Solar Resource Estimation Based on Correlation Matrix Response for Indian Geographical Cities

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Abstract- Global environmental concerns and gradual escalation of fuel cost linked with conventional energy sources encouraged the use of renewable energy in electric power supply sector greatly. India is blessed with great environmental wealth of solar energy due to its favourable location (40ºS to 40ºN). This research work explores the viability of great solar potential of 14 Indian geographical locations by estimating Global Solar Radiation (GSR) for four summer months using Artificial Neural Network (ANN). Initially, eight parameters are chosen as input data set for ANN from a number of environmental factors influencing GSR, based on their natural dependence on it. But, less correlated inputs as training data set for ANN results lead to more sensitive outputs. So, lately, inputs to the ANN are extracted based on Spearman rank-correlation coefficient, where only positively correlated input factors are considered as the input data set for the ANN to enhance its performance. Spearman rank-correlation coefficient describes the extent of correlation between two variables using a monotonic function by utilizing rank-order of the data regardless of distribution between two data sets. This makes it suitable not only for discrete and continuous variables but also ordinal variables (data sets including inconsistent values).A multi layered, feed forward, standard ANN model with one hidden layer and five hidden neurons corresponding to least mean square error is considered among various ANN models with different training algorithms, hidden layers and neurons, for the prediction of GSR. It is found that correlation based ANN predominates simple ANN.

Keywords Artificial Neural Networks, global solar radiation, correlation analysis, monotonic function, Spearman rank-correlation coefficient.

1. Introduction

Solar has been observed as a viable substitute for power generation in the midst of the existing clean energy resources, which has the highest global warming mitigation prospective [1]. Photovoltaic (PV) and concentrating solar power (CSP) thermal systems may have slightly differing requirements, but both need accurate solar radiation information. GSR is measured by a pyranometer but its installation is a very costly, time taking and uncommon exercise, particularly in the developing countries like India [2]. Estimation of daily GSR by the sunshine based models (Linear, Quadratic and Cubic) model has been made and compared. The comparison showed that the cubic model is equivalent to the quadratic model and the most constructive statistical results are given by the quadratic model [3]. Several generalized empirical model have been used for estimating the diffuse radiation and found that the third order functions are best fit for predicting the radiation for Indian stations [22 and 18]. Three regression models are developed for estimating the hourly GSR using meteorological parameters. In this, hour wise models have performed well as compared to other techniques in forecasting diffused and direct components of data [24]. Later the research on computing techniques increased and it was found that ANNs are best in forecasting to speed up the process [4]. Artificial Neural Network methods are utilized as auxiliary tools in the prediction of GSR at the places where there is no instrument to measure [5]. The Multi layered feed forward networks employ parameters like latitude, longitude, altitude and the sunshine duration for estimating the GSR [6].An inter model comparison is done between the Multi Layer Perceptron (MLP) and Radial Basis Functions (RBF) networks and observed that results produced by both these are mixed and have a minute difference [7]. MLP network with synthetic series are used for generating hourly irradiation [8]. Recurrent Neural Networks use geographical and meteorological data as inputs in estimating Solar Radiation [9, 10]. RBF networks are applied in predicting the ambient temperature and maximum solar radiation [11, 12]. ANNs are verified by Angstroms model in estimating the GSR of a particular place [13].Large numbers of the real-world input data samples to train artificial neural networks (ANNs) normally creates confusion over ANNs during the learning process and thus, degrade their prediction. The prediction of GSR was dependent on so many variables like measured solar radiation, temperature and sunshine duration using a suitable forecasting model based on ANN and Hardware Description Languages, designed on configurable Field Programming Gate Array (FPGA) [14].Clearness index-beam transmittance numerical correlation was proposed using measured Ambient Temperature and Relative Humidity Data to estimate hourly solar radiation [15]. A Data Mining Method using Classification and Regression Trees (CART) is proposed to determine the priority of input variables to predict GSR [16].

