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ORIGINAL PAPER

Weather Forecasting for Renewable Energy System: A Review

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Abstract

Energy crisis and climate change are the major concerns which has led to a significant growth in the renewable energy resources which includes mainly the solar and wind power generation. In smart grid, there is a increase in the penetration level of solar PV and wind power generation. The solar radiation received at the earth surface is greatly dependent on various atmospheric parameters. Forecasting of solar radiation and photovoltaic power is a major concern in terms of efficient integration of solar PV plants in the power grid. There are significant challenges in smart grid energy management due to the variability of large-scale renewable energy generation. Renewable energy forecasting is critical to reduce the uncertainty related to renewable energy generation for a wide range of planning, investment and decision-making purposes. As renewable energy sources are highly intermittent and variable, all the forecasting models available in the literature contain errors. This paper presents an overview of current and new development of weather forecasting such as solar and wind forecasting techniques for renewable energy system in smart grid. Many forecasting models such as physical models, statistical models, artificial intelligence based models, machine learning and deep learning based models were discussed. It is observed that, despite having no clear understanding on atmospheric physics, the artificial intelligence based methods such as machine learning and deep learning method produces reasonable weather forecasting results.

1 Introduction

Climate change and energy crisis are biggest threat in twenty-first century. The climate system is very complex in India. Climate predictions are important for future planning and for adapting to climate change. Various literatures foretell on the need of climate projections as current day weather and climate holds a vital role in the daily updates to the society. Renewable energy is a major solution for fighting climate change. To design the electrical energy system and to evaluate the yearly energy production, forecasting of weather conditions (solar radiation, wind speed) is very essential. In continuation with this, many forecasting methods have been developed by researchers and scientists around the world. For proficient utilization of solar energy, it is mandatory to have an accurate understanding about the different components of solar radiation. Conventionally, Pyranometers are located in various locations to measure the amount of global solar radiation (GSR) for a given location. This conventional procedure of measuring GSR requires frequent maintenance and data recording which leads to increase in the cost for GSR data collection. Hence prediction and forecasting of solar radiation using suitable techniques is the need of this hour. Similarly the wind speed prediction is very important for integration in to the electricity grid and also helps the power system operators decrease the possibility of irregularity of power supply.

There are four broad categories of wind and solar forecasting namely physical, statistical methods, artificial intelligence and machine learning based methods and hybrid algorithms [1–5]. The commonly used meteorological inputs

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for the prediction of wind speed are maximum, minimum and mean temperature, relative humidity, wind direction, air pressure and so on. For the estimation of solar radiation, time and location plays a main role. The models available in the literature are mathematical models [6–8], statistical models [9, 10], regressive models [11, 12], and computational intelligence based methods like artificial neural networks (ANN) [13–17], persistence method, machine learning and deep learning algorithm based models [18–24]. The forecasting methods using mathematical models have different time-scales and gives good performances for short term prediction. In Nonparametric regression method, the wind speed is predicted using linear regression model and improves the RMSE values [25]. Artificial intelligence based methods are commonly used for wind speed and solar energy forecasting [26–34]. An ARIMA model belongs to statistical methods for the forecasting of time series data. The time series ARMA model is applicable for short term wind forecasting [35]. Compared to statistical models artificial intelligence based models are good in prediction with better performance metrics. Many hybrid models are available in the literature with better prediction results [36–40]. Many researchers' reviewed different solar and wind power forecasting methods especially for renewable energy integration [1, 41–51]. Recently machine learning techniques are widely used for forecasting applications and this approach provide accurate prediction results in real world cases [52–56]. Many researchers recommended Ensemble forecasts to improve forecast accuracy of the models [57, 58]. In recent times, time series forecasting has become a popular research field [59, 60]. A deep learning neural network have been confirmed to be commanding and is producing high prediction accuracy, especially in time series forecasting [61–66]. Hybrid deep learning, hybrid models such as LSTM–CNN, DWT–CNN–LSTM and others produced more accurate forecasting results compared to conventional and other standalone artificial intelligence-based models [67–71].

2 Need for Forecsting

In India, there was a scarcity of solar radiation maps until 2008. Based on the interpolation of measured data, the India Meteorological Department (IMD) provides the Global Horizontal (GHI) maps and global data sets are available with NASA–SSE. There are 45 IMD stations in India to measure the global and diffuse components of solar radiation and most of these are situated in important cities or in the airports etc. Figure 1 shows the Indian map with radiation measuring stations of IMD, Pune.

Recently MNRE has launched a network of nationwide automatic solar and meteorological measuring stations called the Solar Radiation Resource Assessment (SRRA)

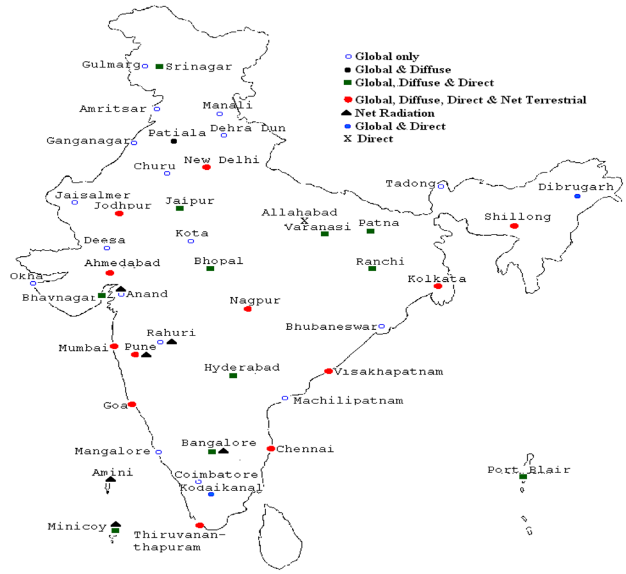

Fig. 1 Network of 45 radiation stations of IMD, India

Stations. Figure 2 shows the map showing the location of SRRA stations in India.

