Prediction of Daily Global Solar Radiation using Neural Networks with Improved Gain Factors and RBF Networks

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Abstract – Solar radiation data plays significant role in solar energy study. These data are not accessible for the area of interest because of the absence of meteorological stations. In this way, it is a highly challenging task to forecast solar radiation for a site utilizing distinctive climatic factors. Techniques including neural network with the back-propagation algorithm as training function, firefly algorithms and time series models suffer from slow convergence rates, high computational times and lack of recognizing the non-linear series respectively. Hence, in this work simple artificial neural network (ANN), ANN with forward unity gain and ANN with regression networks are proposed for forecasting the daily global solar radiation (DGSR) of 10 Indian cities. The data set consisting of the minimum temperature, maximum temperature, average temperature, wind speed, relative humidity, precipitation, extra-terrestrial radiation and sunshine hours are considered as inputs to the proposed approaches while predicting the DGSR. Statistical indicators (R^2 , $RMSE$, MBE and $MAPE$) are evaluated to determine the forecasting accuracy and are utilized for comparing the results of the proposed approach with recent researches available in the literature. It is found that the proposed approaches predict the DGSR with an error of 14.84%, 14.68% and 16.32% by the ANN, ANN with forward unity gain and ANN with RBF networks respectively. This shows the superiority of ANN with a forward unity gain approach over the other proposed approaches and approaches available in recent literature.

Keywords – Daily global solar radiation, artificial neural network, radial basis functions, regression networks.

1. Introduction

Solar energy is the most essential vital source that has turned into a piece of the answer to present world's energy challenges. Solar radiation data give the information about the entire energy that comes to the earth, which is required for utilization, planning, and designing of solar power plants. The different fundamental applications of solar radiation data are solar water heater, photovoltaic (PV), space solar heating, cooking and many other industrial and rural projects. The data ought to be contemporary, reliable and available for the design and evaluation of solar technologies for any particular location. A solar radiation forecasting model can be utilized as a part of a logical means for researching the future feasibility of solar energy possibilities. The measurement of solar radiation data is the most part accessible in a specific zone because of its underlying and repair cost. Subsequently, alternate solar energy modeling technique is becoming more and more vital because of the extending prerequisite of the arrangement, execution assessment and improvement of the solar energy applications [1], [2], [3], [4]. Since, the sun based radiation achieving the Earth's surface relies on the climatic states of the place, an investigation of solar radiation under nearby climatic conditions is excessively important. It is assessed similar to sunshine hours or in terms of direct, diffuse and global radiation. Without solar radiation information, the requirement for an empirical model for the forecasting of solar radiation is desirable [5]. Different empirical models have been utilized for evaluating the diffuse radiation and found that the cubic equations are the best fit for predicting the radiation for Indian stations [6]. The diffuse radiation coefficient $\left(\overline{H}_d / \overline{H}_0\right)$ is measured for 22 Indian cities through the application of three linear regression based models. The three models are formed based on the several combinations obtained from different environmental parameters (T, RH and N) [7]. But, demerits of the linear regression models are that they will underachieve when used to model nonlinear frameworks which are the reason of the issue we are interested [8]. Unlike, traditional models have been presented by researchers to predict global solar radiation (GSR) utilizing diverse meteorological factors. But most of the regression models do not predict the irregular series like GSR predictions accurately. The subject field goes forward to predict the monthly mean DGSR for the cities in Tamilnadu. The data set consisting of 565 samples is considered and 94% of it is used as training and rest as testing. Various architectures of ANN are employed and performances of these are evaluated using MBE, $MAPE$, $RMSE$ and Student's $t-test$. The results show that the average $MAPE$ as 5.47% [9]. Two different configurations of ANNs are used for predicting the DGSR for the city Moroccan city. The architecture with 1 hidden layer and 9 neurons in it produces a minimal $MAPE$ and $RMSE$ of 1% and 1.2 MJ/m^2-day, respectively [10]. Maximum values of $MAPE$ for ANN-1, ANN-2, and ANN-3 are 20.12%, 6.89%, and 9.04% respectively. ANN-2 shows high accuracy which utilizes most relevant input variables and can be used for the prediction of solar radiation at any sites in India [11]. Three combinations of input variables (latitude, longitude, elevation above sea level and sunshine hours) are considered for prediction. The RBFNN using input parameter has $MAPE$ of 4.94% and the absolute fraction of variance $\left(R^2\right)$ of 96.18% and gives better results than other conventional solar radiation prediction models [12]. The prediction of monthly GSR and efficiency evaluation has been performed using ANN and DEA approach at different cities of Jharkhand. The result showed R^2 and the average efficiency score was 0.9859 and 0.8435 respectively. The months May, June, and July produce more than 90% efficiency because of their input combinations [13]. The computational algorithm incorporates the estimation of global, diffuse and direct components through clear sky conditions. The estimates of ANN model show amazing similarity with observations of overall $RMSE(\%)$ and $MBE(\%)$ for the global radiation as 5.19 and –0.194, respectively. The $RMSE$ values for wet months (July, August, September and October) are relatively higher than those of the dry months (January, February, March and April) due to the intensive monsoon in the Indian region (New Delhi) [14]. Estimation of GSR utilizing MLP and RBF is used as ANN learning calculations. The results prove the superiority of MLP over RBF techniques in most of the cases, namely, models 1 and 7–11, with coefficients of determination exceeding 90% and low MBE, $MAPE$ and $RMSE$ values [15]. A set of ANN models to estimate daily GSR on a horizontal surface using meteorological variables. Model-4 has a better $RMSE$ of 0.1169 than the other models [16]. Various combinations of input variables and architectures are applied to forecast DGSR in order to get the best input data set and neural network architecture. The results show that ANN-1 (7 Inputs) gives a better outcome than the other cases with $MAPE$ and $RMSE$ about 1.36087% and 1.58994 MJ/m^2-day, respectively [17]. Similarly, ANN techniques are implemented to predict monthly average GSR in UAE. Training data (1995-2004) while testing and validation data (2005-2007). The values of $RMSE$, MBE, $MAPE$ and R^2 are 35%, 0.307%, 3.88% and 92%, respectively [18]. The measured data (air temperature and relative humidity) between 1998 and 2001 were used for training and the remaining was used as testing for the neural networks. The percentage $MAPEs$ values were 10.3, 11.8 and 4.49 for the three different input combinations of ANN [19]. DGSR is estimated using 6 different ANN combinations (T, RH, N and day of the year, 1998-2002). A comparative review between ANN models and conventional regression models were displayed. It was observed that the model utilizing sunshine duration and air temperature as data sources, gives the best outcome since the correlation coefficient is 97.65% [20]. Modeling of the solar energy potential of 195 cities in Nigeria for a period of (1983-1993) using ANN (MLP, FFN, and BP) with various architectures were designed using the neural toolbox for MATLAB. The correlation coefficients are observed higher than 90% [21]. The global average solar radiation of city Darwin in Australia was predicted using Linear Regression (LR), Angstrom Prescott Page (APP) and ANN methods. The $RMSEs$ occurred during this survey were 6.72%, 13.29% and 8.11% for the proposed three methods respectively [22]. Similar examination amongst ANN and multi-nonlinear regression models used for evaluating monthly average day by day GSR of Turkey (2000-2006). $MAPE$ and correlation coefficient (R) for the testing data utilizing the acquired ANNs demonstrate in light of the MNLR investigation was 5.34% and 0.9936, individually [23]. The Support Vector Machine–Firefly algorithm (SVM–FFA) based model is anticipated to predict the GSR for various locations in Nigeria like Iseyin, Maiduguri and Jos and the model is compared with other approaches [24].

