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REVIEW
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Adaptive Neuro-Fuzzy Approach for Solar Radiation Forecasting in Cyclone Ravaged Indian Cities: A Review

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The measurement of solar radiation and its forecasting at any particular location is a difficult task as it depends on various input parameters. So, intelligent modeling approaches with advanced techniques are always necessary for this challenging activity. Adaptive neuro-fuzzy inference system (*ANFIS*) based on modeling plays a vital role in the selection of relevant input parameters for undertaking precise solar radiation prediction. Numerous literature works focusing on ANFIS-based techniques have been reviewed during the estimation of solar energy incidents in the eastern part of India. During solar forecasting, the input parameters considered for this model are the duration of the sunshine, temperature, and humidity whereas the clearness index value has been considered as an output parameter for calculation. For designing the model, practical data sets have been prepared for some specified locations. Finally, the outcome is compared with several other techniques. During this course of analysis, several studies have been reviewed for a comprehensive literature survey work.

Keywords: solar radiation, forecasting, neural network, fuzzy logic, adaptive neuro-fuzzy, ANFIS

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INTRODUCTION

With the rapid increase in global energy demands and depleting fossil fuel reserves, the world is opting for renewable sources of energy. Non-conventional energy sources (Notton et al., 2002) play a great role in mitigating power necessity and have become promising alternatives for the consumers. Among all such energy sources, solar energy plays a leading role because of its widespread availability. Prediction or forecasting of solar energy (Xue, 2017; Almaraashi, 2018a) is extremely important and has to be carried out before the selection of any site for a solar-based power plant. Solar forecasting analysis is necessary for the design and modeling of the solar conversion system. The collection of solar radiation data at a particular location is made possible with the use of designated measuring instruments. Many models have been developed related to the global solar radiation using parameters such as relative humidity, duration of the sunshine, temperature, latitude, and longitude. Basically, it is difficult to deal with systems having uncertain features through conventional mathematical tools and hence advanced controllers are needed to deal with the uncertainties.

Many literature works have repeatedly utilized ANN, fuzzy, and ANFIS-based algorithms to estimate solar radiation forecasting for various applications based on numerous meteorological parameters and outputs. Fuzzy rule–based systems utilize linguistic variables such as the $IF - THEN - ELSE$ rule and connect between antecedents and consequents. These rules also possess lots of antecedents associated with logical AND, OR operators. The prediction of GSR in Tehran province of Iran usingANN has been carried out (Ramedani et al., 2013a) based on inputs such as temperature (maximum and minimum) and the duration of sunshine. The best model considered here contains one hidden layer with 37 neurons. Researchers have introduced a combination of neural network and FIS for predicting solar radiation data on a day to day basis on the horizontal surface (Rahoma, 2011). This approach was not used for Helwan, Egypt (NRIAG), because the measurement of solar radiation was not viable. In order to get more efficiency, they used $ANFIS$ in which the combined outcome is of $FLC\&ANN$. The results obtained from this combination indicate better performance of the fuzzy model with accuracy of more than 96 percent and $RMSE$ of less than 6 percent. Fuzzy systems have been implemented for various applications using solar forecasting data (Iqdour, 2006). Based on the SOS (second-order statistics) techniques, the outcome of fuzzy-based models has been compared with the linear models. After prediction, the $RMSE$ and accuracy of the fuzzy model are 0.52 and 0.96, respectively, as compared to the linear model with $RMSE$ = 0. 61 and accuracy = 0. 89. Different feature selection methods (Almaraashi, 2018a) have been used to predict GSR in different parts of Saudi Arabia. Mainly four feature selection algorithms such as Relief, Monte Carlo uninformative variable elimination, random frog, and Laplace score algorithms have been used followed by the multi-layer neural network as a predictor. For the improvement of (Xue, 2017) efficiency of the back-propagation neural model (BPNN), optimization algorithms such as PSO and GA are used during the prediction of daily diffuse solar radiation. Seven parameters such as month of the year, sunshine duration, mean temperature, rainfall, wind speed, relative humidity, and daily global solar radiation have been picked as evaluating indices. A hybrid model (Ibrahim and Khatib, 2017) has been suggested for forecasting hourly global solar radiation with random forests technique and firefly based algorithm. Hourly meteorological data have been used to develop the proposed model. The firefly algorithm has been utilized for the optimization of the random forest technique by finding the best number of trees and leaves per tree in the forest (Hassan et al., 2017). In this study, several machine learning algorithms for modeling global solar irradiation have been examined. Four different heuristic (Keshtegar et al., 2018) regression models such as Kriging, response surface method (RSM), multivariate adaptive regression (MARS), and M5 model tree (M5Tree) are investigated for the accurate estimation of solar radiation. Monthly solar radiation (SR) from Adana and Antakya stations are used as case studies taking parameters such as maximum–minimum temperature, sunshine hour, and wind speed along with relative humidity (Achour et al., 2017). Because of the deficiency of solar energy forecasting measuring stations in the past, prediction of the said energy source has gathered great interest in the recent years. In this particular work, fourteen solar radiation models have been implemented to assess monthly mean GSR on a horizontal plane (Hassan et al., 2018). Two networks have been developed for prediction of the solar irradiance.

Many places in India are prone to natural calamities. The four eastern coastal states, West Bengal, Odisha, Andhra Pradesh, and Tamil Nadu, and one western state Gujarat are susceptible to cyclonic events. Solar radiations in these particular localities are more or less haphazard. So for finalizing any project based on renewable energy such as SPV or STWM (solar thermal wind machine), solar data collection becomes crucial. Generally, traditional methodologies are practiced to forecast the solar irradiation in major Indian cities. Moreover, less measuring equipment is utilized in coastal regions due to high wind effects. Some climatic parameters are needed to develop and estimate the global diffuse solar radiation. Several literature works are found describing the use of ANFIS models for many applications. The forecasting of measles cases has been described (Uyar et al., 2019) and greenhouse gas prediction has been mentioned in the article (Ludwig, 2019). In this study (Nguyen and Liao, 2011; Motepe et al., 2018), the author has applied ANFIS for load forecasting to get accurate results. Authors have also discussed its application in the prediction of electricity including forecasting of several renewable energy sources such as PV, wind, and fuel cell (Notton et al., 2002; Gairaa et al., 2016; Singh and Rizwan, 2018a; Yadav et al., 2018a; Campos et al., 2018; Ilmi et al., 2018; Karri et al., 2018; Maitra et al., 2018; Yousefi et al., 2018; Sujil et al., 2019a; Fachini and Lopes, 2019; Perveen et al., 2019; Pourdaryaei et al., 2019).

The proposed review work is arranged in the following manner. **Section 2** presents the material and methodology used for the prediction of solar radiation. It also discusses the implementation of intelligent modeling technique such as ANFIS for solar energy forecasting in Eastern Indian cities. **Section 3** presents the simulation and modeling of a standalone solar system with ANFIS. **Section 4** presents results and discussions. The conclusion has been carried out in **Section 5** and **Section 6** presents the references.

MATERIAL AND METHOD USED FOR PREDICTION OF SOLAR RADIATION

Description of Dataset

A total of 6 years data [Appendix], monthly average value of temperature, humidity, and sunshine duration are obtained from the solar radiation handbook and NREL (National renewable energy laboratory) are used for training and the remaining 1 year is used for testing. Recent datasets of 2015–17 have also been prepared with the help of IMD Bhubaneswar center for further studies and experimentation.

Artificial Neuro-Fuzzy Inference System

As we know that solar energy is unpredictable and uncertain, there is an urgent need to mitigate the uncertain nature of solar radiation. Conventional methods fail to predict the solar irradiation properly because of the uncertain behavior of Sun.

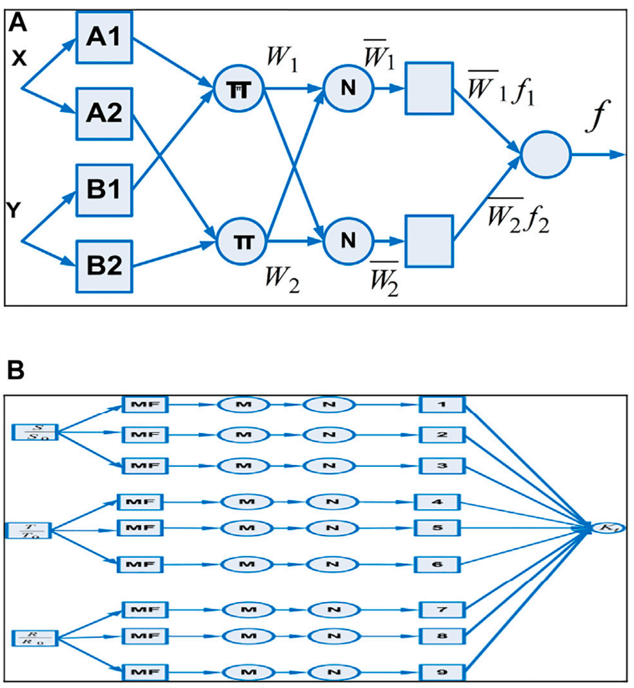

FIGURE 1 | (A) ANFIS structure. **(B)** Detailed *ANFIS* structure with three inputs and three membership function.

So soft computing happens to be an innovative approach with an ability of a human mind. The application of various soft computing tools such as multi-layer perceptron (MLP), ANFIS, RBF, RNN, NARX, GNN, FL, FG, NFG, NG, and SVM are suitably employed to predict and estimate the solar irradiance.

An adaptive neuro-fuzzy inference system has been used to predict the daily global solar radiation of the eastern zone of India. The data on daily solar radiation, sunshine duration, humidity, and temperature for the period of 5 years are collected from the renewable energy source laboratory, NASA, and the solar radiation handbook. A total of 2,190 day (2000–2005) datasets are used in the *ANFIS* model. Out of 2,190 days, 1825 days are considered as training and the rest 365 days are considered for testing. Later, the latest data have been applied for further research work.

ANFIS Model and Architecture

The typical structure of *ANFIS* has been divided into three parts: (I) a rule based, (II) a database, and (III) reasoning mechanism. ANFIS as shown in **Figure 1** is a hybrid method which combines algorithms such as back propagation, least-square algorithm, and gradient-descent for optimizing the system output.

The ANN network is depicted in **Figures 1A,B**. Possessing lots of nodes joined through the directional linking. In order to minimize the error, couple of basic learning rule–based method has been used in the network such as back-propagation technique. A fuzzy model having rules is as follows:

$$\begin{aligned} &Rule\, I\colon If\; x_1 = A_1 \& y_1 = A_2 \Rightarrow M_1 = p_1 x + q_1 y + r_1,\\ &Rule\, II\colon If\; x_1 = B_1 \& y_1 = B_2 \Rightarrow N_1 = p_J x + q_J y + r_2, \end{aligned} \tag{1}$$

where x_1, y_1 symbolizes input values.
$M_1 \& N_1$ symbolize outputs.
$A_1 \& A_2$ stand for the fuzzy sets (**Figures 1A,B**)

The model (as shown in **Figures 2**, **3**) uses six dissimilar membership type function such as (Gauss mf, triang mf, two side Gaussian mf, Bell mf, Difsig mf, and Trap mf) along with (i.e., linear &constant) membership function. The dataflow has been explained from **Eqs 3–8**).