The instrument used for measuring wind speed is shown in Fig. 3 and measurement of radiation components by Fig. 4. The first version of satellite-based solar radiation map was released by NREL at 2009 and an updated version in 2010 which covers whole of India. Owing to high expenditure and difficulties in measurement techniques there is a short of solar radiation data in India. All the above said reasons have paid path for the demand of solar resource data for India.

The wind power is highly attractive and popular because of less pollution and higher efficiency. However, these renewable energy sources are highly intermittent and variable. This intermittent nature may leads to fluctuation of WECS power generation which results in high operating cost. Forecasting of wind power is a major concern in terms of efficient integration of WECS in the power grid [72, 73]. Many weather forecasting models are available in the literature. In spite of having the most excellent models, the top computers, the finest observation system, the most excellent instruments, and the outstanding satellites and so on, India is behind in weather prediction because of the following reasons.

The climate of India is mainly tropical. The weather systems in the tropics are fast changing and are not understood very well. Hence the complex numerical models set a great challenge for our Indian scientists. Longer the period of forecast, the more uncertainty there is. Seasonal forecast is still in the research mode. Need to undertake high-resolution modeling by incorporating local causal factors. Also difficulties in calibration and upkeep of weather instruments

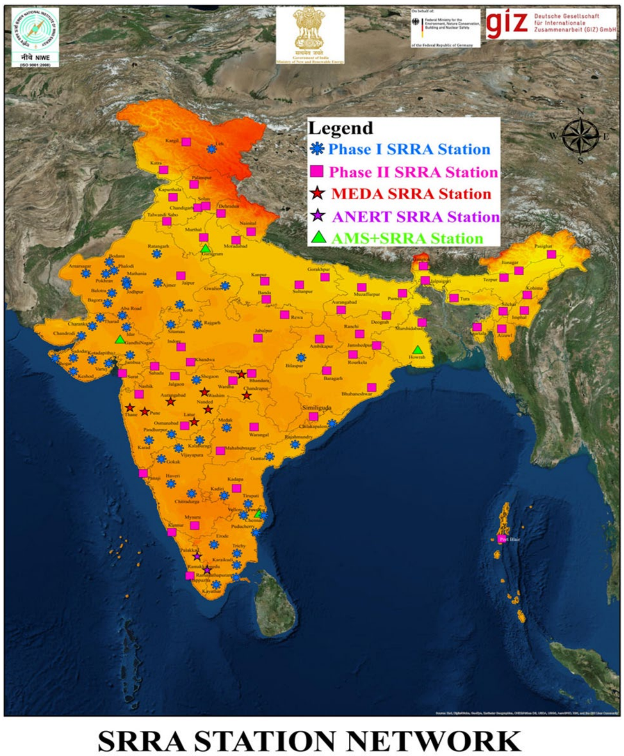

Fig. 2 SRRA station network, India

Fig. 3 Instrument for measuring wind speed

and India need more number of radars. Number of weather stations need to be increased. Deficient information affects climate adaptation policy making and implementation in India. Difficulties in understanding the physics and precursor conditions of extreme causing weather pattern and thus the conventional physics based models and numerical weather prediction (NWP) cannot reliably predict extreme events. There is a need for emerging techniques namely artificial intelligence, machine learning, and deep learning methods not only to produce forecast but also to distribute location specific information for various kind of weather systems over the targeted area.

3 Methods of Forecasting

There are three broad categories of forecasting models namely physical model, statistical and computational models and hybrid models. Figure 5 shows the classification of forecasting models. Physical methods are based on meteorological data like temperature, pressure etc. as their inputs. Statistical models are suitable for short time periods. Table 1 summarizes the time horizon based classification of forecasting models namely short term, medium term and long term forecasting.

3.1 Data Set

The common input parameters used for forecasting wind speed and solar radiation are maximum temperature (T_{max}), minimum temperature (T_{min}), mean temperature (T_{mean}), relative humidity (RH), air pressure, bright sunshine hours (S), day length (S_0), month numbers, extra terrestrial radiation (H_0), wind Speed, wind direction etc. The values of the geographical parameters like latitude, longitude, climatic classification and altitude values of the study sites are also considered for forecasting. Authors of papers [20, 21] obtained the measured parameters for the selected Indian cities namely Hyderabad, Chennai, Patna and Bhubaneswar, Nagpur, New Delhi and Mumbai from India Meteorological Department, Pune and also from Atmospheric Science Data Centre of NASA. Authors of paper [54] utilized the wind speed data at 80 m and 100 m from NREL web portal. Figure 6 shows some of the measured input parameters utilized in solar radiation prediction models. Table 2 presents an overview of solar power and wind forecasting models. The common input parameters used for forecasting wind speed and solar radiation are summarized in Table 2.

3.2 Physical Model

Physical model or deterministic method depends on physical data. This method is based on lower atmosphere or numerical weather prediction utilizing meteorological parameters such as pressure, surface roughness, temperature, and obstacles. Basically, wind speed acquired from the domestic meteorological service and transformed to the wind turbines at the wind farm is changed to wind power. The physical models are complex and time consuming.

