

# ARTIFICIAL NEURAL NETWORK FITTING TOOL BASED PREDICTION OF SOLAR RADIATION FOR IDENTIFYING SOLAR POWER POTENTIAL

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**Abstract-** In this study details implementation of artificial neural network fitting tool is presented for prediction of solar radiation which can be used for assessment of power potential. Solar radiation data from 14 cities of Himachal Pradesh India is used in Network. The input variables are latitude, longitude, atmospheric pressure and wind speed and solar radiation as output parameter. The correlation coefficients are higher than 91%, proving high accuracy of model for solar energy potential. The procedure of using neural network fitting tool (nftool) and matlab code are developed for prediction of solar radiation to identify the solar power potential at any site worldwide.

**Keyword:** neural network fitting tool, matlab code, solar radiation, prediction, error histogram

## 1 Introduction

The solar radiation is one of the vital parameter for power generation. The measured solar radiation data is not available for most of sites. Therefore Artificial Neural Network (ANN) Technique is used for prediction using several meteorological and geographical variables. Rehman and Mohandes [1] utilized relative humidity, number of day and air temperature as inputs for predicting radiation. It is found that mean absolute percentage error (MAPE) is 4.49%. Sozen and Arcaklioglu [2] used ANN to forecast solar radiation for Turkey. The input variables used in the model are mean temperature, latitude, mean sunshine duration, longitude, altitude and month. The MAPE is less than 3.832% and R is 99.9738% for the selected stations which indicate that predicted values are closed to the measured values for all the months. Behrang et al. [3] predicted daily global solar radiation for Dezful city in Iran using different ANN techniques based on different combination of meteorological variables. 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. [4] has used RBF network for predicting solar radiation and compare performance of RBF with MLP model using latitude, altitude, longitude and sunshine duration as input parameters. The MAPE for MLP model is

12.6 and MAPE for RBF model is 10.1. Yadav and Chandel [5] used ANN model for solar radiation prediction for at 12 Indian stations with different climatic conditions. The input parameters are latitude, longitude, height above sea level, sunshine hours and solar radiation as output. The Levenberg-Marquard (LM) algorithm is used for training. The root mean square error (RMSE) in ANN model range from 0.0486 to 3.562. Yadav and Chandel [6] presented reviews of solar radiation prediction using ANN models and found that matlab code of artificial neural network based solar radiation prediction of is important for researcher for assessment of power generation worldwide.

In the present study longitude, latitude, atmospheric pressure and wind speed values are used to predict global solar radiation using artificial neural network fitting tool for 14 cities (Chamba, Kangra, Hamirpur, Bilaspur, Shimla, Una, Mandi, Solan, Kullu, Nahan, Kyelang, Kaza, Kalpa and Rekong Peo) in different regions of Himachal Pradesh India.

## 2. Artificial Neural Network

An Artificial Neural Network (ANN) is connection of processing units similar to biological processing elements called as neurons [7]. The computational capability of ANN is given by connection weights, architecture and training algorithm. ANN acts as vital tools for researcher as these are able to compute data classification, non-linear function approximation, clustering and simulation. ANNs have been used in different fields of science and technology [8-11] and in solar radiation modeling [12]. ANNs have been used in computation of beam solar radiation [13], forecasting solar potential [14], prediction of global radiation [15] and solar radiation estimation [16, 17]. ANNs extract the information from data so it can be used to solve nonlinear problems. The networks utilize input layer, hidden-layers and an output layer. The inputs are multiplied by a connection weights and its products and biases are added and then passed through an activation function to generate an output. During training weights and biases (network parameters) changes in each step to minimize the

mean square of output error. The error in network is evaluated by following equations, where  $n$  is the total number of input and output pairs (which can be vector quantities) used for training.  $SR_{i(ANN)}$  is the output predicted by the neural network and  $SR_{i(actual)}$  is the actual target output of the  $i^{th}$  training example.