Layer 1. Every node i in this layer is an adaptive node with a node function.

$$o_{1,i} = \begin{Bmatrix} \mu_{A_i}(x)\; for\; i = 1,2 \\ \mu_{B_{i-2}}(y)\; for\; i = 3,4 \end{Bmatrix}. \tag{2}$$

Y or X = input node I.
A_i or B_{i-2} = linguistic value.
$O_{1,\,i}$ = membership grade.
Membership grade satisfies the quantifier A.

$$\mu_{Ai}(x) = \begin{Bmatrix} 0 & x \le a_i \\ \dfrac{x - a_i}{b_i - a_i} & a_i \le x \le b_i \\ \dfrac{c_i - x}{c_i - b_i} & b_i \le x \le c_i \\ 0 & x \ge c_i \end{Bmatrix}, \tag{3}$$

Layer no 2: Every node in the layer is fixed, where the output symbolizes product of all input signals.

$$o_{2,i} = w_i = \mu_{Ai}(x)\mu_{Bi}(y) \quad i = 1,2. \tag{4}$$

The node output indicates the firing strength. Any other T-norm which performs fuzzy is used as a node function. Layer no three is fixed and is labeled as N. Furthermore, the *i*th node decides about the *i*th rule's firing capacity for the sum of all the rule's firing capacity.

$$o_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} i = 1,2 - where\text{ the outputs idicate normalized firing strength.} \tag{5}$$

Layer 4. Every node i in this layer is an adaptive node with function.

$$o_{4,i} = \overline{w_i} f_i = \overline{w_i}\left(p_i x + q_i y + r_i\right) i = 1,2, \tag{6}$$

where $\overline{w_i}$ is a normalized firing strength from layer three and = parameter sets of the node.

Layer no 5. Here, in this case; a single node is a fixed node and is given as Σ. This calculates the overall output as sum of all the incoming signals.

$$output\; o_5 = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}. \tag{7}$$

Related Work

Based on the geographical coordinates and following meteorological parameters such as relative humidity and

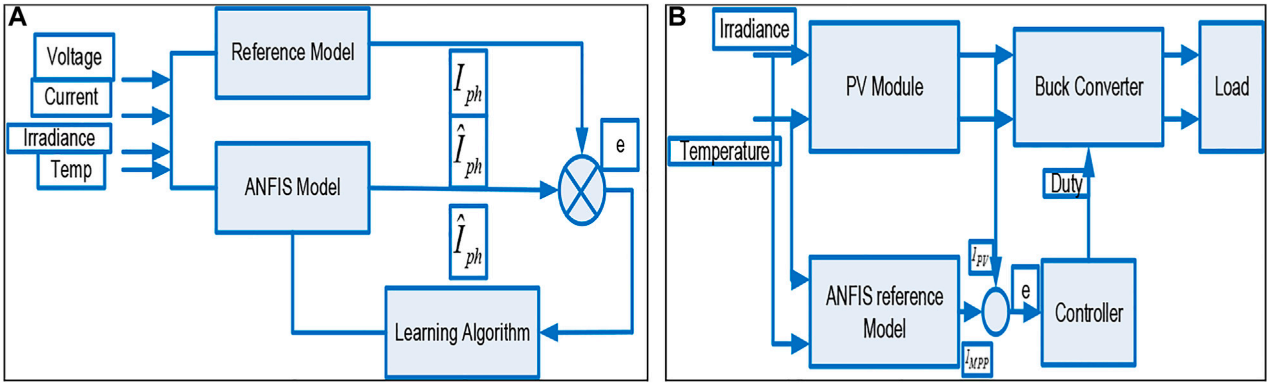

FIGURE 2 | (A,B). *ANFIS* structure with different input parameters.

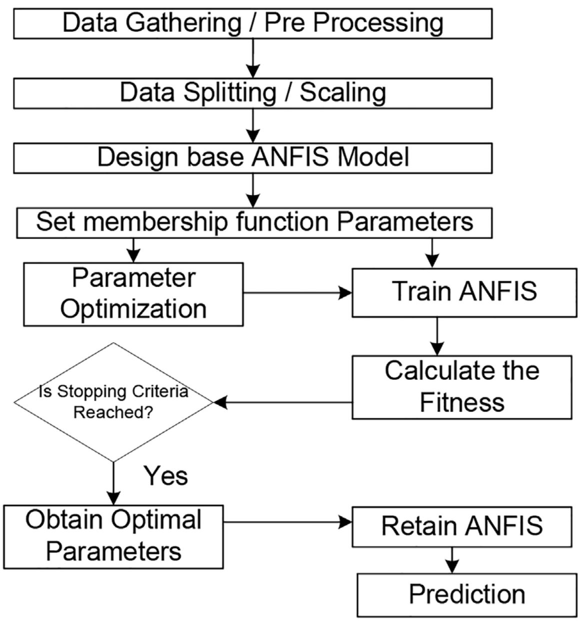

FIGURE 3 | Dataflow and processing of the *ANFIS* model.

sunshine duration, the isolated places of Nigeria (Ojosu and Komolafe, 1987; Ododo et al., 1995) are studied for forecasting daily global solar radiation using (*RMSE*) and *MAPE* values. Further advantages of this model in (Olatomiwa et al., 2015a) the accuracy of the model are measured using the ANFIS-based soft computing technique for predicting solar radiation. The model uses the following meteorological parameters such as monthly mean maximum and minimum temperature and sunshine duration. Finally, the accuracy using ANFIS is compared with experimental results in terms of RMSE and coefficient of determination (R^2). Further research has been carried out using a hybrid machine learning technique for solar radiation prediction based on some meteorological data (Olatomiwa et al., 2015b; Olatomiwa et al., 2015c; Olatomiwa et al., 2015d). For this, a novel method named as SVM–FFA is developed by hybridizing the support vector machines (SVMs) with the firefly algorithm (FFA) to predict the monthly mean horizontal global solar radiation using three meteorological parameters such as sunshine duration ($\bar{n}$), maximum temperature (T max), and minimum temperature (T min) as inputs. The prediction accuracy of the proposed SVM–FFA model is validated compared to those of artificial neural networks (ANNs) and genetic programming (GP) models. The root mean square error (RMSE), coefficient of determination (R^2), correlation coefficient (r), and mean absolute percentage error (MAPE) are used as reliable indicators to assess the models' performance. In this work, the authenticity of the soft computing method in forecasting based on the number of meteorological data of Nigeria is studied. The simulation work has been performed using the SVM where the inputs are monthly maximum temperature T max, monthly mean temperature T min, and monthly Sunshine (Bahel et al., 1987a; Asl et al., 2011). The sizing of the standalone photovoltaic system is designed with the help of a solar radiation pattern. Mohammadi et al. (2016a) have also used the *ANFIS* model for finding out the most suitable parameters for the forecasting of daily horizontal diffused solar radiation. Here, the author suggests a single input for case 1, both $H\&H_O$ combination for case 2 and $H, H_O\&n$ combined value for the third case. A comparative study has been carried out between ANN&ANFIS to predict daily solar radiation *GSR* in different parts of Iran (Bahel et al., 1987b; Robaa, 2009; Abdo and EL-Shimy, 2011; Ramedani et al., 2014a; Mohammadi et al., 2016a). Mehmet et al. (Rahimikhoob, 2010; Koca et al., 2011; Demirhan, 2014; Demirhan and Kayhan Atilgan, 2015; Yıldırım et al., 2018) have drawn a comparison between statistical and neuro-fuzzy network models to forecast the weather of Istanbul. A long period of 9 years ranging from 2000 to 2008 has been considered taking parameters such as daily temperature average (dry–wet) and pressure of air and speed of wind. Different models such as *ANFIS* and autoregressive integrated moving average (*ARIMA*) have been incorporated in this particular research work. Further several training and testing datasets have been considered to find out the effectiveness of these models. The performance is determined after comparing several parameters with respect to the moving average error (*MAE*) and root mean square error

TABLE 1 | Geographical and meteorological data related to places of Eastern India.

Station	Latitude (degree)	Longitude (degree)	Height above sea level (ft)	Max global solar insolation (MJ/m^{2}day)
Bhubaneswar	20.29	85.82	49	28.54
Kolkata	22.65	88.45	6	27.90
Vizag	17.72	83.23	3	27.79
Ranchi	23.35	85.33	616	26.96
Patna	25.60	85.10	60	27.79
Assam	26.14	91.77	108	30.52
Lucknow	26.75	80.88	128	26.42
Hyderabad	17.37	78.48	545	27.86

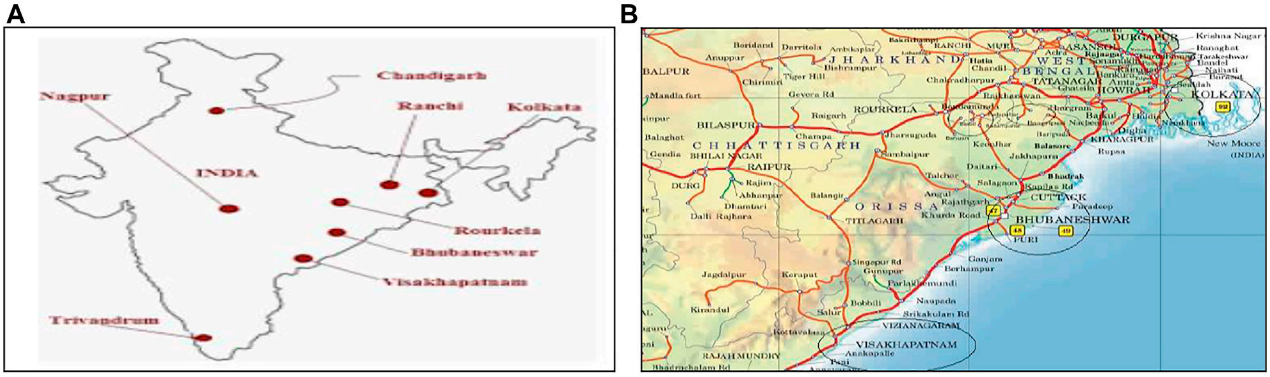

FIGURE 4 | (A,B) Map of Eastern India showing three important stations.

