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Artificial Neural Network based Solar Radiation Estimation

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ABSTRACT: Solar radiation is well estimated by Artificial Neural Network. Meteorological data, Location details and Solar radiation data of 13 stations of Sri Lanka belonging from each part are used for Training, Testing and Validation of Neural Network. The present study is performed with all three types of training algorithm, Levenberg-Marquardt (LM), Bayesian Regularization (BR) and Scaled Conjugate Gradient (SCG). Their performance are compared on the basis of Mean Square Error (MSE), Regression Value (R), Slope of Regression line (m) and Intercept of Regression line (c), which are found in the range of 0-0.18131, 0.95581-0.99991, 0.89-1.0 and 0.00019-0.087 respectively for selected stations of Sri Lanka.

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

I. INTRODUCTION

Solar radiation data are essential part of solar voltaic applications. Due to the abundancy of Solar Radiation across the globe, it takes great lead over other type of renewable energy [1-2]. Optimization of solar energy harvesting is possible only when solar radiation is estimated well in advance which is measured by devices such as solarimeter, pyranometer, pyrheliometer etc. installed at meteorological stations. These stations are scarce, also the maintenance cost and installation of these devices are very costly [3]. These issues are well addressed by development of solar radiation estimation model. These models take location and meteorological data to input and provides solar radiation data at output. In ancient days only mathematical models were developed. However, now a days soft computing based models are generally developed. These models are trained, tested and then implemented at the locations of interest where measuring devices are not there.

ANN based solar radiation modeling has great lead over other types like Fuzzy Logic, GA, SVM etc. due to its advantages. ANN can be well used to solve complex mathematical problems, such as non linear functions etc. [4]. Researchers have worked on several soft computing techniques in last 10-15 years and found that ANN is a better option in comparison to others [5-7].

In the present study, ANN based solar radiation model is developed based on the data of stations of Sri Lanka. Performance of all three types of training algorithms are compared. The data are collected form CLIMWAT and CROPWAT of FAO, UN. Latitude, longitude, altitude, months of a year, maximum temperature, minimum temperature, humidity, wind velocity and sunshine duration are used to predict the solar radiation.

In section II, ANN in solar radiation estimation is briefed, section III, solar radiation estimation model is developed, section IV is for result and discussion while section V is for conclusion, future scope and limitations.

II. ANN IN ESTIMATION OF SOLAR RADIATION

ANN is a tool for estimation related issues. It provides efficient way of determining nonlinear relationships. The architecture of ANN is shown in Fig. 1.

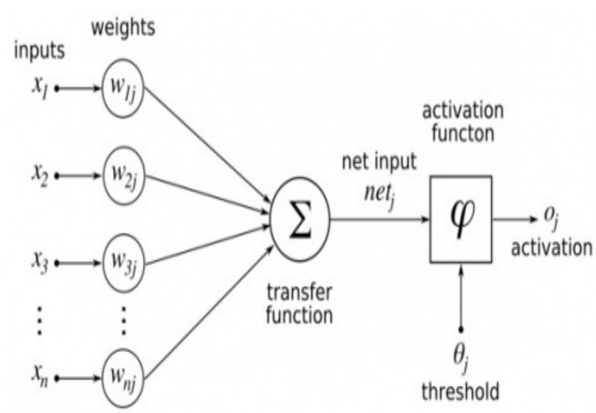


Fig. 1. Architecture of the artificial neural network.

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

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

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

Several researchers are there who have developed number of ANN models and tested at the different part of the world [8-12].

III. SOLAR RADIATION ESTIMATION MODELLING 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, data of 13 stations (Table 1) are taken into consideration. They all belong to Sri Lanka, represented in Fig. 2. Their geographical properties are shown in Table 1. The radiation and meteorological data of selected stations are downloaded from CLIMWAT 2.0 and CROPWAT 8.0 of FAO, UN.