3.3 Statistical Model

Five types of regressive model used for time series forecasting available in the literature are Autoregressive, Moving

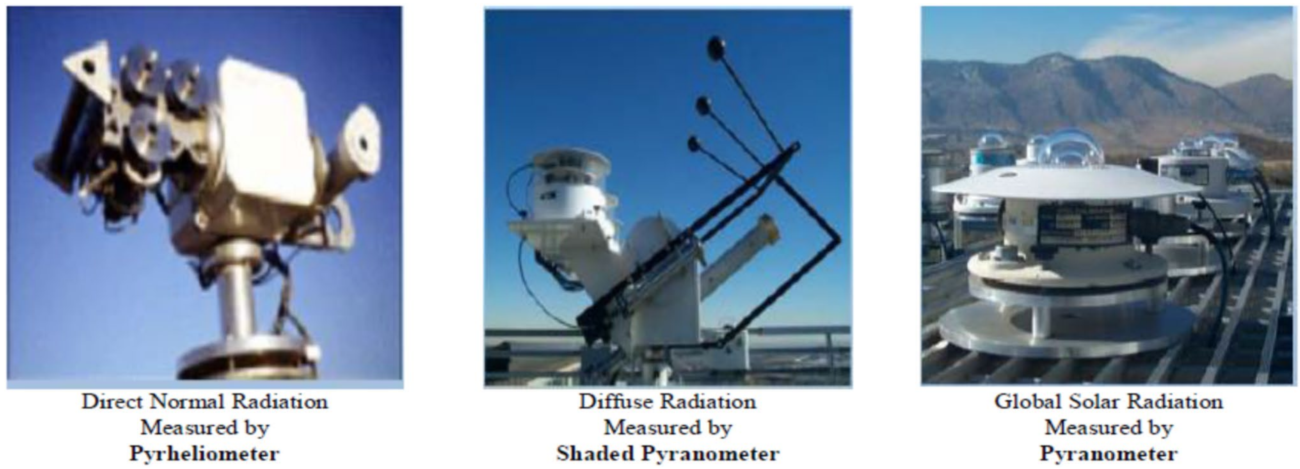

Fig. 4 Instruments for measuring solar radiation component [7]

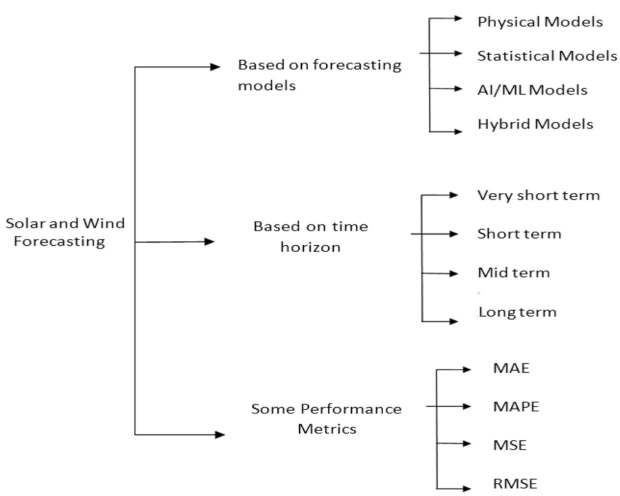

Fig. 5 Classification of forecasting models

Table 1 Time horizons in forecasting [19]

Time horizon	Range	Purpose
Short term	12–48 h ahead	Load reasonable decisions Economic load dispatch planning
Medium term	A week ahead	Generator offline/online decisions Operational security in electricity market Unit commitment decisions
Long term	A month ahead	Maintenance planning Operation management Best operating cost Wind feasibility study

average, Autoregressive moving average, Autoregressive Integrated Moving Average, and Seasonal Autoregressive Integrated Moving Average models.

3.4 Autoregressive Moving Average Model (ARMA)

A famous and commonly used statistical method for time series forecasting is the ARMA model. This algorithm is based on the concept that the details in the past historical values of the time series can only be utilized to estimate the future values. In this model the result is obtained in a short span of time with high accuracy.

$$X_t = \sum_{j=1}^{p} aX_{t-j} + \sum_{k=0}^{q} b_k e_{t-k} \tag{1}$$

The understanding of the time series X at time t relies on the linear grouping of observations of X made in the past along with e which is the moving average of the series. In the above Eq. (1), X is known as an ARMA (p, q) process, where p, q are the order of the autoregressive process of X and the moving-average error term respectively.

3.5 Artificial Intelligence Based Models

ANN is inspired by biological neural network. This model is economically profitable. The benefit of the artificial intelligence based model is that they do not need the complex mathematical calculations between the variables and offer a superior solution for different issues. The general motivation behind utilizing the tool is learning from the data. An ANN consist of three layers namely the input layer, hidden layer and the output layer. The network has a complex non linear statistical data between inputs and outputs.

The artificial neuron model is shown in the Fig. 7. x_1, x_2, x_3 are the inputs and w_1, w_2, w_3 are weights linked with the inputs respectively. An artificial neuron that collects a signal then processes it and can signal neurons associated to