An effort has been established to develop a linear regression model for predicting solar radiation in Jharkhand region. Angstrom constants (a & b) were obtained and averaged in order to develop the linear regression model which is ranging between 0.203 to 0.211 and 0.489 to 0.514 respectively [30].

The short period variation of solar radiation was calculated by analyzing sky image data as observed by cameras for the estimation of PV power one or two hours earlier at the PV generating site [31]. A nonlinear regression model based on an evolutionary technique, namely the genetic programming for estimating solar radiation on a horizontal surface with respect to the measured Climatological data [32]. The method utilizing nonlinear autoregressive neural networks (NAR) predicted a clearness index to forecast global solar radiations. The NAR model is based on the feed forward multilayer perception model with two inputs and one output. The obtained results showed an improvement of the NAR model over ARMA in term of mean absolute error (MPE) of 23.89% and a decrease in RMSE values of about 15.50% while the coefficient correlation was found to be 0.91 [33].

The estimation of global solar radiation (GSR) for four summer months using ANN at 14 Indian geographical locations. Initially, eight parameters are chosen as the input data set for ANN from a number of environmental factors influencing GSR, based on their natural dependence on it [34]. Developed three hourly regression models for measuring data classified as annual, seasonal and hour wise (6AM to 6PM). It is found that the hour wise model performs better and hence is recommended for determination of diffused and direct components of available data [35]. A method is established in order to deduce sunshine durations from irradiation measurements and daily solar radiation is computed with the Angstrom formula. This new procedure gives clear improvements both in data facility acquisition and record reliability [36].

Many other Artificial Intelligence based models are also presented in the literature, but lacks in forecasting GSR accurately due to iteration count and other reasons. Hence, in the present work, the benefits of ANN are utilized for forecasting the daily GSR of 10 Indian cities. And a comparative analysis with respect to other models is also presented to show the efficacy of the proposed approaches.

