Prediction of Solar Energy Based on Intelligent ANN Modeling

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Abstract- The work proposes artificial neural network (ANNs) based estimation of daily GSR in an Indian city, Varanasi $\left(25^{\circ}16^{'}\mathrm{N}, 82^{\circ}57^{'}\mathrm{E}\right)$. Average, minimum and maximum values of temperature, relative humidity, wind velocity, extraterrestrial radiation and precipitation are considered as input variables for the estimation purposes. Different combinations of the input variables and architectures are applied to estimate GSR in order to find the best input data set and ANN architecture. Mean absolute percentage errors (MAPE), root mean square error (RMSE) and mean bias error (MBE) are employed to evaluate the performance of the approach. The minimal values of MAPE, MBE and RMSE are found as 1.36087, 0.35751 and 1.58994 respectively, with the input data set consisting of all the parameters. The results obtained are compared and validated with many other techniques and observed that the proposed approach is outperformed in terms of quality and computational efficiency.

Keywords- Global solar radiation, artificial neural network, meteorological data

1. Introduction

Ever-increasing energy demand together with rising conventional fuel prices and environmental awareness made renewable energy sources very popular in the developing countries like India. Among the different alternative renewable energy technologies, the solar energy occupies one of the most significant positions [1]. It is a clean resource which delivers a huge potential to meet the rapid growth of energy demands. Most of the Indian region receives an abundant amount of solar energy due to its geographical location and less industrialization [2]. Solar resource modeling or mapping is one of the essential management tools for proper development, planning, and pricing of solar energy systems [3].

A precise knowledge of the solar radiation profile of a particular geographical location is of vital importance for the growth and performance evaluation of solar energy devices [4]. Solar potential evaluation of a region requires information about the global, diffuse and direct solar radiation measured on horizontal and inclined surfaces for different locations respectively [5]. The global solar radiation (GSR) measurements are produced at a few locations in a country, which may or may not be the same as the actual site of development and utilization [6 and 13]. Solar radiation available on the earth's surface depends on local climatic conditions and knowledge of this is important as it enables best suitable sites for Photovoltaic (PV) installations [7]. Meteorological and Climatological variables are the key parameters that are utilized for measuring the solar radiation for a selected country. Referable to the higher costs, limited cities are owned with the measuring equipments that are used for the exact measurements of the different parameters. Moreover, the data related to solar radiation are rarely available around the globe due to the limitation by fiscal and technical obstacles [14]. This follows up on the use of alternative numerical techniques with the evolution of other observed meteorological data to estimate the amount of global solar radiation (GSR) on the earth's surface in the other regions of the country [8]. This can be estimated either by using regression techniques or by applying artificial intelligence based models [9].

Long term data are utilized to evaluate GSR by employing various statistical and empirical models [6]. In the empirical models, the relation between solar radiation and various other meteorological parameters have been assessed and employed for estimation of GSR [10]. Angstrom-Prescott initiated the empirical correlations, which correlated the global solar radiation with the ratio of sunshine hours [4]. In order to estimate global solar radiation in many regions around the world, a considerable number of empirical models have been proposed over the previous decades and several input variables have been utilized accordingly. Extensive works have also been done on the first type of empirical models to estimate the global and diffuse solar radiations on both horizontal and inclined surfaces respectively [11]. The higher order empirical models lack in estimating the GSR accurately for different locations. This too increases the error in the performance while handling with increased number of variables [12]. Therefore, it is indispensable to acquire the methods to estimate the solar radiation on the basis of the most readily available meteorological data [13]. Many of the recent research works proposed artificial intelligence based models to forecast the GSR at different positions of interest using various Meteorological and Climatological parameters [14].