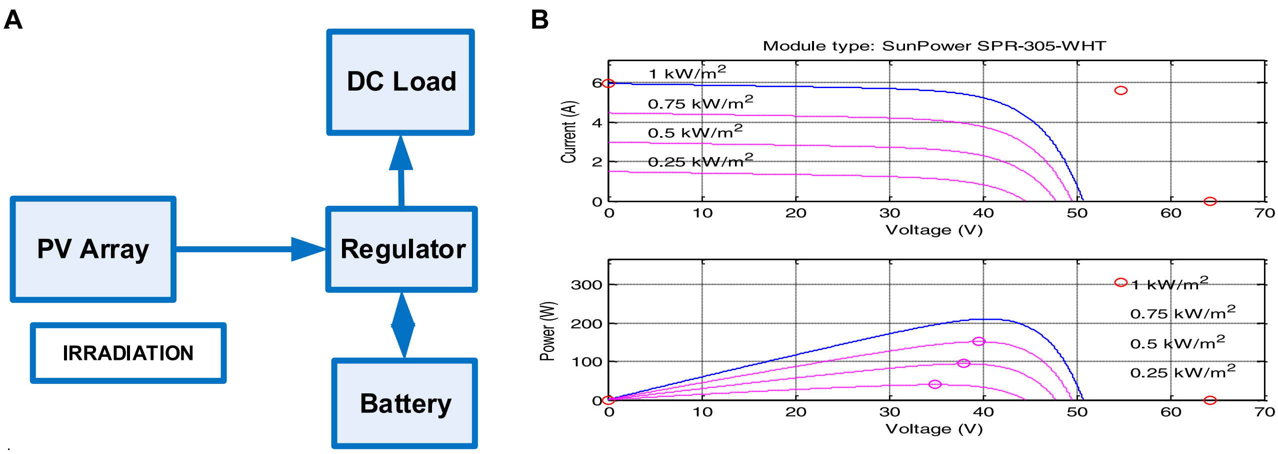

FIGURE 5 | (A) PV system and its operating blocks, **(B)** I-V and P-V based characteristics at 25° with changing radiation.

($RMSE–R^2$). Teke and Yıldırım (2014) estimates monthly global solar radiation for twelve cities of the eastern Mediterranean region based on meteorological data based on the following statistical test (MBE, RMSE, and MPE). The result shows that the Angstrom–Prescott model is most suitable for the calculation of GSR in the sites of Bonger, Pala, and Am-Timan mongo. Al-Mostafa et al. (2014) developed a sunshine based GSR model in Riyadh, Saudi Arabia as it is easily and reliably measured with wide availability of data. Almorox et al. (Quej et al., 2016) estimate empirical models for predicting daily GSR in Peninsula, Mexico. A total of 13 different models were developed based on following parameters such as temperature, rainfall, and air humidity. But by taking temperature as the input parameter, model performs the best result. On the basis of

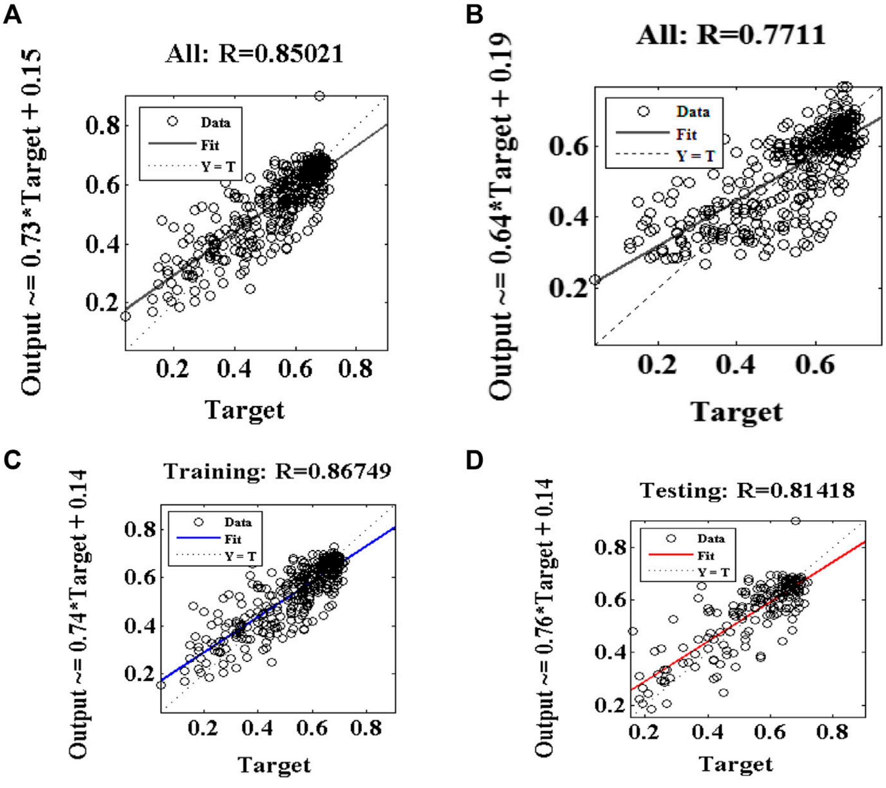

FIGURE 6 | (A,B) Regression plot of.*ANFIS*. **(C,D)** Training and testing plots through ANFIS network.

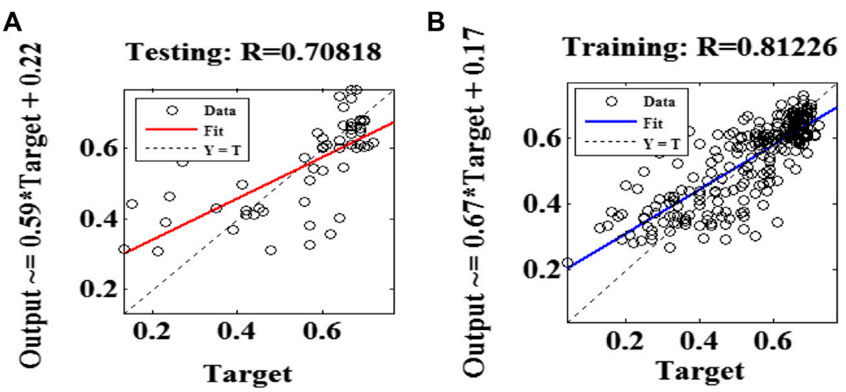

FIGURE 7 | (A,B) Training and testing plots based on *ANFIS*.

statistical indicators RMSE, MBE, MPE, and coefficient of determination, Prescott (1940) developed an empirical model to calculate monthly average daily global solar radiation on a horizontal surface from monthly average daily total insolation on an extra-terrestrial horizontal surface by using the following equation $H/H_0 = a + b\ (S/S_0)$.

Yacef et al. (2012) prepare a comparative study between Bayesian neural network (BNN), classical neural network (CNN), and empirical models for estimating the daily global solar irradiation (DGSR) of AI-Madinah (Saudi Arabia) from 1998 to 2002. A comparative study has also been carried out between the Bayesian network with the classical neural network and the empirical model developed using the Angstrom–Prescott equation. Mellit (2005) and Mellit et al. (2007) applied an ANFIS model for estimating the sequence of monthly mean clearness index (k_t) and daily solar radiation data in isolated areas of Algerian location with some geographical coordinates (latitude, longitude, and altitude) and meteorological parameters such as

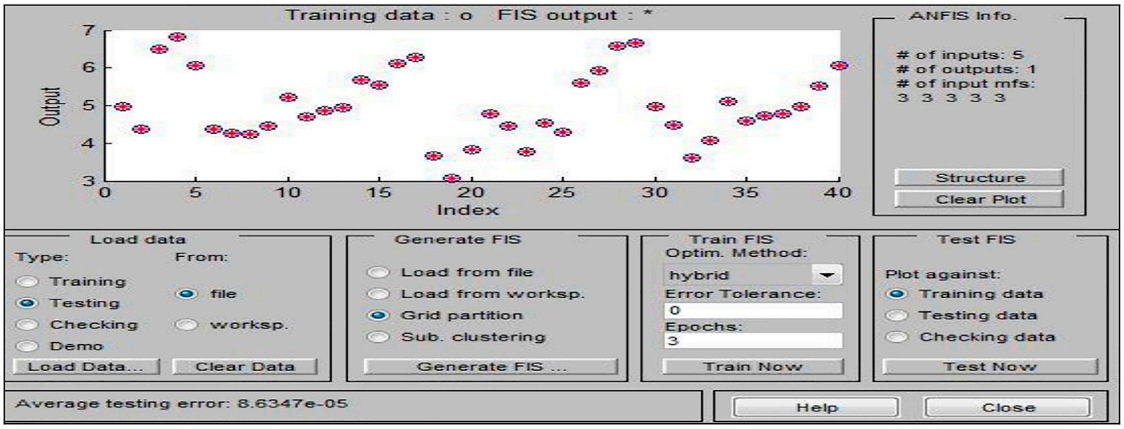

FIGURE 8 | Training and testing of the *ANFIS* model.

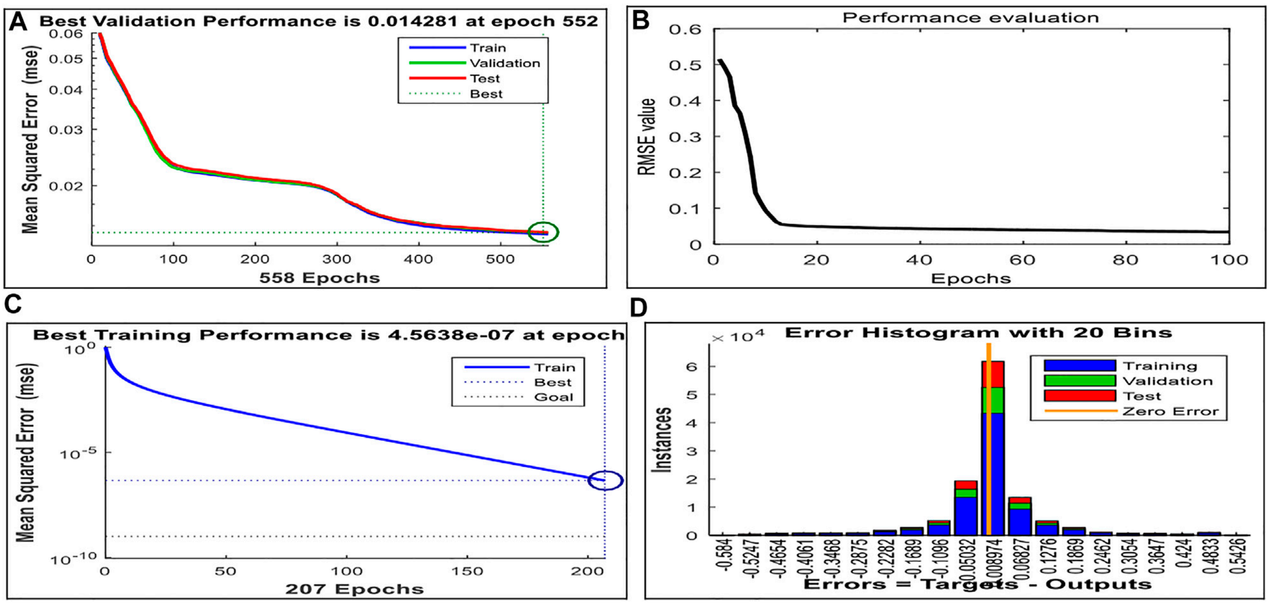

FIGURE 9 | (A–D) Performance testing, testing, and validation of different models.

temperature, humidity, and wind speed. The comparison has also been made between ANFIS and ANN by evaluating the RMSE and MAPE.