Concisely, in the present research work, artificial neural network based forecasting methodology is proposed as an alternative in estimating DGSR for Indian cities. A simple neural network, neural networks with unity forward gain and neural network with regression are proposed as novel methodologies in forecasting. An arrangement of normalized environmental input parameters ($T_{\min}$, $T_{\max}$, T_{avg}, w_s, RH, P, $\overline{H}_g$ and N) is considered as the input data set for the proposed model while predicting DGSR. Statistical indicators like R^2, MBE, $RMSE$ and $MAPE$ are considered as the error measures while forecasting with the proposed approach.

The timeline of this study is as follows: Section 2 gives an idea about the methodologies developed for forecasting DGSR. The details of the data considered for this study are presented in section 3. Results, comparative analysis, and related discussions are shown in section 4. The conclusion of the present work exhibited in section 5.

2. Methodologies

2.1. Artificial neural networks

MLP trained with the back–propagation (BP) algorithm may be viewed as a realistic means for performing a nonlinear input/output mapping. Gradient based and Hessian based algorithms are more popular in training the neural networks. Most of the gradient based BP applies the steepest plunge technique to revise the weights. It has a moderate convergence time and frequently yields imperfect arrangements. Hence, training algorithms based on Newton's method are introduced as a substitute for the previous one. One of these types of algorithms is Levenberg-Marquardt algorithm which is utilized in the minimization of a nonlinear least square type of objective functions. The weights are often updated on sequential implementations in which weights are only updated after a complete sweep through input/output data set. A three layered perceptron model is shown in Fig. 1. The output values of the unit i and j in the hidden layer are given by:

$$Y^{ih}(q) = f\left(\sum_{q=1}^{n} W^{ih}(q) \times X(q) + \vec{b}^{ih}(q)\right) \qquad (1)$$

$$Y^{o}(r) = f\left(\sum_{i=1}^{m} W^{o}(r) \times Y^{ih}(r) + b^{o}(r)\right) \qquad (2)$$

where, $W^{ih}(q)$ are the weights from the input to the hidden layer, $\vec{b}^{ih}(q)$ are the biases of the hidden layer, $W^{o}(r)$ are the weights of the hidden layer to the output layer, $b^{o}(r)$ are the biases of the output layer and $X(q)$ values are the input features. $Y^{o}(r)$ values are the output for the daily GSR, n is a training pattern index, and m is the number of hidden layer units. The error obtained at the output node is shown as:

$$Error = \frac{1}{2}\sum_{p=0}^{n}\left(t(p) - Y^{o}(p)\right)^{T}\left(t(p) - Y^{o}(p)\right) \qquad (3)$$

Here, $t(p)$ is the actual target and $Y^{o}(p)$ is the value obtained from the neural network.

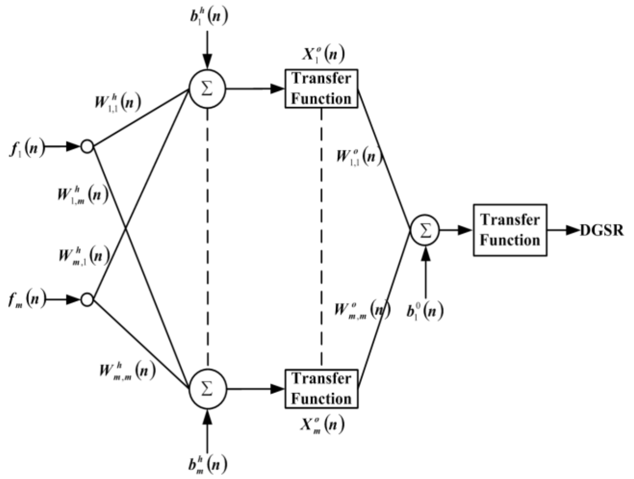

Fig. 1. Implementation of ANN.

2.2. Artificial neural networks with unity forward gain

In this, a modification in feed forward neural networks is implemented to forecast DGSR of the Indian locations. In general, the conventional ANNs have the connections between the input layer and hidden layer neurons, similarly hidden layer neuron to output layer neurons. But in the proposed model a connection between the input layer neurons and output layer neurons is also added (in the case of three layered architecture) to get the benefits of forward connections. A sample of this architecture is shown in Fig. 2. Like ANNs, this model likewise utilizes back propagation algorithm for updating of weights, yet the fundamental side effects of the system are that every neuron is identified with all past layer neurons. The storage and computation requirement of Levenberg-Marquardt training algorithms increases as the square of the size of the network [25]. Hence, a forward connection from each layer to the output layer is added and a BP training algorithm is used to obtain the best execution as far as convergence time and architectures.

