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Artificial Neural Network based Solar Radiation Prediction – A Review

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***Abstract*—**Accurate prediction of global solar radiation (GSR) is very important for all solar energy applications such as design of solar energy system, management of solar power plants and so on. But GSR data is not easily available in all the locations of India due to cost and other technical issues in measurement techniques. Hence it is essential to predict the solar radiation by employing solar radiation prediction models with available meteorological parameters as inputs. The input parameters include sunshine duration, temperature, wind speed, atmospheric pressure, and relative humidity and so on. This work is focused on the review of Artificial Neural Network (ANN) based solar radiation prediction.

***Keywords** - Solar Radiation Prediction; Solar (PV) Energy Modeling;Artificial Intelligence (AI); Artificial Neural Networks (ANN)*

I. INTRODUCTION

Solar energy is one of the most important renewable energy sources in India due to primary geographical location. India has a huge solar energy potential for generating green electricity. The accurate information about solar radiation is very essential for the optimal design of solar energy based system. Due to cost and other technical issues in measurement, the radiation data is not readily available in all the locations of India. Basically, installing the high precision measuring equipment is the best method to obtain the solar radiation data. Indeed despite the continuous efforts to establish more solar radiation measurement stations in recent years, the number of meteorological stations measuring the solar radiation data is still restricted. Hence it is economical to develop proper solar radiation prediction models. There have been several papers that presented different solar radiation models using various meteorological data namely regression models, ANN models and other hybrid models to predict GSR for the solar energy based applications [1-8]. For all solar energy applications GSR is considered as the most important parameter. The main objective of this study is to reviewdifferent ANN based models for the prediction of solar radiation.

The paper has been organized as follows; Section 2 covers the neural network architecture and activation functions. Section 3 presents the performance metrics of solar radiation models. Section 4 contains the results and discussion. Section 5 covers the conclusion of this study.

II. METHODOLOGY

A. Artificial Neural Network

An artificial neural network provides a computationally proficient way of determining nonlinear relationship between a number of input variables and one or more outputs. This ANN technique has been applied for modeling, identification, optimization, prediction, forecasting and control of complex systems [10-16].

B. Neural Networks and its architecture

A Neural Network can be defined as an interconnection of neurons, such that neuron outputs are connected, through weights, to all other neurons including themselves. Fig.1 shows the neuron model and Fig.2 shows the simple model of an artificial neuron. X1, X2,.Xn represents the inputs to the artificial neuron and w1 w2…wn are the weights attached to the input links. Through dentrites, biological neuron receives all the inputs, sums them and produces output if the sum is greater than a threshold value. Different types of artificial intelligence models which include,

- Multilayer Perceptron Neural Network(MLP),
- Recurrent Neural network(RNN),
- Radial Basis network(RBN)

The above mentioned models have its own specific structure, training method and area of application. Tree-based model is the one method of nonlinear regression analysis which is called "regression tree" on the regression problem and "classification tree" or "decision tree" in classification problem.

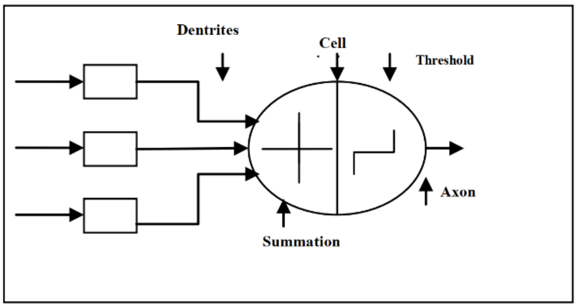


Fig.1 Neuron Model

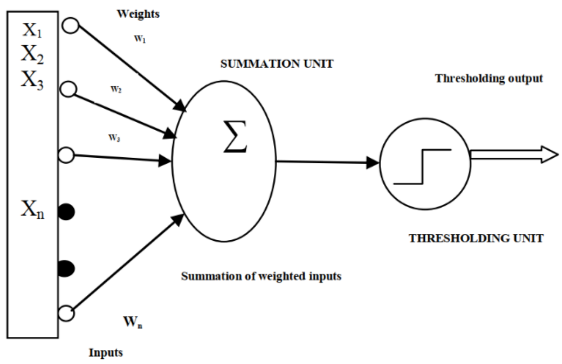


Fig.2 Simple Model of an Artificial Neuron

Al the above mentioned models have its own precise structure, training method and area of application. Tree-based model is the one method of nonlinear regression analysis which is called "regression tree" on the regression problem and "classification tree" or "decision tree" in classification problem. Fig.3 shows Feed forward network adopted back propagation method [9] and Fig.4 shows an example of tree based model, where S is dividing condition, t is the number of node and Y is mean value of output.