Mean absolute percentage error:

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

Sum of square error:

$$SSE = \sum_{i=1}^n (SR_{i(ANN)} - SR_{i(actual)})^2 \quad (2)$$

Mean square error:

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

Absolute fraction of variance:

$$R^2 = \left( 1 - \frac{\sum_{i=1}^n |SR_{i(ANN)} - SR_{i(actual)}|^2}{\sum_{i=1}^n SR_{i(actual)}^2} \right) \times 100 \quad (4)$$

### 3. Artificial Neural Network Fitting Tool (nftool)

It is used for static fitting problems with standard two layer feed forward neural network trained with Levenberg-Marquardt (LM) algorithm. In this tool training is automatically done with scaled conjugate gradient in spite of the data set is very large and performance is evaluated by using MSE and regression analysis. The presented data to the network are automatically mapped into the range -1 to 1. The data are randomly divided into 60% training, 20% testing and 20% validation. The training data are used to adjust network weight as per error. The validation data are used for network generalization and to halt training when generalization stops improving. The testing data have no effect on training and it provides an independent measure of network performance and it provides an independent measure of network performance during and after training. The hidden layer neurons are increased when network is not performing well after training. The training stops automatically when generalization stops improving as indicated by an increase in the mean square error of the validation data samples. Training multiple times generates different results due to different initialization of connection weights and different initial condition. The mean squared error is the average squared difference between normalized outputs and targets; zero means no error and over 0.6667 means higher error.

The nftool is used for predicting solar radiation of cities in Himachal Pradesh. The ANN architecture used in this work, shown in Figure 1 has an input layer with four inputs

(longitude, latitude, atmospheric pressure and wind speed), one hidden layer with 20 neurons and a sigmoid activation function  $\phi$ , defined by the logistic function:  $\phi = 1/(1 + \exp(-x))$ ,  $x$  being the corresponding inputs. For the output layer, a linear activation function  $\zeta$  is used in

the implementation. The approximating function  $\hat{SR}$ , representing solar radiation, is defined as :

$$\hat{SR}(X) = \zeta \left( \sum_{i=1}^N y_i \cdot w_2(i) + b_2 \right) \quad (5)$$

$$\text{where } y_i(X) = \phi \left( \sum_{j=1}^M x_j \cdot w_1(j, i) + b_1(i) \right) \quad (6)$$

$w_1(j, i)$  is the weight between  $j^{th}$  input and  $i^{th}$  hidden layer neuron  $w_2(i)$  is the weight between  $i^{th}$  hidden layer neuron and the output neuron,  $b_1(i)$  is the bias term directed to the  $i^{th}$  hidden layer neuron,  $b_2$  is the bias for the output layer neuron  $\phi$  is the sigmoidal activation function at the hidden layer  $\zeta$  is the linear activation function at the output layer. The equations are written in matrix form:

$$\hat{SR} = \zeta(W_2 \cdot \phi(W_1 \cdot x + b_1) + b_2) \quad (7)$$

where,  $W_1$  is a  $(20 \times 4)$  weights matrix between each input and hidden neuron;  $W_2$  is a  $(12 \times 20)$  matrix of weights between each hidden neuron and the output neuron;  $b_1$  is a  $(20 \times 1)$  matrix of biases applied to the hidden neurons;  $b_2$  is the  $(12 \times 1)$  bias term applied to the

output layer neuron;  $x$  is the  $(4 \times 1)$  input matrix. The network is trained with Levenberg-Marquardt back propagation algorithm (trainlm).

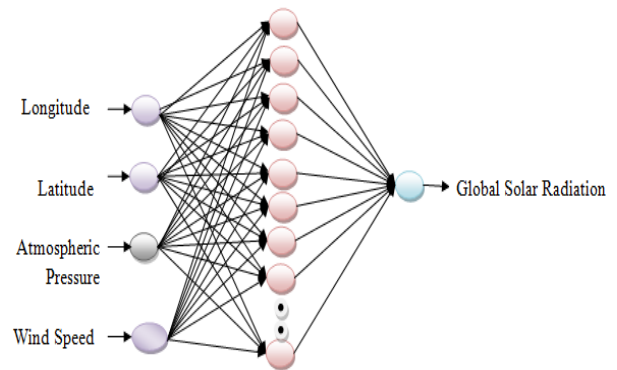


Figure 1. ANN nftool with twenty neurons in hidden layer

A computer program is developed with MATLAB R2011b using Neural Network Fitting Tool (nftool). The detailed procedures of nftool and used matlab code are shown in Appendix A and Appendix B respectively. The Table 1 shows cities Chamba, Kangra, Hamirpur, Bilaspur, Shimla, Una, Mandi, Solan, Kullu and Nahan are used for training data and cities Kyelang, Kaza, Kalpa and Rekong Peo are used for testing data.