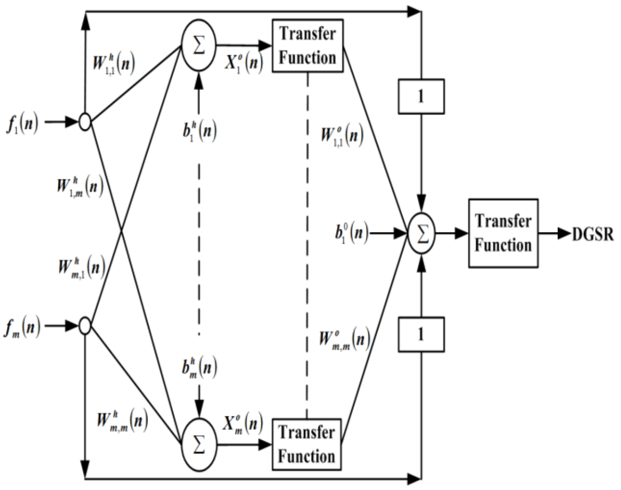

Fig. 2. Implementation of artificial neural network with unity forward gain.

2.3. ANN with regression networks

In this case, the radial basis network is combined with linear regression networks to have the benefits of both the functions. The architecture of the combination of radial basis and regression networks is shown in Fig. 3. Like radial basis networks, it has a marginally unique second layer. Thus, the output comes out from this hybrid model has a refined effect of both radial basis and regression networks. In this model, at the earlier stage the network seems like radial basis functions which have a single hidden layer entirely operates on the spread factor of the network. The detailed information regarding this model can be found in the neural system tool compartment some portion of MATLAB documentation. Conditions that are utilized as a part of the neural network model are shown in Eqs. (4) – (7).

$$X_j = \phi\left(\left\|\vec{f} - \vec{c}_j\right\| \times b^{ih}\right) \quad (4)$$

$$\phi(x) = \exp\left(-x^2\right) \quad (5)$$

$$Y_i = \frac{\sum_{j=1}^{h} W_j^{ho} \times X_j}{\sum_{j=1}^{h} X_j} \quad (6)$$

$$b^{ih} = \frac{0.8326}{s} \quad (7)$$

where, $j = 1, 2, \ldots, h$ (number of hidden neurons), Y_i is the i^{th} output (DGSR), $\vec{f}$ is the 10–dimensional real-valued input vector, W^{ho} is the regression layer weights, $\vec{c}_j$ is the center vector of the j^{th} node, s is the real constant known as spread factor, b^{ih} is the biasing term of radial basis layer, and $\phi(.)$ is the nonlinear radial basis function (Gaussian).

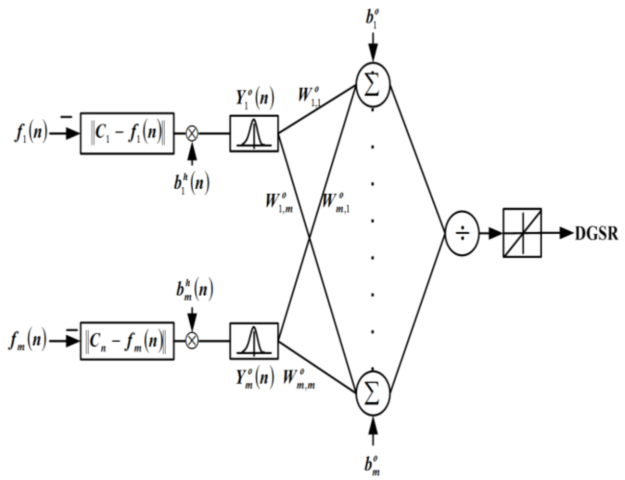

Fig. 3. Implementation of neural network with regression networks.

The neural network models are trained until the errors become to a predetermined value resembling a specific input prompt to a specific target output. A few endeavors were made until the best possible number of hidden layers, numbers of neurons in the hidden layer and the spread factor were reached. The network architecture chose after these attempts deliver the insignificant error in both training and testing. The execution of the trained network is then assessed by correlation of the network output with its genuine esteem via statistical errors.

3. Data Acquisition

This study explores the feasibility of using neural networks while modeling the nonlinear relationship between solar radiation and other meteorological variables. In this paper, various environmental parameters including $T_{\min}$, $T_{\max}$, T_{avg}, WS, RH, P, $\overline{H}_g$ and N are measured by the National Aeronautics and Space Administration (NASA) satellite at various Indian locations, between the year 2008 and 2010 were utilized in forecasting DGSR using the proposed model [28]. 90% of the accumulated data is utilized as training purposes and 10% is used for the testing. This implies the input dataset is a matrix constituting of 8 rows and 986 columns which is huge in means of ANN. Likewise, the testing data set constitutes of 8 rows and 110 columns. The geographical locations and their related parameters are shown in Table 1. Similarly, the summary statistics of these parameters for the considered period of study are placed in Table 2.

