July – August 2020
ISSN: 0193-4120 Page No. 5163 - 5177

Development of Solar Radiation Estimation Model for North Eastern Stations of India Using Artificial Neural Network

Amar Choudhary[1*], Deependra Pandey[2], Saurabh Bhardwaj[3]

[1*]Research Scholar, Electronics and Communication Engineering Department, Amity School of Engineering and Technology, Amity University, Lucknow, Uttar Pradesh, India-226010

[2]Assistant Professor, Electronics and Communication Engineering Department, Amity School of Engineering and Technology, Amity University, Lucknow, Uttar Pradesh, India-226010

[3]Associate Professor, Electrical and Instrumentation Engineering Department, Thapar Institute of Engineering and Technology, Thapar University, Patiala, Punjab, India-147001

([1*]amar.giet.ece@gmail.com, [2]dpandey@lko.amity.edu, [3]saurabh.bhardwaj@thapar.edu)

Article Info
Volume 83
Page Number: 5163 - 5177
Publication Issue:
July - August 2020

Article History
Article Received: *25 April 2020*
Revised: *29 May 2020*
Accepted: *20 June 2020*
Publication: *10 August 2020*

Abstract

Estimation of solar radiation is a thrust area for the number of researchers since the 20th century for optimal utilization of solar energy. Due to the scarce availability of meteorological stations, estimation is carried out by mathematical and soft computingbased solar radiation estimation models. In this paper, artificial intelligence technique, in particular, artificial neural network-based solar radiation estimation model is developed for North Eastern part of India using latitude, longitude, altitude, months of a year, maximum temperature, minimum temperature, humidity and sunshine hour. These data are collected from CROPWAT-8.0 for ten stations of North-East part of India. These stations are mostly hilly and sunshine duration and temperature remain lesser than the other parts of India. Meanwhile, the humidity remains generally higher. The LM algorithm with a feed-forward backpropagation network is used in the present analysis. For simulation purposes, MATLAB R2016a is used. The obtained results are compared with the measured data and RMSE is calculated for each station and overall too. The RMSE in the developed model varies from 0.39842 to 0.17586 for North Eastern stations of India.

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

I. INTRODUCTION

Solar radiation data estimation is an essential part of the optimization of solar energy applications like solar heating, drying, and cooking, etc. [1-2]. These data are not easily accessible at the locations under interest because of the limited availability of meteorological stations. Also, the installation and maintenance cost of solar radiation measuring devices are very high. So, various empirical models are formulated and tested to estimate solar radiation worldwide [3-4].

An artificial neural network is an excellent tool for prediction related issues. It can resolve non-linear functions with a capacity to select the best input for the prediction of output. ANN is used by various researchers to estimate solar radiation in India too [5-7].

In recent decades, ANN is a good choice for several researchers for solar radiation estimation having justification of suitability over other regression models [8-9].

A. K. Yadav et. al. [5] used the nftool of MATLAB for the estimation of solar radiation of twelve different stations of India with several climatic conditions for training and testing of the model. They found a range of RMSE of 0.0486-3.562 for Indian cities. The Levenberg-Marquardt (LM) algorithm was used by them.

Hasmat Malik et al. [6] used feedforward with backpropagation (FFBP). Backpropagation was used for learning. They used a three-layer network with 1 hidden layer. Data to 67 cities in India were used. They were exclusively divided into training and testing sets. They took 19 inputs or one output. They got 94.65% and 78.86% regression value for 18 and 30 hidden layer neurons respectively. They enlisted the future scope of interest nicely.

Qin et al. [10] used six remote sensing products as input for training and testing of the model with built feed-forward ANN with hyperbolic tangent sigmoid as a transfer function in the hidden layer with twelve neurons. They chose the Levenberg-Marquardt (LM) algorithm along with the Bayesian regulation function. They used 07 years of data for training and 05 years of data for testing the model and obtained RMSE of 8.47%.

PremalathaNeelamegama et al. [11] tried to devise the ANN model for better prediction of solar radiation. They considered four types of backpropagation algorithms for two models for training and testing. They collected the meteorological data for the last 10 years of 5 different stations of India for the training of models. The model with minimum MAE, RMSE, and R was found to be the best one. They found estimated global solar radiation 98-99% closer to the recorded values for all the stations in the second model.