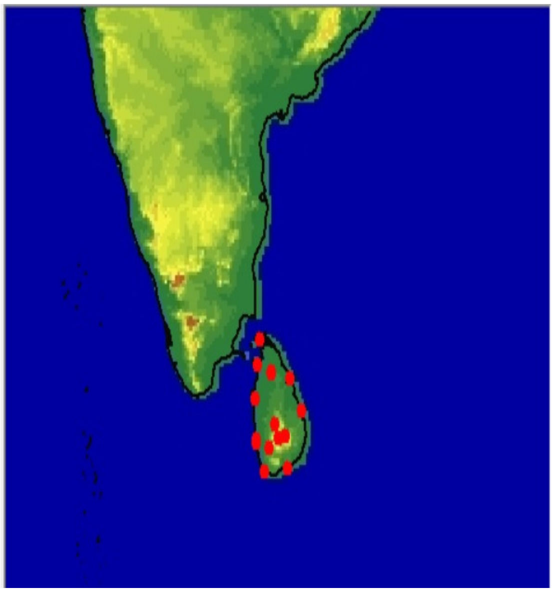


Fig. 2. Selected stations of Sri Lanka for study.

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

Stations	Latitude (°N)	Longitude (°E)	Altitude (m)
Badulla	6.98	81.05	667
Batticaloa	7.71	81.70	12
Colombo	6.90	79.86	7
Galle	6.03	80.21	18
Hambantota	6.11	81.13	20
Jaffna	9.65	80.01	03
Kandy	7.33	80.63	480
Mannar	8.98	79.91	03
Nawara	6.96	80.76	1880
Puttalam	8.03	79.83	2
Ratmalana	6.81	79.88	5
Tricomalee	8.58	81.25	7
Vavuniya	8.75	80.50	98

As the downloaded data are having different measuring units as well as scale so, it needs to be normalized before use. Max-Min normalization is used (Equation-2) to maintain the simplicity and ease of calculation.

$$v_i' = \left[\left(\frac{v_i - B}{A - B}\right).(M - N)\right] + N \qquad (2)$$

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

There are two Neural Network tool (NF Tool and NN Tool) in MATLAB. In the present study NF Tool is considered. Tan-Sigmoid activation function is used here in this study. A computer program is performed under MATLAB-R2016a using Neural Fitting Tool (NF Tool), configured as detailed in Table 2. The network type used is Feed Forward Back Propagation.

Table 2 : Customization detail of Neural Fitting Tool.

S. No.	Particulars	Configuration Details
1.	Network Type	Feed Forward Back Propagation
2.	Training Algorithm	TRAINLM, TRAINBR and TRAINSCG
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: 10
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), Bayesian Regularization and Scaled Conjugate Gradient
12.	Performance	Mean Squared Error (MSE)
13.	Calculation	MEX
14.	Plot Interval	1 Epochs

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.

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

Here,

n : number of input,

$SR_{i(ANN)}$: predicted solar radiation,

$SR_{i(\text{actual})}$: actual solar radiation.

IV. RESULTSAND DISCUSSION

Neural Network Fitting Tool is customized as per Table 2. Normalized input (Latitude, Longitude, Altitude, Months of a year, Maximum Temperature, Minimum Temperature, Humidity, Wind Velocity and Sunshine Hour)is provided to NF Tool and Solar Radiation is provided at Output. The architecture of Neural Network and default division of data into Training, Testing and Validation are shown in Figs. 3 and 4 respectively.

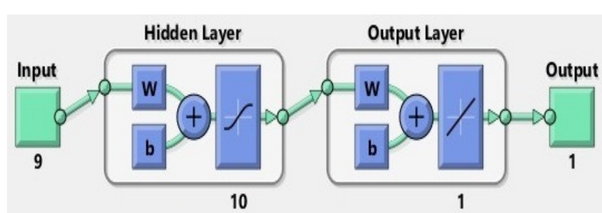


Fig. 3. ANN Network Architecture

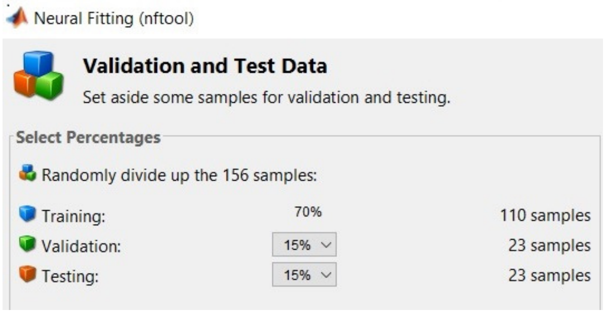


Fig. 4. Default data division.