C. Activation Functions

The activation function helps in achieving the exact output, on applying the net input over the network. A function is associated with the input's processing. This function serves to combine activation, information or evidence from an external source. A nonlinear activation function is used to make sure that a neuron's response is bounded. There are several activation functions as:

- Identity Function
- Binary Step Function
- Sigmoidal Function
- Ramp Function

III. PERFORMANCE METRICS

The performance of the model is evaluated using the statistical parameters namely Root mean square (RMSE) and correlation coefficient (R). For better modeling R value should be closer to 1 and RMSE value should be zero.

Root mean square: Root mean square is given by

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(H_{im} - H_{ic})^2} \qquad (1)$$

where n is total number of observations, Hi,c is ith calculated value and Hi,m is the ith measured value of solar radiation.

Mean bias error: The mean bias error is defined as

$$MBE = [\sum(H_{i,m} - H_{i,c})]/N \qquad (2)$$

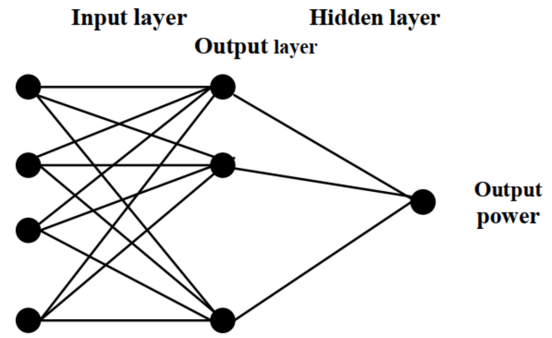


Fig.3 Feed forward Back propagation netwok

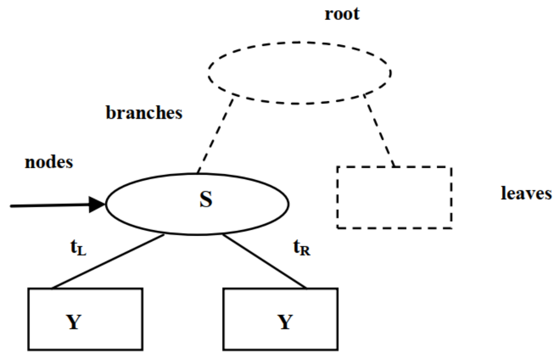


Fig.4 Example of tree-based model

TABLE 2: A summary of input variables used in ANN based prediction of solar radiation

InputvariablestoANN Model	Predictionaccuracy	Reference	Model	Applications
Dailyairtemperature,sunshine duration and the GSR.	Meanrelative error of 1.34 % Correlation coefficient(R)-0.98	Mellit.A[3]	RadialBasisFunction Model (RBF)	Sizing Stand-alone solar PVPowerSystem
Latitude, longitude, altitude, clearnessindex,temperature, sunshine hoursand extraterrestrial radiation	Correlation coefficient-0.97	AmitKumar Yadav[15]	J48 algorithm for selecting input variablesforANN model	Todevelopthesolar maps for Himachal Pradesh,India
Latitude,longitude,elevation, month,maximumtemperature and minimum temperature.	(R^2)of99%forall the selected locations	Egeonu,D.I [16]	Multi-layered feed forward(MLFF),back-propagation neural networks	Optimal system design and modelingofsolar energy based processes
Altitude,longitude,altitude and sunshine duration	MSE-0.01 R^2- 0.99	JuhiJoshi [14]	MLFFnetworkwith Levenberg-MarquardalgorithmandAngstrom Prescott model	EstimationofGSR to install Solar System
Latitude, longitude, altitude, relativehumidity,month,time, wind speed, rainfall and air temperature	MBE- 0.3133%, RMSE - 4.61% R^2 - 0.99 MS	Krishnaiah1T. [1]	MLFFneuralnetwork withbackpropagation learning	Design of solar energysystemsin India