M.A. Behrang et al. [12] used several ANN techniques with a different combination of variables for estimating GSR in Iran. They found MAPE of 5.21% and 5.56% for MLP and RBF respectively.

In this study an ANN-based solar radiation estimation model is developed based on the data of ten different stations of North Eastern part of India. In section II, the ANN approach is briefed in solar radiation estimation. Section III is for data collection, processing. Section IV deals with the methodology of simulation. Lastly results, conclusions are briefed in section V and section VI respectively.

II. ARTIFICIAL NEURAL NETWORK BASED APPROACH

As per Kalogirou [13], Artificial Neural Network can manage very huge and compound data having several mutually related parameters. It discards the less important input as compared to the more important. Backpropagation is the most common learning algorithm in ANN. The learning takes place in two stages: forward and backward pass. The inputs are applied in the first one while the error is propagated in the network in the second one. The synaptic weights of the network are modified during these passes. The actual output of the network is subtracted with targets and errors are produced.

ANN has input, output, and hidden layers. The present study, Multi-Layer Perceptron model is used with 2 hidden layers and 16 neurons. ‘TRAINLM’ is used for training and tan-sigmoid for activation function.

III. DATA COLLECTION AND PROCESSING

The present study and analysis are carried out for the North-Eastern part of India. So, ten different stations (Cherapunji, Dhubri, Dibrugarh, Dibrugarh-Mohanbari, Guwahati, Lumding, Shillong, Sibsagar, Silchar, and Tezpur) belonging from that part are selected for the

July – August 2020
ISSN: 0193-4120 Page No. 5163 - 5177

study. The selected stations are shown in red inFig. 1 below.

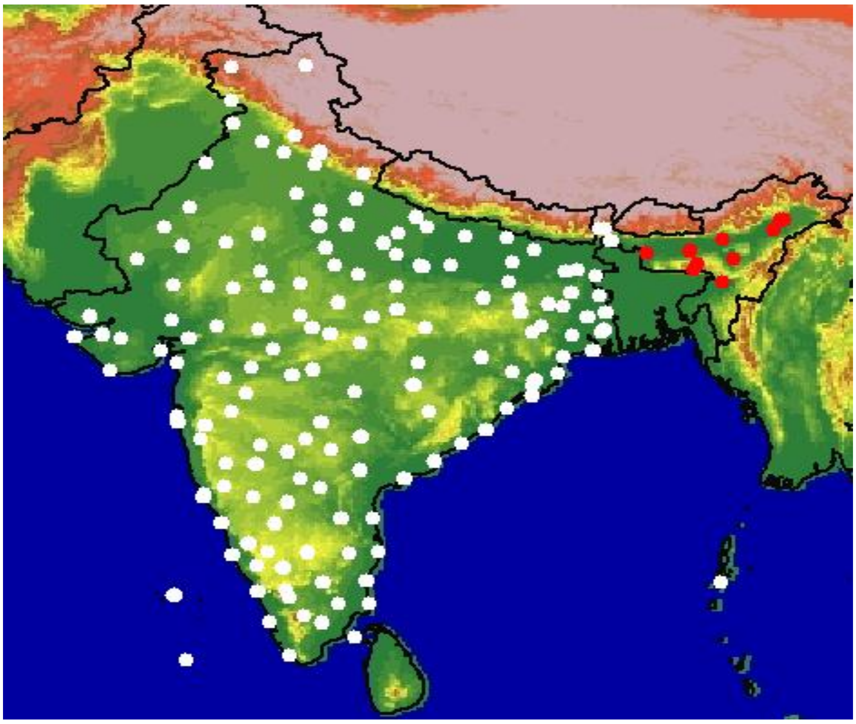

Fig. 1.Selected Stations of India for Study

Table 1: Geographical details and solar radiation data of selected stations

Sl. No	Stations	Latitude ($°N$)	Longitude ($°E$)	Altitude (m)	Radiation ($MJ/m^2/day$)
1	Cherapunji	25.25	91.73	1313	18.7-13.2
2	Dhubri	26.01	89.98	35	21.4-14.6
3	Dibrugarh	27.43	94.90	106	15.3-11.5
4	Dibrugarh-Mohanbari	27.48	95.01	111	16.0-12.5
5	Guwahati	26.10	91.58	54	19.3-13.1
6	Lumding	25.75	93.18	149	19.7-14.2
7	Shillong	25.56	91.08	1598	19.5-10.5
8	Sibsagar	26.98	94.63	97	16.0-10.7
9	Silchar	24.75	92.80	29	20.9-14.6
10	Tezpur	26.61	92.78	79	21.5-15.1