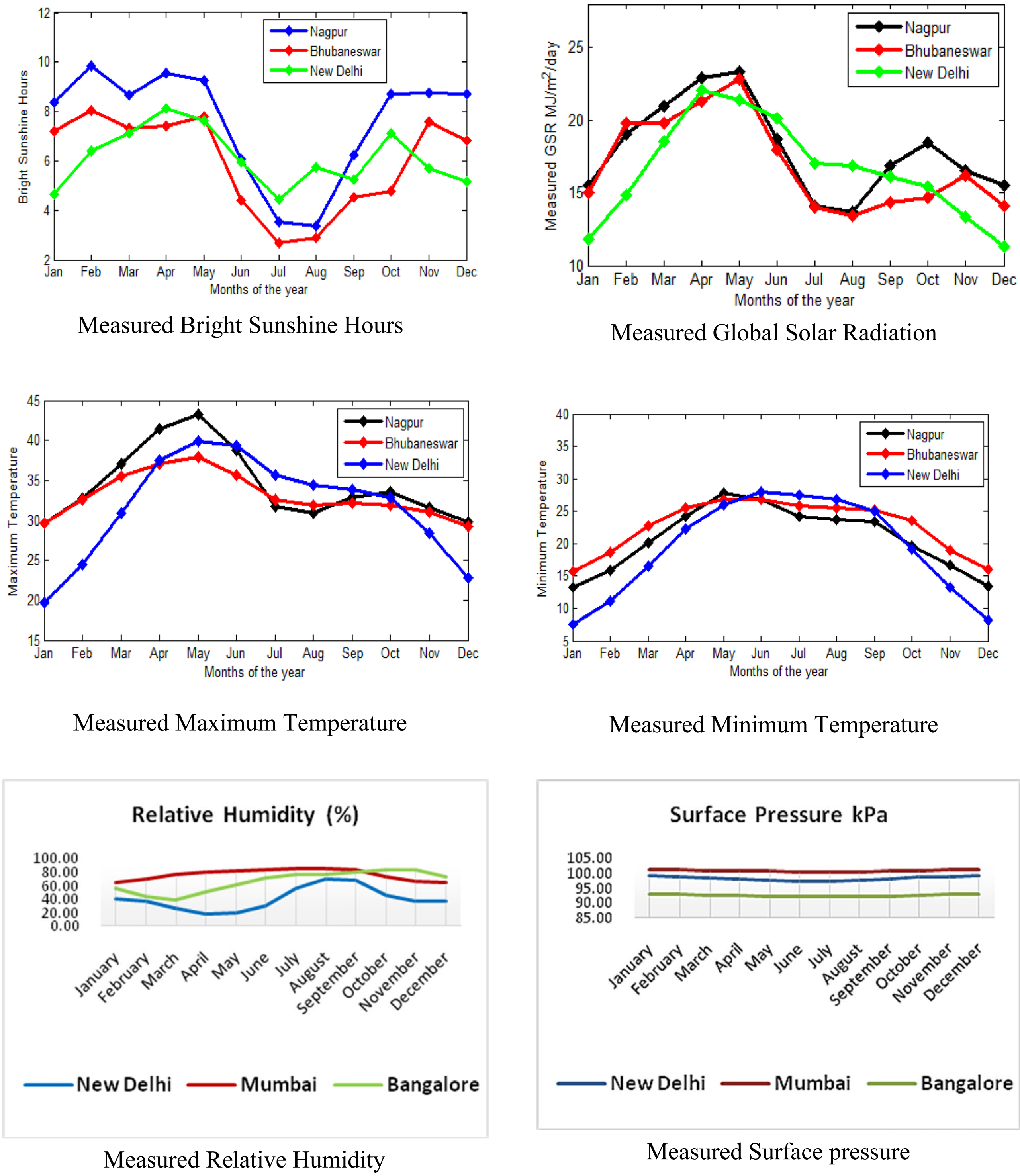

Fig. 6 Measured Input parameters used in forecasting models

it. Applications of ANN include system identification and control, image processing, prediction and forecasting, Face identification, Signal classification, etc.

Some of the important neural network types are given below.

Table 2 Overview of wind and solar forecasting models

S. no.	References/source	Research area	Input parameters	Methods	Performance metrics
1	Marović et al., 2017	Wind speed prediction using ANN model [96]	Wind speed and Wind direction Air temperature Air humidity Air pressure	Artificial neural network model	MSE—0.075 R^2—0.93
2	Ramesh and Arulmozhivarman, 2014	Forecasting of wind speed using ANN [98]	Temperature Humidity Pressure	ARMA model, ANN–BPN model, ANN–GRNN model, ANN–RBFN mode	BPN MSE—0.19 MAE—0.31 GRNN MSE—0.023 MAE—0.041 RBFN MSE—0.009 MAE—0.022
3	Lawan et al., 2018	Wind speed prediction [97]	Nine meteorological inputs and the output is wind speed	Radial basis neural network (T-RBNN)	RMSE—7.18% Covariance—0.0098
4	Sharma and Singh, 2018	Wind power and wind speed forecasting [2]	Temperature Pressure Wind direction	Artificial neural network (ANN)	NRMSE—9.49% NMAE—4.44%
5	Schicker et al., 2017	Short-range wind speed predictions [99]	Temperature Wind direction Relative humidity Pressure	Artificial neural network (ANN)	MAE—1.22 to 1.97
6	Filik and Filik, 2017	Wind speed prediction [29]	Temperature Wind speed Wind direction Weather pressure	ANN based multivariable model	RMSE—0.6 MAE > 0.5
7	Lima et al., 2017	Wind forecasting [30]	Atmospheric Pressure Air temperature	Singular spectrum analysis Artificial neural networks	ANN MAPE-17.96%
8	Guo et al., 2010	Wind forecasting [73]	Past value of wind speed	Autoregressive moving average (ARMA) GARCH model SVM	ARMA MAE—0.57 MRE—32.08 GARCH MAE—0.67 MRE—34.2 SVM MAE—0.56 MRE—32.8
9	Jiao, 2018	A hybrid forecasting method for wind speed [36]	The wind speed and wind direction data of different height	ARIMA Autoregressive Integrated Moving Average model Artificial Neural Network (ANN) model	ARIMA Model MAE—0.58 and MSE—0.63 ANN Model MAE—0.64 and MSE—0.74 HYBRID Model MAE—0.054 and MSE—0.0068
10	Zhang et al., 2014	Hybrid wind speed forecasting [37]	Temperature, humidity, pressure, wind speed and direction	SSA algorithm	RMSE—1.33
11	Ferreira et al., 2019	Short-term forecast of wind speed [6]	Air pressure, wind speed, wind direction	Artificial neural network Holt–winters (HW) Hybrid time-series models	HW RMSE—2.14 m/s MAE—1.62 m/s Hybrid RMSE—2.27 m/s MAE—1.84 m/s

Table 2 (continued)

