Artificial Neural Networks Based Solar Radiation Estimation using Backpropagation Algorithm

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Abstract- Being at the cutting edge for a long time, solar energy has found several applications in various areas. Optimal harvesting of solar energy is one of the thrust areas of the researchers and developers in 21st century. Solar energy optimization solely depends on radiation received by the solar panels. Radiation is measured by various devices and it may be estimated by various estimation models. Solar energy needs to be estimated well in advance if the system to be designed has to be completely dependent on solar energy. This is a very challenging job since solar radiation depends on several parameters such as location changes and seasonal changes. Artificial Neural Network is one of the most preferred technique for the researchers in prediction related cases. This paper proposes a methodology to estimate solar radiation using feed forward back propagation neural network. A three-layer neural network is used here with one hidden layer. The data of 14 stations of Uttar Pradesh, India are obtained data from FAO, UN and it further divided into three sets of 'Training', Validation' and 'Testing'. This study is based on nine input parameters and one output parameter. Feed forward back propagation is used here to estimate solar radiation. The proposed model is validated for Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient training algorithms. The obtained results of Mean Square Error (MSE), Regression Values (R), Slope Values (m) and Intercept Values (c) in all three cases are justifying the suitability of the proposed model.

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

Nomenclature:

AI:	Artificial Intelligence	**ANN:**	Artificial Neural Network
LM:	Levenberg-Marquardt	**BR:**	Bayesian Regularization
SCG:	Scaled Conjugate Gradient	**MSE:**	Mean Square Error
NF Tool:	Neural Fitting Tool	**CVNN:**	Complex Valued Neural Networks
FCWN:	Fully Complex Valued Wavelet Network	**CWN:**	Complex Wavelet Network
NWP:	Numerical Weather Prediction	**MLP:**	Multi-Layer Perceptron
RCN:	Recurrent Neural Neywork	**SVR:**	Support Vector Regression

1. Introduction

The limited availability of non-renewable energy resources and their environmental impacts, attracted the researchers and developers for optimization of renewable energy specially solar energy due to its huge abundancy across the globe [1-3]. Earlier only low power devices were using solar energy but now a days heavy industries are also planning to meet their power requirements by solar energy. One of the short coming with solar energy is that it is not consistent and abrupt fluctuations are also widely observed [4]. The solar energy depends on location parameters such as latitude, longitude, altitude and meteorological parameters such as temperature, humidity, wind speed, sunshine hours which makes solar energy relatively unpredictable with respect to traditional energy resources. Still then, considerably large investment are being planned for solar power plants and solar energy based industries. This attracts the researchers to work for estimation of solar energy well in advance. Previously, statistical models were mainly used for this purpose which were very prone to errors (less accurate estimation). Solar radiation estimation came under the purview AI. Practically, ANN based system could be used of estimation related problems. The prediction may be Short-Term Forecasting, Mid-Term Forecasting and Long-Term Forecasting.

Solar radiation is measured by devices like solarimeter, pyranometer, pyrheliometer etc. but these devices are of very high cost and installed at meteorological stations which may not be the location of interest [5]. This shortcoming is well addressed by solar radiation estimation models. Several researchers have proposed ANN based solar radiation estimation models especially for locations of India [6-9].

Type and techniques of solar irradiance forecasting and solar power forecasting is well elaborated by Mehmet Yesilbudak *et. al*. [10] and hundred related models have been comparatively studied by them.

Long term solar radiation forecasts of NWP is well explained by Miki Ueshima *et. al.* [11]. They examined all the correction methods used for this and predicted solar radiation for up to a week. Based on statistical analysis they improved the prediction accuracy.

M. Colak *et. al.* [12] integrated grey wolf optimizer algorithm MLP algorithm to forecast daily total horizontal solar radiation. They tested their model for all types of transfer function (sigmoid, sinus and hyperbolic tangent) in the MLP and found that grey wolf optimizer based MLP is most suitable one for predicting daily total horizontal solar radiation.

Abdulsalam Alkholidi *et. al.* [13] compared and analysed the sun irradiation for southern European countries and proposed a solution for encouragement of solar energy market in Albania. They considered the villages of Alabnia in their study where public electricity is not available.

Rami AI-Hajj *et. al.* [14] proposed the ensemble learning approach of combining RNN and SVR for forecasting solar radiation strengths on horizontal surface. Their proposed approach provided improved accuracy of one-day-ahead forecasting.