Artificial neural networks are applied in several areas like aerospace, defense, automotive, mathematics, engineering, medicine, economics, meteorology, psychology, neurology, and many others [9]. The neural networks are highly nonlinear and require no prior assumptions concerning the data relationships in estimating the various parameters [16 and 12]. Among the multiple service of program the ANN (such as shape recognition and classification, function approximation, prediction, etc.), we emphasize their growing habit of data analysis, extending an effective alternative to more traditional statistical techniques in many scientific fields [3]. Several authors have aimed and proven the effectiveness of the ANN modeling for the estimation of direct solar radiation [18, 19 and 20], diffuse radiation [21] and global radiation at various locations [2, 22, 23, 24, 25 and 27]. The prediction of solar radiation using ANN models incorporates input-output mapping of various meteorological parameters which are considered as inputs and outputs [15]. Especially, in the meteorological and solar energy resources fields, ANN based models have been successfully trained to model different solar radiation variables improving the existing empirical and statistical approaches [16]. ANNs are used for the estimation of GSR based on measured temperature and relative humidity data [6]. The past investigations considered only single target variable such as either global or diffuse or direct radiation in the ANN model for the estimation [2]. Many of the recent researches demonstrated different ANN modeling for estimation of GSR using several parameters, but lacks in input normalization techniques. This would produce confusion in ANNs training for repeated input data sets with lesser deviations. Hence, to overcome the drawbacks, present work proposes an intelligent methodology for the prediction of GSR at Varanasi using the various meteorological data sets. Different performance indicators are applied to determine the accuracy of the proposed approach.

In this paper, GSR at an Indian city is reckoned by the application of ANNs employing the normalized input data sets is presented. Three bands of data are weighed to ascertain the suitability of the proposed approach. Further, the paper is organized as: section 2 provides different methodologies for estimation and performance evaluators. Input and output data for the proposed work is discussed in section 3. Results and related discussions are presented in section 4. Findings of research are presented as conclusions in the section 5.

2. Methodology

The present section provides the mathematical formulations for the models used in predicting the daily GSR and evaluating the errors.

2.1. Artificial Neural Networks for predicting GSR

ANNs are mostly preferred due to their ability to imitate natural intelligence in its learning from previous experiences [6]. A neural network is a type of artificial intelligence technique made up of simple processing units called neurons that behave similar to human brains [17]. It is capable to model any linear and nonlinear systems by using an input layer, hidden layer (s) and an output layer. The mathematical expression for estimating daily GSR by the application of neural network can be represented as below:

$$T_j = f\left(O_j - b_j\right) \tag{1}$$

$$O_j = \sum a_{ji} p_i \quad \forall i = 1,2,....,r \tag{2}$$

where,

T_j	Output of the hidden layer/ output neuron (s)
$f(.)$	Activation function of the neuron in the hidden/ output layer
b_j	Bias value of the neuron
r	Number of input signals
p_i	Input signal
a_{ji}	Weights between the neuron i in the input/ hidden layer to neuron j in hidden/output layers

Neural networks are developed, so that a particular input leads to a specific target output. The difference between output and the target is used as updating rule for ANNs until the output achieves the target. Figure 1 shows the generalized structure of the neural network consisting of neurons, input layer, hidden layer (s), an output layer, weights and biases. In this work, *Trainlm* is used as a network training function that updates weight and bias values according to the Levenberg-Marquardt (LM) optimization algorithm. The tangent sigmoid activation function $f(v)$ is described as:

$$f(v) = 2/(1+\exp(-2v)) \quad (3)$$

where,

v Input of the activation function

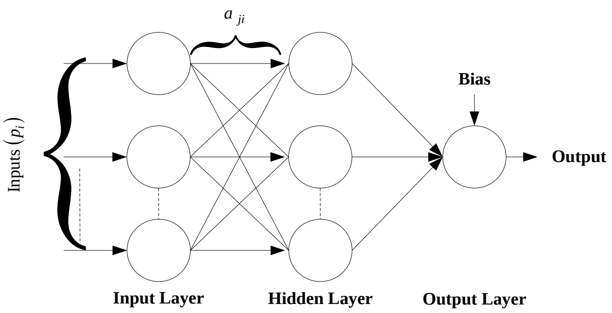

Fig. 1. Schematic diagram of neural network

In general, *Trainlm* is used as a network training function that updates weight and bias values according to the Levenberg-Marquardt (LM) optimization algorithm. In this, weights and biases are updated based on the network's performance, evaluated through mean squared errors (MSE). *Learngdm* is the gradient descent algorithm with momentum weight and bias learning functions. It updates the weights from the neuron's input and MSE. Input vectors are mapped to target vectors in the training stage of the network until it reaches the less error. The term back propagation (BP) refers to the way in which the gradient is computed for nonlinear multilayer networks.