S. no.	References/source	Research area	Input parameters	Methods	Performance metrics
12	Shukur and Lee, 2015	Daily wind speed forecasting [39]	Daily wind speed data from two meteorological stations	Hybrid AR-ANN AR-KF Models	Hybrid AR-ANN MAPE for Iraq and Malaysia 43.32 and 14.32 Hybrid AR-KF MAPE for Iraq and Malaysia were 42.22 and 15.55
13	Rozas-Larraondo et al., 2014	Wind speed forecasting [25]	The airport identifier, date and time of the observation, wind cloud cover temperature dewpoint pressure	Method based on nonparametric multivariate locally weighted regression	RMSE—2.68
14	Ehsan et al., 2019	Advanced wind speed prediction [22]	Vertical temperature Moisture	Machine learning	RMSE—0.5–0.6
15	Santamaría-Bonfil et al., 2015	Wind speed forecasting [53]	Wind speed Wind direction Humidity Solar radiation Temperature Atmospheric pressure Heat radiation	Machine learning: Support vector regression (SVR)	MASE—0.08% NMAE—14.6%
16	Akash et al., 2020	Day-ahead wind power forecasting [54]	Wind speed and corresponding power data	Multiple linear regression (MLR), decision tree (DT) and random forest(RF)	MAE—2.65 RMSE—3.38
17	Voyant et al., 2017	Solar radiation forecasting [5]	Solar radiation	Machine learning: SVM, regression trees and random forests Ensemble forecast	An improvement in RMSE by 36%
18	Karasu et al., 2017	Prediction of solar radiation [55]	Recorded wind speed, temperature, humidity parameters, pressure and solar radiation	Machine learning: linear regression and Gaussian process regression models	MAE—0.016620 MSE—0.000514 RMSE—0.022674
19	Wang et al., 2018	Solar irradiance forecasting [67]	Irradiance dataset from NREL Irradiance dataset from NOAA	Hybrid deep learning: discrete Wavelet transformation (DWT), the convolutional neural network (CNN), and long short-term memory (LSTM)	MAE CNN–LSTM—93.694 DWT–CNN–LSTM—89.503 RMSE CNN–LSTM—142.194 DWT–CNN–LSTM—139.133
20	Brahma and Wadhvani, 2020	Solar irradiance forecasting [63]	Solar iirradiance	Deep learning: LSTM models	LSTM RMSE—9.788 MSE—9.721
21	Tian et al., 2018	Short-term load forecasting [90]	Solar irradiance	Deep learning Hybrid CNN–LSTM	RMSE LSTM—1324.0463 CNN—1293.8648 CNN–LSTM—1134.1791

Table 2 (continued)

S. no.	References/source	Research area	Input parameters	Methods	Performance metrics
22	Rajagukguk et al., 2020	Solar irradiance and photovoltaic power forecasting [59]	Solar irradiance	Deep learning: RNN, CNN LSTM and Hybrid CNN–LSTM	Hybrid CNN–LSTM outperforms the stand alone models
23	Narvaez, 2021	Site adaptation and solar radiation forecasting [18]	Solar radiation	Machine learning algorithms	38% better than traditional methods
24	Meenal and SSelvakumar, 2019	Solar resource Map [20]	Minimum temperature Maximum temperature	Machine learning algorithms	R—0.9776 RMSE—0.799
25	Meenal et al., 2018	Solar Mapping of India [21]	Minimum temperature Maximum temperature	SVM Machine Learning algorithm	R—0.99 RMSE—0.422
26	Ahn and Park, 2021	Photovoltaic power short-term forecast with deep RNN model using power IoT sensors [80]	On-site weather IoT dataset and power data	Deep RNN-based forecast model	R^2-scores—0.988 and 0.949
27	Sun and Zhao, 2020	Short-term wind power forecasting using VMD decomposition, convLSTM networks [69]	Data sets obtained from two wind farms in China	VMD-ConvLSTM-LSTM	RMSE—37.45 kW MRE—0.022 kW MAE—33 kW

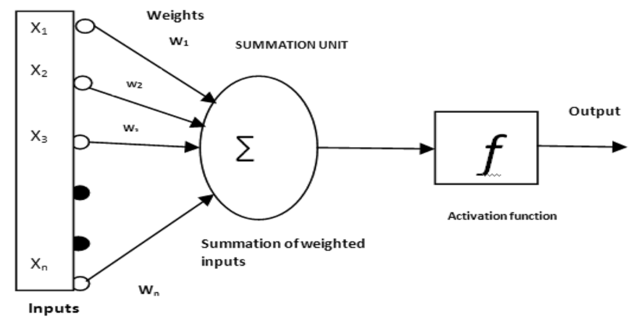

Fig. 7 Simple model of an artificial neuron

3.5.1 ANN–BPN

Back propagation networks (BPN) is more efficient through learning without huge programming. This BPN model not only learns smooth prediction but also to find short term regularity in a time series data. This model was formulated as,

$$Y_j = f\left(\sum_i w_{ij} X_{ij}\right) \tag{2}$$

In Eq. (2), *Yj* Y_j is the output of node j, w_{ij} network connections between node j and node i and X_{ij} is the input signal from node i to node j.

3.5.2 ANN–RBFN

Radial basics function network (RBFN) involves three layers input layer, hidden layer, output layer. Distinctive characteristic of this model is that the process is executed on hidden layer.

$$y_i = \sum_{k=1}^{h} \varphi_k(\|x - c_k\|) \bullet w_{ik} \tag{3}$$

$$\varphi_k(x) = exp\left(-\frac{\|x - c_k\|^2}{{\delta_k}^2}\right) \tag{4}$$

where $x = [x1, x2, \ldots, xn]$ is an input vector, n is the number of input nodes, c_k is the kth center node in the hidden layer, $k = 1, 2, \ldots, h$, h is the number of hidden nodes. $\|x - ck\|$ denotes the Euclidean distance between ck and the input vector x. wik is the weight between hidden layers and output nodes.

