ESTIMATION OF GLOBAL SOLAR RADIATION IN INDIA USING ARTIFICIAL NEURAL NETWORK

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Abstract

In this study, global solar radiation was predicted using artificial neural networks. Gradient descent back propagation with adaptive learning rate was used for training the artificial neural network. In order to train and test the neural network, meteorological day average data like maximum ambient temperature, minimum ambient temperature and minimum relative humidity values were used for predicting global solar radiation in future time domain using artificial neural network method. The measured data was randomly selected for training and testing the neural networks. Obtained results show that using the minimum ambient temperature and day of the year outperforms the other cases with absolute mean percentage error of 6.65% and mean squared error of 0.008. This neural network, therefore, can be used for estimating global solar radiation for locations where only ambient temperature data are available.

Index Terms: *Global solar Radiation, Artificial Neural Networks, Ambient temperature, Relative humidity, Gradient descent back propagation*

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1. INTRODUCTION

Due to exponentially increasing costs of fossil fuels, uncertainty of availability, and increasing environmental pollution, the green sources of energy are being encouraged in recent times. The green sources of energy include solar, wind, biomass, hydro, tidal, wave, ocean, etc. Among these sources of energy, solar, wind and hydro are the common ones currently in use.

Solar photovoltaic technology, despite being relatively costly compared to wind and other green sources of energy, is being used commonly for the domestic and industrial thermal applications and for the generation of electricity for both grid connected and standalone power systems. For proper, economical and efficient development and utilization of solar energy (performance prediction of renewable energy systems, particularly in sizing photovoltaic (PV) power systems, agriculture and building design, a perfect knowledge of the availability and variability of solar radiation intensity both in time and spatial domain is very critical.

In developing countries, where the number of solar observation sites is poor, the global solar radiation (GSR) measurements are usually made at few locations, which may or may not be the same as the actual site of solar energy development and utilization. In order to consider the behavior of solar radiation at the site of interest, long-term data from a nearby location along with empirical, semi-empirical, physical, neural networks, wavelets, fractals, etc. techniques is used [1].

Among the meteorological parameters, air temperature, relative humidity, sunshine duration and cloud cover are the most widely and commonly used data to predict daily global solar radiation and its components [2].

An extensive amount of work on Angstrom type of empirical models for the estimation of GSR on horizontal surface using measured sunshine duration values has been cited in the literature [3-8]. In recent years, neural network methods have been employed for the prediction of GSR both in time and spatial domains as can be seen from these references [9-18].

Since the temperature and relative humidity records are more readily available around the globe, these values are being used to estimate the GSRs. Elizondo et al.[9] used meteorological parameters such as air temperature, precipitation, clear-sky radiations, day length and day of the year as input into the feed forward neural network technique for the estimation of daily GSR.

Al-Alawi and Al-Hinai[10] predicted total radiation to an accuracy of 93% by using meteorological parameters as input into artificial neural network (ANN) models. Togrul and Onat[13] used geographical and meteorological parameters along with the ANN methods for the prediction of GSR for a city in Turkey. Kalogirou [17] used a recurrent neural network method to estimate the maximum solar radiation using measured values of air temperature and relative humidity as input. Sozen et al. [19] used meteorological and geographical Parameters as input into the neural networks model for the prediction solar potential for Turkey. In another study, Yang and Koike [20] utilized upper air humidity values for the estimation of solar radiation on the surface of the earth through ANN method.

In this paper, ANN using gradient descent back propagation with adaptive learning rate is used for the estimation of global solar radiation based on measured ambient temperature and/or relative humidity data at Madurai city located in Tamilnadu state of India.

2. ARTIFICIAL NEURAL NETWORKS

The interest in ANNs is largely due to their ability to mimic natural intelligence in its learning from experience [21]. They learn from examples by constructing an input-output mapping without explicit derivation of the model equation. ANNs have been used in a broad range of applications including: pattern classification [22, 23] function approximation, optimization [17], prediction [9] and automatic control [24] and many others. Additionally, ANNs have been used extensively for meteorological applications. An ANN consists of many interconnected identical simple processing units called neurons. Each connection to a neuron has an adjustable weight factor associated with it.