This research work estimates GSR of the 14 Indian geographical stations for four summer months with clear sky and long sunny days. Initially, eight parameters are chosen as input data set for ANN from a number of environmental factors influencing GSR, based on their expected dependence on it. These are Rainfall, Sunshine hours, Temperature, Vapour pressure, Relative humidity, No. of rainy days, Wind speed and Extraterrestrial radiation. Later on, inputs to the ANN are extracted based on Spearman rank-correlation coefficient, where only positively correlated input factors are considered as the input data set for the ANN to enhance its performance. The complete algorithm to estimate Global Solar Radiation is shown in fig. 1.It is found that correlation based ANN predominate the simple ANN.

Further the paper is organized as follows: section 2 describes the methodologies used for data analysis and forecasting. The parameters considered as inputs and outputs are explained in section 3. Section 4 deals with results of proposed methodologies, related discussions and performance of proposed research work. The findings of the research work are concluded in the section 5.

2. Evaluation Methodologies

2.1. Correlation Analysis

The correlation provides the degree of linear association between two variables, which entails how strongly the two variables are related to each other. It is performed by determining the correlation coefficient, whose value is bounded between -1 and 1. There are three possibilities of being positively correlated, negatively correlated and not correlated for the correlation coefficients with values near to 1, -1 and 0 respectively. The procedure to compute the correlation coefficients is the following:

1. Consider two data sets X and Y and convert them to standard units and determine mean and standard deviation of each data set.
2. Compute the products of the standard units of the x-values and the y-values.
3. Take the average of the products.

Correlation is one of the most common and useful statistical analysis tools that can be used in data modelling and analysis to evaluate degree of relationship between two variables.

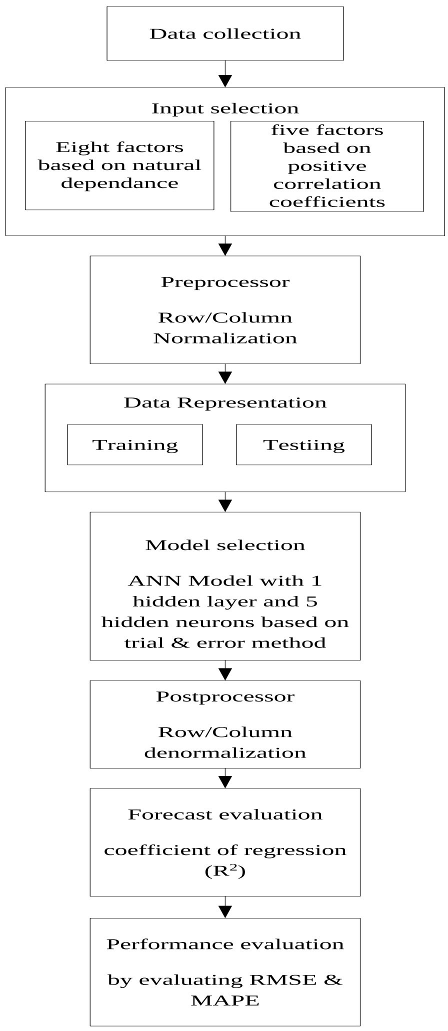

Fig. 1. Complete flowchart of the algorithm to estimate Global Solar Radiation

The aim of this test is to check which set of environmental parameter is highly correlated with Global Solar Radiation. In this research work, correlation between GSR and various other environmental factors are analyzed and the parameters corresponding to higher correlation coefficient are employed to the artificial neural network. The correlation coefficient is obtained by using a nonparametric measure of statistical dependence between two variables called Spearman rank-correlation coefficient, whose one important characteristic is that it utilizes rank-order of the data regardless of distribution between two data sets. It describes the extent of correlation between two variables using a monotonic function. It is suitable not only for discrete and continuous variables but also ordinal variables. This makes it appropriate for the data sets including unusual values too, as the inconsistent values don't have any considerable influence on the evaluated outcomes. The expression of Spearman rank-correlation coefficient for its calculation is given as