2.2. Performance evaluation

The performance of the aforementioned prediction models is evaluated in terms of mean absolute percentage error (MAPE), mean bias error (MBE) and root mean square error (RMSE).

i. *Mean Absolute Error (MAPE)*

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left(\left|\frac{D_{ie}-D_{im}}{D_{im}}\right|\right) \quad (4)$$

ii. *Mean Bias Error (MBE)*

$$MBE = \sum_{i=1}^{N}(D_{ie}-D_{im})/N \quad (5)$$

iii. *Root Mean Square Error (RMSE)*

$$RMSE = \sqrt{\sum_{i=1}^{N}(D_{ie}-D_{im})^2/N} \quad (6)$$

where,

D_{ie} Estimated value

D_{im} Measured value

N Number of observations

3. Data considered for the study

The selection of input and output parameters is the fundamental step in the process of estimating the GSR for the Indian location employing ANNs. In the present study, seven input parameters have been applied for estimation of GSR. Data for the five years have been collected from National Aeronautics and Space Administration (NASA), which deals with daily values of different parameters [26]. The data consisting of several parameters were collected over the period 2000-2004 for the considered location.

The various input parameters are considered for the study as follows:

Average temperature in degrees centigrade $(^{\circ}C)$

Maximum temperature in degrees centigrade $(^{\circ}C)$

Minimum temperature in degrees centigrade $(^{\circ}C)$

Extraterrestrial radiation in Mega-Joule/meter^2/Day (MJ/m^2-day)

Relative humidity in terms of percentage $(\%)$

Wind velocity in Meters/Second (m/s)

Precipitations in Millimeter/ Day (mm/day)

Similarly, the output parameter considered for the study is:

Global Solar Radiation in Mega-Joule/Meter^2/Day (MJ/m^2-day)

An overview of the statistical analysis of the solar radiation across Indian geographical locations is presented in the below Table 1.

Table 1. Statistics of Global Solar Radiation in India [12]

Particulars	Value (MJ/m^2/year)	Place
Average Global Solar Radiation	7000	India
	7200	Peninsular India
Annual highest receiving of Global Solar Radiation	8000	Rann of Kutch
Daily average of Global Solar Radiation	22	Rann of Kutch
	16.5	Kashmir Valley
	15	North East India
Daily average of GSR during month January	<5	Kashmir Valley
	≅ 20	Deccan Plateau
	<15	North Indian Plains
Daily average of GSR during month of April	>20	India
Maximum daily average GSR during month April	>25	Rajasthan & Saurashtra

4. Results and Discussions

In this work, the daily global solar radiation (GSR) is estimated using 7 meteorological parameters by the application of Artificial Neural Networks (ANNs). The MAPE, RMSE and MBE are used as the performance evaluators for the proposed approach.

The neural networks are trained with large number of input data sets to obtain minimum error at both training and testing stages. Daily values of average temperature, maximum temperature, minimum temperature, extraterrestrial radiation, relative humidity, wind velocity and precipitations are employed for training the neural networks. Out of 5 years data, 80% is considered as training and the rest is considered for the testing purposes. It is obvious that, a big number of training iterations to the neural network leads to the prediction of the GSR at least error. An unknown testing data set is represented before the ANN to predict the daily GSR for the Indian city.

In this work, three ANN models are trained with different input data sets to achieve suitable model and the input data set in predicting the GSR for the particular city. Neural Networks containing 5, 10 and 15 neurons in the hidden layers are treated as ANN-1, ANN-2 and ANN-3 respectively. Daily GSR is predicted by using various combinations of input parameters and models, and their statistical errors have been evaluated. The values of statistical errors obtained from different models are shown in Table 2. Out of these, the values of interested are bold faced. In the table, column 1 determines the various input data sets; column 2 determines models of ANN; columns 3, 4 and 5 represent the values of statistical errors respectively.