	E-0.002			
Latitude, longitude, day numberandsunshineratio.	MAPE-5.92%, MBE1.46% and RMSE-7.96%	TamerKhatib [6]	Feedforwardmultilayer perception model	Predictionof clearnessindexused to predict GSR
Daily GSR on a horizontal surfaceatDakhlainMorocco.	RMSE-0.56kw/m^2	RadouaneIqdour[2]	MLP Neural Networksusing Polack-Ribièrealgorithm	Applicationtosolar process
A one hour average data on ambient air temperature, relativehumidity,globalsolar radiation	MAPE-6.65%and MSE - of 0.008.	N.Premalatha[7]	Gradientdescentback propagation with adaptive learning rate	ToestimateGSR forlocationswith temperature only data.
Monthnumber,latitude longitude, altitude , Day length, extraterrestrial radiation, sunshine duration, maximum and minimum temperature,relativehumidity and wind speed.	MAPE-.47%.	Sivamadhavi V[8]	Multilayerfeedforward (MLFF)neuralnetwork using back propagation algorithm.	To estimate monthlymeandaily GSRinTamilNadu
Maximum temperature, minimumtemperature,average temperature, and irradiance.	R=0.99559 Bestvalidation performanceis 4.4514 e^{-07}at epoch199	Aminmohammad Saberian [13]	General regression neuralnetwork(GRNN) feed forward back propagation (FFBP)	Modeling of PV Panel output power andapproximatethe generated power.
Air temperature, sunshine duration,relativehumidity, and the day of Year.	R^2-97.65%. MPE-2.5200 RMSE-0.044121 MBE-1.1789	BenghanemM A.Mellit[4]	Feed-forwardNeural Network	Designing, sizing andperformance of renewableenergy systems
Temperature, wind speed, pressure,relativehumidity Precipitation	Reduced MAE by theuseofRandom Forest and NN.	AtsushiYona[9]	NNtrainedbytreebasedmodel	Fore-casting ofsolarheatutilization system using NN.

IV. REVIEW OF SOLAR RADIATION PREDICTION USING ANNS

A. Inclusion criteria

In order to make certain a high pleasant of the publications protected in our assessment, an automated seek changed into completed at the databases of the most prestigious publishers with extra criteria. This was followed with the aid of including works stated in formerly selected guides so that it will have a listing that is as exhaustive as possible. During our search process, conference articles, running papers, commentaries, and eBook evaluation articles were excluded [15].

B. Distribution of literature researches

In the following section, we present the distribution of thereviewed publications according to journal publisher (fig.1.a)and prediction horizon (fig.1.b).

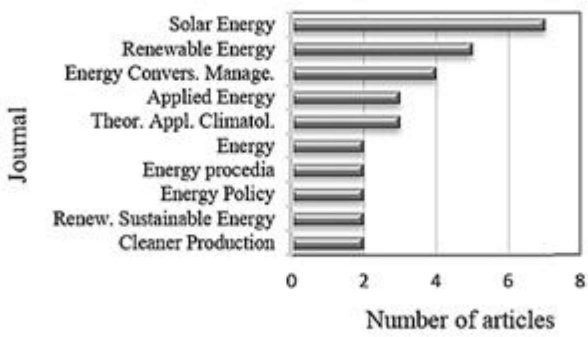
C. Monthly/Daily/hourly solar radiation prediction

In existing studies works, we discover different prediction horizons: monthly, each day, and hourly. In fact, month-to-month prediction permits a realization of a pre-sizing of sun devices, at the same time as the day by day and hourly sun radiation values are essential for a dependable and specific sizing. Indeed, our first standards of study are to categorize papers with the aid of the prediction horizon. The acquired results of month-to-month and each day/hourly sun radiation prediction category are illustrated in Table III and IV respectively. In these tables, we've categorized the courses chronologically by way of specifying the anticipated factor, the ANN architecture, the location, and the corresponding overall performance assessment signs[16,17]. Tables display that more works were achieved at the prediction of world solar radiation in comparison with diffuse and beam (direct) additives. Furthermore, we observe that the selected research burns up to forty neurons in a single hidden layer and few of them undertake two hidden layers with up to sixty-nine neurons. The ANN models used one of a kind input parameter depending on available meteorological and geographical statistics. Concerning overall performance assessment signs, the maximum used in examined articles are R2, MAPE, RMSE, and MBE. The found MAPE values falls in the range [0.3 - 10.1] which is high prediction accuracy according to [18]. All the models show good performances with a coefficient of determination (R2) between 0.82 and 0.99.

V. DISCUSSION AND RECOMMENDATION FOR FUTURERESEARCH WORKS

In the following section we will point out some observations and problems we have noted during our study of the already mentioned papers with our corresponding recommendations.

To take a look at and validate sun power prediction models, long term climate data are required. However, such data aren't effortlessly available due to the excessive price of measuring devices and the issue inaccessibility of the measuring websites which puts intense dilemma in conceiving reliable and correct fashions [19]. Through our inspection of the studied literature, we've got noticed the dearth of a fashionable database having a large range of entering kinds with the recording intervals of facts. Also, the education and test subsets in the sort of database need to be statistically representative in order to have correct fashions (One rule of thumb is that the education set size must be 10 times the community weights to accurately classify information with ninety% accuracy [20,21]). In all the ANN fashions, the range of hidden layers and corresponding neurons is decided experimentally (which may additionally require massive computational evaluation) and there may be no mentioned systematic method to optimize this number. This task remains an open and challenging problematic and must be addressed in future works. Genetic algorithms, Particle Swarm optimization, simulated annealing techniques can be considered as optimization techniques for this aim[22].