$$\rho = 1 - 6\sum_{i=1}^{n} D_i^2 \big/ n\left(n^2 - 1\right) \tag{1}$$

Where, $D_i = x_i - y_i$

2.2. Artificial Neural Networks

Artificial Neural Networks have been greatly utilized in broad areas of research like pattern recognition, classification, function approximation, optimization and prediction. Many models of ANN havebeen proposed for forecasting GSR but the multilayer perceptron (MLP) is the best known and most widely used [19]. In generalanMLP network consists of 3 layers; those are input layer, hidden layer and output layer.The basic step in accurate approximation of any nonlinear mapping can be accomplished by sound training of the neural network. The ANN is trained based on 6 statistical parameters which are extracted based on model A. The output of the neurons can be determined as shown below.

$$Y_i = f\left(\sum_{j=1}^{N} u_{ij} b_j\right) \tag{2}$$

The learning stage of the network is performed by updating the weights and biases using the back propagation algorithm with the gradient descent method in order to minimize a mean squared error performance index.

$$u_{ij}^{k}(new) = u_{ij}^{k}(old) - \Delta u \tag{3}$$

Where, $\Delta u = -\dfrac{\partial J}{\partial u}$,

$$J = \frac{1}{2}\sum_{i=1}^{N} x_i^{desired} - x_i^{computed} \tag{4}$$

In this study, a Multi Layered Perceptron model of ANN is found to be sufficient to get good accuracy and generalization of the proposed scheme. The transfer function used for the hidden layers is *tansig* and for the output layer is *purelin*. The training function used is *trainlm*. Once a satisfactory degree of input-output mapping has been reached, the MLP network training is completed. A large number of testing data have been used to check the proposed solution in the most objective way at practically all possible parameter variations. The set of completely unknown test data was applied for validation. The best performance is obtained with one hidden layer containing 5 neurons. The absoluteerror is calculated according to the equation (4) shown below:

$$\text{Absolute error} = \frac{|\text{ANN - Measured}|}{\text{Measured}} \tag{5}$$

The root mean square error can be calculated as

$$\text{RMSE} = \left\{ \frac{\left[\underset{\forall\ \text{observations}}{\sum} \left(\text{Estimated - Actual}\right)^2 \right]}{\text{Total no. of observations}} \right\}^{\frac{1}{2}} \tag{6}$$

3. Data Analysis

India has been making solar radiation measurements since 1957 on a network scale. Due to the shorter day duration and low solar elevations in the month of January and its adjoining months, various parts of the country receives less than 20 MJ/m^2 of daily Global Solar Radiation. The details of solar radiant exposure in India are shown in the fig. 2. In this study it is focused to predict the Global Solar Radiation for the months of April, May, June and July only.The details of inputs variables used for proposed methodologies are described in table1.

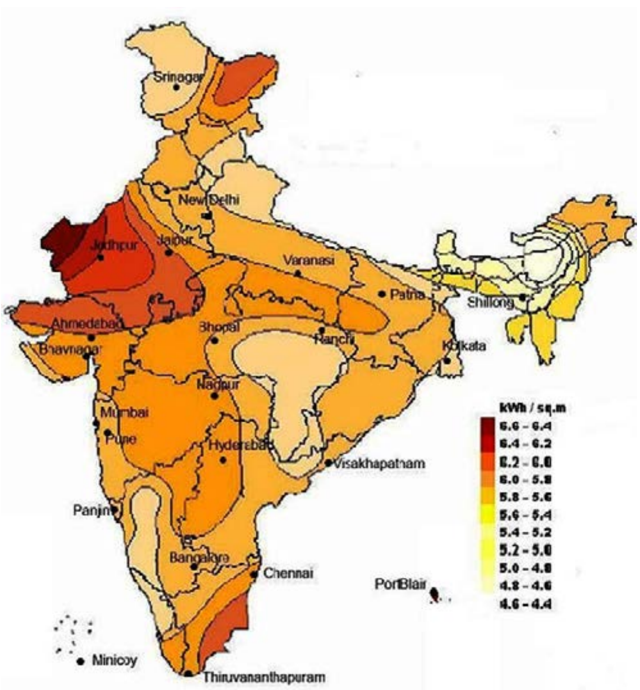

Fig. 2. Status of solar potential in India (Source:www.stfi.org.in)

