SOLAR ENERGY POTENTIAL MAPPING OF INDIA USING ARTIFICIAL NEURAL NETWORK

Pariksheet Ganguly,[1,2] and Rasika Chougale*,[1,2]

[1] *Centre for Disaster Mitigation and Management, VIT University, Vellore-632014.*
[2] *Department of Environment and Water Resource Engineering, SCALE, VIT University, Vellore-632014.*

---***---

Abstract - *The initial objective of the study is to forecast the solar irradiation potential of India using artificial neural networks (ANNs) method. Mapping the predicted potential using GIS software on monthly basis is the second objective. The data was obtained from satellite database for nine years (2002-11) for 32 locations in India to train the neural network. Solar forecasting using ANN feed forward and feed forward back propagation algorithm; has been compared in this study. The ANN model uses 9 inputs i.e. global solar radiation, wind speed, wind direction, pressure, dew point temperature, time and date to predict daily solar radiation. Pearson correlation is performed between the used parameters and solar radiation. It was studied that wind direction had an anti-correlation with solar radiation, unlike others. The appropriate number of neurons were found to be 30, which gave the MAPE result 4.2%. Performance evaluation of the measured and estimated values of irradiation was done by using statistical error methods. The RMSE values for ANN using FF and FFBP models are 2.98% and 0.48%. Monthly solar radiation maps were produced for six months from January to June, based on the predicted data using the multivariate model. Solar potential knowledge could prove useful for implementation of solar energy system using these maps.*

***Key Words*: Global solar radiation, ANN, Pearson correlation, RMSE and mapping.**

1. INTRODUCTION

Challenges faced by Indian electricity system are unending as the energy demand within the next decade is expected to grow rapidly while fossil fuels as the domestic energy resource remains a constraint. Renewable sources account for 12% i.e. 31.69 GW, of the installed capacity of 258.7 GW in India. [13]. Recently, the strong decrease in the prices of PV module has increased the deployment of photovoltaic systems. An increase of PV power penetration in electricity supply has created new opportunities but at the same time has given rise to issues regarding grid operation. Energy generation variability of PV is the major consequence of high penetration of this system [5].

New challenges, arising from the variable nature of solar energy generation, must be tackled in order to keep a stable and balanced power grid. PV power output depends essentially on the irradiance incident on the panels, which can change very fast due to moving clouds [6]. [9] The prediction of the power profiles with intermittent RES is essential to formulate saving and dispatching plans. The analysis of the current forecasting scenario in the country depicts that generation forecasting is at its infancy [13].

Network operation uncertainties arises from the variability of PV power output due to weather and hence the large-scale integration becomes a challenge to the system operators. Short timescale irradiance changes can harm the equipments used by consumers by introducing voltage flicker. Furthermore, the generators must be able to mitigate the large magnitude occurrences for proper load following, by immediately changing their output with large ramp rates so that proper load follow can be carried out. Forecasts of PV generation are also important in minimizing reserve costs [1], for participating of independent power producers to the electricity market, for increasing the competitiveness of the renewable energy technologies [12], for monitoring the production and adjusting the load. In the context of smart grids PV forecasts are necessary to manage distribution networks or micro grids where other options coexist to PV generation like active demand, storage etc. [1].

Zhu H et.al. developed forecasting model based wavelet decomposition and ANN. The ANN and ANN + Wavelet analysis was compared using RMSE, MAE and MAPE. The proposed hybrid model gave better forecasting precision in less convergence time [38]. Alzahrani et.al. used the back propagation neural network; Nonlinear Autoregressive Network along with Exogenous Inputs (NARX) to pv station of Vichy-Rolla National Airport. Hourly solar irradiance was predicted using the time series model which includes parameters like day of the year, pressure, time, wind speed and sky cover. Simulations were conducted using data from National Solar Radiation Database (NSRDB). Consideration of three cases is done using variable numbers of 3, 5 and 6 for solar prediction. The MSE values obtained for the three cases are 5.7%, 5.5% and 8.2%. Their results depict that NARX network performance outweighs the linear regression models. The authors suggested that this model could be improved by addition of other meteorological parameters [29].

In Ref. 32; ANN technique is used for solar prediction of 4 cities in India namely, Bangalore, Hyderabad, Thiruvananthapuram and Chennai. Parameters like average, maximum and maximum temperature along with altitude were taken into consideration in training the ANN model. The MAPE values obtained, when compared to the measured Indian Meteorological Department, values for the cities in sequence above are 5.13%, 8.09%, 6.29% and 7.39%. The error values obtained ate less and hence the model proves to be suitable for solar irradiation prediction in the remaining locations in India, according to the authors.