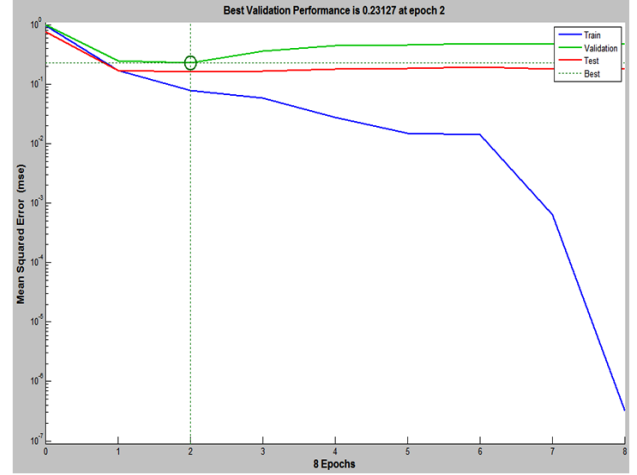
**Table 1. Input data in nftool model**

City Name	Latitude (°N)	Longitude (°E)	Atmospheric Pressure (kPa)	Wind Speed (m/s)
Chamba	32.33	76.10	73.34	5.3
Kangra	32.04	76.16	73.4	5.3
Hamirpur	31.38	76.36	84.8	4.7
Bilaspur	30.18	77.18	84.8	4.7
Shimla	31.07	77.09	73.2	5.0
Una	31.28	76.19	84.8	4.7
Mandi	31.40	76.59	84.8	4.7
Solan	30.54	77.06	86.3	3.4
Kullu	31.59	77.06	73.2	5.0
Nahan	30.33	77.18	86.3	3.4
Kyelang	32.57	77.03	62.7	5.8
Kaza	32.22	78.07	58.5	5.6
Kalpa	31.55	78.26	65.0	5.0
Rekong Peo	31.38	78.45	65.0	5.0

The network incorporates twenty two year meteorological data measured by the National Aeronautical and Space Administration (NASA) for training and testing. The high resolution global insolation data from NASA SSE is used in the present ANN Model. This data is derived for a period of 22 years (July1st, 1983–June30th, 2005) and is validated with Baseline Surface Radiation Network (BSRN) data with RMSE of 10.25% as such can be used for solar potential assessment with sufficient accuracy. Although, the ground measured data are more accurate than the satellite-derived values yet the measurement and operational uncertainties, or data gaps are not known accurately for many ground site data sets [18]. As per the World Climate Research Program estimation in the year 1989 the uncertainties ranging from 6 to 12% were found in the most of the routinely operated ground sites. The specialized high quality research meteorological stations are expected to be more accurate than routinely operated ground meteorological stations.

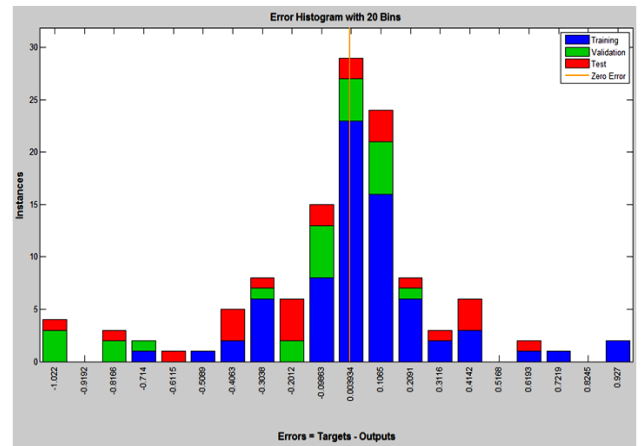
#### 4. Results and Discussion

The performance plot shows that MSE become small as number of epochs (one complete sweep of training, testing and validation) are increased (Figure 2). The error of validation set and test set has similar characteristics and no significant over fitting has occurred by epoch 2 (where best validation performance has occurred).



**Figure 2. Performance Plot**

The error histogram plot for training data is shown in Figure 3 to provide additional verification of network performance. It indicates outliers. The blue, green and red bars represent training data, validation data and testing data respectively. The most data fall 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 set. If the outliers are valid data points, but are unlike the rest of the data, then the network is extrapolating for these points.