An ANFIS model (Mellit, 2004; Mellit et al., 2008) is presented for estimating the mean monthly clearness index (K_t) and total solar radiation data in isolated sites based on geographical coordinates. These data have been collected from 60 locations in Algeria. The magnitude of solar radiation is the most important parameter for sizing photovoltaic (PV) systems. The ANFIS model is trained using MLP based on fuzzy logic (FL) rules. The inputs of the ANFIS model are the latitude, longitude, and altitude, while the outputs are the 12-values of mean monthly clearness index K_t. The results show that the performance of the proposed approach in the prediction of mean monthly clearness index K_t is favorably compared to the measured values. The RMSE between measured and estimated values varies between 0.0215 and 0.0235 and the MAPE is less than 2.2%. Data from 60 locations in Algeria are taken into account, and the performance of the model is found out through the *RMSE* and mean relative error (*MRE*) (Angstrom, 1924; Garg and Garg, 1983; Takagi and Sugeno, 1985; Bahel et al., 1987c; Hawlader et al., 2001; Kalogirou, 2001; Iqdour and Zeroual, 2004; López et al., 2005; Tymvios et al., 2005; Bosch et al., 2008; Zounemat-Kermani and Teshnehlab, 2008; Behrang et al., 2010; Tektaş, 2010; Coulson, 2012; Boland et al., 2013; Jafarkazemi et al., 2013; Will et al., 2013; Ramedani et al., 2014b; Choubin et al., 2014; Varzandeh et al., 2014; Mohammadi et al., 2015; Choubin et al., 2016a; Choubin et al., 2016b; Mohammadi et al., 2016b; Despotovic et al.,

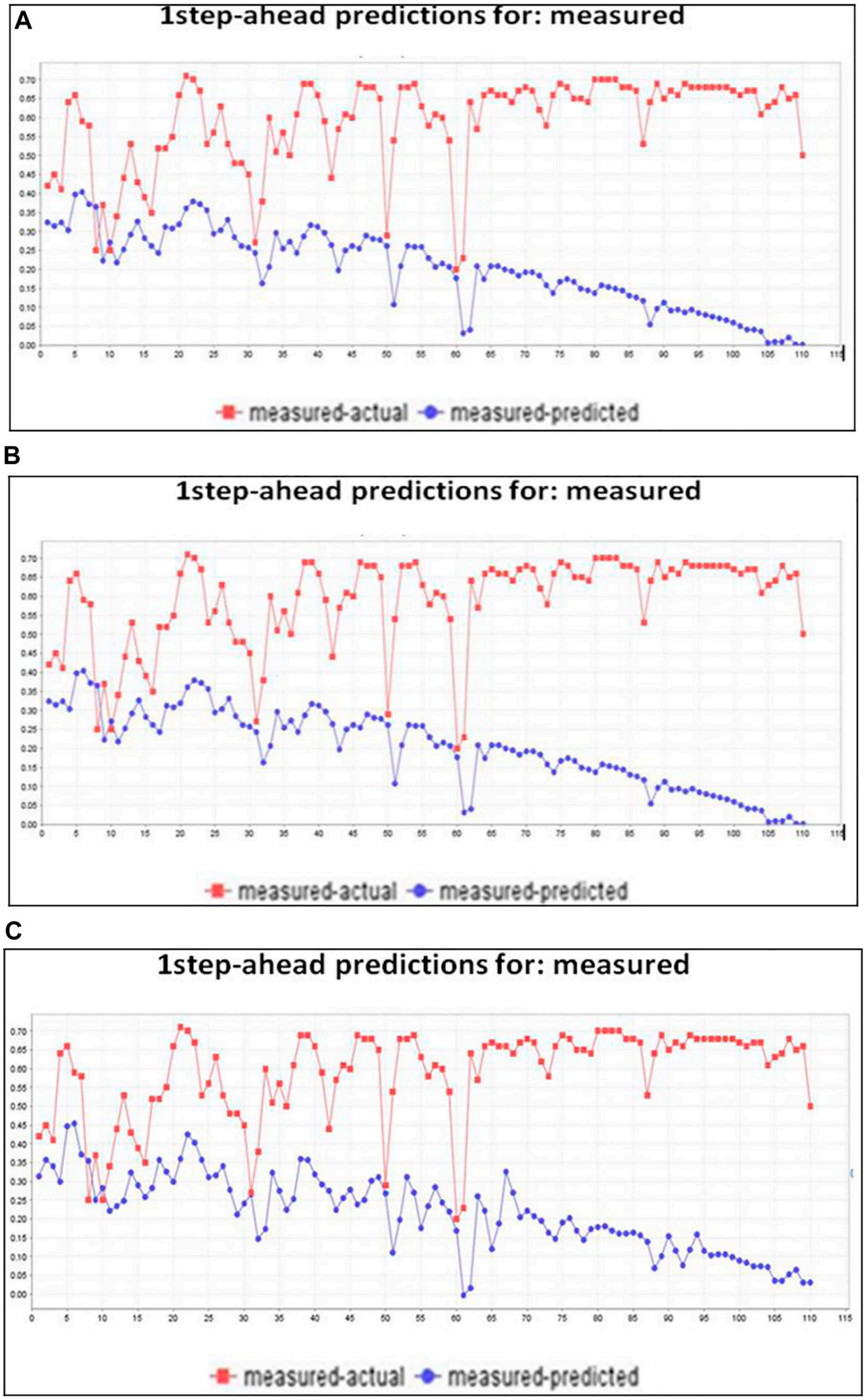

FIGURE 10 | (A) Prediction of solar radiation for the city of Bhubaneswar. **(B)** Solar radiation forecasting of Kolkata. **(C)** Prediction of solar radiation for the city of Visakhapatnam.

2016; Kaplanis et al., 2016; Wu and Wang, 2016; Quej et al., 2017; Zou et al., 2017; Almaraashi, 2018b; Halabi et al., 2018; Khosravi et al., 2018; Rafiei-Sardooi et al., 2018). Yadav et al. (2014) have applied the J48 algorithm and WEKA software for selecting significant input parameters such as clearness index, altitude, and longitude for the better prediction of solar radiation in

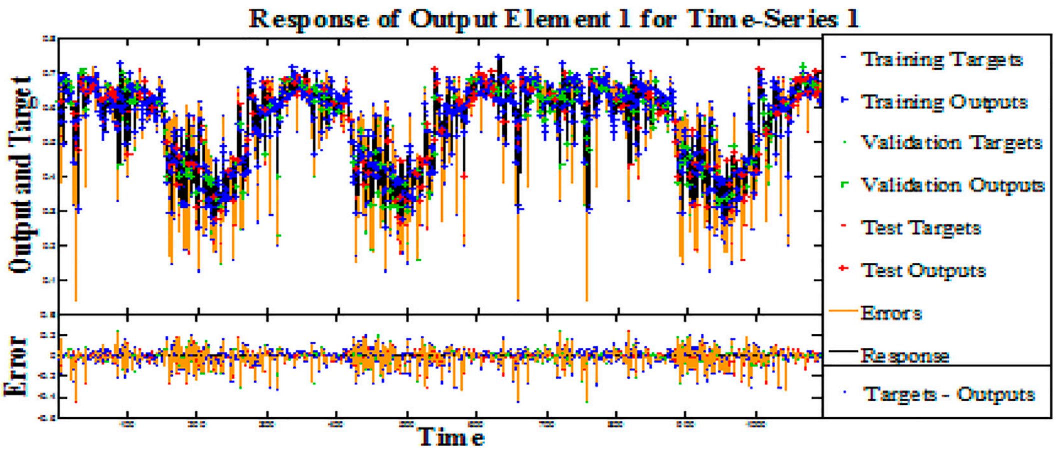

FIGURE 11 | Figure showing error response.

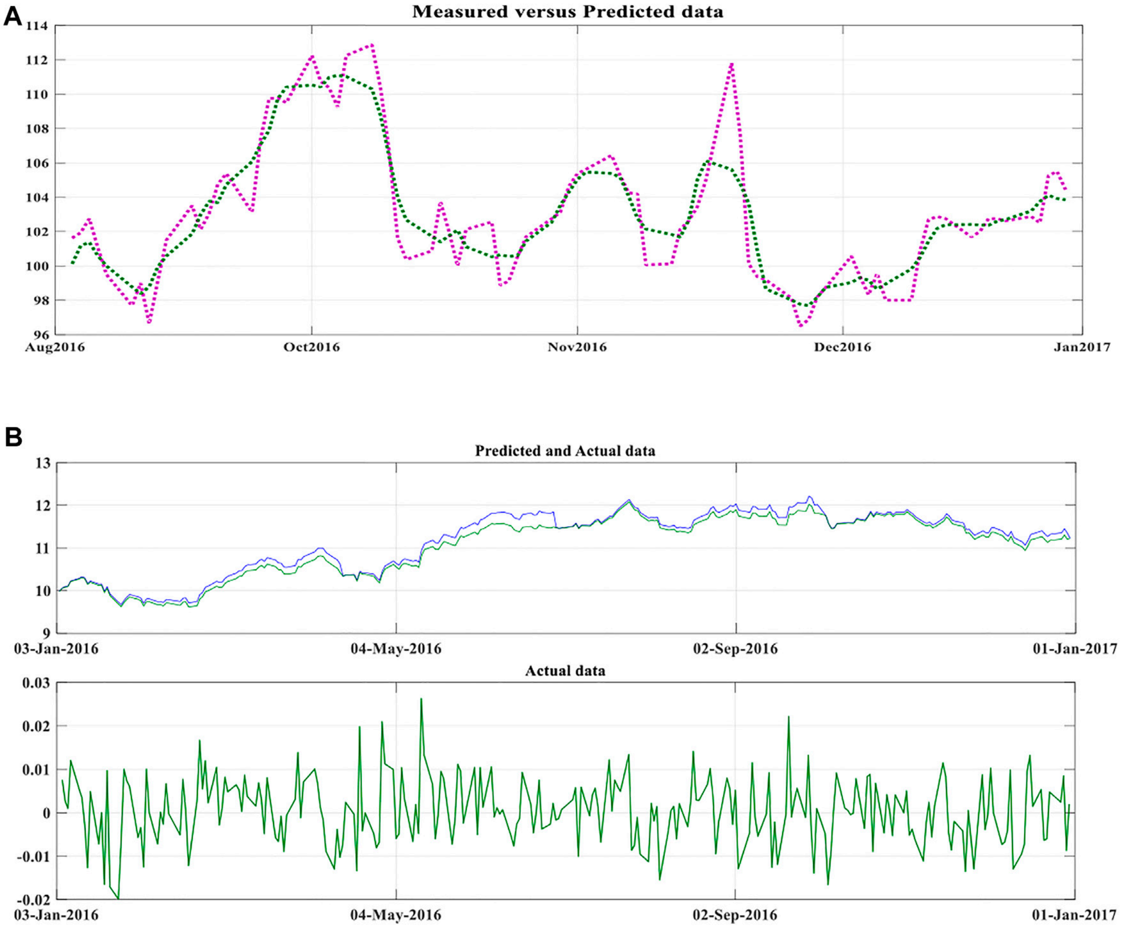

FIGURE 12 | (A,B) ANFIS-based comparison between latest measured and prediction solar data.