July – August 2020
ISSN: 0193-4120 Page No. 5163 - 5177

Table 1. represents the solar radiation range of selected stations with respective geographical properties. The stations are first selected on CLIMWAT 2.0 and then data are downloaded from CROPWAT 8.0. Both software is developed by the food and agriculture organization of the United Nations. This is a depository of meteorological and radiation of fifteen years. First, CLI and PEN files are downloaded then imported on CROPWAT 8.0 for retrieving of respective station data with parameters. The data are consisting of latitude, longitude, altitude, months, maximum temperature, minimum temperature, humidity, wind speed, sunshine hour, and solar radiation.

As the downloaded data were having different units of measurements and ranges so they all are normalized by below max-min normalization equation to make them suitable for input to the neural network.

$$x_{normalized} = \frac{x - x_{minumum}}{(x_{maximum} - x_{minimum})} \quad (1)$$

IV. PROPOSED METHODOLOGY

The two-layer (MLP) and feed-forward backpropagation are used in the present study. The number of neurons in the hidden layer is calculated by the below equation.

$$\text{No. of Neurons} = \left[\left(\frac{\text{Input} + \text{Output}}{2}\right) . (\text{Sample})^{1/2}\right] \quad (2)$$

$$\text{RMSE} = \left[\left(\frac{1}{n}\right) \sum_{i=1}^{n} \left(SR_{i(predicted)} - SR_{i(actual)}\right)^2\right]^{1/2} \quad (3)$$

In this analysis, there are nine inputs, one output, and one hundred twenty samples. By equation (2), the number of hidden neurons is sixteen (approx.). Using random division 70% (84) samples are considered during training, 15% (18) during validation, and rest 15% (18) during testing. A total of 10 iterations are achieved using NF Tool in MATLAB R2016a. The goal of the simulation is to achieve the minimum Root Mean Square Error (RMSE).

V. RESULTS

Network Fitting tool of MATLAB R2016a is customized (detailed in table 2) by trial and error approach to get minimum errors. The network is trained again and again to achieve the target. The neural network customized architecture with other details are represented in Fig. 2.