Table 1. Details of input variables

S. No	Input	Name of the Parameter	Units	Remarks
1	Input	Rainfall	mm	Total rainfall
2	Input	Sunshine hours	h	Total no. of hours of sunshine
3	Input	Temperature	˚C	Mean monthly temperature
4	Input	Vapor pressure	hPa	The pressure exerted by the molecules of a vapor, especially that part of the total pressure exerted by vapor in a mixture of gases, as by water vapor in the air.
5	Input	Relative humidity	%	The ratio of actual to saturation vapor pressure
6	Input	No. of rainy days	days	Total no. of rainy days
7	Input	Wind speed	kmph	Velocity of the Wind for considered months
8	Input	Extraterrestrial radiation	MJ/m^2	Solar radiation incident on the outer limit of the Earth's atmosphere

Data for the 8 parameters (measured values) have been collected from India Meteorological Department which deals with the monthly mean values of different parameters [17] and are divided into two subsets called input data set and testing data set. ANNs are trained with training data set with targets as actual GSR. Similarly, these are tested with unknown test data set containing all the input parameters considered for the study.

4. Results and Discussions

In the present research work estimation of GSR is presented. Accurate Prediction of GSR using ANNs is highly sensitive and dependent on inputs, output selection. Presence of unimportant variables can intensify ambiguity and sometimes may lead to wrong prediction and make the analysis meaningless. Therefore, only the effective variables need to be considered. Here, prediction of GSR through ANN using the important variables is performed, whose results & discussion are as shown below.

4. 1. Selection of Input and Output Data set

In this study, firstlycorrelations between the various environmental data and GSR are examined. It is found that the Extraterrestrial radiation, Rainfall, Sunshine hours, Temperature, No. of rainy days, Relative humidity,Vapor pressure and Wind speed are the important parameters that influence the GSR greatly, hence the output of the neural network.Correlation measures the strength of the relationship between two variables. The results of the correlation on the input data set are shown in table 2. In the present work only positively correlated input factors are considered as the input data set for the Neural Networks to enhance its performance.Further, a comparative view of correlation based ANN and simple ANN is also highlighted.

Table 2. Correlation result between the several environmental parameters for the month May

	GSR	Extra terrestrial radiation	Rainfall	Sunshine hours	Temperature	Vapor pressure	Humidity	Rainy day	Wind Speed
GSR	1								
Extra terrestrial radiation	0.6482	1							
Rainfall	-0.3860	-0.2361	1						
Sunshine hours	0.6869	0.4900	-.3603	1					
Temperature	0.6368	0.2739	-0.1449	0.4068	1				
Vapor pressure	0.2672	0.0153	0.3116	0.1173	0.7638	1			
Humidity	-0.3260	-0.1607	0.5173	-0.4050	-0.2822	0.3156	1		
Rainy day	-0.8792	-0.7516	0.4048	-0.7338	-0.5236	-0.1144	0.3879	1	
Wind Speed	0.4531	0.1733	0.0309	0.3847	0.6690	0.6011	-0.1848	-0.3811	1

4. 2. Estimation of Global Solar Radiation

ANNs were trained by the selected data set with the aim of minimizing error. The famous multi layer perceptron model is used to estimate the Global Solar Radiation (GSR) for the months of April, May, June and July for the 14 Indian cities. The mean monthly values of Extraterrestrial Radiation, Rainfall, Sunshine Hours, Temperature, Vapor pressure, Relative humidity, No. of rainy days, Global Solar Radiation and Wind Speed for different 14 Indian geographical sites for the months of April, May, June and July are collected from the Indian Meteorological Department [17].The various ANN models are developed with different training algorithm, hidden layers and neurons along with their corresponding errors. Finally, a multi layered, feed forward, standard ANN model with least MAPE is obtained and employed for the prediction of GSR based on trial and error method. The best model is validated by comparison between estimated and measured values of GSR.Further, a comparative view of correlation based ANN and simple ANN is also highlighted. The design and training parameters of the ANN model are summarized in table 3.