M. Mujahid Rafique [15] used a simplified design for assessment of solar PV system for household electrification in Pakistan. They determined life cycle cost and per unit electricity cost using developed model. They obtained 50-55% cheaper way of generating electricity in comparison to traditional energy. Finally, their developed model seems to be promising one for policy maker and common people of Pakistan to prefer solar energy over conventional energy.

This paper is dedicated to ANN based solar radiation estimation. Backpropagation is used here and simulation is executed for LM, BR and SCG training algorithms.

ANN based solar radiation estimation is briefed in section 2, data collection and model development is detailed in section 3 and in section 4, 5 results are presented and conclusions are made.

2. ANN Based Solar Radiation Estimation

Authors ANNs have parallel structure (Fig. 1) which makes it capable of fast learning and computing from data trend [16]. It ensures an efficient way of establishing a non-linear relationship between input and output. ANN is a more accurate tool for determining solar radiation in comparison to non-linear, fuzzy, conventional, Angstrom model, etc. models Several researchers have well proposed ANN based solar radiation estimation [17-28].

The mathematical representation of ANN is shown in Fig. 1 which consists of multiple input, output, weights and biases, transfer and activation function. The output on ANN is determined by Eq. 1.

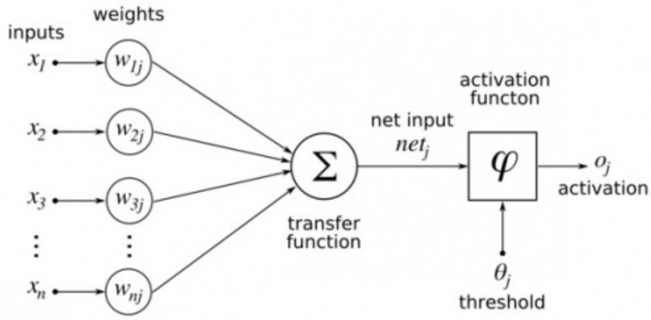

Fig. 1. Typical architecture of multilayer neural network.

$$O_j = \sum_{i=1}^{n} x_i . w_i + \emptyset . \theta_j \quad (1)$$

Here,

O_j is the output of ANN, x denotes the input of ANN, w represents the corresponding weights of ANN, θ_j represents the threshold and $\emptyset$ denotes the activation function.

Neural network needs to be trained before it can be used for prediction of data and testing for accuracy.

Backpropagation is used here since it is the most effective tool for quickly reducing the errors. In this paper, LM, BR and SCG all are used, compared for proposed model.

3. Solar Radiation Estimation Modeling

In the current analysis, most populous state of India, Uttar Pradesh is considered which have approximately 200 million inhabitant with 75 districts. The meteorological data and solar radiation data are downloaded from Food and Agriculture Organization (FAO), UN. By virtue of CLIMWAT 2.0 and CROPWAT 8.0 the data are collected for 14 stations. The stations are represented in Fig. 2.

Table 1 represents location details such as latitude, longitude and altitude of stations while Table 2 represents annual averaged meteorological details of maximum temperature, minimum temperature, humidity, wind speed, sunshine hours and solar radiation.

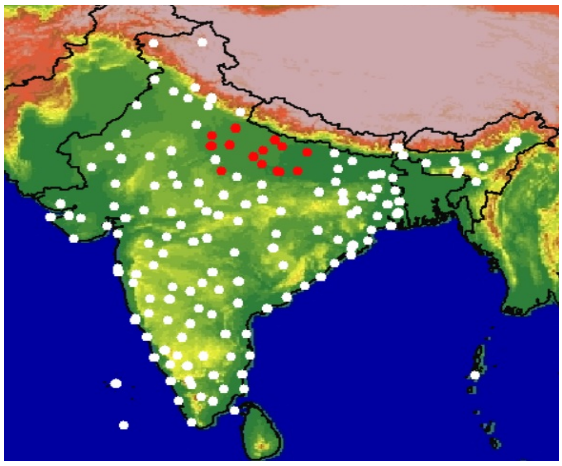

Fig. 2. Stations under study of Uttar Pradesh (India) courtesy: Food and Agriculture Organization (FAO), United Nations.