Simulation is carried out for three different types of Training Algorithm and their respective plots and results are recorded.

A. Training Algorithm: Levenberg- Marquardt (trainlm)

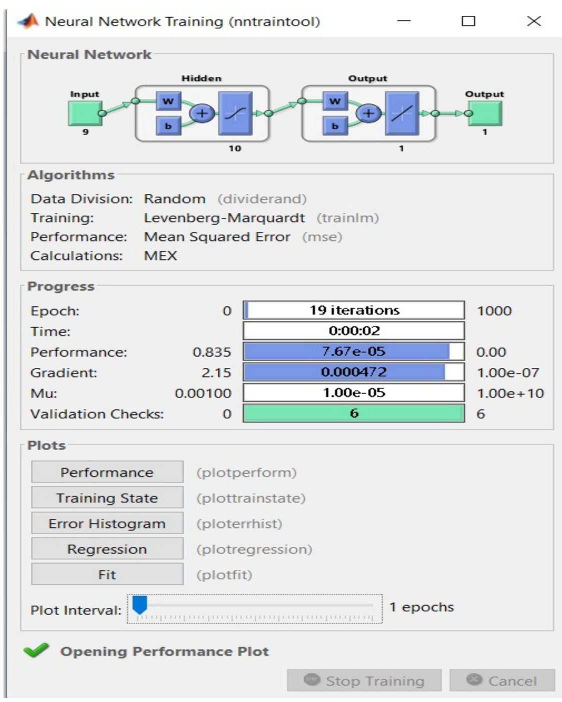


Fig. 5(a) Training Environment.

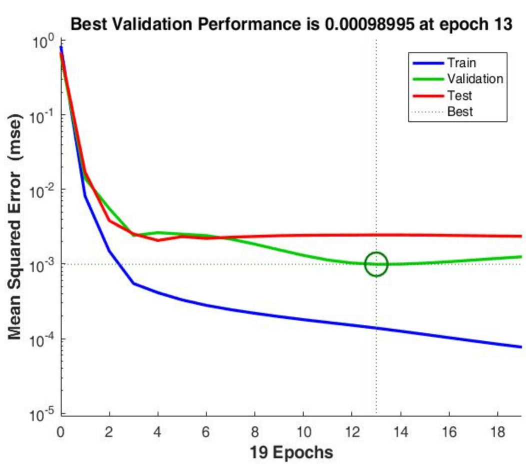


Fig. 5(b) Performance Plot.

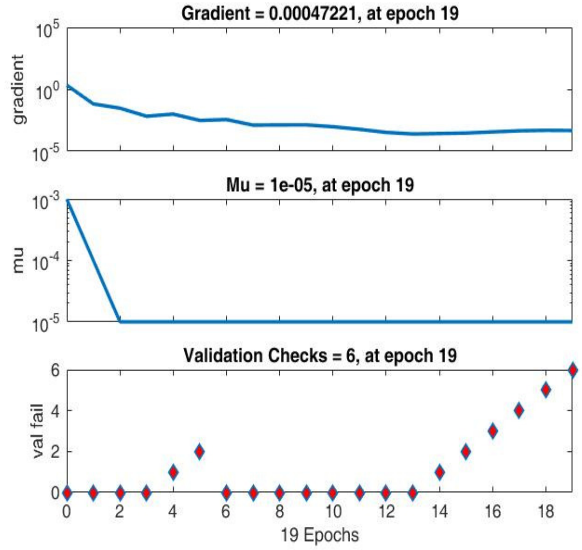


Fig. 5(c) Training State Plot.

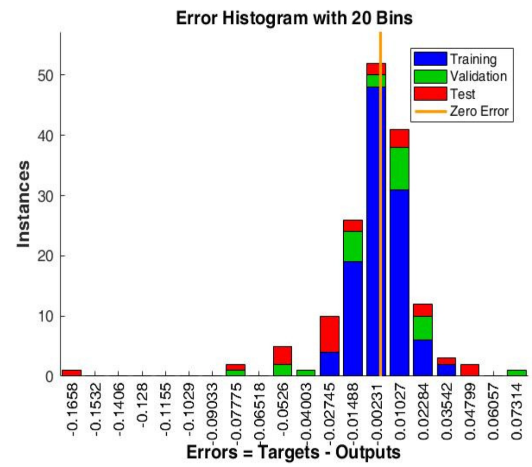


Fig. 5(d) Error Histogram.