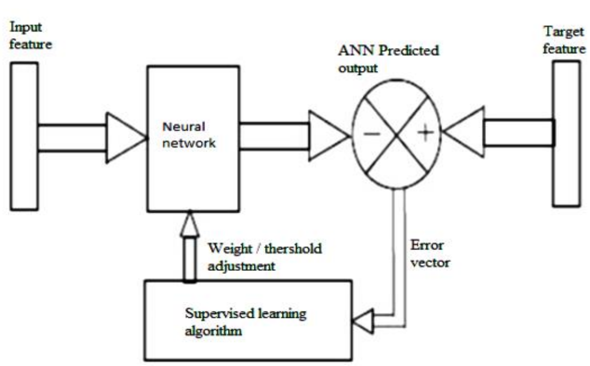

Fig 1: Model of supervised learning algorithm

The weights of the connections are adjusted during the training process to achieve the desired input/output relation of the network as shown in figure 1. A multilayer feed forward network has its neurons organized into layers with no feedback or lateral connections. Layers of neurons other than the input and output layer are called hidden layers. The input signal propagates through the network in a forward direction, on a layer-by-layer basis.

The back propagation algorithm [25] is a supervised iterative training method for multilayer feed forward nets with sigmoid nonlinear threshold units. It uses training data consisting of input output pairs of vectors that characterize the problem. Using a generalized least-mean-square algorithm, the back propagation algorithm minimizes the mean square difference between the real network output and the desired output [26].

Relative error (RE) variation between the measured and predicted global solar radiation is calculated as follows [27];

$$RE= \frac{|\text{Measured-Predicted}|}{\text{Measured}} \text{ X } 100$$

In the present study, feed-forward, back-propagation, multilayer perceptron artificial neural network is developed and trained by using gradient descent back propagation with adaptive learning rate algorithm on ‘Neural Network Toolbox’ in MATLAB version 9 , to predict the average global solar radiation using the data of Madurai city located in Tamilnadu state of India.

For model 1, only the day of the year and daily average maximum ambient temperature was used as inputs and GSR as output. In model 2, the day of the year and daily average minimum value of ambient temperature were used as inputs and GSR as output. In model 3, the daily average maximum ambient temperature and minimum relative humidity, along with day of the year, were used as input to the ANN model and GSR as output. In the last model 4, the day of the year and daily average minimum value of ambient temperature and minimum relative humidity were used to predict the GSR.

The essence of this study was to investigate the feasibility of using ANN to model the non-linear relationship between solar radiation and other important meteorological parameters. Hence, the model can be used to predict the average global solar radiation potential for specific locations in Tamilnadu of India where there are no records of solar radiation such as meteorological ground stations. The predicted solar radiation values from the model can be used easily for design and assessment of solar application systems.

3. NORMALIZATION OF DATA

In this study, ambient air temperature and relative humidity values, collected at Madurai station located in Tamilnadu state of India, were used for GSR prediction using ANN. Daily average Global Solar Radiation, minimum and maximum air temperature and minimum relative humidity data are normalized according to the following Equation[27],

$$X_N=0.8\ X\ \left(\frac{X_R - X_{min}}{X_{max} - X_{min}}\right)+0.1$$

X_N = Normalized value
X_R = Value to be normalized
X_{min}=Minimum value in all the values for related variable
X_{max}= Maximum value in all the values for related variable

4. DATA DESCRIPTION

In the present study , gradient descent back propagation with adaptive learning rate neural network method is used for the estimation of the average global solar radiation for Madurai, a city in the south region of the Tamilnadu state of India and daily maximum or minimum air temperatures and/or relative humidity as input to the ANN model. The data for 250 days during March 2010 and December2010 was randomly selected for training and testing the data.

A one hour average data on ambient air temperature, relative humidity, global solar radiation, etc. at Madurai city is collected for ten months from a weather monitoring station. The solar radiation data collection station is situated at a latitude of 9.58 N, longitude 78.10 E and an altitude of 131 meters above sea level [28].