Table 3. Design and training parameters of the ANN model

Sl. no.	Parameter	Selected value	Remarks
1	No. of hidden layers	1	Model with least mean square error was selected
2	No. of hidden neurons	5	Picked such that it minimizes the error and avoids over fitting
3	Activation function (Hidden layers)	*tansig*	$F(x) = \frac{2}{1+\exp(-2x_i)} - 1$

4	Activation function (Output layer)	*purelin*	$F(x) = x$
5	Training function	*trainlm*	Levenberg-Marquardt back propagation algorithm is used
6	Learning function	*learngdm*	Newton's Gradient decent with momentum learning function is used to update the weights and biases.
7	Learning rate	0.001	Adaptive learning rate algorithm was used
8	Performance function	mse	Mean squared error is chosen to avoid over fitting
	Inertia coefficient	0.6	alpha
9	Goal	0.0001	Default value
10	No. of Epochs	1000	Default value

The fig. 3a, 4a, 5a and 6a describes the actual and estimated values of Global Solar Radiation for 14 Indian geographical locations in the month of April, May, June and July respectively.

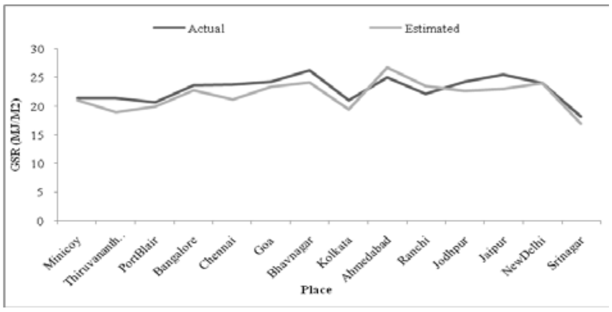

Fig. 3a. Shows the estimated and measured values of GSR for the month April for all the 14 Indian stations

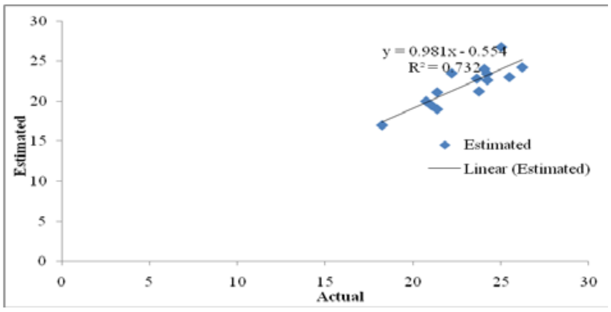

Fig. 3b. Scatter plot between the estimated and measured value for the month April

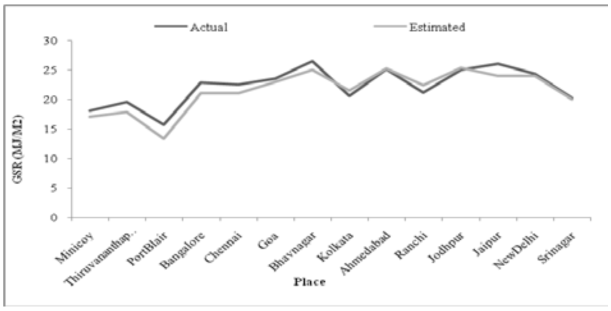

Fig. 4a. Shows the estimated and measured values of GSR for the month May for all the 14 Indian stations