Rumbayan M., Abudureyimu A. and Nagasaka K. determined the solar potential of Indonesia using ANNs multilayer perceptron. The use of nine input variables is done for 25 locations, which include average relative humidity, average precipitation, average sunshine duration, average temperature, average wind speed, month of the year, altitude, latitude and longitude to estimate monthly solar radiation. The model was tested on 5 locations. MAPE was the statistical error method used to evaluate performance of the model which gave the best result of 3.4% for 9 neurons in the hidden layer. The GIS maps were produced based on the predicted values on monthly basis [33]. Levenberg-Marquard (LM) algorithm was used by Yadav A.K. and Chandel S.S. for solar prediction for 12 Indian cities using ANN, based on various climatic conditions. The model includes sea level height, longitude, latitude, and sunshine hours for simulation. RMSE values were in the range of 0.0486 to 3.562 [36].

The authors in Ref. [37], developed exogenous and endogenous models using ANN, for prediction of solar irradiation in Bangladesh. The endogenous model uses precipitation, wind direction and speed, and humidity as the input parameters. The model training was done using Levenberg -Marquard algorithm and performance observation was calculated using MSE. The error value were in the range of 0.0029 to 0.0087. The predicted values were used for sizing of the PV systems in Bangladesh.

Solar energy can be utilized to its fullest potential on the basis of solar irradiation potential knowledge depending on locations. This knowledge is necessary at an early stage of solar technology setup. The estimation renewable energy potential of a region should be determined beforehand for adequate output from the system. Solar radiation atlas could prove enough details for further evaluation and planning for site location. Solar radiation maps based on monthly basis could be a useful background for setup of renewable energy projects in India and such maps are yet not been compiled and published so far.

To begin with, the objectives include investigation of the ANN technique for radiation potential estimation in numerous areas in India in view of satellite information. Second, present the GIS based maps in view of the consequence of ANN evaluation. The contribution of this review is to create neural system models for assessing monthly solar potential in numerous areas of India based on satellite information. This mapping is established on ANN predictions utilizing GIS innovation.

2. DATA AND METHODOLOGY

In order to simulate the model, the data used was obtained from satellite. The data consists of date from 2002 to 2011, time, direct solar radiation, global solar radiation, diffused solar radiation, dry bulb temperature, dew point temperature, wind speed and wind direction. The training was processed on 31 cities all over India. The cities selected are the capital locations of the states in India. The data for the geographical regions in India on the basis of latitude, longitude and altitude is given in Table 1.

Table -1: Latitude, longitude and altitude of the selected cities

Sr.No.	**Cities**	**Latitude**	**Longitude**	**Altitude (m)**
1	**Adilabad**	19°40'0"	78°32'00"	269
2	**Bangalore**	12°58'18"	77°35'37"	914
3	**Bhopal**	23°15'35"	77°24'45"	496
4	**Bhubaneshwar**	20°17'45"	85°49'28'	46
5	**Chennai**	13°05'16"	80°16'42"	14
6	**Delhi**	28°38'41"	77°13'00"	222
7	**Gandhinagar**	23°13'59"	72°39'05"	81
8	**Gangtok**	27°20'20"	88°36'23"	1509
9	**Hydrebad**	17°23'13"	78°29'30"	498
10	**Imphal**	24°48'50"	93°57'01"	784
11	**Itanagar**	27°05'12"	93°36'35"	326
12	**Jaipur**	26°55'19"	75°46'43"	432
13	**Kolkata**	22°34'21"	88°21'50"	14
14	**Mumbai**	18°55'00"	72°54'00"	11
15	**Nagpur**	21°08'47"	79°05'19"	311
16	**Patna**	25°36'45"	85°09'31"	58
17	***Ranchi***	***23°23'00"***	***85°23'00'***	***651***
18	***Shillong***	***25°34'32"***	***91°52'23"***	***1525***

19	**Shimla**	**31°06'16"**	**77°10'24"**	**2195**
20	**Srinagar**	34°05'01"	74°47'50"	1587
21	**Trivandrum**	08°29'00"	76°59'00"	10
22	**Agartala**	23°49'45"	91°16'40"	13
23	**Aizwal**	23°43'27"	92°43'02"	1132
24	**Chandighar**	30°44'29"	76°46'05"	341
25	**Dispur**	26°08'36"	91°47'23"	55
26	**Dheradun**	30°19'18"	78°01'35"	653
27	**Kohima**	25°39'30"	94°06'19"	1444
28	**Lucknow**	26°51'00"	80°55'00"	123
29	**Pondicherry**	11°54'57"	79°48'44"	3
30	**Diu**	21°44'24"	70°16'57"	0
31	**Raipur**	29°54'00"	75°15'00"	298
32	**Haryana**	29°36'57"	75°05'08"	850

The correlation between the parameters used is evaluated by using Pearson Correlation coefficient. The design of the proposed ANN model uses feed forward algorithm initially for next day solar prediction and secondly, feed forward network with back propagation learning is used.