Table -1: Developed models using different sets of input parameters

Model	Input parameters
1	Day of the year and maximum air temperature
2	Day of the year and minimum air temperature
3	Day of the year , maximum air temperature and minimum relative humidity
4	Day of the year , minimum air temperature and minimum relative humidity

For Model 1, a feed forward network has been trained to estimate the daily average GSR based on the day of the year and daily average value of maximum air temperature. After many tests, it was found that a network with two inputs, one hidden layer (twenty four neurons), hyperbolic tangent sigmoid transfer function for hidden layer, one output unit, linear transfer function (purelin) for output layer, and gradient descent back propagation with adaptive learning rate training was applied for such application.

For Model 2 also, feed forward network was trained to estimate daily GSR based on the the day of the year and daily average value of minimum air temperature. A network of two inputs, one hidden layer (thirty two neurons), hyperbolic tangent sigmoid transfer function for hidden layer, one output, linear transfer function (purelin) for output layer and training was done by Gradient descent back propagation with adaptive learning rate.

For Model 3, a neural network was trained to estimate daily GSR based on the day of the year , daily average value of maximum air temperature and minimum relative humidity for the third case. A network with three inputs, one hidden layer (thirty six neurons), hyperbolic tangent sigmoid transfer function for hidden layer, one output unit, linear transfer function (purelin) for output layer and Gradient descent back propagation with adaptive learning rate was used for training.

Lastly, for Model 4, a neural network with three inputs, two hidden layers (thirty six neurons in each hidden layer) with hyperbolic tangent sigmoid transfer function, and one output unit with linear transfer function (purelin) was trained based on day of the year, daily average minimum air temperature and minimum relative humidity to predict the GSR by using Gradient descent back propagation with adaptive learning rate. The same range of datas were used for training and testing

5. RESULTS AND DISCUSSION

First, a feed forward ANN was trained to estimate the global solar radiation based on the daily average maximum air temperature and day of the year. After several experiments it was found that a network with two inputs, 24 hidden neurons in one layer, and one output unit was sufficient for such an application. The daily maximum air temperature and daily total global solar radiation values data for 250 days during March 2010 and Dec 2010 were used for training, testing and validation purpose. A maximum of 3,000 iterations were allowed. The estimated Daily GSR values were compared with that ANN measured values as shown in Fig.2. The mean squared error for these data was found to be 0.011, while the mean absolute percentage error was 8.39 %. The regression results for the model 1 are shown in Fig.3.

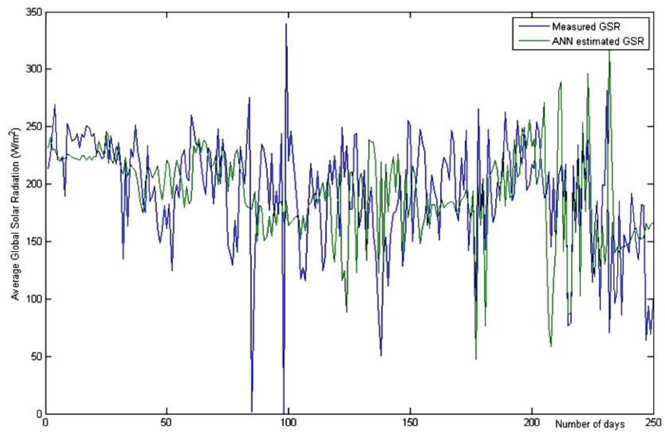

Fig- 2: Comparison of Measured GSR with ANN estimated GSR by using GD Method (Model 1)

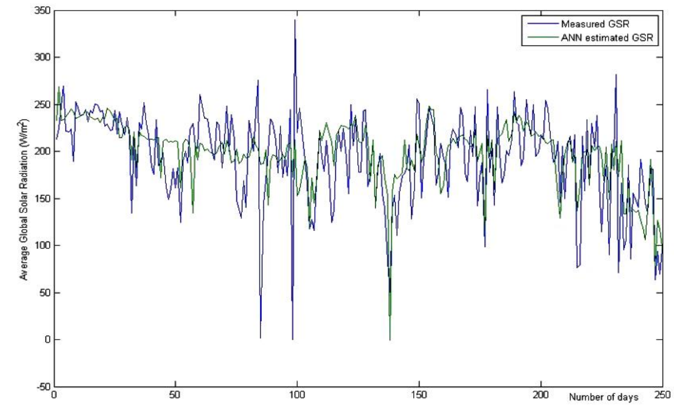

Fig- 4: Comparison of Measured GSR with ANN estimated GSR by using GD Method (Model 2)