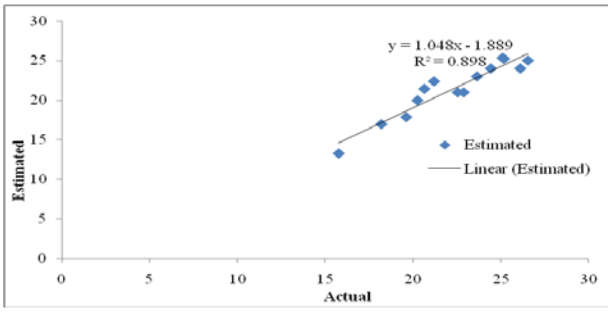

Fig. 4b. Scatter plot between the estimated and measured value for the month May

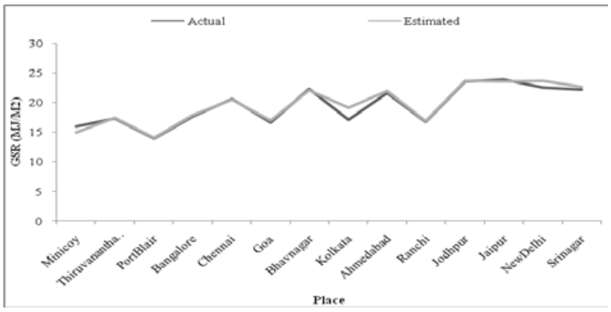

Fig. 5a. Shows the estimated and measured values of GSR for the month June for all the 14 Indian stations

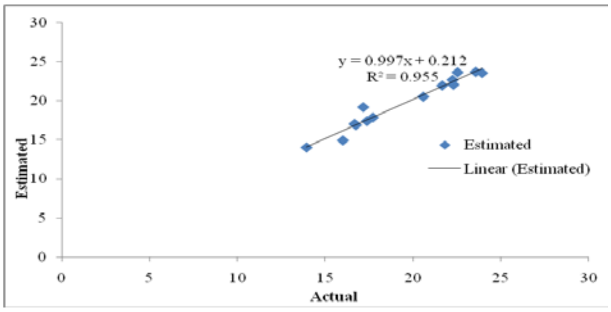

Fig. 5b. Scatter plot between the estimated and measured value for the month June

The graphs show an almost agreement between the estimated and the actual values of GSR. It can be said that maximum GSR is available at Bhavnagar and minimum is at Srinagar during the month of April. Similarly, maximum GSR is available at Bhavnagar, Jaipur and Srinagar in the months of May, June and July respectively. The regression plots between the estimated value of GSR and actual value of GSR for the months April, May, June and Julyare shown in fig. 3b, 4b, 5b and 6b respectively. The coefficient of regression (R^2) is observed as 0.7322, 0.8987, 0.9553 and 0.9467 for the months April, May, June and July respectively. This reveals the closeness of the estimated value with the actual value.

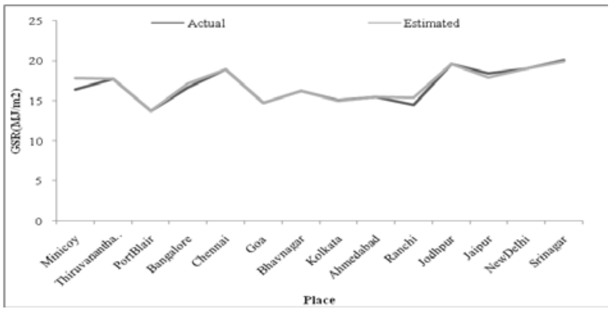

Fig. 6a. Shows the estimated and measured values of GSR for the month July for all the 14 Indian stations

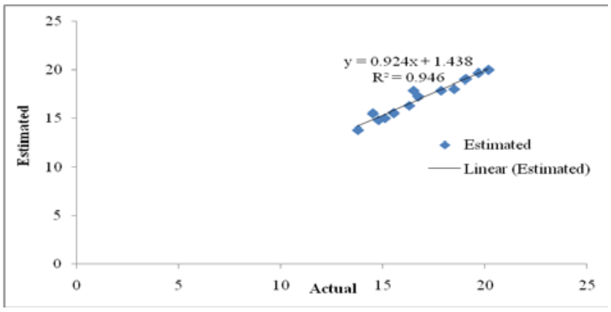

Fig. 6b. Scatter plot between the estimated and measured value for the month July