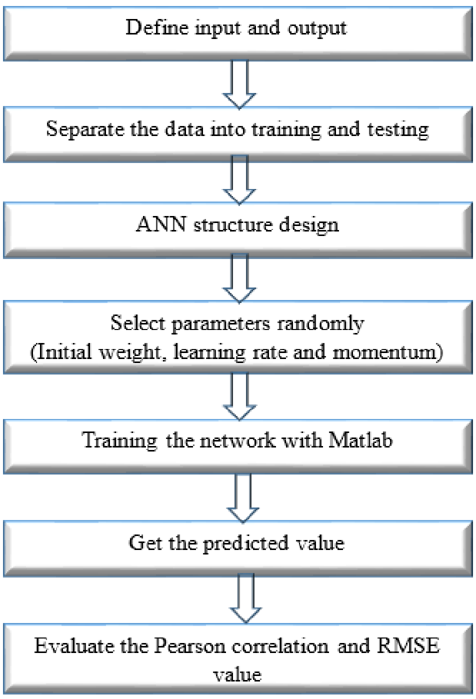


Fig -1: Steps of ANN model used in this study

Multilayer perceptions were created and tested for solar irradiation forecasting in India. In this study, the hidden layers used in the first case were 10 and in the second case were 30 based on the best MAPE result. The algorithm used is Levenberg-Marquardt. The steps used are: (a) develop input Matrix (Global radiation, wind direction, wind speed, dew point temperature, pressure, time and date), (b) ANN model design and development by parameter alteration (initial weight, momentum along with learning rate), (c) plot the graph for time versus global radiation (measured and predicted) for each location and (d) evaluating performance of the measured and estimated prediction; as illustrated in Fig.1.

Data linked to locations is captured, saved, processed, managed and deduced in Geographic information system (GIS). GIS thus merges statistical data and database techniques. The value from database is put in the form of features on the location map. The overview of the profile of parameters changing over a time lapse can be produced from mapping. Depiction and processing of data in various layers is also known as mapping algebra as it includes addition and subtraction of information. The potential to segregate data in layers and produce maps by combining the data with various layers makes GIS important for research purposes [23].

3. RESULTS AND DISCUSSION

3.1 Multi-Layer Perceptron Structure Selection

The algorithm used in the analysis is feed forward back propagation. Number of neurons were varied and trained in a single hidden layer, while developing the ANN model. Mean Absolute Percentage Error (MAPE) is a statistical method to assess the performance of forecasting model. Input, hidden and output layers are indicated by MLP structures in terms of number of neurons. A comparative study of estimated and measured values are inspected by MAPE. Table 4.1 gives the various MLP structures performance used in this study.

As shown in Table 2, the error values are less than 5%, which depicts an agreement amongst the measured and estimated values of average monthly global solar radiation. The best estimation achievable is from the least MAPE value of 4.22% consisting MLP structure of 9-30-1, respectively.

3.2 Pearson Correlation

Measure of the relationship between two variables is produced by Pearson correlation coefficient. The parameters used in the ANN are related with the output parameter i.e. the global radiation. The effect of these parameters is evaluated by this method by relating pressure, wind speed, wind direction and dew point to the global radiation by r1, r2, r3 and r4. The correlation between global radiation and pressure in given by r1; whereas wind speed, wind direction and dew point are associated with global radiation by r2, r3 and r4. As seen in table 1, wind speed is directly related and have a major influence on GR. Pressure and dew point are also directly affect the radiation but to a lesser extent. Wind direction has anti-correlation to the GR as it has negative value for all the six cities. Thus, brighter days on non-windy days whereas high windy days have dimmer days [27].

Table 2: The performance of MLP structures by statistical error MAPE.