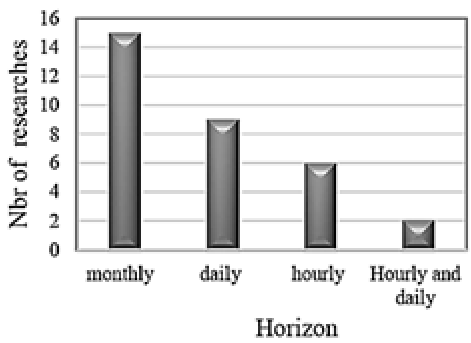


Fig. 1. Distribution of the reviewed publications according to journal (a), according to prediction horizon (b)

Table 3: Monthly Solar Radiation Prediction Publication of Our Study

Component	Reference	Authors	Journal	The ANN architecture	Performance indicators	Location
Global	[19]	A.K. Yadav et al.	Renew. Sustainable Energy Rev.	One Hidden Layer (5-10-1)	MAPE(%) = 6.89	India
Diffuse	[20]	Y.Jiang	Energy Policy	One Hidden Layer (2-5-1)	R^2=0.90 MPE(%)=1.55 MBE(MJ/m^2)=0.040 RMSE(MJ/m^2)=0.746	China
Global	[21]	J.Mubiru et al.	Solar Energy	One Hidden Layer (6-15-1)	R=0.974 MBE(MJ/m^2)=0.059 RMSE(MJ/m^2)=0.385 MAPE=0.3	Uganda
Beam	[22]	S.Alam et al.	Renewable Energy	One Hidden Layer (7-3-1)	RMSE(%)= from 1.65 to 2.79	India
Global	[23]	F.S. Tymvios et al.	Solar Energy	Two Hidden Layer (3-46-23-1)	MBE(%)= 0.12 RMSE(%)= 5.67	Cyprus ,Athen

Global	[24]	A.Sozen et al.	Energy Coners. Manage.	Two Hidden Layer (6-2-5-1)	MAPE(%)= 6.735 R^2= 0.993 RMS(%)= 4.465	Turkey
Global	[25]	A.Sozen et al.	Applied Energy	(6-N/A-1)	MAPE(%)= $\leq$6.73 R^2(%)= 99.89	Turkey
Global	[26]	A.S.S.Dorvlo et al.	Applied Energy	(5-N/A-1)	RMSE(%)= 0.83	Oman

• From posted literature, the best desire for geographical and meteorological enter parameters are vital to expect sun radiation with reliability and higher accuracy. Unless few studies running in this tricky [23, 24], there is but no automated technique sporting out the choice of maximum relevant input variables for ANN models.

• In the work of [25], the impact of the sunshine period at the prediction accuracy has been highlighted. This observation have to be generalized to peer the impact of every variable on the overall ANN model performances.

• Regarding desk III and IV showing the fewness of papers on diffuse and beam solar radiation predictionthe use of ANN and because of the significance of those components for the strength packages, greater studiesare required in destiny works[26,27].

• In order to pick out the first-class ANN prediction models, a comparison of various ANN fashions such as MLP, RBF, Generalized Regression Neural Network, and so forth. In the prediction of solar radiation has been finished [28-30]. Unfortunately, confined attention has been given to the assessment between ANN and different prediction models [31, 32, 33].

• As indicated in [34], special ANN fashions want to be evolved the usage of latitude, longitude, altitude, extraterrestrial radiation as entering parameters and checked for accuracy[35]. This could be useful for the ones places wherein no meteorological stations have been hooked up even if it is found that range and longitude have minimal impact on solar radiation prediction as established in [36].

CONCLUSION

Accurate prediction of global solar radiation is very important for all solar energy applications. Solar radiation is estimated by number of solar radiation models. In this paper a detailed study on papers using ANN models are reviewed. The use of artificial neural networks in solar energy estimation was thoroughly investigated in this paper. An in-depth familiarity with the consistency and variability of solar radiation is essential for the development of renewable solar energy. The superior capacity of ANN models to describe dynamic, non-linear, and time-varying input-output systems makes them the preferred choice for accurate solar radiation forecasting. Consequently, this page compiles one-of-a-kind experiments with a primary emphasis on artificial neural network models for solar radiation forecasting. Our research also features an updated evaluation to better inform future investigations into this field. It makes use of a well-established body of literature, time frame for projection, artificial neural network design, and measurements of overall success. Investigating these manuals has also served to draw attention to issues like the lack of a universal database (covering a variety of input types and recording eras) and the absence of a scientific method for creating the ANN's architecture. In addition, there is no mechanism for choosing the most important input variables for ANN designs until some research is undertaken on the topic. A few articles have been found that use artificial neural networks to calculate the sun's radiation output (spread and beam). it can be concluded that papers using ANN model give better results than classical regression methods and these methods offer many advantages over traditional approaches.

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