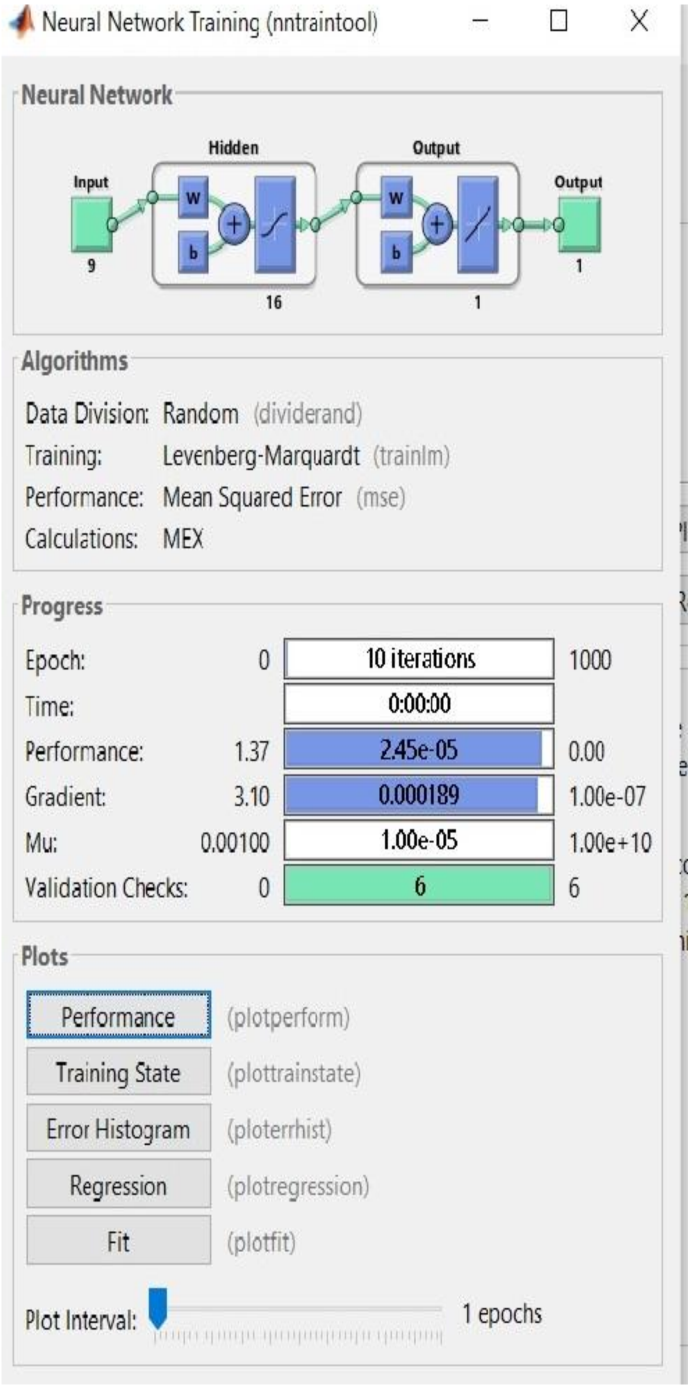

Fig. 2. Neural Network Training Environment

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	Hidden Layers	02
6	Layer-1Transfer	TANSIG
7	No. of Neurons	16
8	Layer-2 Transfer Function	TANSIG
9	Training Parameters	Epochs: 1000, max_fail: 6
10	Data Division	Random (dividerand)
11	Training	Levenberg-Marquardt
12	Performance	Mean Squared Error (MSE)
13	Calculation	MEX
14	Plot Interval	1 Epochs

Additional tests on every ten stations are also performed (detailed in Table 3). Best simulation for training, validation, and testing are achieved after 10 iterations with minimum RMSE, represented in Table 4.

Table 3: Optionally performed additional tests on selected stations

S. No.	Stations	RMSE
1	Cherapunji	0.33056
2	Dhubri	0.23365
3	Dibrugarh	0.39842
4	Dibrugarh-Mohanbari	0.33556
5	Guwahati	0.28101
6	Lumding	0.21502
7	Shillong	0.17586
8	Sibsagar	0.28694
9	Silchar	0.27504
10	Tezpur	0.20674

Table 4. Simulation Errors

Results	Samples	RMSE
Training	84	0.15435
Validation	18	0.38891
Testing	18	0.31407

The performance plot is observed and shown in Fig. 3. It is the plot between epochs and mean squared error. The mean squared errors are getting reduced as the number of epochs is increased. The validation performance of 0.00082583 is achieved at epochs 4.

The training state plot (Fig. 4) is the plot between val fail, mu (momentum constant), gradient, and epochs. The best values of Gradient, Mu, and validation checks are 0.00018889, 0.00673794, and 6 respectively at 10 epochs.

Error Histogram plot (Fig. 5) errors (target-output) and instances. The plot shows Error Histogram with 20 bins.

Figure 6 is the Regression Plot between target and output for training, validation, testing, and all. The plot between target and output measures how well the variation in output is achieved for the target.

For Training, Validation, Test, and All, the value of R is 0.099876, 0.099292, 0.9861, and 0.99517 are obtained respectively. The total R-value of 0.99517 (99.51%) for the total response. Slope and intercept values for overall are 0.98 and 0.011 respectively which predict the fit is satisfactory.