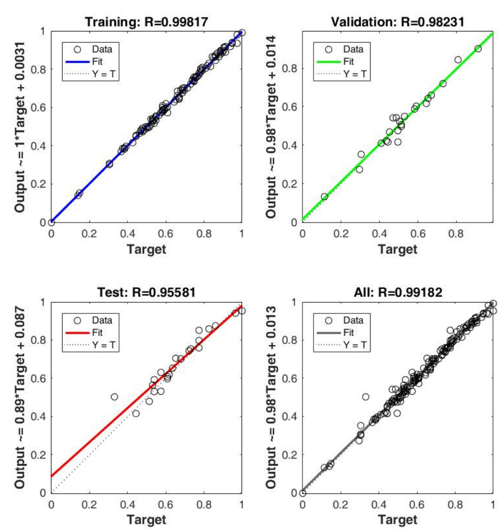


Fig. 5(e) Regression Plot.

B. Bayesian Regularization (trainbr)

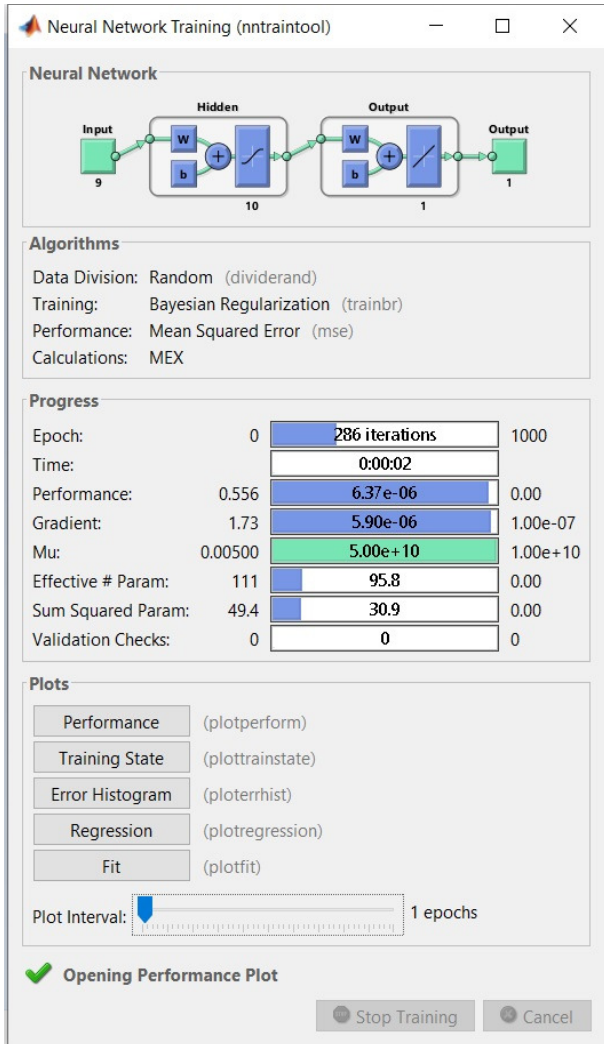


Fig. 6(a) Training Environment.

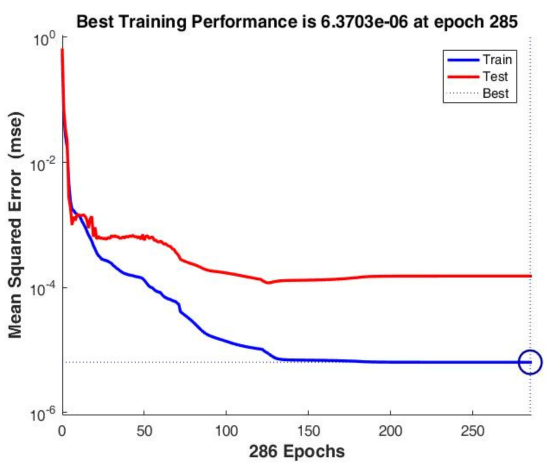


Fig. 6(b) Performance Plot.

