may be deployed/used for the estimation of solar radiation in the remote areas where the solar

radiation measuring devices are scarce. In future, work may be extended more properly for hilly areas where sea level varies a lot with slight change in latitude and longitude. Installation and maintenance of solar panels and equipment is quite difficult in such areas.

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Conflict of Interest. We do not have conflict of interest to any of the institution, firm, organization, author or publisher.

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