Table 1. Geographical details of stations under observation

Stations	Latitude (°N)	Longitude (°E)	Altitude (m)
Agra	27.16	78.03	169
Aligarh	27.88	78.06	187
Allahabad	25.43	81.81	98
Allahabad-Bamhrauli	25.43	81.73	98
Bahraich	27.56	81.60	124
Bareilly	28.36	79.40	154
Fatehpur	25.93	80.83	114
Gonda	27.13	81.96	110
Gorakhpur	26.75	83.36	77
Jhanshi	25.45	78.58	21
Kanpur	26.43	80.36	126
Lucknow	28.86	80.93	111
Mainpuri	27.23	79.05	157
Varanasi-Babatpur	25.43	82.86	85

Table 2. Annual average meteorological details and solar radiation data of stations

Stations	Maximum Temp.(°C)	Minimum Temp.(°C)	Humidity (%)	Wind Speed (km/day)	Sunshine (hours)	Solar Radiation (MJ/m^2/day)
Agra	19.3	32.6	49	74	7.3	17.7

Aligarh	18.7	31.9	51	112	7.9	18.4
Allahabad	19.1	32.2	60	126	9.4	20.7
Allahabad-Bamhrauli	19.3	32.4	55	122	7.1	17.6
Bahraich	19.1	31.5	59	95	8.7	19.6
Bareilly	18.9	31.5	56	78	7.4	17.7
Fatehpur	19.5	32.4	59	74	7.8	18.6
Gonda	18.8	31.5	62	88	7.7	18.2
Gorakhpur	20	31.4	60	78	7.3	17.7
Jhanshi	19.7	32.8	46	97	8.8	20
Kanpur	19.3	32.1	53	158	7.9	18.6
Lucknow	19.4	32.3	58	52	7.9	18.5
Mainpuri	18.7	32.8	53	67	7.5	18
Varanasi-Babatpur	19.8	32.2	55	115	7.3	18
Max-Min Values	20 and 18.7	32.8 and 31.4	62 and 46	158 and 52	9.4 and 7.1	20.7 and 17.6

The measuring units and scale of meteorological and location parameters of Table 1 and 2 are different from each other. To make it suitable for ANN Model, min-max normalization (in the range of 0-1) of is executed as per Eq. (2):

$$x_{normalized} = \frac{x - x_{minumum}}{x_{maximum} - x_{minimum}} \tag{2}$$

Here, x is the variable to be normalized.

After this, the process of simulation starts. NF Tool of MATLAB- R2016a is used here. In the current study, there are nine inputs (latitude, longitude, altitude, months of a year, maximum temperature, minimum temperature, humidity, wind speed and sunshine hours) and one output/target (solar radiation) shown in Fig. 3. The customization details of NF Tool are presented in Table 3. All three types of training algorithms (LM, BR and SCG) are executed here with data set and their results are compared.

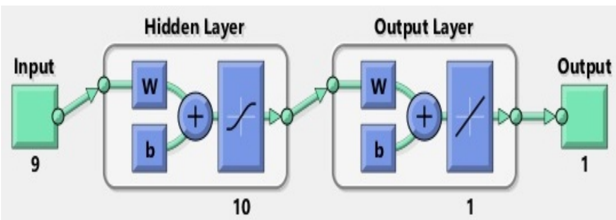

Fig. 3. Network architecture

Table 3. Customization of NF Tool

Particulars	Configuration Details
Network Type	Feed Forward Back Propagation
Training Algorithm	TRAINLM, TRAINBR and TARINSCG
Error Function	MSE
Number of Hidden Layers	02
Transfer Function	TANSIG
No. of Neurons	10
Training Parameters	Epochs: 1000, max_fail: 6
Data Division	Random (dividerand)
Performance	Mean Squared Error (MSE)
Calculation	MEX
Plot Interval	1 Epochs

The normalized data set is segmented into three parts (Fig. 4) as per default setting of NF Tool. Out of 168 samples, 70% (118 samples) are used for training the neural network, 15% (25 samples) for validation and rest 15% (25 samples) for testing the network.

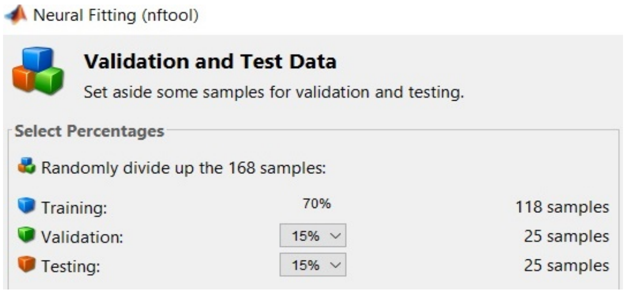

Fig. 4. Data division

Once the model is designed, data applied, it's validity/reliability needs to be tested and verified. Solar radiation estimation models are judged by means of statistical error testing. In this study, the model is evaluated on the basis of MSE given in Eq. (3):

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

Here, n is the number of input, SR is the solar radiation.