Western Himalayas with *ANN* (Mani, 2008; Yadav et al., 2014; Yadav and Chandel, 2015). By using the four g-bell input membership function, statistical analysis shows the maximum regression value; R (R = 0.99) in comparison to the other membership function (Bhardwaj et al., 2013a; Ramedani et al., 2013b). M Rizwan et al. (Khan et al., 2008; Rizwan et al., 2012;

TABLE 2 | Relative outcome with ANN, ANFIS, and SVM algorithms. Model comparison of different regions.

Month	Measured	Prediction (NN)	Prediction (ANFIS)	Prediction (SVM)
Jan	0.799364	1.118,864	0.79,994	0.5966
Feb	0.1730	1.1188	0.1731	0.2730
March	0.4948	0.4948	0.49,494	0.5113
April	0.2110	0.2110	0.2111	0.3083
May	0.1	0.6463	0.1	0.2644
June	0.9	1.1477	0.9	0.6003
July	0.1008	0.1008	0.1009	0.2310
Aug	0.5277	0.5277	0.5278	0.4277
Sept	0.1757	0.1757	0.1758	0.2537
Oct	0.5983	0.5983	0.5983	0.3353
Nov	0.4616	0.4616	0.4616	0.5292
Dec	0.1119	0.1119	0.1119	0.2992

Model comparison of different regions.

TABLE 3 | Performance evaluation of Bhubaneswar, Kolkata, and Visakhapatnam with different algorithms.

Technique	Location	MAPE	RMSE	MBE	R^2
MLP	Kolkata	6.93	7.0	0.93	0.04
	Bhubaneswar	7.73	7.8	0.92	0.01
	Visakhapatnam	6.8	6.9	0.89	0.03
NARX	Kolkata	9.08	9.11	0.91	0.03
	Bhubaneswar	8.9	9.02	0.92	−0.01
	Visakhapatnam	9.2	9.4	0.90	0.04
RNN	Kolkata	8.60	8.7	0.88	0.04
	Bhubaneswar	8.45	8.5	0.92	0.01
	Visakhapatnam	8.7	8.8	0.91	0.00
GRNN	Kolkata	9.35	9.4	0.92	−0.03
	Bhubaneswar	9.20	9.28	0.91	0.02
	Visakhapatnam	9.15	9.28	0.90	0.07
FL	Kolkata	6.83	6.9	0.89	0.02
	Bhubaneswar	6.53	6.7	0.90	0.01
	Visakhapatnam	6.9	7.0	0.91	0.05
SVM	Kolkata	7.35	7.4	0.89	0.04
	Bhubaneswar	7.40	7.5	0.90	−0.02
	Visakhapatnam	7.25	7.35	0.91	0.07
RBF	Kolkata	9.33	9.4	0.92	0.05
	Bhubaneswar	8.5	8.7	0.93	0.02
	Visakhapatnam	7.4	7.7	0.89	−0.03
ANFIS	Kolkata	4.70	4.75	0.93	0.04
	Bhubaneswar	4.5	4.6	0.94	0.02
	Visakhapatnam	4.83	4.9	0.95	0.01
NFG	Kolkata	7.5	7.7	0.91	−0.04
	Bhubaneswar	7.3	7.5	0.89	0.02
	Visakhapatnam	7.78	7.9	0.92	0.01
NG	Kolkata	7.2	7.4	0.91	−0.07
	Bhubaneswar	6.8	6.9	0.9	0.05
	Visakhapatnam	6.9	7.0	0.89	0.01
LR-GA	Kolkata	8.2	8.3	0.87	0.03
	Bhubaneswar	8.5	8.7	0.88	−0.02
	Visakhapatnam	9.2	9.4	0.89	0.04

Chaudhary and Rizwan, 2018; Perveen et al., 2018; Sadhu et al., 2018; Chaudhary and Rizwan, 2019) focused on the *GNN* model in order to predict global solar energy in India. Parameters used as inputs in this particular model include latitude, longitude, and altitude (Iqbal et al., 2010; Patel and Parekh, 2014; Singh and Rizwan, 2018b; Yadav et al., 2018b; Sujil et al., 2019b; Singh et al., 2019; Vanitha et al., 2019) with temperature ratio, Sunshine/hour whereas the clearness index stands for the output parameter. Solar radiation data set has been prepared for several Indian states for training and performance is evaluated through the mean absolute error. The *MAPE* during the estimation of global solar energy prediction is found to be nearly 4 percent using *GNN* but it becomes 6 percent during estimation with the fuzzy logic (Ajil et al., 2010; Chandra et al., 2013; Verma et al., 2019). Joshi (2013) estimated the monthly global solar radiation utilizing the Angstrom model (Angstrom, 1924) forecast solar irradiation with the help of *ANN* with variables. Thorough comparisons have been carried out between the *ANN* model and Angstrom model in order to judge the efficiency of the models with mean squared error (MSE) and regression coefficient (R^2). From the learning of MSE and R^2 values with Angstrom models they come close to (0.1225 and 0.3965) for Ahmedabad, (0.0059 and 0.0149) for Bangalore, (0.1024 and 0.404) for Dehradun, and (0.0625 and 0.0498) for Kolkata whereas the MSE and R^2 values for the *ANN* model as (0.002 and 0.99) for Ahmedabad, (0.006 and 0.98) for Bangalore, (0.01, 0.90) for Dehradun, and (0.006 and 0.99) for Kolkata. The selected *ANN* model performs better with less *RMSE* value with maximum regression value than the empirical model. Kadhambari et al. (2012) proposed a recurrent neural network model to estimate the global solar radiation of the Thiruvallur region. Input parameters utilized in this work are all days of month, all day temperature, humidity (relative), pressure of air, and solar azimuth angle. The *RNN*-based models are trained by the evolutionary swarm optimization–based algorithm. The performances of these algorithms are verified and compared with each other by calculating the RMSE value. The *RMSE* value of the evolutionary algorithm comes around 0.0667 which is lower in comparison to the *RMSE* value of the *PSO* algorithm. Poudyall khem et al. estimate [*GSR*] depending on the sunshine duration in the Himalayan region. The performance parameters of the model are investigated on the basis of *RMSE* value, *MBE* value, *MPE* value, and correlation coefficient R^2 value. Solar radiation data for a span of 3 years of Indian cities have been studied by Katiyar and monthly daily mean clear sky radiation has been estimated.

A thorough comparison on the basis of (*RMSE*) and (MBE) has been initiated which shows the percentage of MBE with a new constant for each station vary from 0.22 to 2.09% whereas with

TABLE 4 | *ANFIS* models for Bhubaneswar, Kolkata, and Visakhapatnam (single input).

ANFIS model	Input	MBE (trn)	MBE (tst)	MSE (trn)	MSE (tst)	R (trn)	R (tst)
Bhubaneswar							
I	T/To	1.4532	1.3212	2.4332	2.2,143	0.9584	0.9537
II	S/So	1.2,156	1.2054	2.1564	2.0326	0.9798	0.9778
III	R/Ro	1.7638	1.5738	2.3125	2.1967	0.9389	0.9327
IV	P/Po	2.4363	2.1532	3.6738	3.3453	0.8754	0.8778
Kolkata							
I	T/To	1.7658	1.7257	2.6732	2.6685	0.9527	0.9498
II	S/So	2.0397	1.9274	3.7843	3.4508	0.9362	0.9316
III	R/Ro	1.4785	1.4586	2.3472	2.3369	0.9869	0.9845
IV	P/Po	2.9845	2.8648	3.4538	3.2,375	0.8858	0.8845
Visakhapatnam							
I	T/To	2.2,302	2.1036	3.0234	2.9846	0.9378	0.9326
II	S/So	1.5747	1.5592	2.4782	2.2,461	0.9546	0.9616
III	R/Ro	1.9725	1.8245	2.8723	2.8278	0.9489	0.9420
IV	P/Po	3.2345	3.2267	4.5327	4.4562	0.8743	0.8698

RMSE it varies from 2.22 to 10.37%. Krishnaiah et al. (2007b) suggest the neural network approach for modeling which suggests the superiority of the neural network–based model compared to conventional regression models. Premalatha and Arasu (2012) estimated the GSR of India utilizing ANN based on the input parameters such as maximum and minimum ambient temperature with least relative humidity.

The monthly global solar radiation in 31 districts of Tamil Nadu, India was predicted by using *ANFIS* in Verma et al. (2019). Considering the input parameters such as solar radiance, ambient temperature collector, tilt angle, and working fluid mass flow rate, the flat plate collector efficiency was predicted using the MLP and ANFIS model (Verma et al., 2019). This specific model *MLP* utilizes the Levenberg–Marquardt algorithm with logistic sigmoid function. Comparative analysis proves *ANFIS* model's superiority over normal controlling architectures. After the introduction of unglazed flat plate solar collectors, analytical and experimental studies have been carried out on a solar-assisted heat pump water heating system (Chandra et al., 2013). Mohammad Hossein et al. (2014) use the *WNN* (wavelet neural network) and *ANFIS* algorithm for the prediction of meteorological station in Tehran, Iran. The results establish better performance in the field of solar radiation estimation and wind short-term solar radiation velocity time series. The analysis in terms of R^2 and *RMSE* establish that with lower *RMSE* and higher R^2 values a perfect model can be achieved. Dushyant Patel and Falguni Parekh (Chandra et al., 2013) used *ANFIS* for forecasting the flood of the Dharoi dam on the Sabarmati river in Mehsana in the state of Gujarat in India. In this case, statistical indices such as *RMSE*, correlation coefficient (R), and discrepancy ratio (D) are used. The evaluation of the model for forecasting has been carried out by comparing the *ANFIS* model and statistical method such as the log-Pearson type III method. The comparison indicates that the *ANFIS* model accurately addresses the forecasting of flood. In another work, rainfall forecasting with *ANFIS* has been developed by Jignesh Patel and Falguni Parekh (Krishnaiah et al., 2007a; Ajil et al., 2010; Premalatha and Arasu, 2012; Chandra et al., 2013; Joshi, 2013; Awasthi and Poudyal, 2018) for Gandhi Nagar station. Eight models based on different membership functions and climatic parameters such as temperature, relative humidity, and wind speed are developed. In this case, a generalized bell-shaped membership function has been chosen. The outcome of the hybrid model with seven membership functions and three inputs produces better results with a correlation factor of 0.99 for training and 0.92 for validation. The application of *ANFIS* for wind energy short-term forecasting was first developed by Pousinho et al. (Krishnaiah et al., 2007a). Experiments established the efficiency of neuro-fuzzy inference system and proved its performance regarding $MAPE\&Error$ variance in comparison to $ARIMA\&NN$.