Table 1. Geographical coordinates of 10 Indian cities [11]

S. No.	City	Latitude (˚N)	Longitude (˚E)	Mean Sea Level (m)
1	Ahmedabad	23.04	72.38	169
2	Bhopal	23.25	77.42	523
3	Bhubaneswar	20.27	85.82	45
4	Chennai	13.08	80.27	6
5	Jaipur	26.92	75.82	431
6	Kolkata	22.39	88.27	6
7	New Delhi	28.35	77.12	216
8	Pune	18.52	73.84	560
9	Varanasi	25.45	82.85	81
10	Visakhapatnam	17.43	83.14	3

Table 2. Statistics of 10 Indian cities

Variables	Mean	Maximum	Minimum	Standard Deviation
$T_{\max}(C^\circ)$	31.8354	46.05	21.23	4.9227
$T_{avg}(C^\circ)$	22.8480	31.4	10.98	4.4862
$T_{\min}(C^\circ)$	26.8772	37.2	16.41	4.3182
$P(mm)$	3.2767	84.76	0	9.2632
$WS(m/s)$	3.4357	8.96	0.83	1.4331
$RH(\%)$	64.2403	96.45	21.5	19.4896
$\bar{H}_g(MJ/m^2-day)$	33.5403	43.847	23.769	5.5683
$\bar{N}(h)$	12.0208	13.356	10.644	0.9375
$\bar{H}_0(MJ/m^2-day)$	19.5490	28.375	2.685	5.1599

All the data are normalized [2] using the equation shown below before passing them through proposed models.

$$X_{Norm} = 0.8 \times \left(\frac{X_R - X_{\min}}{X_{\max} - X_{\min}} \right) + 0.1 \qquad (8)$$

where, X_{Norm} is the normalize value, X_R is the value to be normalized, $X_{\min}$ & $X_{\max}$ are the minimum and maximum values in all the values for related values.

4. Results and Analysis

In this work, three different neural network based models are proposed for the predicting the daily GSR of 10 Indian cities. The proposed models are:

Model 1: Simple artificial neural network

Model 2: Artificial neural network with unity forward gain

Model 3: Artificial neural network with regression network

The statistical errors R^2, $RMSE$, $MAPE$ and MBE are evaluated to assess the precision of the proposed models. The positive value of MBE indicates the amount of overestimation and the negative value indicates the underestimation. Similarly, $RMSE$ and $MAPE$ values indicate the divergence between the observed and calculated values and hence, lesser values of $RMSE$ and $MAPE$ implies more precise in estimating.

$$R^2 = \frac{\sum \left(H_{gc,i} - H_{go,a}\right)\left(H_{go,i} - H_{go,a}\right)}{\left[\sum \left(H_{gc,i} - H_{gc,a}\right)^2 \sum \left(H_{go,i} - H_{go,a}\right)^2\right]^{1/2}} \qquad (9)$$

$$RMSE = \left[\frac{\sum \left(H_{gc,i} - H_{go,i}\right)^2}{n} \right]^{1/2} \qquad (10)$$

$$MAPE = \frac{1}{n} \sum \left| \frac{\left(H_{go,i} - H_{gc,i}\right)}{H_{go,i}} \right| \times 100 \qquad (11)$$

$$MBE = \frac{1}{n} \sum \left(H_{go,i} - H_{gc,i}\right) \qquad (12)$$

where, $H_{go,i}$ and $H_{gc,i}$ are the i^{th} observed and calculated values while $H_{go,a}$ and $H_{gc,a}$ are the average observed and calculated values of solar radiations [5].

The proposed models have been applied to predict DGSR for the Indian cities using the 8 input variables. In this work, the hidden layer neurons of Model 1 & 2 are varied in step size 1 to obtain the best network architecture. Similarly, the spread factor for the Model 3 is also varied in a step size of 0.1 from 0.5 to 1.5. The various numbers of hidden layer neurons and their respective mean $MAPE$ scores are reported in Table 3. It is noticed that 11 and 15 numbers of neurons in one hidden layer produce least mean $MAPE$, while predicting the DGSR for different locations in India by Model-1 and Model-2 respectively. It is also observed that the spread factor of value 1.5 produces least $MAPE$ while predicting the DGSR with the Model-3. The individual $MAPE$ values for all the cities have been shown in Table 4.

It can be observed that the minimum value of $MAPE$ is observed for Ahmedabad city while predicting DGSR by all the three models. Similarly, the DGSR for the Chennai city is predicted with highest $MAPE$ with all the three proposed models. The mean value of $MAPE$ is observed as 14.84%, 14.68% and 16.32% for the Models 1, 2 and 3 respectively.