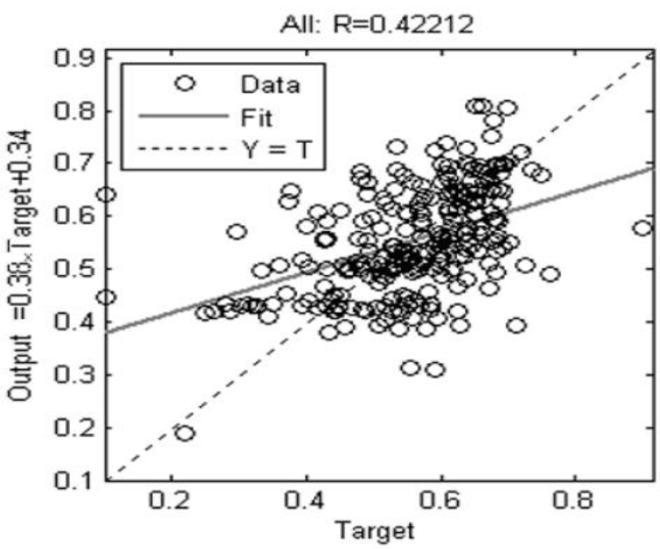

Fig- 3: Regression plot by using GD Method (Model 1)

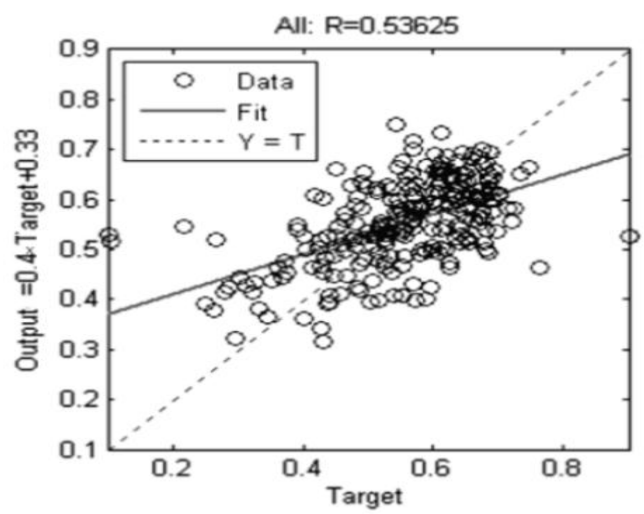

Fig- 5: Regression plot by using GD Method (Model 2)

To further explore the effect of daily minimum temperature on GSR, another feed forward ANN was trained to estimate GSR based on the daily Minimum air temperature and day of the year. A network of two inputs, 32 hidden neurons in one layer, and one output were found to perform reasonably good for this case. With the same data division as done in the previous case, the obtained mean squared error was 0.008 while the absolute mean percentage error for testing data was 6.65%. The measured and estimated values of daily GSR for this case are shown in Fig. 4. The Regression results for the Model 2 are shown in Fig. 5.

A neural network with three inputs, 36 hidden neurons in one layer, and one output unit was trained on day of the year, daily minimum relative humidity, and daily maximum air temperature to predict the GSR. The same range of 250 days datas are used for training and testing. Fig. 6 shows comparison of the measured and estimated GSR for the above mentioned data. The mean squared error for this case was 0.048, while the absolute mean percentage error for testing data was 18.03%. The Regression results for the Model 3 are shown in Fig. 7.