4. Results

The simulation is executed on all three types of training algorithm in this section, one by one and their performance is compared.

4.1. Levenberg-Marquardt (trainlm)

LM algorithm require comparatively more memory than other algorithms. This algorithm is recommended as first choice supervised algorithm. It is the fastest backpropagation algorithm in the toolbox.

The training environment using LM algorithm is shown is Fig. 5. The best network performance is obtained after 33 iterations and 6 validation checks.

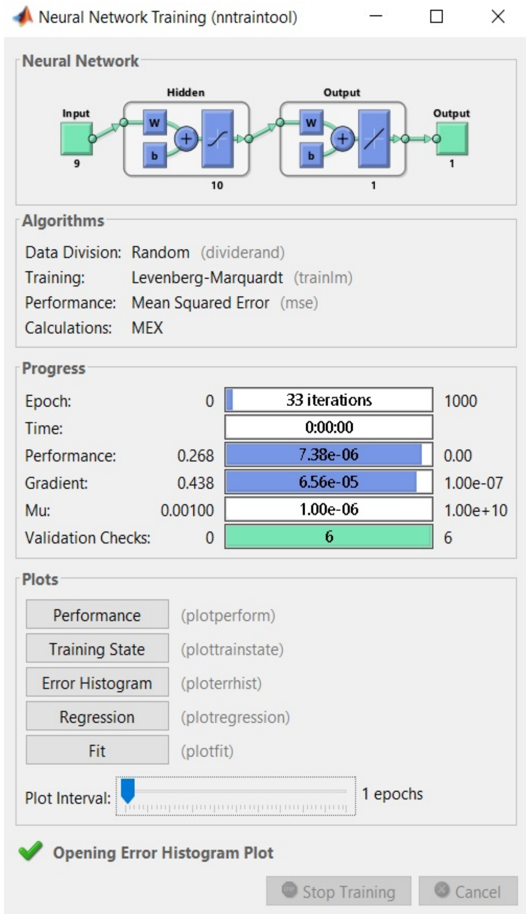

Fig. 5. Training Environment with learning algorithm tarinlm

The performance of the network is represented in Fig. 5. The best validation performance of 0.06295 is obtained at epoch 27.

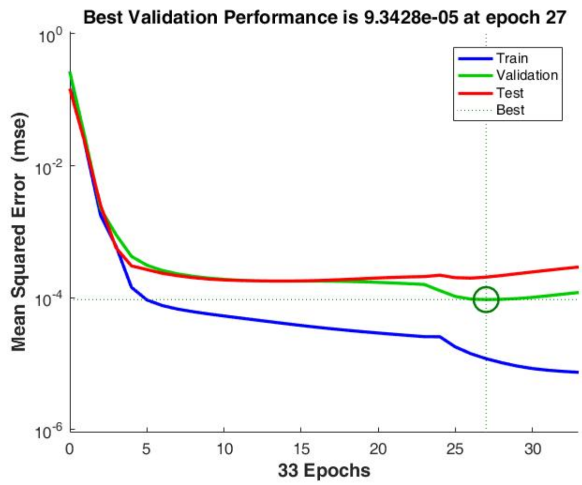

Fig. 6. Performance plot with learning algorithm tarinlm

Fig. 7. is for training state plot in which Gradient of 0.04421, Mu of 0.002 and Validation Checks of 6 are obtained at epochs of 33.

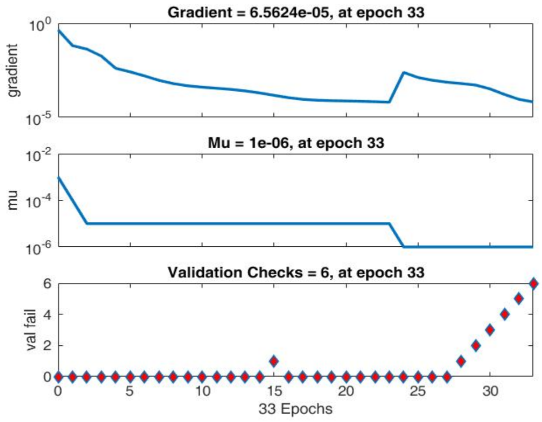

Fig. 7. Training State plot with learning algorithm tarinlm

The Error Histogram is shown in Fig. 8. It is plot between error and instances. It is with 20 Bins. Zero Error is shown by orange line and maximum bars fall considerably lower to this.