MLP Structure	R squared value	MAPE
9-25-1	0.9364	4.24
9-26-1	0.9341	4.25
9-27-1	0.8632	4.44
9-28-1	0.9187	4.32
9-29-1	0.8459	4.45
9-30-1	0.9452	4.22
9-31-1	0.9035	4.43
9-32-1	0.9411	4.23
9-33-1	0.8762	4.44
9-34-1	0.8754	4.44

Table 3: Pearson correlation between parameters

City	r_1	r_2	r_3	r_4
Bhopal	0.0686	0.6505	-0.2864	0.0985
Delhi	0.3195	0.3633	-0.0844	0.0811
Mumbai	0.1212	0.6638	-0.2216	0.1006
Chennai	0.0876	0.6508	-0.1740	0.0165
Kolkata	0.1052	0.7277	-0.1496	0.0741
Itanagar	0.1492	0.6440	-0.2586	0.1054

3.3. Solar Irradiation Forecasting Results

The measured and estimated values using FF (Feed Forward) and FFBP (Feed Forward Back Propagation) models are shown in Table 4. The R squared values are more than 0.87 for all the cities studied, whereas for time series prediction the R^2 values are less than 0.87. The ANN model with feed forward back propagation algorithm gives the best possible performance for monthly global solar radiation Prediction.

City	Actual	FF	R^2	FFBP	R^2
Adilabad	753	595.2	0.8332	719.3	0.9351
Bangalore	688	586.8	0.7826	689.3	0.928
Bhopal	788	612.1	0.8409	748.9	0.9375
Bhubaneshwar	660.9	519.7	0.8115	660.9	0.9232
Chennai	715.7	576.9	0.826	715.9	0.92
Delhi	490	481.3	0.8519	596.4	0.9453
Gandhinagar	805	631.3	0.8703	788.1	0.946
Gangtok	111	459.6	0.6436	377.9	0.8815
Hydrebad	814	590.7	0.8269	771.7	0.9248
Imphal	943	559.9	0.7401	563.1	0.8948
Itanagar	805	414.1	0.6702	271.8	0.9038
Jaipur	709	613.8	0.8809	775.6	0.943
Kolkata	549	447.1	0.8023	533	0.915
Mumbai	767	591.6	0.8359	756.6	0.9452
Nagpur	765	595.3	0.8349	731.5	0.934
Patna	369	474	0.8257	534	0.9304
Ranchi	604	574.8	0.8153	705.7	0.9204
Shillong	99	468	0.6804	334.5	0.8757
Shimla	99	468.3	0.6784	335.5	0.8757
Srinagar	484	394	0.7402	262.7	0.937
Trivandrum	826	556	0.8069	652.6	0.8951
Agartala	876	475.5	0.7813	438	0.9
Aizwal	981	539.4	0.7544	382.7	0.8899
Chandighar	706	527.8	0.8413	648.6	0.9453
Dispur	97	468	0.7612	377.9	0.9062
Dheradun	658	545	0.8097	486.9	0.9298
Kohima	848	426	0.6428	165	0.8657
Lucknow	397	455.8	0.8293	550.5	0.9339
Pondicherry	705.8	594.6	0.8362	706	0.9259
Diu	753	628.8	0.8679	756.6	0.9538
Raipur	725	587	0.8292	705.7	0.9327

Table 4: Actual and Predicted solar radiation using FF and FFBP

The correlation coefficient value R is large i.e. nearer to 1, then the MSE value is much smaller than the mean target variance. This indicates that the net has successfully managed to model most of the variation in the input to target transformation. The highest GHI values obtained are for Gandhinagar and Jaipur. The lowest values are observed in the north-east India. The maps are depicted based on these predicted values in the maps using GIS. The graphs of measured versus the estimated values of Jaipur and Itanagar are shown in Fig. 2 (a,b). The actual and predicted values are nearly same with predicted value showing a slight change in time.