**Figure 3. Error Histogram plot for Training data**

The correlation coefficient (R-value) measure the correlation between outputs and targets. R value of 1 and 0 means a close, random relationship respectively. The R-value between the predicted and the actual values of monthly mean solar radiation are shown in Figures (4,5,6,7) for training, validation, testing and the whole datasets and errors for training cities. R-values of 0.97, 0.93, 0.94 and 0.95 are obtained for the training, validation,

testing and the whole dataset, respectively. This shows that nftool predicted solar radiation values are very close to the actual values for all the datasets. The maximum and minimum MAPE are 8.7833% and 0.8722% for Hamirpur and Nahan, respectively (Table 2).

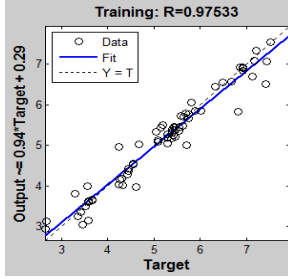


Figure 4. Training plot

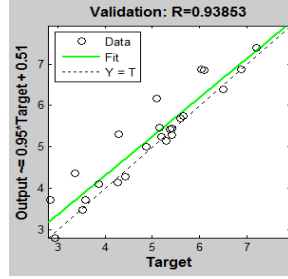


Figure 5. Validation plot

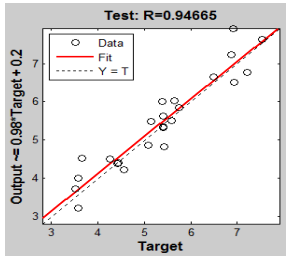


Figure 6. Testing plot

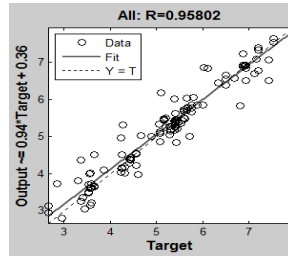


Figure 7. Over all plot

Table 2. Error values of the ANN during training

Cities	MSE (%)	RMSE	MAPE (%)	SSE	R <sup>2</sup> (%)
Chamba	0.0816	0.2857	5.1316	0.9793	98.45
Kangra	0.0946	0.3075	5.5526	1.1347	98.21
Hamirpur	0.4255	0.6523	8.7833	5.1065	91.25
Bilaspur	0.1117	0.3341	5.6164	1.3398	97.81
Shimla	0.0457	0.2137	2.8844	0.5480	99.16
Una	0.2009	0.4482	6.7145	2.4103	95.98
Mandi	0.0256	0.16	2.5408	0.3074	99.50
Solan	0.0747	0.2733	3.9233	0.8963	98.59
Kullu	0.0602	0.2454	3.8396	0.7228	98.85
Nahan	0.0031	0.05566	0.8722	0.0371	99.94

The error evaluation for testing cities is shown in Table 3 and comparison between predicted and actual solar radiation in Figure 8. The maximum MAPE for testing cities is 8.2606 % which is highly accurate as per prediction accuracy evaluation given by Lewis [19].

Table 3. Error values of the ANN approach during testing

Station	MSE (%)	RMS	MAPE (%)	SSE	R <sup>2</sup> (%)
Kyelang	0.1879	0.4335	8.2606	2.2550	95.99
Kaza	0.1704	0.4128	7.0026	2.0445	96.66
Kalpa	0.1114	0.3338	5.9248	1.3371	97.59
Rekong Peo	0.0282	0.1679	3.4963	0.3382	99.39