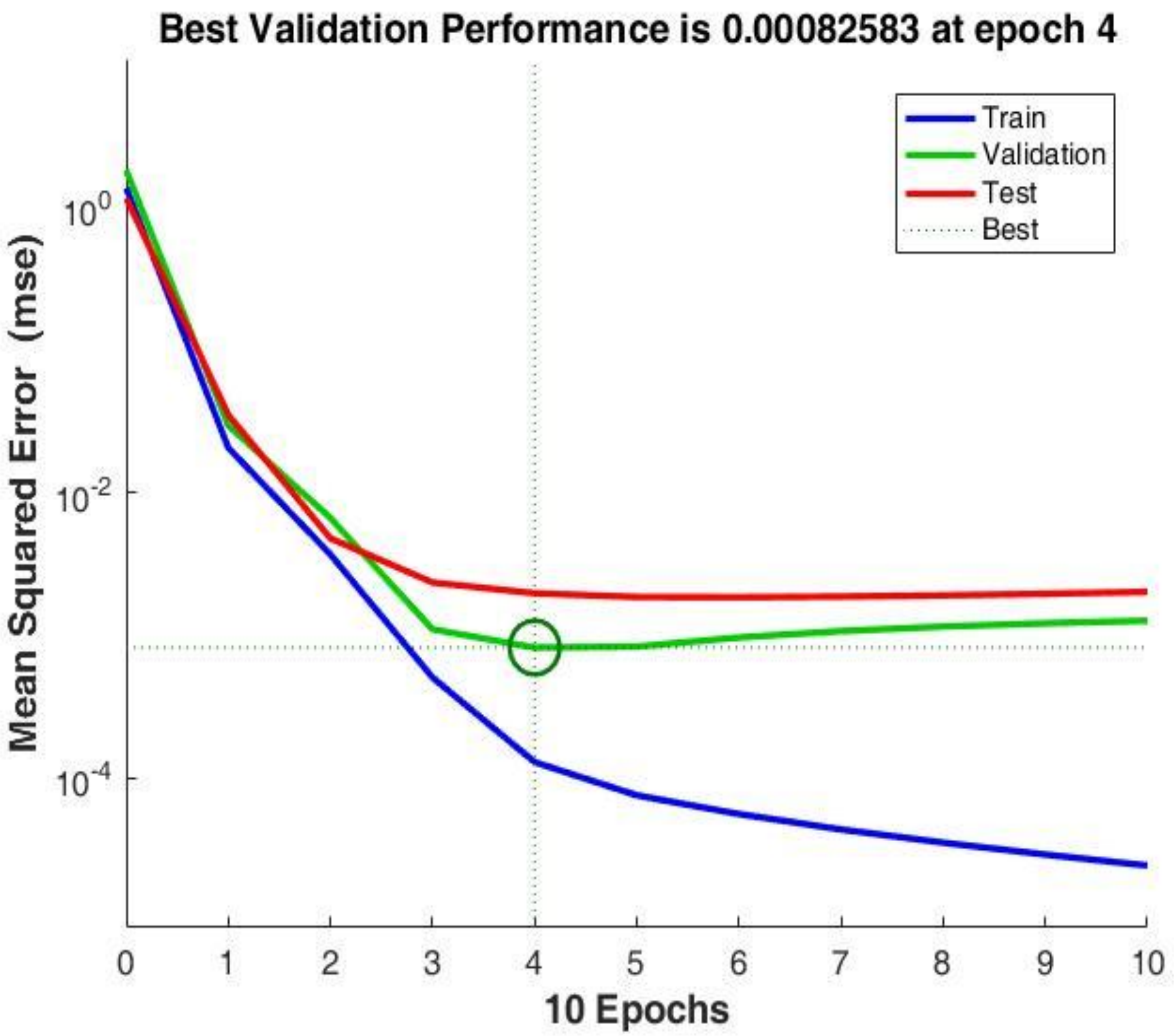

Fig. 3. Performance Plot

July – August 2020
ISSN: 0193-4120 Page No. 5163 - 5177

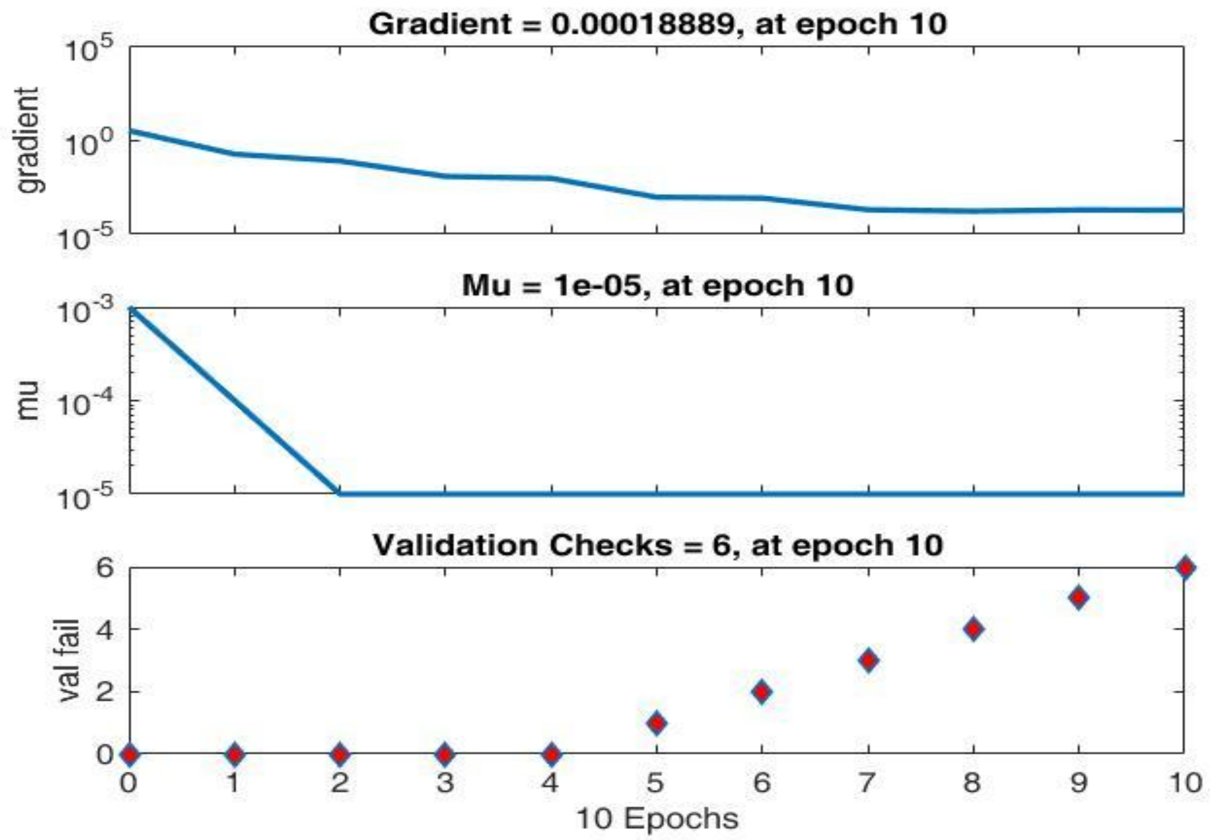

Fig. 4. Training State Plot

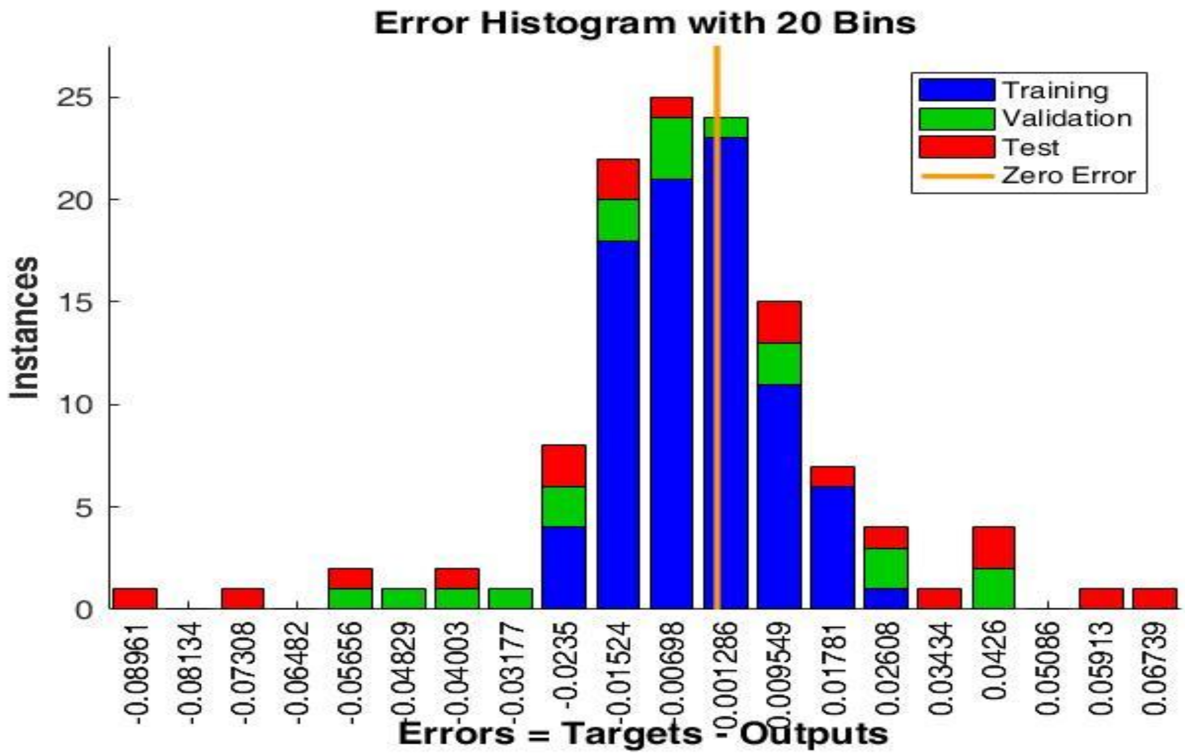

Fig. 5. Error Histogram

July – August 2020
ISSN: 0193-4120 Page No. 5163 - 5177

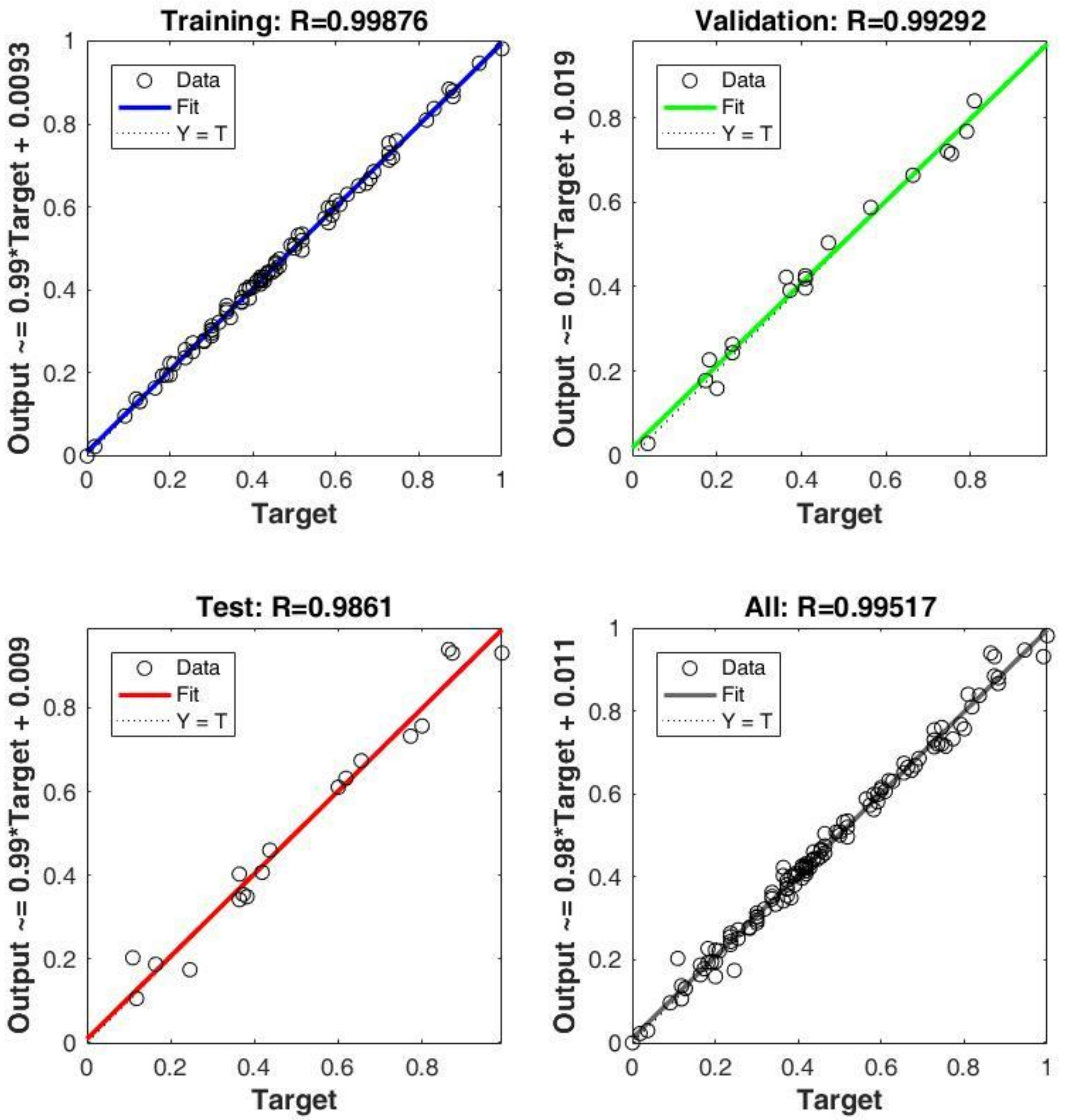

Fig. 6. Regression Plot

VI. CONCLUSION AND FUTURE SCOPE

The obtained values of Root Mean Squared Errors for the ten stations lie in between 0.39842 to 0.17586 which justifies the quality of work. The developed model uses normalized latitude, longitude, altitude, months, maximum and minimum temperature, humidity, and sunshine hours as input, producing solar radiation as output. Values of regressions, slope, and intercepts justify the good simulation results. The performance, training state, and error histogram plot have better results than the earlier one. This developed model can be best utilized in the North-Eastern part of India with a considerable good geographical area of 3.287 million Km^2.