3.5.3 ANN–GRNN

Generalized neural network (GRNN) is different from other classical neural network and its estimation is based on the probability density function. The main drawback of this model is amount of computation required for finding the signal from training. This model is given by the following Eq. (5),

$$(x) = E\left[y/x\right] = \frac{\sum_{i=1}^{n} y_i exp\left(d_i\right)}{\sum_{i=1}^{n} exp\left(d_i\right)} \tag{5}$$

where x, y are the actual observed values of input X and output Y respectively and di is the distance function between input vectors and centers recorded in pattern nodes.

$$d_i = \frac{\left(x - x_i\right)^T \left(x - x_i\right)}{2\sigma^2} \tag{6}$$

σ is the smoothing factor in Eq. (6).

3.6 Activation Functions

The exact output is achieved in ANN with the help of activation functions. The activation function is also known as transfer function. There are two types of activation function namely the linear and non-linear activation functions. The most widely used activation function is the nonlinear activation function which is applied to make convinced that a neuron's response is bounded. Various activation functions are given as identity function, ReLu function, hyperbolic tangent function, binary step function, logistic activation function and ramp function.

The disadvantages of ANN are:

- Requires huge training time for a big dataset.
- Very complicated optimization step.
- The accuracy of artificial neural network changes for each and every simulation.
- Local minima problem

Artificial intelligence and statistical models are used to estimate the solar radiation for Indian states [21]. The architecture of the artificial neural network model used is shown in Figs. 8 and 9 presents the comparison of predicted radiation using statistical and ANN model with the observed value of monthly mean daily solar radiation for Indian cities namely Hyderabad, Chennai, Patna and Bhubaneswar. Authors concluded that artificial intelligence based models performed better than the statistical models [100, 101].

3.7 Machine Learning Models

Machine learning is the branch of study that gives computers the ability to learn from data without being clearly programmed. It is the branch of artificial intelligence in which the model can learn by itself with the given data to make decision and to predict new or future data. Every field like medical, banking, government, transportation, forecasting etc. are using machine learning models for their various purpose. Regression, random forest, support vector machine, decision tree, k-means, logistic regression, naïve bayes, k nearest neighbour, etc. are some of the algorithms in machine learning. The following are some of the models which are used for the prediction of wind speed.

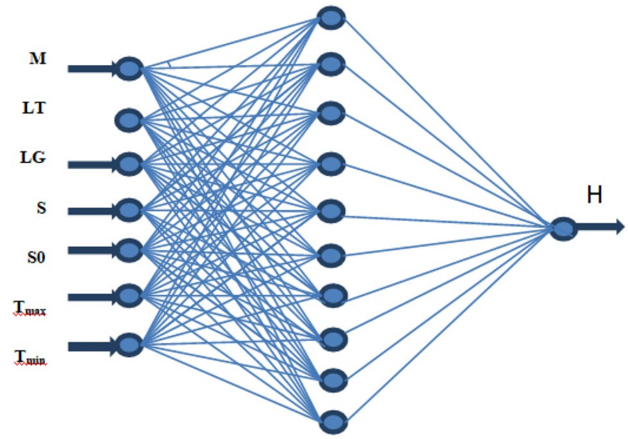

Fig. 8 Architecture of the ANN model [21]

3.7.1 Random Forest Machine Learning

Random forest is an ensemble algorithm developed by Breiman [74]. This algorithm is based on decision tree predictors. The block diagram of decision tree is shown in Fig. 10. Random forest classification algorithm is applicable for the analysis of huge data sets. This algorithm is very famous because of higher accuracy in prediction results and presents information on the importance of parameters for classification. Random forest tree diagram is shown in Fig. 11. This algorithm does not require complex training procedures like artificial neural network or support vector machine. The main variable to adjust is the number of trees. Also training is faster with RF algorithm compared with ANN and SVM. RF machine learning models are also robust to outliers and noise if sufficient number of trees is used. Figure 12 shows the India Map with the predicted Annual global solar radiation in MJ//m^2/day and Tami Nadu Solar Resource Map using Random forest machine learning technique [95]. Figure 13 shows the day-ahead forecast of wind power using random forest machine learning technique for the NREL sites at 80 m and 100 m heights [54].