Furthermore, to check the robustness of the proposed model the other statistical errors like $RMSE$ and MBE are also evaluated as shown in Table 5. The $RMSE$ and MBE values are minimum for the city Ahmedabad and maximum for the city Chennai. The $RMSE$ values range between 1.955 and 3.482 MJ/m^2 for Model-1, 1.895 and 3.410 MJ/m^2 for Model-2 and 1.859 and 3.822 MJ/m^2 for Model-3 respectively. The mean values of MBE are –0.098, 0.051 and –0.126 for the Models 1, 2 & 3 respectively. This shows that the Models 1 and 3 underestimate the DGSR for Indian cities when compared to the Model-2.

Further, the plots between the actual and predicted values have been presented in Figures 4a, 4b, and 4c. From the figures, it can be achieved that the predicted values by different models follows the trend in actual values and shows a good agreement. Errors are a little bit more while predicting the DGSR by Model-3 when compared to the others. The regression plots between estimated and actual values are also plotted in the Figures 5a, 5b, 5c and 5d. The plot also constitutes the value of regression coefficient, which is also a measure of accuracy. From these figures, it can be presumed that higher regression coefficients or lesser deviations from 1:1 line are observed in the Model-2 with 15 neurons in a solitary hidden layer.

Table 3. *MAPE* results (hidden layer neurons as a variable quantity)

Model-1		Model-2		Model-3	
Neurons	DGSR	Neurons	DGSR	Spread Factor	DGSR
5	15.40	5	15.84	0.5	19.76
6	15.64	6	15.44	0.6	19.06
7	15.96	7	15.32	0.7	18.59
8	15.99	8	15.21	0.8	18.43
9	14.82	9	14.94	0.9	18.27
10	15.22	10	15.43	1.0	18.02
11	14.62	11	15.91	1.1	17.76
12	14.74	12	15.71	1.2	17.56
13	15.43	13	15.20	1.3	17.38
14	15.12	14	14.88	1.4	17.22
15	15.16	15	14.59	1.5	17.08

Table 4. Overall *MAPE* results of 10 cities obtained through proposed approach

City	DGSR		
	Model-1 (11 Hidden layer Neurons)	Model-2 (15 Hidden layer Neurons)	Model-3 (Spread factor = 1.5)
Ahmedabad	9.20	8.76	8.36
Bhopal	12.79	11.94	13.66
Bhubaneswar	17.27	17.46	20.08
Chennai	22.03	22.29	27.02
Jaipur	16.59	16.68	20.27
Kolkata	16.70	16.37	17.39
New Delhi	12.48	12.52	13.81
Pune	12.73	13.71	13.23
Varanasi	10.97	11.16	10.94
Visakhapatnam	17.61	15.89	18.43
Avergae	14.84	14.68	16.32

Table 5. Overall *RMSE* and *MBE* results of 10 cities obtained through proposed approach

City	Model-1		Model-2		Model-3	
	RMSE	MBE	RMSE	MBE	RMSE	MBE
Ahmedabad	1.955	-0.111	1.895	0.042	1.859	0.003
Bhopal	2.540	0.024	2.442	0.152	2.750	0.370
Bhubaneswar	2.652	-0.076	2.651	-0.093	2.955	-0.209
Chennai	3.482	-1.109	3.410	-1.084	3.822	-1.268
Jaipur	2.516	0.009	2.615	0.267	2.991	0.149
Kolkata	2.714	-0.809	2.629	-0.624	2.855	-0.976
New Delhi	2.123	-0.130	2.129	0.046	2.413	-0.339
Pune	2.961	0.772	3.065	1.032	3.041	0.682
Varanasi	2.054	0.124	2.103	0.502	2.179	0.134
Visakhapatnam	2.836	0.322	2.738	0.269	2.913	0.191
Average	2.583	-0.098	2.568	0.051	2.778	-0.126

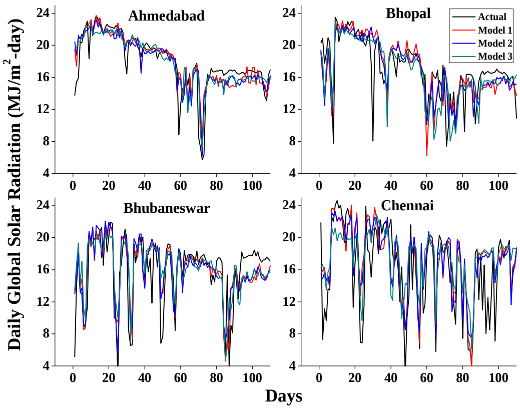

Fig. 4a. Comparison of models with actual values at Ahmedabad, Bhopal, Bhubaneswar and Chennai.