The performance of ANN models used for computing the Global Solar Radiation is compared with measured data, by calculating the Root means Square Error (RMSE) for each of the cities according to the equation (5). The results of RMSE are shown in table 4. It reveals that RMSE varies from 0.5621 (New Delhi) to 1.5862 (Jaipur). The RMSEs of many of the cities have been scored under 1, which shows the high-quality of prediction by the ANN. The values of RMSE in the present research workof various cities are compared with previous researches of similar studies.The RMSE obtained for the city Ahmedabad during the summer by ANN model is 0.7088 [20], whereas the present research workestimates it as 0.8631. This reveals that the key role of inputs and structure of Neural Network to be used for the prediction.Estimation of GSR through the ANN for the cities like Kolkata, Goa, Jodhpur and New Delhi is better than third order equation or second order equations as the RMSEs of these are (4.33, 2.31, 2.6 and 2.89 respectively [18]) more as compared to RMSEs obtained in this study.

Table 4. Comparison of RMSE results obtained through proposed model and other similar models

City	Proposed ANN	Simple ANN	[18]			[20]	[22]
			Third Order	Second Order	Best model	Eq. 1	Simple ANN
Minicoy	1.012205	1.1666	-	-	-	-	-
Thiruvananthapuram	1.466063	1.5172	0.87	0.87	-	2.31	-
Port Blair	1.281846	0.8141	-	-	-	-	-
Bangalore	1.091655	1.0492	-	-	0.344	-	-
Chennai	1.486306	0.9666	0.29	0.29	-	2.6	-
Goa	1.541895	0.7680	2.31	2.31	-	4.62	-
Bhavnagar	1.279463	1.0664	0.58	0.58	-	5.2	-
Kolkata	1.315367	1.1412	4.33	4.91	0.150	9.53	0.1836
Ahmedabad	0.863159	0.7088	1.73	-	-	10.4	0.1664
Ranchi	1.002871	1.0196	-	-	-	-	-
Jodhpur	0.818314	0.6942	2.6	2.6	-	8.37	0.2581
Jaipur	1.586285	1.0400	-	-	-	-	1.8822
New Delhi	0.562162	1.2047	2.89	2.31	0.235	13.28	-
Srinagar	0.625673	0.6967	-	-	-	-	-

The lower RMSE values of the proposed model exhibits better performance over the previous researches. The MAPE values are alsoevaluated for further favoritism in the analysis of accuracy. This reveals that cities like Ranchi and Kolkata shows maximum absolute error of 1.11% during the months May and June respectively. The contribution towards absolute error for the cities like Port Blair, Goa, Bhavnagar, Ahmedabad and New Delhi are zero in the months of April and July. The MAPE values of all the 14 cities are 1.92%, 4.68%, 3.6% and 2.1% for the months April, May, June and July respectively. This confirms good potentiality in predicting the Global Solar Radiation by ANNs for 14 Indian geographical locations.

5. Conclusion

In this paper, the mean monthly GSRis estimated over the months of April, May, June and July for 14 Indian geographical cities using a nonparametric nonlinear modeling technique, Artificial Neural Network. Initially, eight parameters are chosen as input data set for ANN from a number of environmental factors influencing GSR, based on their probable dependence on it. However, consideration of unrelated inputs as training data set for ANNresults lead to more sensitive outputs. So, inputs to the ANN are extracted based on Spearman rank-correlation coefficient, where only positively correlated input factors are considered as the input data set for the ANN to enhance its performance. Spearman rank-correlation coefficient describes the extent of correlation between two variables using a monotonic function by utilizing rank-order of the data regardless of distribution between two data sets. This makes it suitable not only for discrete and continuous variables but also ordinal variables (data sets including inconsistent values).A progressive model with feed forward network with one hidden layer and 5 hidden neuronshas been trained to estimate mean monthly GSR. The best model is validated by comparison between estimated and measured values of GSR. The validation of the model was performed with unknown data, which the model did not see before. It is found that correlation based ANN predominates simple ANN.Analysis of RMSE values concludethat the prediction through the proposed MLP network is more appropriate and accurate as compared to the other empirical models.Further, the MAPE results are also presented to overcome the squaring processed disproportionate weight in RMSE results.

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