MATHEMATICAL MODELING AND SIMULATION

Important Eastern stations of India such as Bhubaneswar, Kolkata, Visakhapatnam, Ranchi, Patna, Assam, Lucknow, and Hyderabad with their geographical and meteorological features are presented in **Table 1** and **Figures 4A,B**. The map of Eastern India shows three important stations.

Estimation of the PV Parameters

The ANFIS-based PV model predicts the I-V and P-V characteristics of the PV modules in a given environmental setting. For a certain irradiance and temperature combination of the PV cell, the voltage of PV array (from zero to open-circuit voltage) can be determined on the manufacturing datasheet. The corresponding anticipated current set is obtained from the proposed PV estimation model. The equivalent circuit of the PV is described as follows:

$$I = I_{ph} - I_o\{\exp(V + IR_s/n_s V_t) - 1\} - (V + IR_s/R_{sh}), \quad (8)$$

$$\boldsymbol{V_t = kTA/q}, \quad (9)$$

$$I_{ph} = (G/G_{STC}) I_{ph(STC)} (1 + k_i (T - T_{STC})), \quad (10)$$

TABLE 5 | Performance evaluation of different models with respect to number of inputs.

Author Name	Model	Location	Input Parameters	Output parameter	Results obtained
Sumithira (Yadav et al., 2014)	ANFIS	Tamil Nadu, India	Ambient temperature, relative humidity, atmospheric pressure, and wind speed	Monthly GSR	RMSE = 0.78, Accuracy = 0.98
Yadav et al. (Yadav et al., 2014)	J48 algorithm and WEKA software	Western Himalayan	Air temp, sunshine duration, clearness index, altitude, latitude, and longitude	GSR	ANN-1, MAPE = 20.12
					ANN-2, MAPE = 6.89 ANN-3, MAPE = 9.04
Bhardwaj et al. (Bhardwaj et al., 2013a)	Hidden Markov model with generalized fuzzy model	India	Radiation span	GSR	RMSE = 7.9124
					MAPE = 3.0083 Accuracy = 0.9921
Rizwan M, Jamil M, Kothari DP (Chaudhary and Rizwan, 2019)	GNN-based model	New Delhi, Kolkata, Ahmadabad, Jodhpur, Visakhapatnam, Nagpur, and Shillong	Latitude, longitude, altitude, months of the year, temperature ratio and sunshine duration	Clearness index	Mean absolute relative error = 4% (using GNN) and using fuzzy logic it is equalto6%
Juhi Joshi and Vinit Kumar (Joshi, 2013)	Angstrom–Prescott model and ANN	Ahmadabad, Bangalore, Dehradun, Kolkata	Sunshine hour, latitude, longitude, ,and altitude	Solar Radiation	ANN better than Empirical model
Kadhambari et al. (Verma et al., 2019)	Recurrent neural networks	Thiruvallur region	Days inside a month, daily average air temperature, relative humidity, air pressure, and solar azimuth angle	GSR	RMSE = 0.0667 (Evolutionary algorithm), RMSE = 1.222 (PSO algorithm)
Poudyal Khem et al. (Awasthi and Poudyal, 2018)	Angstrom model	Himalaya Region Kathmandu (Nepal)	Sunshine duration	GSR	$RMSE = 0.71, MBE = 0.055$ $MPE = 0.047, C.C = 0.71$
Katiyar et al. (Ajil et al., 2010)	Least square regression analysis	Jodhpur, Calcutta, Bombay, and Pune	Sunshine duration	Monthly mean daily clear sky radiation	MBE varies from 0.22 to 2.09% and RMSE varies from 2.22 to 10.37%
Krishnaiah et al. (Krishnaiah et al., 2007a)	Neural network approach	India	Latitude and longitude	GSR	MBE = 0.3133%, RMSE = 4.61% and Correlation Coefficient = 0. 999,954
N. Premalatha and A. Valan Arasu (Premalatha and Arasu, 2012)	ANN	Tamil Nadu	Maximum, minimum ambient temperature, and minimum relative humidity	GSR	MPE = 6.65% and MSE = 0.008
T. Sandhya and V. R. Kavitha (Joshi, 2013)	Non-linear autoregressive exogenous input model	Tiruvallur region	Climatic parameters	Solar radiation	MSE = 1.8, accuracy = 0.78

$$I_{MP} = I_{ph} - I_0\{\exp(I_{sc}R_S/n_sV_t)\} - (I_{sc}R_S/R_{Sh}), \tag{11}$$

$$I_{MP} = I_{ph} - I_o\{\exp(V_{MP} + I_{MP}IR_S/n_sV_t)\} - (V_{MP} + I_{MP}IR_S/R_{sh}), \tag{12}$$

$$I_{OC} = 0 = I_{ph} - I_0\{\exp(V_{oc}/n_sV_t)\} - (V_{oc}/R_{sh}), \tag{13}$$

$$|dp/dv|_{V=V_{MP}, I=I_{MP}} = 0, \tag{14}$$

$$|di/dv|_{V=0, I=I_{MP}} = -1/R_{sh}, \tag{15}$$

$$V_t = ((I_{MP}R_s + V_{MP} - V_{OC})/n_s \log B), \tag{16}$$

where I = output current.

I_{Ph} = photo current or generated current under given insolation.

I_O = diode reverse saturation current.

η = ideality factor of PV cell.

R_S = series loss resistance.

R_{Sh} = shunt loss resistance.

V_t = thermal voltage.

$V_{th} = \frac{kT}{q}$, where k is Boltzmann's constant = $1.3806X10^{-23} J/K$.

Input data = solar irradiance G.

Ambient temp = T.

Operating voltage = V.

Output current = I.

RESULTS AND DISCUSSION

The ANFIS technique is used to find out the impact of all important variables such as $n, N, T_{\min}, T_{\max}, T_{avg}, R_h, V_p, p\&H_o$ for forecasting daily GSR, H, and further to find out the ideal set of the input parameters. The performance of the models is evaluated by dividing the data set into two parts, that is, training and testing **(Figures 5, 6)**. First, the model will be trained for some

TABLE 6 | *ANFIS* models for Bhubaneswar, Kolkata, and Visakhapatnam (two inputs).

ANFIS model	Input	MBE (trn)	MBE (tst)	MSE (trn)	MSE (tst)	R (trn)	R (tst)
I	T/To, S/So	0.8349	0.8269	1.8338	1.7749	0.9887	0.9821
II	S/So, R/Ro	0.9212	0.9186	1.8574	1.7948	0.9747	0.9695
III	R/Ro, T/To	1.6853	1.6946	2.7629	2.6539	0.9427	0.9385
IV	S/So, P/Po	2.4576	2.4256	3.2,317	3.2,256	0.9167	0.9123
V	T/To, P/Po	2.6367	2.6243	4.5231	4.5042	0.8934	0.8876
VI	R/Ro, P/Po	2.7369	2.7145	3.9854	3.8956	0.9042	0.9027
I	T/To, S/So	1.8806	1.8764	2.9845	2.9536	0.9526	0.9859
II	S/So, R/Ro	0.9847	0.9778	1.6538	1.6383	0.9888	0.9864
III	R/Ro, T/To	1.2,142	1.2078	2.1384	2.0946	0.9648	0.9689
IV	S/So, P/Po	2.7843	2.7732	3.7842	3.7754	0.8954	0.8918
V	T/To, P/Po	2.5431	2.5514	3.5321	3.4532	0.9465	0.9454
VI	R/Ro, P/Po	2.4573	2.3428	3.4351	3.4256	0.9589	0.9534
I	T/To, S/So	1.9653	1.9598	3.2,426	3.1274	0.9264	0.9298
II	S/So, R/Ro	0.9842	0.9789	1.6849	1.5265	0.9914	0.9906
III	R/Ro, T/To	1.3367	1.3138	2.5743	2.4379	0.9847	0.9834
IV	S/So, P/Po	2.4321	2.4032	3.4214	3.4511	0.9443	0.9398
V	T/To, P/Po	2.6531	2.6489	3.8854	3.7843	0.8921	0.8942
VI	R/Ro, P/Po	2.3243	2.3465	3.3830	3.3798	0.9543	0.9512

TABLE 7 | *ANFIS* models for Bhubaneswar, Kolkata, and Visakhapatnam (three inputs).

Model	Input	MBE (trn)	MBE (tst)	MSE (trn)	MSE (tst)	R (trn)	R (tst)
Bhubaneswar							
I	$S/S_0, T/T_0, R/R_0$	0.777	0.754	1.754	1.743	0.993	0.993
II	$S/S_0, T/T_0, P/P_0$	1.824	1.816	2.248	2.224	0.977	0.973
III	$P/P_0, T/T_0, R/R_0$	2.245	2.226	3.435	3.413	0.924	0.923
IV	$R/R_0, P/P_0, S/S_0$	2.442	2.436	3.683	3.657	0.945	0.941
Kolkata							
I	S/So, T/To, R/Ro	0.8957	0.8865	1.5678	1.5467	0.9956	0.9923
II	S/So, T/To, P/Po	2.5457	2.5376	3.5645	3.5523	0.9356	0.9325
III	$P/P_0, T/T_0, R/R_0$	1.6734	1.6573	2.4562	2.4378	0.9878	0.9845
IV	$R/R_0, P/P_0, S/S_0$	2.2,312	2.2,167	2.9556	2.9476	0.9756	0.9745
Visakhapatnam							
I	S/So, T/To, R/Ro	0.8934	0.8869	1.5938	1.5868	0.9965	0.9936
II	S/So, T/To, P/Po	2.4876	2.4567	3.3452	3.4078	0.9457	0.9423
III	$P/P_0, T/T_0, R/R_0$	1.8745	1.8685	2.5235	2.5023	0.9148	0.9056
IV	$R/R_0, P/P_0, S/S_0$	2.2,858	2.2,789	2.9849	2.9765	0.9778	0.9745

TABLE 8 | Monthly average solar radiation data.

MONTH	Kolkata (West Bengal)				Bhubaneswar (Odisha)				Visakhapatnam (AP)			
	S/S_0	T/T_0	R/R_0	H/H_0	S/S_0	T/T_0	R/R_0	H/H_0	S/S_0	T/T_0	R/R_0	H/H_0
January	0.781	0.750	0.641	0.581	0.751	0.732	0.511	0.622	0.880	0.881	0.622	0.622
February	0.811	0.791	0.841	0.531	0.742	0.831	0.522	0.621	0.961	0.891	0.682	0.631
March	0.681	0.831	0.542	0.564	0.651	0.942	0.491	0.592	0.792	0.932	0.681	0.621
April	0.562	0.853	0.842	0.563	0.642	0.992	0.551	0.592	0.821	0.942	0.712	0.612
May	0.681	0.881	0.712	0.521	0.603	0.991	0.671	0.562	0.771	0.951	0.751	0.571
June	0.631	0.912	0.732	0.432	0.351	0.973	0.782	0.573	0.632	0.961	0.772	0.451
July	0.552	0.921	0.841	0.381	0.263	0.941	0.822	0.671	0.651	0.951	0.781	0.412
August	0.562	0.932	0.672	0.412	0.332	0.942	0.821	0.361	0.722	0.952	0.781	0.431
September	0.681	0.922	0.871	0.421	0.421	0.923	0.801	0.422	0.653	0.942	0.792	0.472
October	0.732	0.881	0.633	0.491	0.621	0.872	0.752	0.521	0.831	0.931	0.741	0.541
November	0.813	0.831	0.771	0.532	0.661	0.802	0.582	0.572	0.871	0.911	0.642	0.572
December	0.741	0.770	0.741	0.522	0.762	0.711	0.491	0.492	0.883	0.881	0.582	0.611

TABLE 9 | Absolute relative error for the three cities mentioned with soft computing methods.