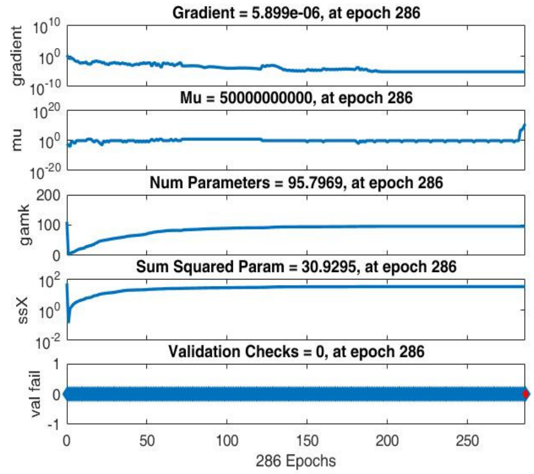


Fig. 6(c) Training State Plot.

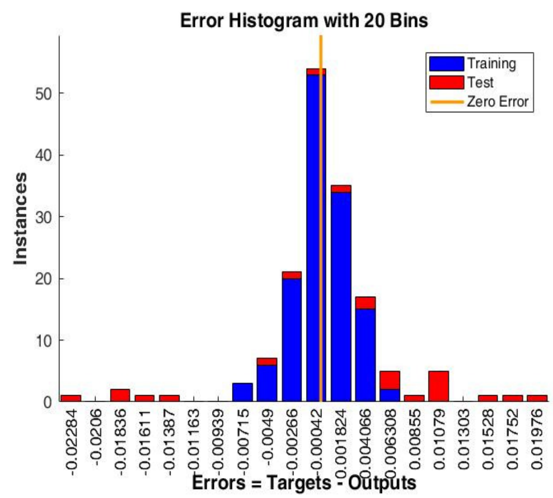


Fig. 6(d) Error Histogram.

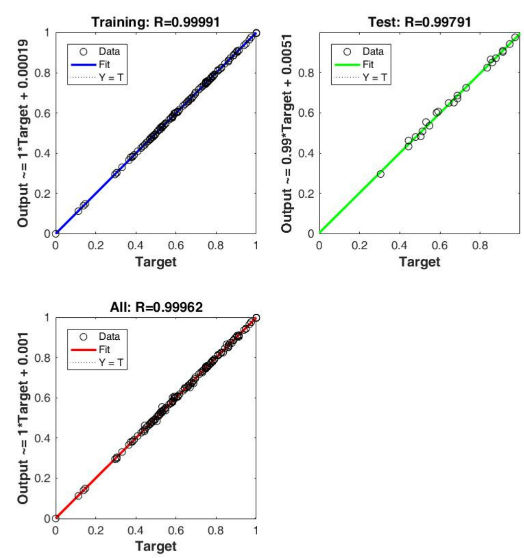


Fig. 6(e) Regression Plot.