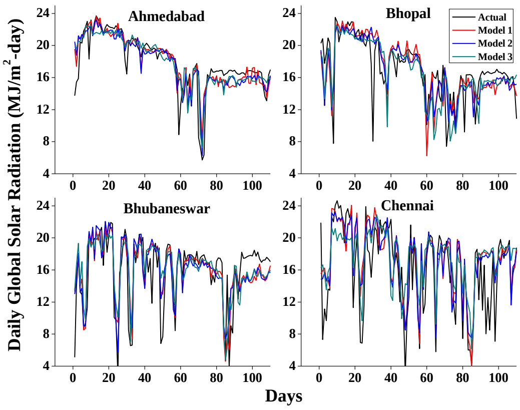

Fig. 4b. Comparison of models with actual values at Jaipur, Kolkata, New Delhi and Pune.

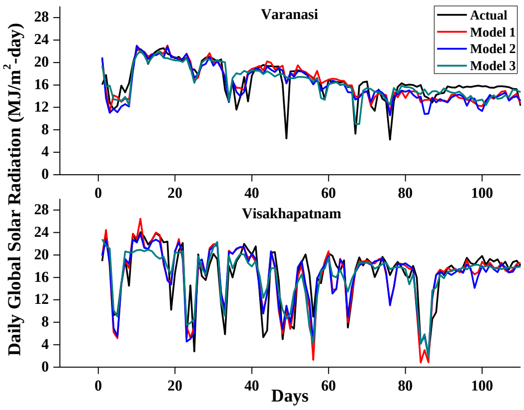

Fig. 4c. Comparison of models with actual values at Varanasi and Visakhapatnam.

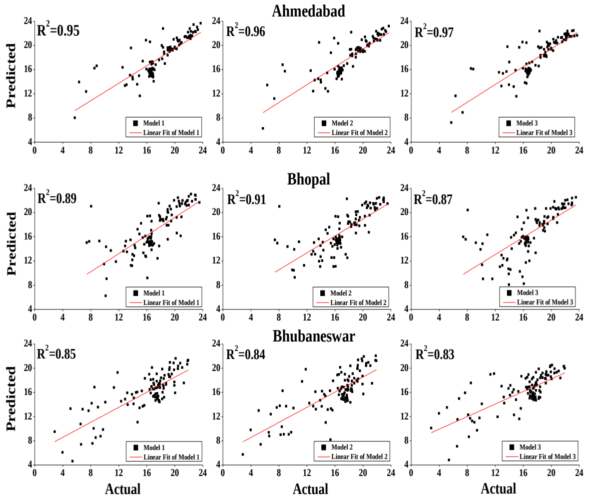

Fig. 5a. Regression plot between actual and predicted values for Ahmedabad, Bhopal and Bhubaneswar.

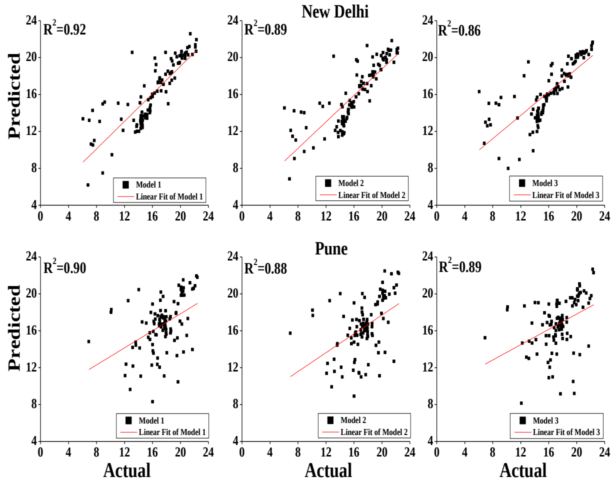

Fig. 5c. Regression plot between actual and predicted values for New Delhi and Pune.

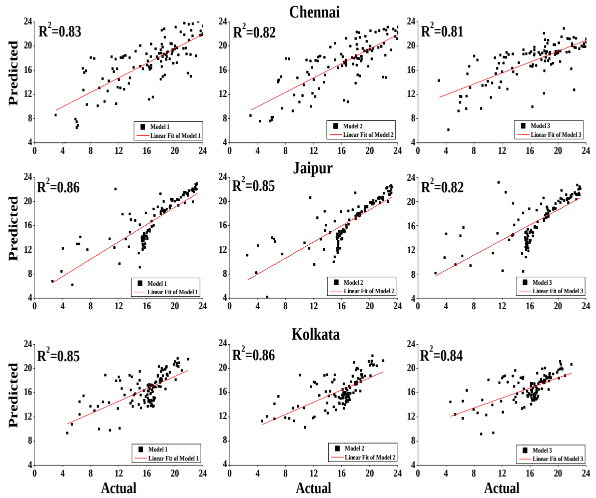

Fig. 5b. Regression plot between actual and predicted values for Chennai, Jaipur and Kolkata.