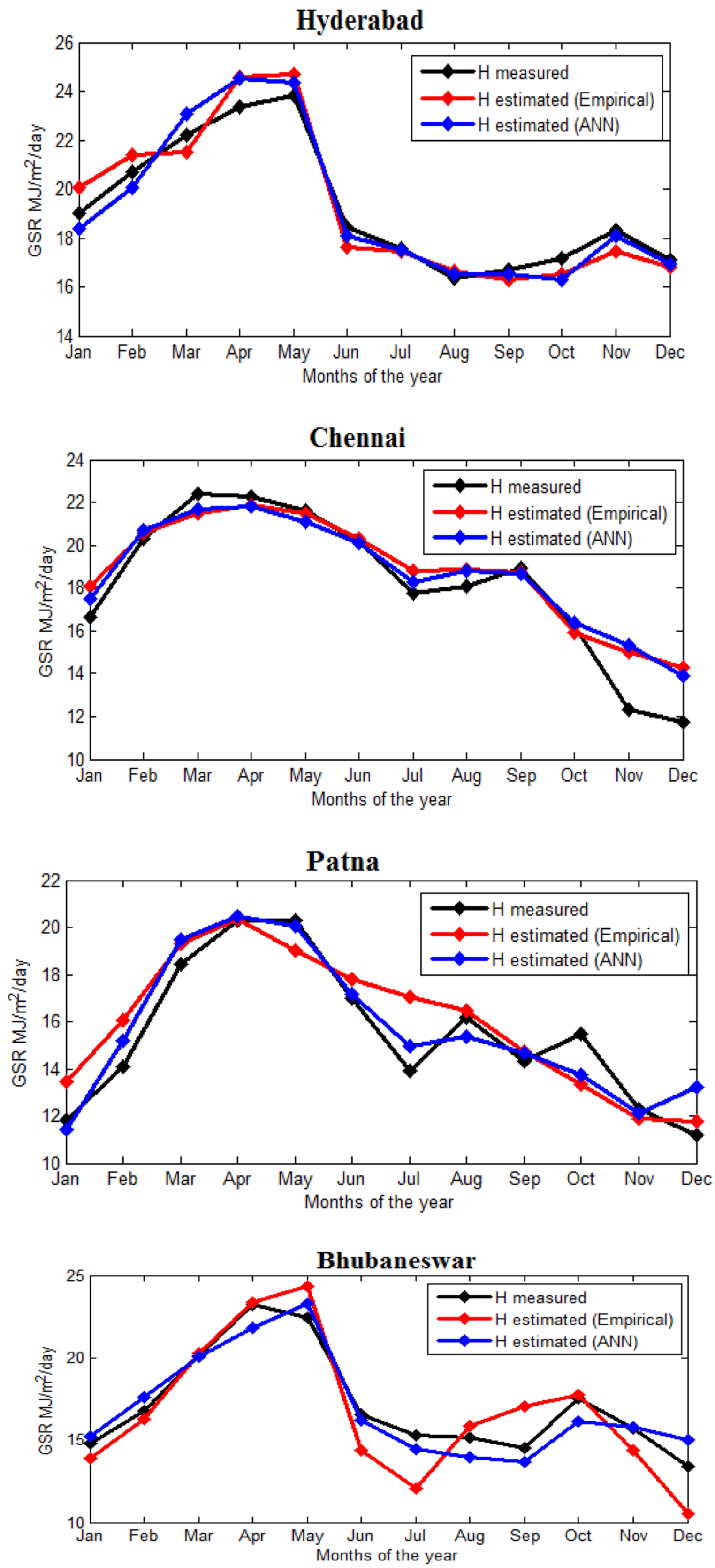

Fig. 9 Comparison of regressive and ANN model with measured monthly mean daily GSR [21]

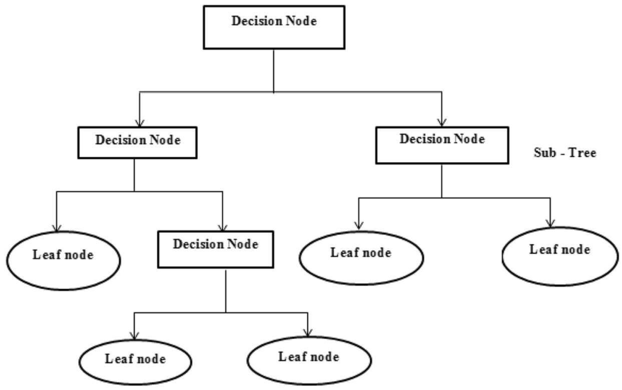

Fig. 10 Block diagram of decision tree [54]

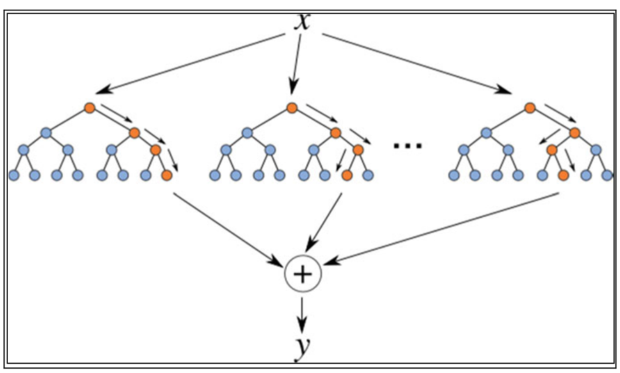

Fig. 11 Random forest—tree diagram [54]

3.7.2 Quantile Regression Forest (QRF)

Quantile regression forest (QRF) is an extension tree model which gives high accuracy. Higher the number of trees will reduce the over fitting and also decreases the correlation between trees.

$$\hat{F}(y|X = x) = \sum_{i=1}^{n} w_i(x) 1_{\{y_i \leq y\}} \tag{7}$$

where w_i *weights*, n is the sample size, and time step i = 1, …, n.

3.7.3 Bayesian Additive Regression Trees (BART)

Bayesian additive regression trees (BART) is averaging of a single tree model. Predictions are calculated to find the probability of distribution of errors. Prediction samples are validation data sets. Comparing this two models in machine learning approach QRF model is better than BART based on error results.

$$Y = \left(\sum_{j=1}^{m} g\left(x; T_j, M_j\right) \right) + \epsilon, \in \sim N\left(0, \sigma^2\right) \tag{8}$$

T_j is the Jth binary tree structure and M_j = {µ1j, …, µbjj} is the vector of terminal node parameters associated with T_j, m is constant, σ^2 is the residual variance.

3.7.4 Support Vector Machine (SVM)

SMOreg is a regression algorithm implements the support vector machine SVM belongs to the supervised machine learning category. It is applicable for both classification and regression problems. It was developed by Vapnik in 1995 [75].

Given a set of data points

$$G = \left\{ \left(x_i, d_i\right) \right\}_{i}^{n} \tag{9}$$

(x_i is the input vector, d_i is the preferred value and n is the size of the data). The function is approximated by the SVM using the following form:

$$f(x) = w\phi(x) + b \tag{10}$$

In the above equation, $\varphi(x)$ is the high dimensional feature space. This is mapped from the input space and the coefficients namely x. w and b are estimated by minimizing the regularized risk function.

SVM machine learning technique is used for predicting solar radiation [21]. Authors proved that SVM based prediction is more accurate than the conventional forecasting models. Figure 14 shows the Scatter plots which presents the comparison between measured and predicted solar radiation using SVM ML technique for the Indian locations.