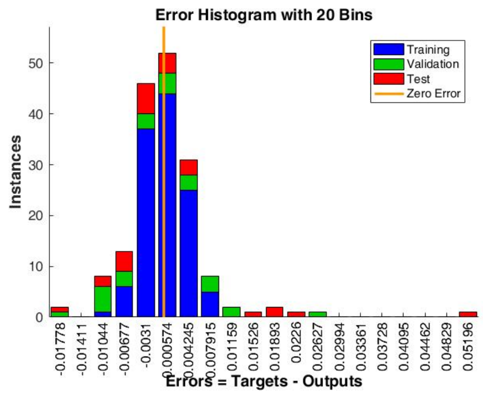

Fig. 8. Error Histogram plot with learning algorithm tarinlm

The Regression Plot is shown in Fig. 9. The best value of R is considered to be 1 and in this case it is almost obtained.

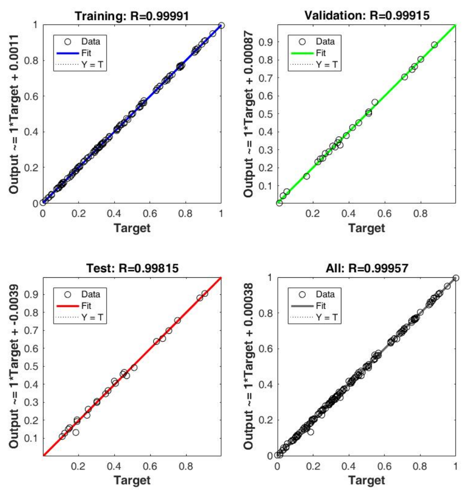

Fig. 9. Regression plot with learning algorithm tarinlm

4.2 *Bayesian Regularization (trainbr)*

This is a network training function that updates it's weight and bias according to LM algorithm. For production of network that mat generalize well, it minimizes combination of squared errors and weights to determine correct combination.

The training environment using 'trainbr' is shown in Fig. 10. The best network performance is achieved after 514 iterations.