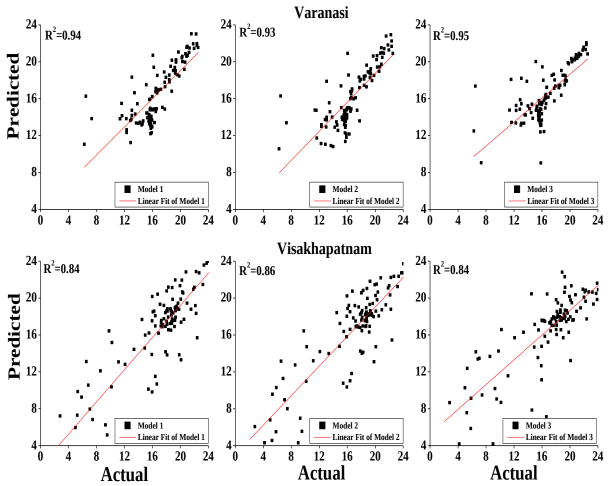

Fig. 5d. Regression plot between actual and predicted values for Varanasi and Visakhapatnam.

A comparative study of the proposed work with recent research works [6], [24], [26] and [29] in terms of mean values of R^2, $RMSE$ and $MAPE$ is presented in Table 6. According to the table, the proposed models are giving accurate results than the conventional approaches proposed in Ref. [27] and slightly more errors when compared to Artificial Intelligence (AI) based approaches are in Ref. [24].

Further, the results of each city, obtained by proposing models are compared with similar research work done in recent. The city wise comparative analysis is shown in Table 7 in terms of both $MAPE$ and $RMSE$ respectively. It can be seen the models proposed in Ref. [6], are producing least value of $RMSEs$ and $MAPEs$ as compared to the proposed model for the cities Kolkata, New Delhi and Pune. Similarly, the vice versa condition is observed with respect to the models proposed in Ref. [14]. Based on this study, it could be affirmed that the proposed model is efficient in predicting the DGSR with a reasonable error for Indian locations.

Table 6. Comparison of averages of various performance indicators

Statistical Error	Proposed Work			[29]	[6]	[26]					[24]		
	Model-1	Model-2	Model-3			ANN-1	ANN-2	ANN-3	ANN-4	ANN-5	SVM-FFA	ANN	GP
$MAPE$	14.84	14.68	16.32	-	7.543	16.91	16.89	16.38	6.89	9.04	11.5192	13.4305	13.2089
$RMSE$	2.583	2.568	2.778	5.185	0.9807	-	-	-	-	-	1.8661	2.0458	1.9532
R^2	0.88	0.87	0.86	-	0.95	-	-	-	-	-	0.5300	0.4659	0.5181

Table 7. Comparison of $MAPE$ and $RMSE$ results with other researchers

City	$MAPE$				$RMSE$				
	Present work			[6]	Present Work			[14]	[6]
	Model-1	Model-2	Model-3		Model-1	Model-2	Model-3		
Ahmedabad	9.20	8.76	8.36	-	1.955	1.895	1.859	3.34	-
Bhopal	12.79	11.94	13.66	-	2.540	2.442	2.750	-	-
Bhubaneswar	17.27	17.46	20.08	-	2.652	2.651	2.955	-	-
Chennai	22.03	22.29	27.02	-	3.482	3.410	3.822	12.63	-
Jaipur	16.59	16.68	20.27	-	2.516	2.615	2.991	-	-
Kolkata	16.70	16.37	17.39	4.711	2.714	2.629	2.855	2.8	0.6372
New Delhi	12.48	12.52	13.81	15.04	2.123	2.129	2.413	4.72	1.354
Pune	12.73	13.71	13.23	2.88	2.961	3.065	3.041	4.79	0.9509
Varanasi	10.97	11.16	10.94	-	2.054	2.103	2.179	-	-
Visakhapatnam	17.61	15.89	18.43	-	2.836	2.738	2.913	2.83	-

5. Conclusions

In this work, approaches like simple ANN, ANN with forward unity gain and ANN with regression networks are applied for forecasting the DGSR of the 10 Indian geographical locations. Dataset consisting of various parameters is utilized for forecasting the DGSR at every location. Results show that $MAPE$ lies between 8.36 (Ahmedabad – Model 3) to 27.02 (Chennai – Model 3), $RMSE$ lies between 1.859 (Ahmedabad – Model 3) to 3.822 (Chennai – Model 3) and R^2 lies between 0.86 – 0.88. Results declare that the ANN model with a forward unity gain predicts DGSR with the least errors for the considered location of interest. The rest of the two algorithms give moderate results as compared to other approaches while predicting the DGSR. Similarly, the results also declare that the DGSR for the cities Chennai and Ahmedabad are predicted with high and low mean errors respectively. The effects of the proposed methodologies are contrasted with recent literature and found that proposed models outflanked the previous ones. Finally, it can be concluded that prediction of DGSR for Indian locations through the proposed approaches is better and overcomes the major roadblocks in the field of solar radiation studies.

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