Table 2. Results for the three ANN models

Input Data Set	ANN Structure	MAPE (%)	MBE	RMSE
7 Inputs	**ANN 1**	**1.36087**	**0.35751**	**1.58994**
	ANN 2	1.53522	0.45609	1.75927
	ANN 3	1.47948	0.39542	1.66683
6 Inputs	ANN 1	3.43214	0.40391	1.68021
	ANN 2	3.08635	0.45218	1.79290
	ANN 3	4.12613	0.43792	1.74541
5 Inputs	ANN 1	6.00426	0.51092	1.80193
	ANN 2	6.15341	0.56327	1.89546
	ANN 3	7.10652	0.54891	1.85012

The above table reveals that the proposed approach in estimating the daily GSR at the Indian city is successfully implemented and found that the ANN-1 with 7 input parameters estimates the daily GSR with a very low error. It is disclosed that the ANN-1 utilizing 7 input parameters produces least MAPE score as compared to other proposed models. It is also observed that ANN-1 estimates the GSR with a MAPE score lie between 1.36087 and 6.00426 for all the considered input data set. Similarly, other models also estimate the GSR with acceptable errors. This shows good agreement between the actual and predicted values of the daily GSR by different models and input data sets. The agreement between the measured and predicted values of the daily global solar radiation is also sustained by RMSE. It is obvious from the Table 2, that the RMSE is positioned between 1.58994 and 1.89546 which also shows a good performance of all the suggested models. To further investigate the performance of the proposed approach, MBE is also evaluated and found in the range of 0.35751 to 0.56327 MJ/m^2-day. The graph between the actual and estimated values of the daily GSR obtained by utilizing the 7, 6 and 5 input parameters is shown in Fig. 2 respectively. Table 3 depicts the comparative analysis of the proposed work with the recent researches proposed in [12, 13 and 15]. The average values of RMSE of the each model are considered for the validation purposes. The table reveals that the proposed approach estimates GSR with a lower RMSE value as compared to other techniques.

Table 3. Comparative analysis of the proposed and other approaches

Particular	Proposed Model			[12]	[13]	[15]
	ANN1	ANN2	ANN3			
RMSE (kWh/m^2-day)	0.4696	0.5044	0.4864	0.7442	0.383	0.4393

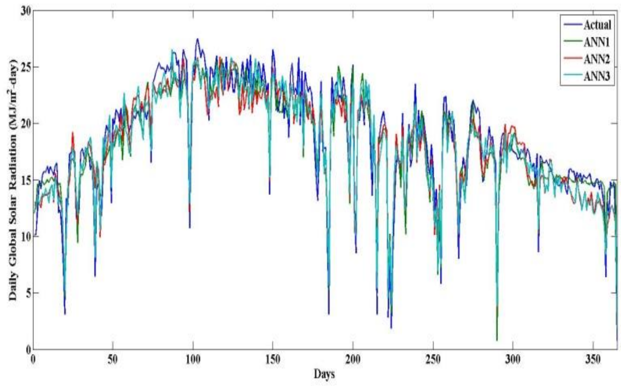

Fig. 2. Graph between the actual and estimated values of the three proposed models

It is obvious from the above pattern that an excellent match between the calculated and observed values is noticed in the case of ANN1. Hence it can be concluded that all the developed models are capable to show their adaptability for Indian weather conditions. However, out of the three proposed models, ANN-1 is realized as the most accurate model.

5. Conclusion

The present paper presents the outcome of an attempt made to predict the GSR based on measured values of average, minimum and maximum temperatures, relative humidity, precipitation, wind velocity and extraterrestrial radiation as these are commonly available parameters. Data for Varanasi city in India are collected for five years out of which 80% is used for training and the rest is used for testing purposes. Three sets of input parameters and three types of neural network architectures are considered to predict the daily GSR. Results revealed that input data set containing all the parameters and neural network containing 5 neurons in the one hidden layer are best in predicting the

GSR at the location of interest. The results also reveal that the proposed models outperform the other cases with least MAPE of 1.36087% and RMSE of 1.58994 MJ/m^2-day. Finally, the results obtained were very effective and the effort made in this work was feasible for estimating the GSR at Indian locations.

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