Acknowledgements

We are highly thankful to Food and Agriculture Organization (FAO) of United Nations for developing CLIMWAT and CROPWAT and maintaining solar radiation and meteorological database of large number of stations worldwide.

REFERENCES

[1] Kumar R, Umanand L. (2005), "Estimation of global radiation using the clearness index model for sizing photovoltaic system", Renewable Energy, 30(15):2221-33.

[2] Wong LT, Chow WK (2001), "Solar radiation model", Applied Energy, 69(3): 191-224.

[3] Mohamed Salah Mecibah (2014), TaqiyEddineBoukeila, Reda Tahtah, KacemGairaa, "Introducing the best model for estimation of monthly mean daily global solar radiation on a horizontal surface (Case study: Algeria)", Renewable and Sustainable Energy Reviews 36, 194-202.

[4] FaribaBesharat, Ali A. Dehghan, Ahmad R. Faghih (2013), "Empirical models for estimating global solar radiation: A review and case study", Renewable and Sustainable Energy Reviews 21, 798-821.

[5] Yadav Kumar Amit, Chandel S.S. (2012), "Artificial Neural Network based Prediction of Solar Radiation for Indian Stations", International Journal of Computer Applications (0975-8887), volume 50- No. 9.

[6] Malik Hasmat, Garg Sidhharth (2019), "Long-Term Solar Irradiance Forecast Using Artificial Neural Network: Application for Performance Prediction of Indian Cities", Advances in Intelligent Systems and Computing, 697, https://doi.org/10.1007/978-981-13-18221-1_26

[7] Kumar Abhishek, Khatri Ravi (2019), " Solar Energy Prediction Using Backpropagation in Artificial Neural Networks", International Conference on Advanced Computing Networking and Informatics, Advances in Intelligent Systems and Computing, 870, https://doi.org/10.1007/978-981-13-2673-8_4

[8] Mubiru J., Banda E.J.K.B. (2008), "Estimation of monthly average daily global solar irradiation using ANN", ScienceDirect (Elsevier), Solar Energy, 82, 181-187.

[9] Sozen A. (2004), "Use of Artificial Neural networks for mapping of solar potential in Turkey", Applied Energy, 77(3):273-86.

[10] Qin J, Chen Z, Yang K, Liang S, Tang W (2011), "Estimation of monthly mean daily global solar radiation based on MODIS and TRMM products", Applied Energy, 2480-9.

[11] PremalathaNeelamegam, ValanArasuAmirtham (2016), " Prediction of solar radiation for solar systems by using ANN models with different backpropagation algorithms", Journal of Applied Research and Technology, 206-14.

[12] M.A. Behrang, E. Assareh, A. Ghanbarzadeh, A.R. Noghrehabadi (2010), "The potential of different artificial neural network (ANN) techniques in daily global solar radiation modeling based on meteorological data", Solar Energy, 84: 1468-1480.

[13] Kalogirou SA (1999), "Application of Artificial Neural Network in energy systems: a review", Energy Conversion Management, 40: 1073-87.