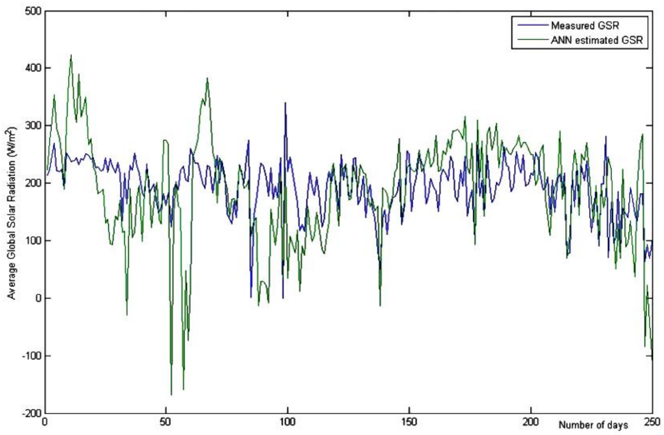

Fig- 6: Comparison of Measured GSR with ANN estimated GSR by using GD Method (Model 3)

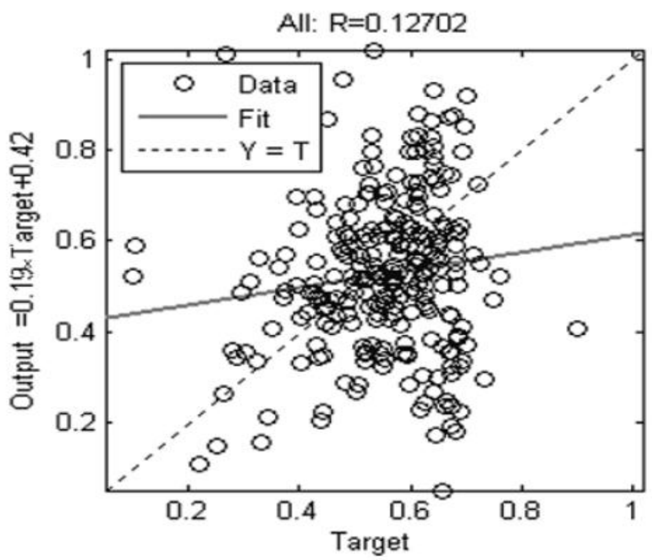

Fig- 7: Regression plot by using GD Method (Model 3)

Finally to further explore the effect of daily minimum temperature on GSR, another feed forward ANN was trained to estimate GSR based on the daily minimum air temperature and day of the year and minimum relative humidity. A network of three inputs, two hidden layers with 36 neurons in each layer, and one output with the same data division as done in the previous case, The obtained mean squared error was 0.029 while the absolute mean percentage error for testing data was 12.34%.The measured and estimated values of daily GSR for Model 4 are shown in Fig.8. Fig. 9 shows the Regression results for the Model 4.

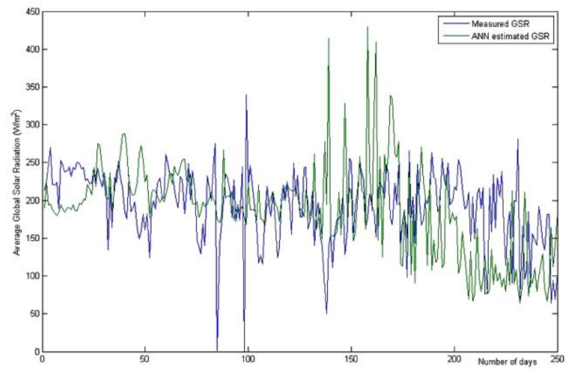

Fig- 8: Comparison of Measured GSR with ANN estimated GSR by using GD Method (Model 4)

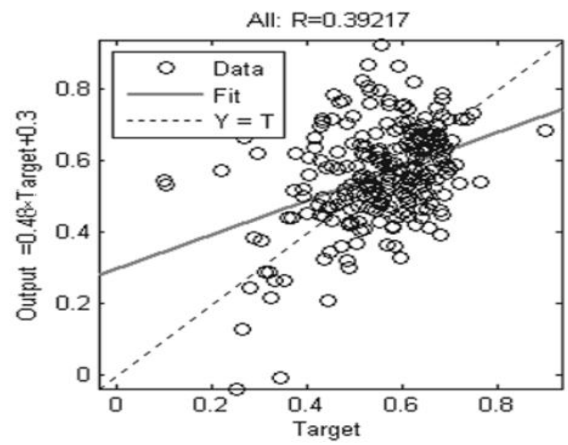

Fig- 9: Regression plot by using GD Method (Model 4)