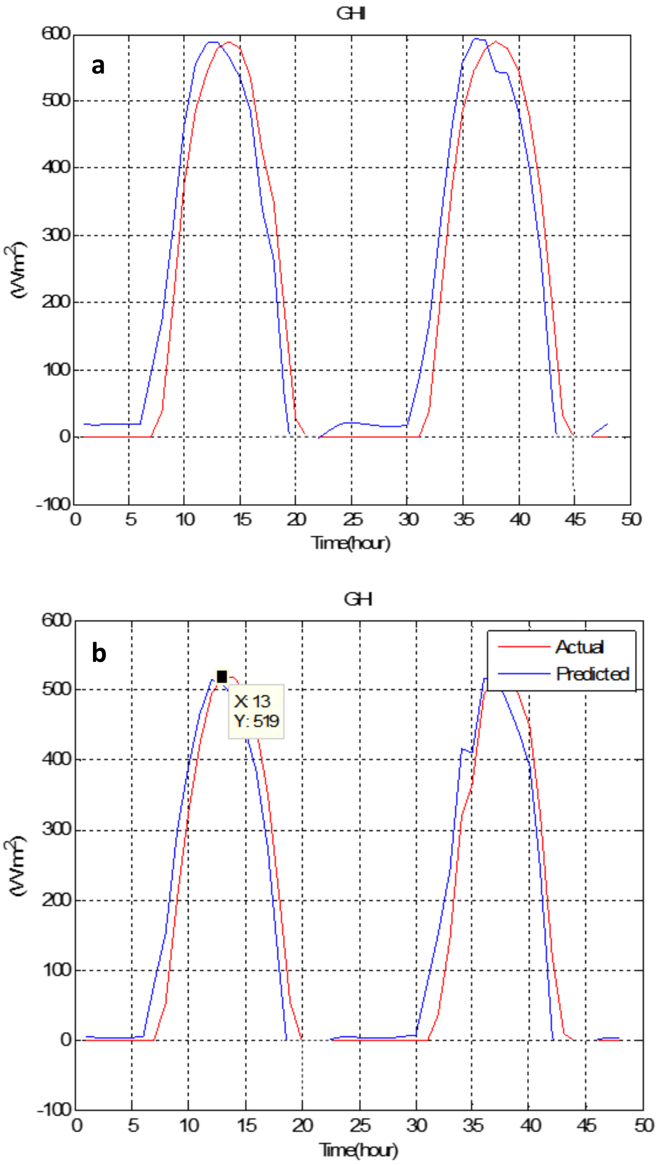


Fig. 2: Measured versus estimated forecast of a) Jaipur and b) Itanagar for two days

3.4. Statistical Error Estimation

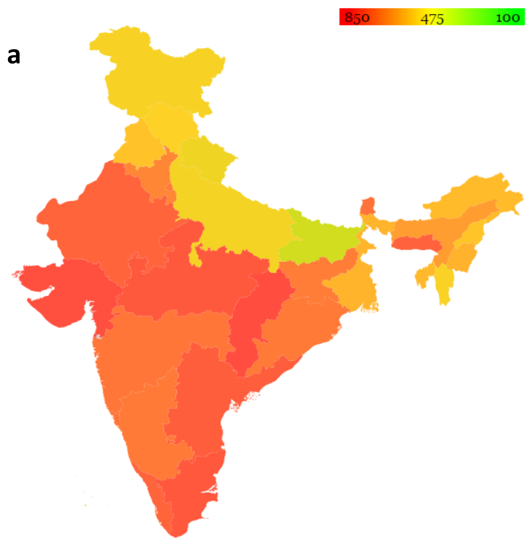
Evaluation of the prediction models performance requires error calculation. The error value gives information about the dependence on the forecast, and also to redo the forecasting in situation of high error. The error values by both the method are less. The ANN with feed forward back propagation algorithm gives the best result with low error values of RMSE, MAE and MaxAE as shown in Table 5.