C. Scaled Conjugate Gradient (trainscg)

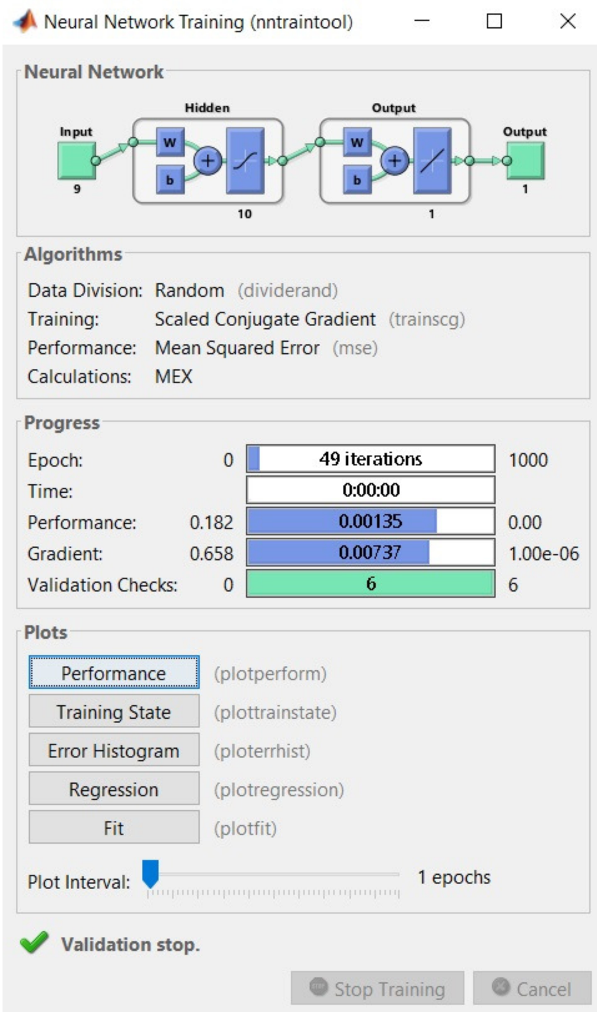


Fig. 7(a) Training Environment.

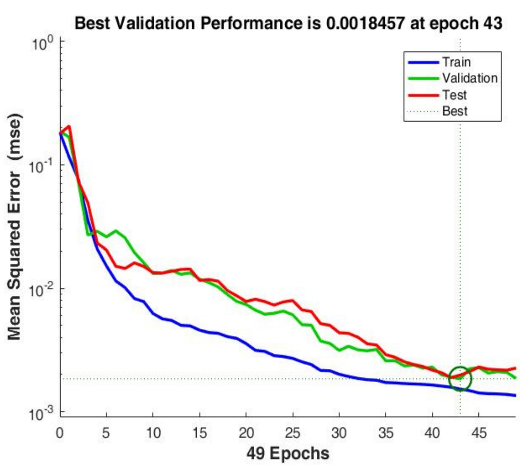


Fig. 7(b) Performance Plot.

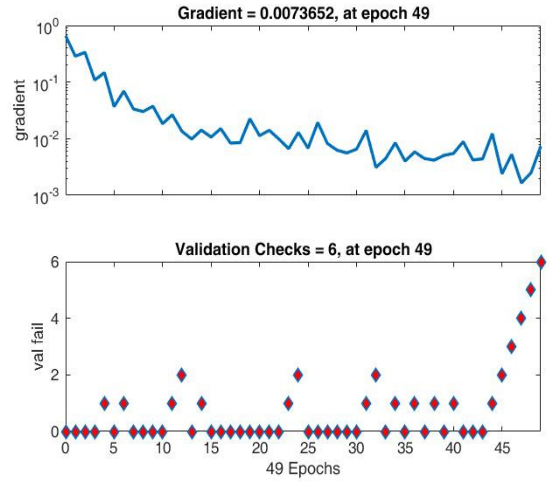


Fig. 7(c) Training State Plot.

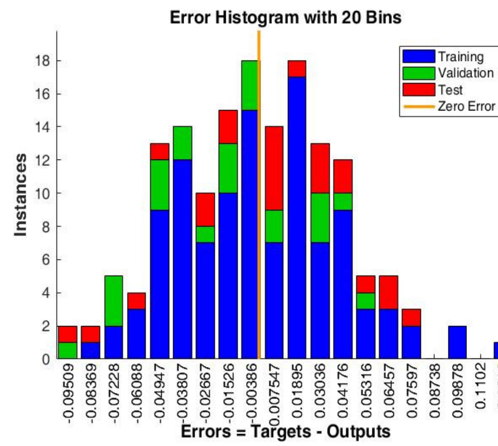


Fig. 7(d) Error Histogram Plot.

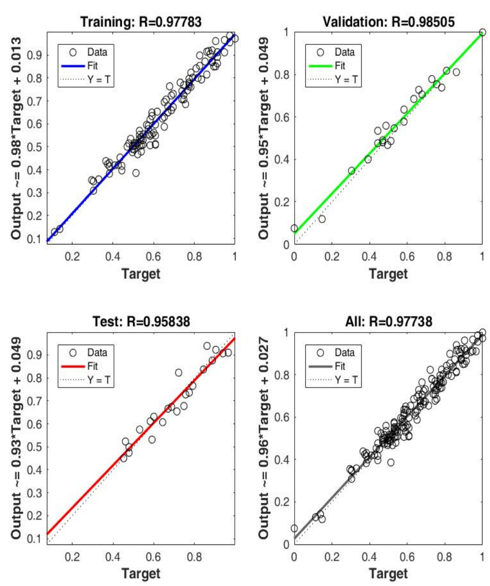
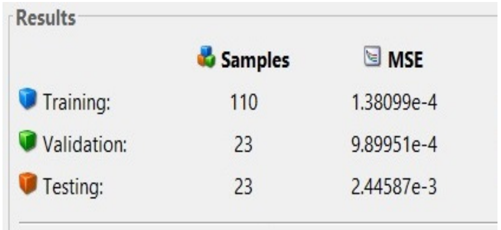