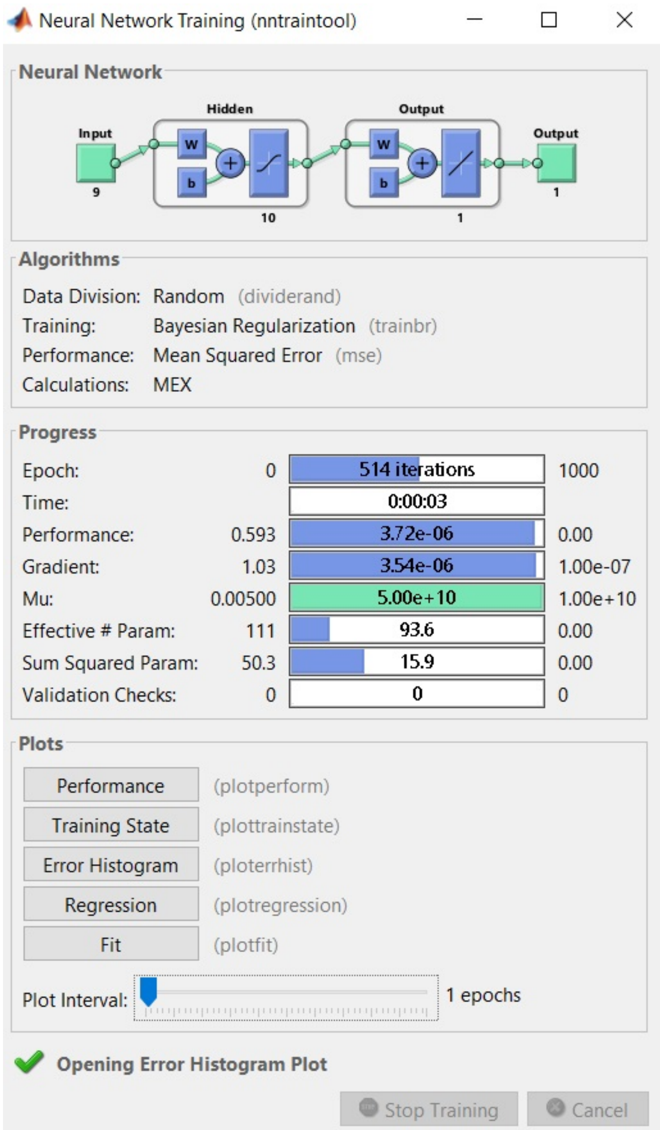

Fig. 10. Training Environment with learning algorithm tarinbr

The performance of the network is represented in Fig. 11. The best validation performance of 0.0092 is obtained at epoch 405.

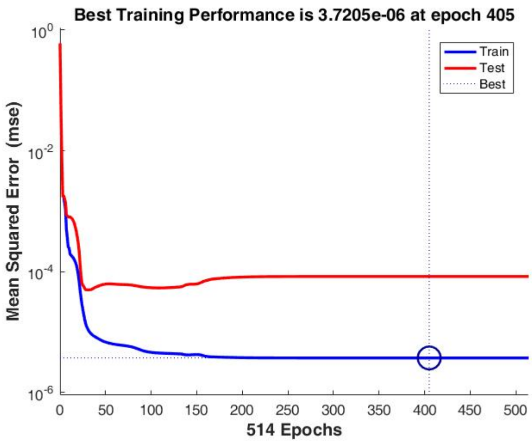

Fig. 11. Performance plot with learning algorithm tarinbr

Fig. 12. is for training state plot in which Gradient of 0.008, Mu of 50000000000, Num Parameters of 93.678, Sum squared Parameter of 15.874 and Validation Checks of 0 are obtained at epochs of 514.

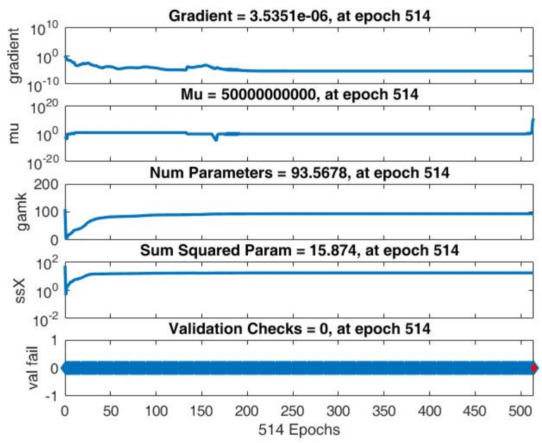

Fig. 12. Training State plot with learning algorithm tarinbr

The Error Histogram is shown in Fig. 13. It is with 20 Bins. Zero Error is shown by orange line and maximum bars fall considerably lower to this.

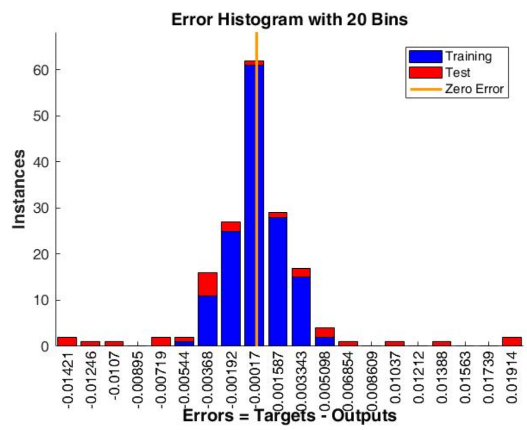

Fig. 13. Error Histogram plot with learning algorithm tarinbr

The Regression Plot is shown in Fig. 14. The value of R is 0.99997, 0.99932 and 0.99987 is obtained for training, validation and testing respectively.

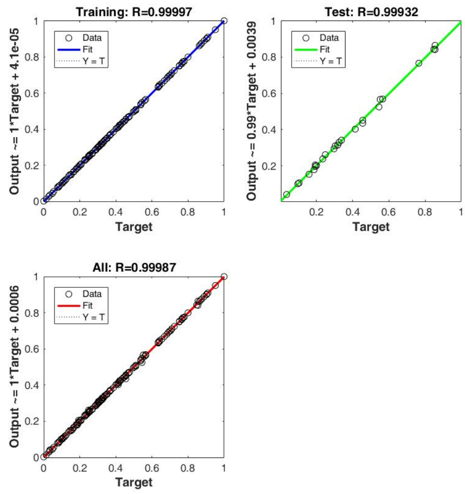

Fig. 14. Regression plot with learning algorithm tarinbr

4.2. Scaled Conjugate Gradient (trainscg)

This is a backpropagation network function which updates it's weight and biases according to gradient scaled conjugate function.