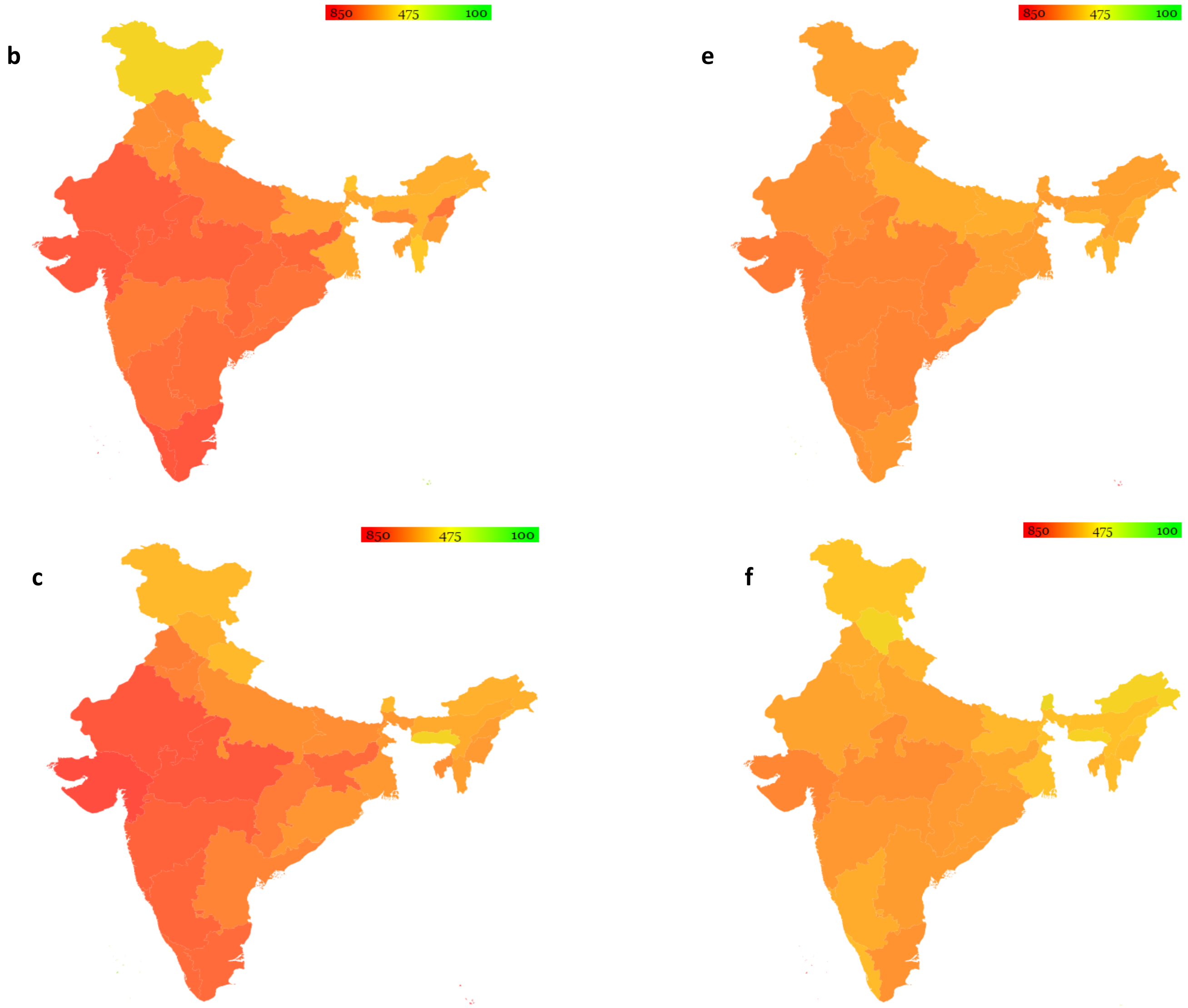
Table 5: Performance evaluation using statistical methods.

ERRORS/ALGORITHM	FF	FFBP
RMSE (%)	2.98	0.48
MAE (%)	2.69	0.35
MaxAE (%)	5.20	1.21

Western India has the most potential for solar energy utilization for solar energy systems especially in Gujarat, Rajasthan, Tamil Nadu and Maharashtra. Most of the parts in India have solar radiation from 475 to 750 W/m^2, except for North-east India. This shows that India has high potential for solar energy.
According to the maps produced, India has solar potential throughout the year in Gujarat, Maharashtra, Rajasthan, Tamil Nadu and Madhya Pradesh. The North eastern parts show potential for harnessing solar energy during post winter seasons (Fig. 2,3,13 and 14).

Insight of the theoretical solar irradiation potential can be gained, by solar radiation mapping on average monthly basis of a year. The constraints such as geographical area, finance and land use also need to be considered for exploitation of this resource. Research based on these limiting factors can be continued to examine economic and scientific potential of solar energy.





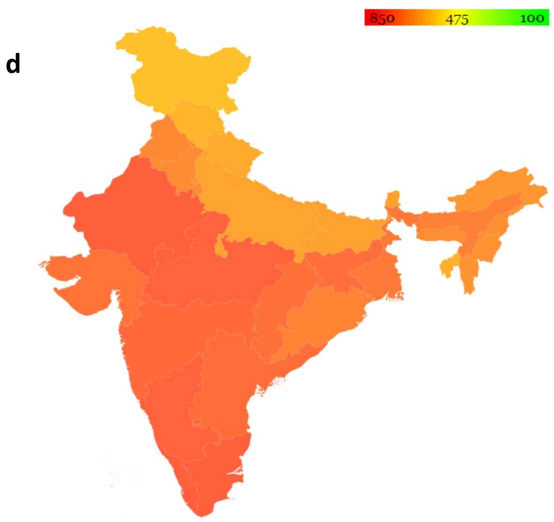


Fig. 3: Monthly Solar irradiation map for January, February, March, April, May and June months (a-f), India