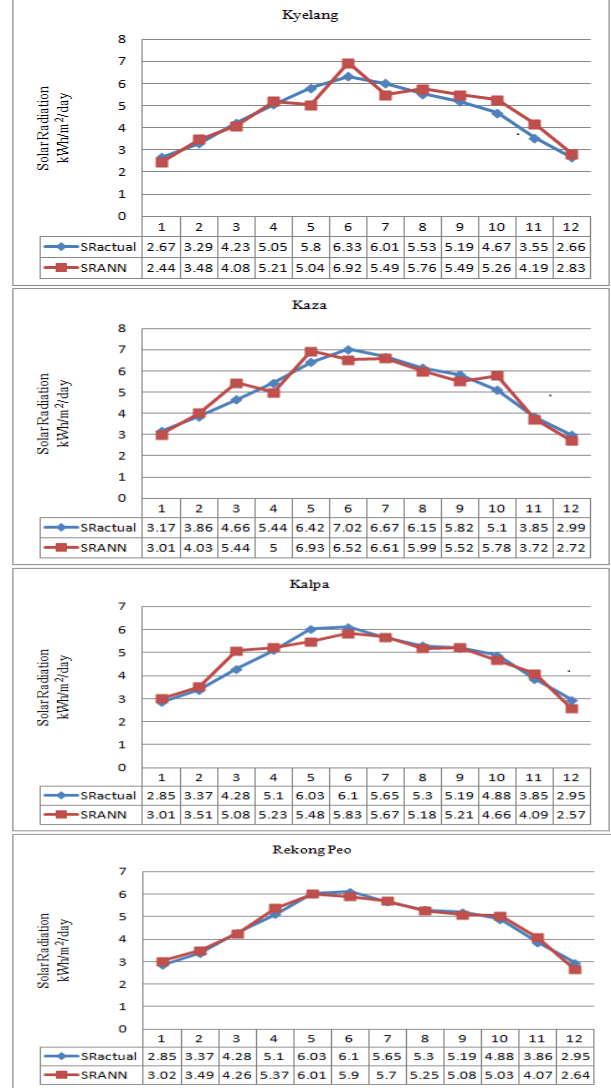


Figure 8. Comparison of solar radiation between the ANN and measured values (testing cities)

## 5. Conclusion

The results of this study indicate that the potential of Artificial Neural Network Fitting tool for prediction of solar radiation for identifying solar tool for potential using longitude, latitude, atmospheric pressure and wind speed. The correlation value R is 95.80% showing good agreement between the measured values and predicted ANN values. The maximum and minimum MAPE for training is 8.7833% and for testing is 8.2606 % showing highly accurate prediction with ANN nftool.

The annual average solar radiation in Himachal Pradesh varies from 4.58 to 5.40 kWh/ m<sup>2</sup>/day which shows a vast solar power potential. The state has 14 % of total barren or

uncultivable land which can be utilized for solar power generation along with south facing mountain slopes. The nftool and developed mat lab code can be used to predict global solar radiation of any site in the region using ground measured solar radiation. The MAPE can also be reduced if the connection weights between the layers are optimized by using different types of optimization technique such as genetic algorithm, multi objective genetic algorithm, simulated annealing techniques etc. The ANN model can also be developed by using different combination of easily available input parameters at particular site which will give minimum MAPE.

#### Appendix A: Steps for solar radiation prediction using Neural Network fitting tool (nftool)

- 1:- Open nftool.
- 2:- Load latitude, longitude, wind speed and atmospheric pressure from workspace as input data and solar radiation value as target data.
- 3:- Select number of neurons in the hidden layer.
- 4:- Train the network.
- 5:- Take performance plot, regression plot, testing plot, validation plot and error histogram plot.
- 6:- Perform additional test on the same network using more number of inputs data.
- 7:- Save the result to workspace and take the network output values.

#### Appendix B: Matlab program to predict solar radiation

```
% ip-input data (longitude, latitude, atmospheric pressure
and wind speed). % tr-target data (solar radiation). % p-
testing data (longitude, latitude, atmospheric pressure and
wind speed).
ip = xlsread('inputdata.xlsx'); tr = lsread('targetdata.xlsx');
p = xlsread('testingdata.xlsx'); inputs = ip'; targets =tr;
% Create a Fitting Network
hiddenLayerSize = 20; net = fitnet(hiddenLayerSize);
% Setup Division of Data for Training, Validation, Testing
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
% Train the Network: [net,tr] = train(net,inputs,targets);
% Test the Network
outputs = net(inputs); errors = gsubtract(targets,outputs);
performance = perform(net,targets,outputs).
% View the Network
view(net); a=sim(net,p'); a1=sim(net,ip')
% weight and bias to hidden layer
b1=net.b{1,1}; W1=net.IW{1,1}
% weight and bias to output layer
b2=net.b{2,1}; W2=net.LW{2,1}
```

% Plots

```
plotperform(tr); plottrainstate(tr); plotfit(net,inputs,targets);
plotregression(targets,outputs); ploterrhist(errors)
```

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