The training environment with 'trainscg' algorithm is shown in Fig. 15. The best validation performance is achieved after 6 validation checks and 77 iterations.

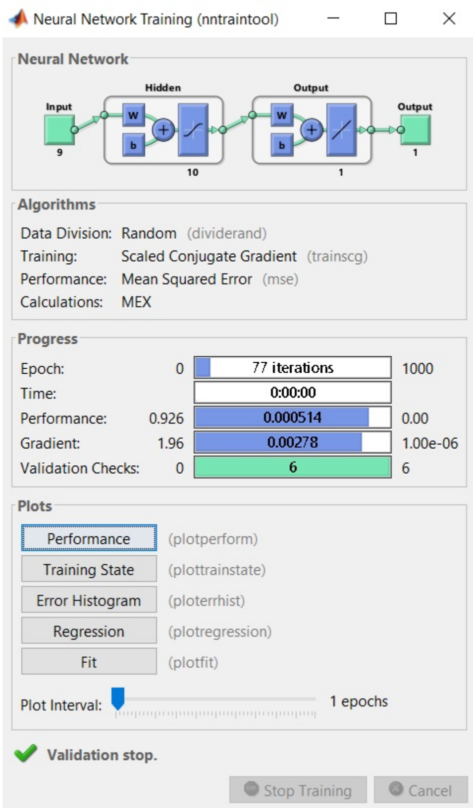

Fig. 15. Training Environment with learning algorithm tarinscg

The performance of the network is represented in Fig. 16. The best validation performance of 0.000807 is obtained at epoch 71.

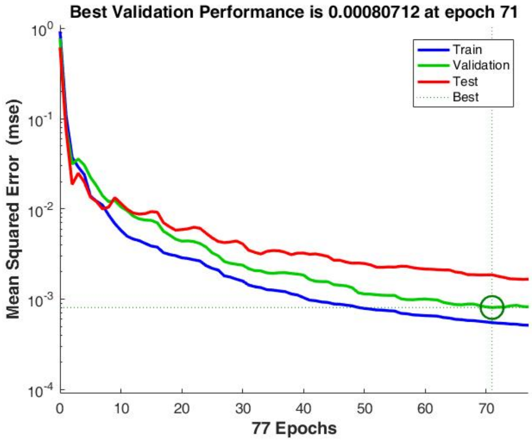

Fig. 16. Performance plot with learning algorithm tarinscg

The training state plot of the network is shown in Fig. 17. The best Gradient performance of 0.0027788 and Validation Checks of 6 is obtained at epochs 77.

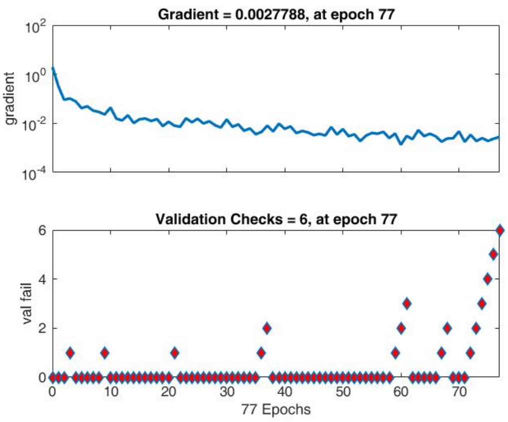

Fig. 17. Performance plot with learning algorithm tarinscg

The Error Histogram plot of the network is shown in Fig. 18 with 20 Bins. The maximum bars lesser than the Zero Error line. This is in support of the simulation executed.