4. CONCLUSION

The best estimation achievable is from the least MAPE value of 4.22% consisting MLP structure of 9-30-1, respectively. According to the Pearson correlation coefficient values wind speed is directly related and have a major influence on global radiation. Pressure and dew point are also directly affect the radiation but to a lesser extent. Wind direction has anti-correlation to the global radiation as it has negative value for all the six cities. The ANN model with feed forward back propagation algorithm gives the best possible performance for monthly global solar radiation prediction. The highest GHI values obtained are for Gandhinagar and Jaipur. The lowest values are observed in the North and North - East India. Western India has the most potential for solar energy utilization for solar energy systems especially in Gujarat, Rajasthan, Tamil Nadu and Maharashtra. Most of the parts in India have solar radiation from 475 to 750 W/m2. The GIS maps produced show good solar potential throughout India.

REFERENCES

[1] Liu BYH, Jordan RC. The interrelationship and characteristic distribution of direct, diffused and total solar radiation. *Solar Energy* 1960; 4(3):1-19.

[2] Hollands KGT. A derivation for diffuse fraction's dependence on the clearness index. *Solar Energy* 1985; 35(2):131-6.

[3] Hollands KGT, Crha SJ. An improved model for diffuse radiation: correction for atmospheric back scattering. *Solar Energy* 1987; 38(4):2336.

[4] Jayaraman R, Maskell RL. Temporal and Spatial Variations of the Solar Radiation Observed in Singapore. *Energy Procedia* 2012; 25: 108 – 117.

[5] Agoua XG, Girard R, Kariniotakis G. Spatio-temporal models for photovoltaic power short-term forecasting. *Solar Integration workshop* 2015.

[6] Remund J, Calhau C, Perret L, Marcel D. Characterization of the spatio-temporal variations and ramp rates of solar radiation and PV. *International Energy Agency Photovoltaic Power Systems Programme* 2015; T14-05.

[7] Camargo MBP, Hubbard KG. Spatial and temporal variability of daily weather variables in sub-humid and semi-arid areas of the United States high plains. *Agricultural and Forest Meteorology* 1999; 93: 141-148.

[8] Ertekin C, Evrendilek F. Spatio-temporal modeling of global solar radiation dynamics as a function of sunshine duration for Turkey. *Agricultural and Forest Meteorology* 2007; 145: 36–47.

[9] Chicco G, Cocina V, Leo PD, Spertino F. Weather forecast-based power predictions and experimental results from photovoltaic systems. *IEEE Conference SPEEDAM* 2014.

[10] Lorenz E, Hurka J, Heinemann D, Beyer HG. Irradiance forecasting for the power prediction of grid-connected photovoltaic systems. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 2009; 2(1): 2-10.

[11] Thornton PE, Running SW. An improved algorithm for estimating incident daily solar radiation from measurements of temperature, humidity, and precipitation. *Agricultural and Forest Meteorology* 1999; 93: 211-228.

[12] Pinson P, Chevallier C, Kariniotakis GN. Trading Wind Generation from Short-Term Probabilistic Forecasts of Wind Power. *IEEE Transactions on Power Systems* 2007; 22(3): 1148-1156.

[13] Christoph Richts (Fraunhofer IWES) ,Dr. Philipp Strauß (Fraunhofer IWES) ,Dr. Detlev Heinemann (University of Oldenburg). Report on Forecasting, Concept of Renewable Energy Management Centres and Grid Balancing. *Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH and Indo – German Energy Programme – Green Energy Corridors*, 2015.

[14] IEA, The power of transformation, Paris: IEA, 2014.

[15] Lave M, Kleissl J, Arias-Castro E. High-frequency irradiance fluctuations and geographic smoothing. *Solar Energy* 2012; 86(8): 2190-2199.

[16] Rumbayan M, Nagasaka K. Resource and economic assessment of solar irradiation potential in an island community. Proceedings of the 4th Indonesia Japan Joint Symposium 2010;vol. 1(1):59.

[17] Rumbayan M, Nagasaka K. Solar radiation estimation with ANN using meteorological data in many locations of Indonesia Tokyo University of agriculture and technology. In: Proceedings of 3rd international conference on computer and informatics. 2011.

[18] Octopal A. Artificial neural network approach to spatial estimation of wind velocity data. Energy Conversion and Management 2006;47:395–406.