Month	Kolkata			Bhubaneswar			Visakhapatnam		
	MLP	ANFIS	RBF	MLP	ANFIS	RBF	MLP	ANFIS	RBF
January	3.0165	0.0016	0.6961	5.9449	0.00,502	3.8024	0.1117	0.0135	1.709
February	4.2,324	0.0381	3.5534	5.3647	0.0033	6.4643	2.5307	0.0044	0.006
March	3.476	0.0053	5.6596	5.6702	0.0077	4.0527	0.86,201	0.0049	8.4653
April	2.7738	0.0426	7.5107	0.9199	0.0012	3.4472	0.3502	0.0355	4.6453
May	2.8363	0.0158	6.1261	3.3133	0.002	6.5792	1.1997	0.0064	5.4589
June	1.1139	0.0059	7.4124	0.8544	0.0047	3.7042	6.1806	0.0066	4.4648
July	1.5638	0.0036	6.193	8.7102	0.004	6.8342	6.0207	0.0089	6.7951
August	4.2,362	0.0091	3.6189	3.4637	0.0253	9.0297	6.7013	0.0119	8.1804
September	4.3099	0.0044	6.9943	8.9104	0.0063	8.3468	1.112	0.0232	6.036
October	4.5103	0.0082	0.8281	6.4035	0.0089	0.3072	3.7027	0.0004	5.8702
November	0.3375	0.0066	2.3547	0.9799	0.0062	3.7557	9.0403	0.0067	6.293
December	1.8914	0.0066	2.7157	6.7407	0.00,053	5.1809	2.3607	0.0065	0.5159

TABLE 10 | Different models of solar radiation forecasting from the latest literature works.

Reference	Year	Model type	Input parameter	Author
Jafarkazemi et al. (2013)	2017	M_1, M_2, M_3...M_{12}	MBE, RMSE, and R^2	Muhammed A. Hassan, A. Khalil, S. Kaseb, and M. A. Kassem
Sobri et al. (2018)	2017	M_1, M_2, M_3...M_{10}	RMSE, RAE, MAE, and R^2	Achour, L., Bouharkat, M., Assas, O. and Behar, O
Achour et al. (2017)	2018	MARS, M5Tree, RSM, kriging	MAE, RMSE, and MBE	Keshtegar, B., Mert, C. and Kisi, O
Bhardwaj et al. (2013b)	2017	SBMsRS1. TBMsRT1, RT2, RT3. MBMs-RM1, RM2, RM3, RM4. DBMs-RD1, RD2	MBE, RMSE, and MPE, R^2	Hassan, M. A., Khalil, A., Kaseb, S. and Kassem, M
Bhardwaj et al. (2013b)	2017	RS1, DS1, PS1, AS1, and VS.1	MBE, RMSE, and MPE, R^2	Hassan, M. A., Khalil, A
Mellit et al. (2008)	2017	RFs, RFs-FFA, ANN, and ANN-FFA	RMSE, MAPE, and MBE	Ibrahim, I. A. and Khatib, T
Zou et al. (2017)	2017	ANFIS, E-IBCM, and IYHM	RMSE, and MAE	Zou, L., Wang, L., Xia, L., Lin, A., Hu, B. and Zhu, H
Meenal and Selvakumar (2018)	2017	SVM and ANN	R, MBE, RMSE, and RANK	Meenal, R. and Selvakumar, A. I
Kadhambari et al. (2012)	2017	BPNN, BPNN-PSO, and BPNN-GA	R, RMSE, and MAE	Xue, X
Halabi et al. (2018)	2018	ANFIS, ANFIS-PSO, ANFIS-GA, and ANFIS-DE	MAPE, RMSE, RRMSE, and MABE	Halabi, L. M., Mekhilef, S. and Hossain, M
Quej et al. (2017)	2017	ANN, ANFIS, and SVM	RMSE, R^2, and MAE	Quej, V. H., Almorox, J., Arnaldo, J. A. and Saito, L
Despotovic et al. (2016)	2018	ReliefF, MCUVE, TandomFrog, and Laplace score	RMSE, MAE, and MBE	Almaraashi, M
Mohammadi et al. (2016b)	2016	ANFIS (9 models)	MABE, RMSE, and R	Mohammadi, K., Shamshirband, S., Kamsin, A., Lai, P. C. and Mansor, Z

data and then the rest of them used for the testing purpose. Out of all data sets, nearly half percent, that is, 0. 5% of the data set is used for training and rest of them (0. 5%) used for testing are shown in **Figures 7A,B**.

A computer code for the *ANFIS* model is developed through *MATLAB*. The training of the model is continued until it gets the optimum results with a lower *MSE* and higher regression value (R). After fulfilling the optimal parameters with input and output membership functions, the results are saved and further utilized for training and testing *ANFIS* models **(Figure 8)**. Depending on the data sets, different training and testing curves are constructed for better understanding.

The regression plot describes the accuracy between the measured and the forecasted value of solar radiation. After splitting the data set, input and output membership functions used in this network are saved and used for training and testing the ANFIS models. **Figure 9** describes the training curve after prediction. This curve shows the number of epochs with respect to error, that is, the curve shows how the error varies with respect to the number of epochs. The optimization is performed either by using the hybrid learning algorithm or the back-propagation method for identifying the MF (input and output) parameters. The output membership function (linear or constant) is used for training fuzzy inference system as mentioned in **Figure 10**.

To validate the accuracy of the developed ANFIS method, its capability has been compared with the artificial neural network (ANN) and support vector machine (SVM). The statistical indicator helps the performance evaluation of the proposed model which indicates lower values of RMSE and MAPE and higher values of R^2 during the comparison with ANN and other model (**Table 2**).

The assortment of different parameters remains the most important criteria for forecasting global solar-based radiation of a particular place. So by means of *ANFIS* methodology,

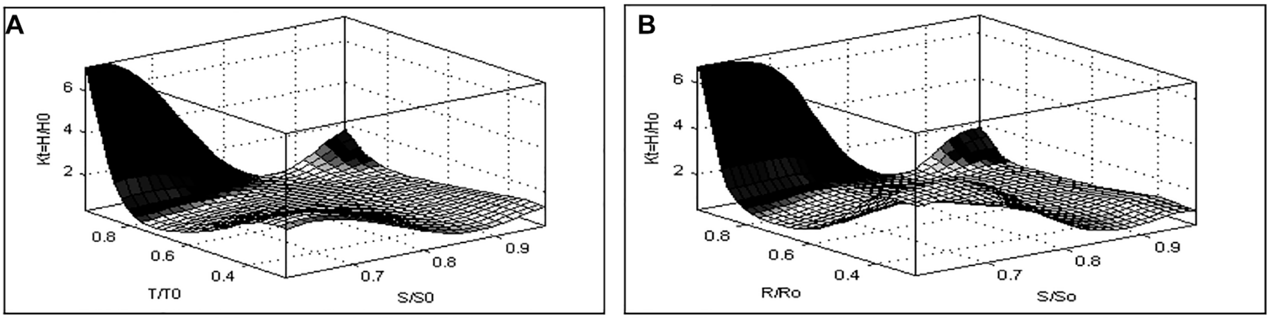

FIGURE 13 | (A–C) Surface plots combining two most important parameters for Bhubaneswar, Kolkata, and Vizag.

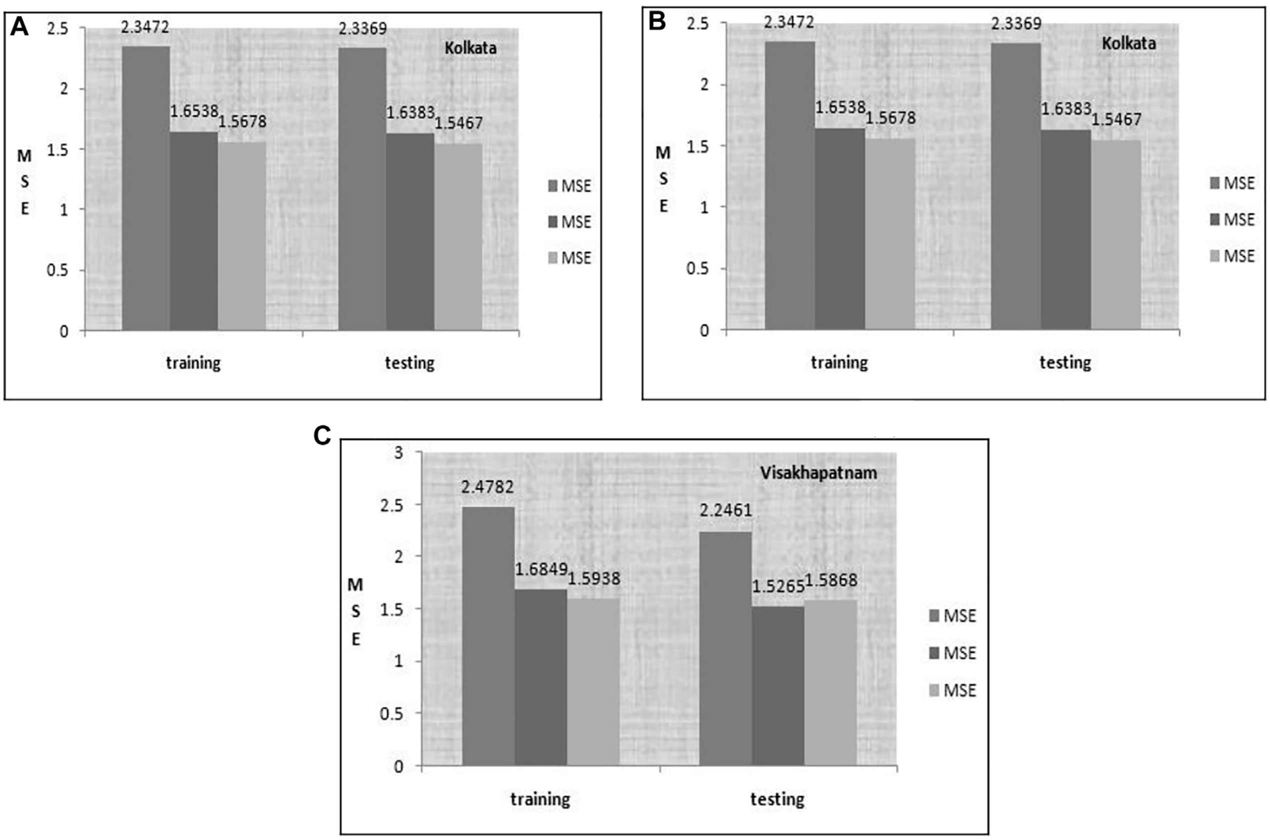

FIGURE 14 | (A–C) *MSE* (MJ/m^2) for the most appropriate blend of parameters with one, two, and three inputs of Bhubaneswar city during training and testing.