Generally regression analysis has many practical uses, like if the goal is prediction, or forecasting, linear regression can be used to fit a predictive model to an observed data set of Y and X values. After developing such a model, if an additional value of X is then given without its accompanying value of Y, the fitted model can be used to make a prediction of the value of Y and vice versa. A linear regression line has an equation in the form of Y= bX + a, where X is the explanatory variable and Y is the dependent variable. The slope of the line is b (slope quantifies the steepness of the line), and a is the intercept (the value of y when x = 0). Better agreement of points presented in with the straight line means also better agreement between measured and predicted points.

The developed equations for the global solar radiation by using the regression plots are as follows (Figures 3,5,7 and 9) :

Output=0.38×Target+0.34 (For Model 1)
Output=0.40×Target+0.33 (For Model 2)
Output=0.19×Target+0.42 (For Model 3)

Output=0.48×Target+0.30 (For Model 4)

Mean square error (MSE) and Mean absolute error can be calculated by using the following equations.

$$MSE = \sqrt{\sum_{i=1}^{N} (D_{ie} - D_{im})^2 / N}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} (D_{ie} - D_{im} / D_{im}) \times 100$$

where , Die represents ith estimated value , Dim represents ith measured value , and N represents total number of observations

Results of the four models are presented in Table 2. It is seen that using the daily average minimum temperature outperforms as compared to the other cases with mean square error (MSE) of 0.008 and mean absolute error of 6.65%. The MSE for the case when only day of the year and maximum temperature were used as inputs was0.011. When maximum temperature was used along with the minimum relative humidity and day of the year was 0.048. For the model 4, when minimum temperature was used along with the minimum relative humidity and day of the year was 0.029.

Table-2: Architecture, Mean square error and Mean absolute error for the developed ANN Models

Model	Architecture	Mean square error (MSE)	Mean absolute error (%)
1	2-24-1	0.011	8.39
2	2-32-1	0.008	6.65
3	3-36-1	0.048	18.03
4	3-36-36-1	0.029	12.34

Finally, for this case when daily minimum temperature was used as input along with day of the year (Model 2), performs well, as compared to the other models was clearly found from table 3 also.

Table-3: Comparison of measured and ANN estimated GSR for various models

Day of the year	Measured GSR (W/m^2)	ANN estimated GSR (W/m^2)			
		Model 1	Model 2	Model 3	Model 4
50	161.21	174.00	167.20	169.30	176.40
100	220.00	190.20	218.90	210.80	195.00
150	251.38	243.10	256.00	235.00	249.50
200	217.42	206.90	216.50	220.90	215.20
250	103.69	97.38	110.40	105.70	106.70

CONCLUSION

In this paper, an ANN model has been developed and used to predict the average global solar radiation based on measured values of ambient air temperature and relative humidity only. This is important because temperature and relative humidity are commonly available parameters, while global solar radiation (GSR) is costly to measure and requires continuous attention of skilled manpower. Data for Madurai, a city in the south region of Tamilnadu state of India was used for training a feed forward ANN using gradient descent back propagation with adaptive learning rate algorithm. Data for 250 days was used to training, testing and validate the performance of ANN system.

For the first ANN model, only the day of the year and daily average maximum ambient air temperature was used as inputs and GSR as output. In the second ANN model, the day of the year and daily average minimum ambient air temperature were used as inputs and GSR as output. In the third ANN model, the daily average minimum ambient relative humidity, along with day of the year and maximum ambient air temperature, were used as input to the ANN model and GSR as output. For the fourth ANN model, average minimum ambient air temperature was used along with the minimum relative humidity and day of the year as input and GSR as output.

These ANN models were used to predict the daily average GSR. These results show that using the daily average minimum ambient air temperature and day of the year outperforms the other cases with absolute mean percentage error of 6.65% and mean squared error of 0.008,when training was done by using Gradient descent back propagation with adaptive learning rate algorithm. Hence, the model developed in the present work could be used to estimate the global solar radiation for locations in southern part of India, if only ambient temperature data is available.

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