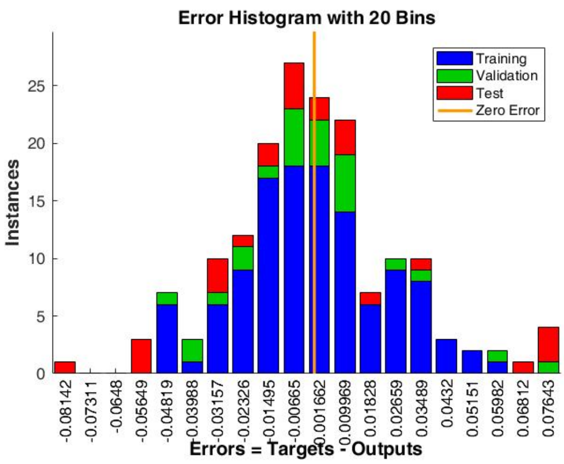

Fig. 18. Error Histogram with learning algorithm tarinscg

The Regression Plot is shown in Fig. 20. The R is obtained as 0.99554, 0.99267, 0.98741 and 0.98741 for training, validation, testing and all respectively.

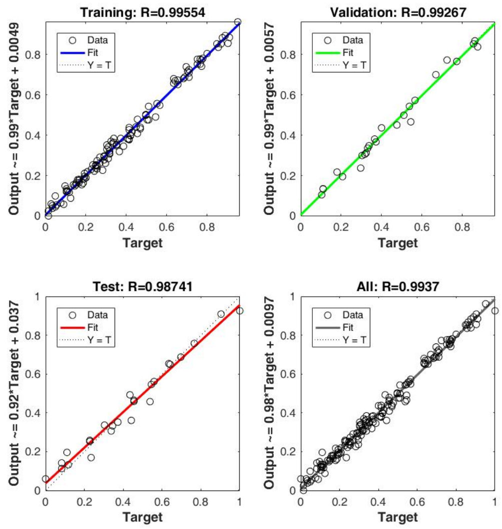

Fig. 19. Regression plot with learning algorithm tarinscg

After analyzing the plots form Fig. 5- Fig. 19, MSE in all three cases are shown in Fig. 20, Fig. 21 and Fig. 22 and they are listed in Table 4 for easy understanding. Similarly, the regression values (R), slope values (m), and intercept values (c) are listed in Table 5 - Table 7 respectively.

	Samples	MSE
Training:	118	1.18637e-5
Validation:	25	9.34279e-5
Testing:	25	2.04718e-4

Fig. 20. Obtained MSE in trainlm

	Samples	MSE
Training:	118	3.72046e-6
Validation:	25	0.00000e-0
Testing:	25	8.30616e-5

Fig. 21. Obtained MSE in trainbr

	Samples	MSE
Training:	118	5.48398e-4
Validation:	25	8.07117e-4
Testing:	25	1.86102e-3

Fig. 22. Obtained MSE in trainscg

Table 4. Mean Square Error (MSE)

Results	TRAINLM	TRAINBR	TRAINSCG
Training	0.00799	0.00925	0.10044
Validation	0.06295	0.00000	0.14782
Testing	0.03749	0.055966	0.09265

Table 5. Regression Values (R)

Results	TRAINLM	TRAINBR	TRAINSCG
Training	0.99817	0.99991	0.97783
Validatio	0.98231	0.99791	0.98505
Testing	0.9581	0.99962	0.95838
All	0.99182	----------	0.97738

Table 6. Slope Values (m)

Results	TRAINLM	TRAINBR	TRAINSCG
Training	1.0	1.0	0.98
Validatio n	0.98	0.99	0.95
Testing	0.89	1.0	0.93
All	0.98	----------	0.96

Table 7. Intercept Values (c)

Results	TRAINLM	TRAINBR	TRAINSCG
Training	0.0031	0.00019	0.013
Validation	0.014	0.0051	0.049
Testing	0.89	0.001	0.049
All	0.013	----------	0.027

After comparing the obtained results with methodologies such as CVNN, ECWN and CWN [29], the proposed model attains better accuracy and other values.

5. Conclusion

In this paper with brief discussion on necessity of solar radiation estimation, ANN based solar radiation estimation model is proposed with nine location and meteorological input paraments. The model is proposed with the help of NF Tool of MATLAB R2016a. The proposed model is executed on the stations of Uttar Pradesh, India. All three types of Training algorithms are tested one by one with the proposed model. The proposed model perform well in all cases, showing considerable lesser MSE, significantly good regression values, good slope and intercept values. “TRAINBR” shown best MSE and regression value, “TRAINLM” shown best values of slope (m) and intercept (c). The obtained results in all three cases advocates the suitability of the proposed model. As, the current model is tested on the stations of plain area and as the solar radiation estimation is location dependent so, the results may vary for the stations of semi or high hilly areas. In future, optimization technique such as PSO may be implemented for higher accuracy.

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