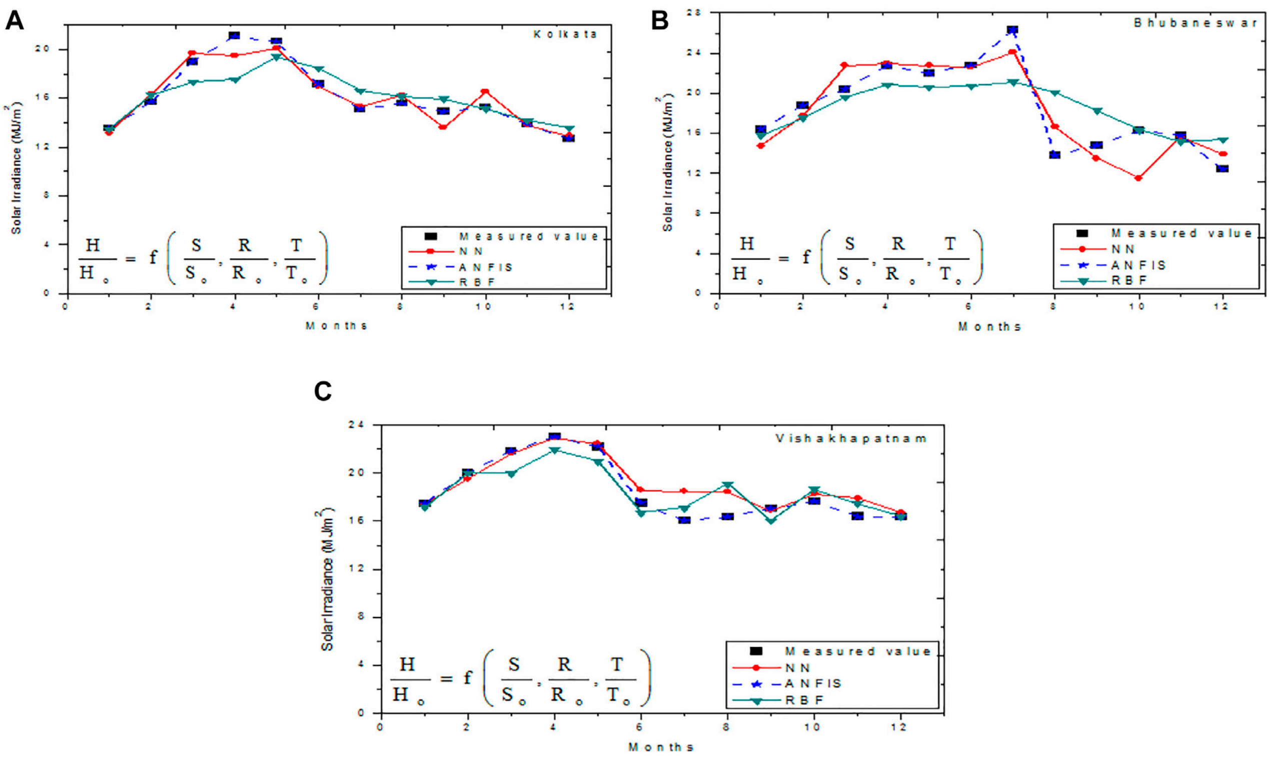

FIGURE 15 | (A–C) Measured and predicted data using different soft computing approaches for Visakhapatnam.

parameters are chosen and dissimilar models are created (**Table 3**).

Case No 1: Parameter Selection (1 Input)

During the training and testing of the model, only one input is considered. The performance outcome of both training and testing are presented in (**Table 4**) considering the sunshine input as the most favorable parameter.

The performance evaluation of different models with respect to the number of inputs is described in **Table 4**.

Case No 2: Parameter Selection (2 Inputs)

Here, two input parameters are combined for the purpose of training and testing. In total, six models have been created. The output obtained has been shown in **Table 6**. The statistical result shows for state Bhubaneswar model 1 with input temperature and sunshine duration produces improved results in comparison to other input combinations. But in the case of Visakhapatnam and Kolkata, model two with inputs (sunshine duration and Relative Humidity) will give a superior outcome compared to other input combinations.

Table 6 shows the statistical analysis with *ANFIS* models for cities Bhubaneswar, Kolkata, and Visakhapatnam.

Case No 3: Parameter Selection (3 Inputs)

Considering three vital input parameters, models have been formulated. Furthermore, all the statistical results have been verified providing better outcome with inputs such as sunshine duration, temperature, and humidity. The outputs after training and testing have been presented in **Table 7**. Proper knowledge about the inputs helps a lot in forecasting solar radiation at any particular place.

In the past, several initiatives have been taken in India regarding solar radiation data forecasting with conventional empirical models. Three important cities of Eastern India have been taken as case studies to carry out analysis for solar radiation prediction purposes. Furthermore, input parameters are fixed such as proportion of surface air pressure P/P_O, temperature T/T_O, sunshine span S/S_O, and relative humidity R/R_O. Few statistical tests such as *MBE*, *MSE*, and correlation coefficient [R] have been calculated from the measured and predicted output (*GSR*). This can be carried out after utilizing the dissimilar input–output membership function of *ANFIS*. Furthermore, this *ANFIS* model utilizes the grid participating method and follows dual output membership functions such as constant and linear membership functions. Adaptive neuro-fuzzy (Krishnaiah et al., 2007a; Awasthi and Poudyal, 2018) system has been utilized to identify most pertinent parameters for the forecasting of daily GSR. Different cities of central and southern Iran are considered for case studies. This work discussed (Kadhambari et al., 2012; Premalatha and Arasu, 2012; Bhardwaj et al., 2013b; Citakoglu, 2015; Meenal and Selvakumar, 2018; Sobri et al., 2018) the accuracy and performances of different soft computing techniques such as ANFIS, ANN, and SVM for the forecasting of daily horizontal GSR. The performance of the model is assessed from statistical indicators such as (RMSE, MAE, and coefficient of determination (R^2). Authors in this particular work (Choubin et al., 2018b) have advocated standalone ANFIS and hybrid models to predict global solar radiation using several meteorological parameters such as sunshine duration, air temperature, and optimization techniques such as PSO and genetic algorithms are used. Monthly solar radiation values (Melin and Castillo, 2005; Pousinho et al., 2011; Melin et al., 2012; Pérez et al., 2012; Choubin et al., 2017; Choubin et al., 2018a) have been modeled with the help of ANN, ANFIS, and empirical equations. Input variables such as meteorological data and month numbers are used as input variables. Authors in this work have emphasized the accuracy (Aguilar et al., 2003; Mohanty et al., 2016a; Mohanty et al., 2017a) of SVM, ANN, and empirical solar radiation models with different combinations of input parameters such as month, latitude, longitude, bright sunshine hours, day length, relative humidity, and maximum and minimum temperature. Four novel empirical models have been introduced and validated with experimental data. Authors have proposed (Choubin et al., 2018b) several models such as ANFIS, E-IBCM, and IYHM and evaluated in order to predict global solar irradiance whereas improved empirical models have been found to be better than other original models for solar radiation forecasting. The ANFIS model produces the best global solar irradiance capability in China among the three models. Algorithms such as MLP, ANFIS, and SVMs have been used. The models have been divided into four groups including sunshine, temperature, and other meteorological parameters. The first network uses five inputs to predict the solar irradiance (N_1) while the second network is the time-series prediction of solar radiation (N_2). MLFFNN, RBFNN, FIS, and SVR models are developed for N_1. MLFFNN, SVR, FIS, and three ANFIS models are developed for N_2. Authors have (Choubin et al., 2018a) compared the neuro-fuzzy model with that of the time-series model for the modeling of the drought. Research studies (Mohanty et al., 2016b; Mohanty et al., 2020) have focused on the novel application of classification and regression tree–based (CART) model. (Mohanty et al., 2016a; Mohanty et al., 2016b; Mohanty et al., 2020). After the process of training and testing, monthly average solar radiation data and statistical analysis have been attempted for three cities Kolkata, Bhubaneswar, and Visakhapatnam (**Tables 5–7, Figures 11**, **12**).

Figures 13A–C show the surface plot for the optimal combination of inputs of three cities at the time of training and testing. The significant combination of parameters having one, two, and three inputs of three cities of Eastern zone of India during training and testing are shown in **Figures 14A–C**. The measured average monthly GSR was compared with measured values of Kolkata, Bhubaneswar, and Visakhapatnam (**Tables 8**, **9**). Due to recurrent cyclonic effects, it is essential to devise new computational methods such as soft computing–based algorithms and their applications. ANFIS predicts better outcomes with calculated values **(Figure 15)**.

In spite of its efficiency and computational ability, additional inputs are always needed for enhanced accuracy and robustness. More emphasis should be given to the input factors where error in computation of training data is found. Further data fluctuations are taken care of because of ANFIS's robustness and computational skill. In this regard, a lot of work(Krishnaiah et al., 2007a; Ajil et al., 2010; Kadhambari et al., 2012; Premalatha and Arasu, 2012; Chandra et al., 2013; Joshi, 2013; Citakoglu, 2015; Awasthi and Poudyal, 2018; Verma et al., 2019) has been done in recent days emphasizing the combination of different models and input parameters for better forecasting studies (**Table 10**).

CONCLUSION

This research work has been prepared as a review study, which focuses on *ANFIS*-based solar radiation forecasting in Eastern part of India. Several studies have been undertaken with soft computing techniques. Suitable models have been developed based on several inputs and detailed analysis has been performed to show the minimum MSE and maximum regression (R) values in different places of Eastern India after training and testing. The main idea behind this study is to find out the significance of forecasting in solar radiation data collection and study its applications in agricultural crop production, hydrological, industrial, and ecological studies along the eastern coast of India. The performance of the ANFIS model in comparison with other prediction models has been studied to establish the significance of the proposed model in estimating solar radiation. After several studies, the ANFIS model seems to be computationally efficient and adaptable in managing different parameters. Consequently, the model is engaged in the estimation of the solar radiation–based data with extensively available meteorological information. It also overcomes errors, as it seems highly robust and efficient in dealing with data fluctuations. It may also be fused with additional soft computing approaches to get better network accuracy. The study also surveys similar ANFIS-based work in different areas of India in particular and other important places in the world. Further improvements are expected with several other combinations of meteorological data such as air pressure, humidity, sunshine duration, cloud index, and many more that can be associated with the model for future studies.

AUTHOR CONTRIBUTIONS

All authors contributed to this work. SM and SM have contributed in generating idea, accumulating information, and preparing the manuscript. All authors have read and approved the final manuscript.

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