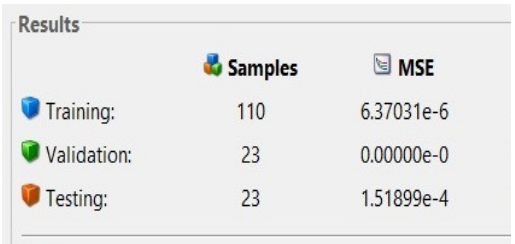
Fig. 7(e) Training Environment.

D. Mean Square Error Analysis



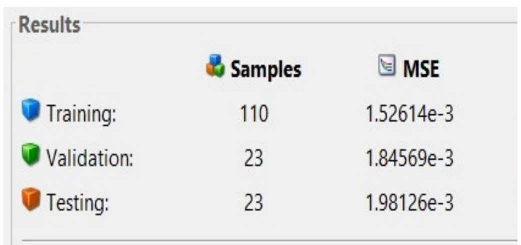
Results	Samples	MSE
Training:	110	1.38099e-4
Validation:	23	9.89951e-4
Testing:	23	2.44587e-3

Fig. 8(a) MSE in case of Trainlm.



Results	Samples	MSE
Training:	110	6.37031e-6
Validation:	23	0.00000e-0
Testing:	23	1.51899e-4

Fig. 8(b) MSE in case of Trainbr.



Results	Samples	MSE
Training:	110	1.52614e-3
Validation:	23	1.84569e-3
Testing:	23	1.98126e-3

Fig. 8(c) MSE in case of Trainscg.

Table 3: Obtained MSE in three cases.

Results	MSE		
	Trainlm	**Trainbr**	**Trainscg**
Training	0.02529	0.01579	0.07598
Validation	0.18131	0	0.09188
Testing	0.12177	0.02782	0.05965

Table 4: Obtained Regression (R) value in three cases.

Results	R		
	Trainlm	**Trainbr**	**Trainscg**
Training	0.99817	0.99991	0.97783
Validation	0.98231	0.99791	0.98505
Testing	0.95581	0.99962	0.95838
All	0.99182	—	0.97738

Table 5: Obtained Slope (m) value in three cases.

Results	M		
	Trainlm	**Trainbr**	**Trainscg**
Training	1.0	1.0	0.98
Validation	0.98	0.99	0.95
Testing	0.89	1.0	0.93
All	0.98	—	0.96

Table 6: Obtained Intercept (c) value in three cases.

Results	C		
	Trainlm	**Trainbr**	**Trainscg**
Training	0.0031	0.00019	0.013
Validation	0.014	0.0051	0.049
Testing	0.087	0.001	0.049
All	0.013	—	0.027

After training the network using different training algorithms, plots 5(a-e), 6(a-e) and 7(a-e) are obtained. Also, snapshot of obtained Mean Square Error are shown in Fig. 8(a-c).
Based on these plots Table 4-6 are placed to retrieve the summary of simulation for all three training algorithms.

V. CONCLUSION AND FUTURE SCOPE

This paper provides ANN based solar radiation estimation modeling using Levenberg-Marquardt (tainlm), Bayesian Regularization (trainbr) and Scaled Conjugate Gradient (trainscg) with the stations of Sri Lanka. The developed model is based on location and meteorological details of stations. Bayesian Regularization has least Mean Square Error and better regression values in comparison to the other two training algorithms whereas Scaled Conjugate Gradient have better values of m and c. Overall performance of the network in all three cases are considerable one.
In future the optimization technique such as PSO may be used for better results. Also, WEKA technique may be used to find the priority of the inputs.
Overall, simulation results are in favor of target and having good consideration for future use.

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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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