[19] Jiang Y. Prediction of monthly mean daily diffuse solar radiation using artificial neural networks and comparison with other empirical models. Energy Policy 2008;36:3833–7.

[20] Al-Alawi SM, Al-Hinai HA. An ANN-based approach for predicting global radiation in locations with no direct measurement instrumentation. Renewable Energy 1998;14:199–204.

[21] Mohandes M, Rehman MS, Halanawi TO. Estimation of global solar radiation using artificial neural networks. Renewable Energy 1998;14:179–84.

[22] Rumbayan M, Nagasaka K. Prediction of solar irradiation potential in island area of Indonesia using artificial neural network method. The official Journal of ISESCO Centre for Promotion of Scientific Research 2010;6:55–61.

[23] Foote KE, Lynch M. GIS as an integrating technology: context, concept and definitions. In: The Geographer's Craft Project. Boulder: Department of Geography, The University of Colorado; 2000.

[24] Sozen A, Arcaklioglu E, Ozalp M, Kanit GE. Use of artificial neural networks for mapping of solar potential in Turkey. Applied Energy 2004;77:273–86.

[25] Gastli A, Charabi Y. Solar electricity prospects in Oman using GIS-based solar radiation maps. Renewable and Sustainable Energy Reviews 2010;14: 790–7.

[26] Ramachandra TV, Shruthi BV. Wind energy potential mapping in Karnataka using GIS. Energy Conversion and Management 2005;41:1561–78.

[27] P. E. Bett and H. E. Thornton, "The climatological relationships between wind and solar energy supply in Britain", *Renewable Energy,* 2016, 87-1 ,96–110.

[28] Ashwani Kumar, Kapil Kumar, Naresh Kaushik, Satyawati Sharma, Saroj Mishra, "Renewable energy in India: Current status and future potentials", *Renewable and Sustainable Energy Reviews*, 14 (2010) 2434–2442.

[29] Alzahrani A., Kimball J.W., Dagli C., “Predicting Solar Irradiance Using Time Series Neural Networks”, *Procedia Computer Science*, 36 (2014) 623 – 628.
[30] Hassan A. N. Hejase and Ali H. Assi, “Time-Series Regression Model for Prediction of Mean Daily Global Solar Radiation in Al-Ain, UAE”, ISRN Renewable Energy, 2012, 412471.
[31] Voyant C., Haurant P., Muselli M., Paoli C., and Nivet M. L. Time series modeling and large-scale global solar radiation forecasting from geostationary satellites data. Solar Energy, 2014, 102, 131-142.
[32] Priya, S. S., and Iqbal, M. H.. Solar Radiation Prediction using Artificial Neural Network. International Journal of Computer Applications, 2015, 116(16).
[33] Meita Rumbayan, Asifujiang Abudureyimu and Ken Nagasaka, “Mapping of solar energy potential in Indonesia using artificial neural network and geographical information system”, Renewable and Sustainable Energy Reviews, 16 (2012) 1437– 1449
[34] Jeong, Yoon-Su, Seung-Hee Lee, Kun-Hee Han, Duchwan Ryu, and Yoonsung Jung. "Design of short-term forecasting model of distributed generation power for solar power generation." *Indian Journal of Science and Technology*, 2015, 8, 261-270.
[35] Christophe Paoli, Cyril Voyant, Marc Muselli, Marie Laure Nivet, “Forecasting of preprocessed daily solar radiation time series using neural networks”, *Solar Energy, Elsevier*, 2010, 84 (12), 2146-2160.
[36] Yadav, A.K. and Chandel, S.S., 2012. Artificial neural network based prediction of solar radiation for Indian stations. *International Journal of Computer Applications*, *50*(9).
[37] Quaiyum Salman, Shahriar Rahman and Saidur Rahman. "Application of Artificial Neural Network in Forecasting Solar Irradiance and Sizing of Photovoltaic Cell for Standalone Systems in Bangladesh." *Int. Journal of Comp. App.* 2011, 32, 51-56.
[38] Zhu H., Li X., Sun Q., Nie L., Yao J. and Zhao G. "A power prediction method for photovoltaic power plant based on wavelet decomposition and artificial neural networks." *Energies*, 9(1) 2015: 11.
[39] Chaturvedi D.K. and Isha, “Solar Power Forecasting: A Review”, International Journal of Computer Applications, 2016, 145(6), 28-50.
[40] Crone, S.F.,”Stepwise Selection of Artificial Neural Networks Models for Time Series Prediction” *Journal of Intelligent Systems*, 2005, 15.