4 Performance Metrics of the Models

The wind speed forecasting models predict the future events and there are different techniques available. These techniques have their own merits and demerits. There are several models available in the real time and it is a challenge to select a suitable model for our case. The selected model should perfectly fit for our data in order to predict the data. The following performance metrics are used to determine the model accuracy.

4.1 RMSE—Root Mean Square Error

It is used to predict errors from the residuals and also is a measure of how far these residuals are spread. The RMSE expression is given by

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{\left(x_i - \hat{x}_i\right)^2}{n}} \tag{11}$$

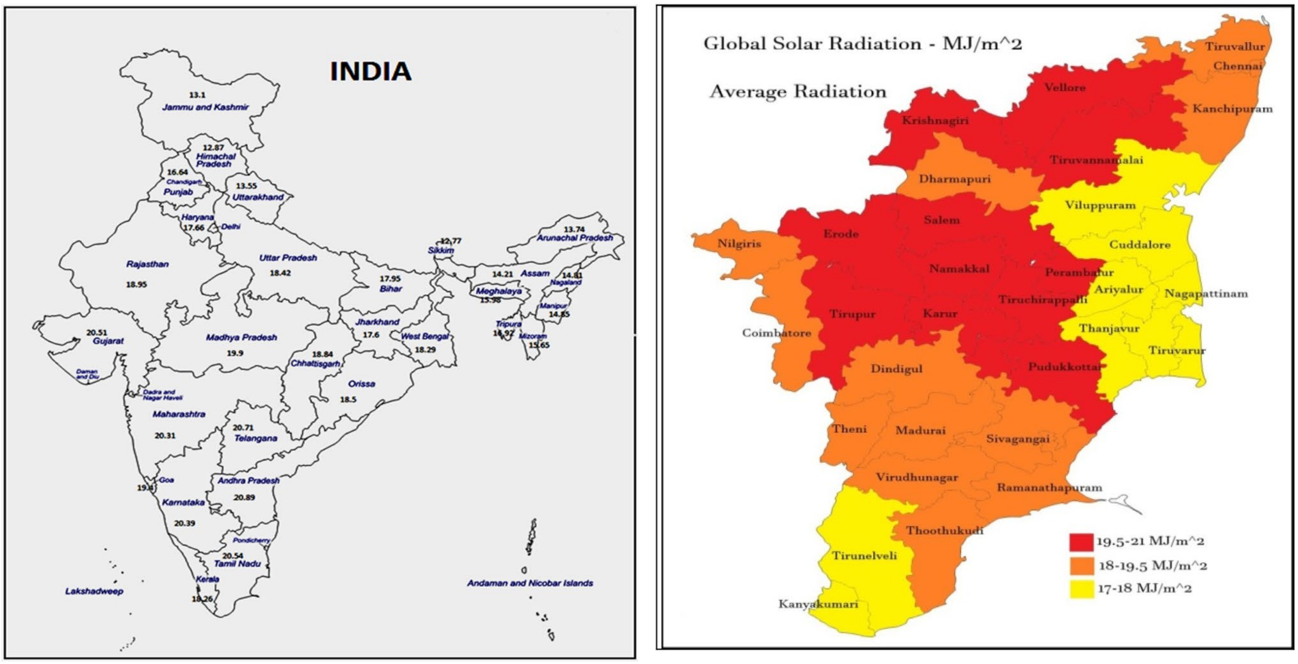

Fig. 12 India map with the predicted Annual global solar radiation in MJ//m^2/day and Tami Nadu Solar Resource Map using Random forest machine learning technique [95]

4.2 MAE—Mean Absolute Error

MAE is the deviation between predicted output and the measured actual output. It is less sensitive to outliers. MAE is given by,

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|x_i - \hat{x}_i\right| \tag{12}$$

4.3 MAPE—Mean Absolute Percentage Error

MAPE is easy to interpret. It can be used only when large volume of data is available. MAPE often take on extreme values. It is calculated as,

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\frac{\left|x_i - \hat{x}_i\right|}{\hat{x}_i} \tag{13}$$

where xi' is the actual value, x_i is the predicted value and n is the sample size of the data.

4.4 Correlation Coefficient (R)

Correlation Coefficient (R) is used to measure the degree of linear relationship between the predicted value and the actual value. The model is fine if the correlation coefficient value is nearer to one.

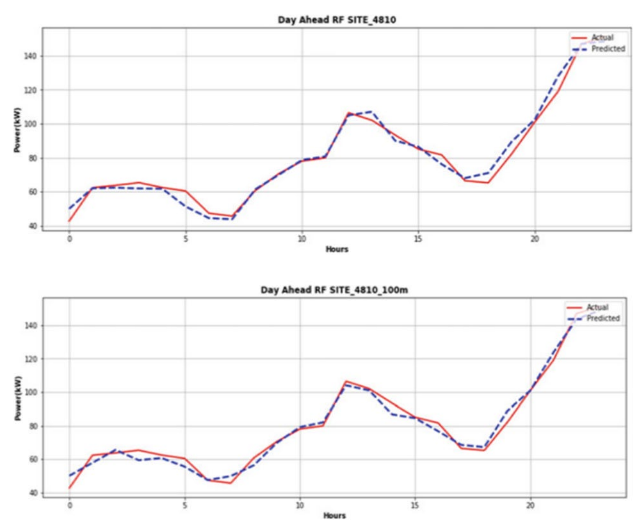

Fig. 13 Day-ahead forecast of wind power using Random Forest algorithm for the NREL site at 100 m and 80 m height [54]

4.4.1 Comparison of Various Forecasting Models

Table 3 summarizes the prediction results of various models used for the prediction of the solar radiation. From the table, it is found that artificial intelligence based models are superior to the statistical models. Machine learning based models are more accurate. In machine learning category; Random

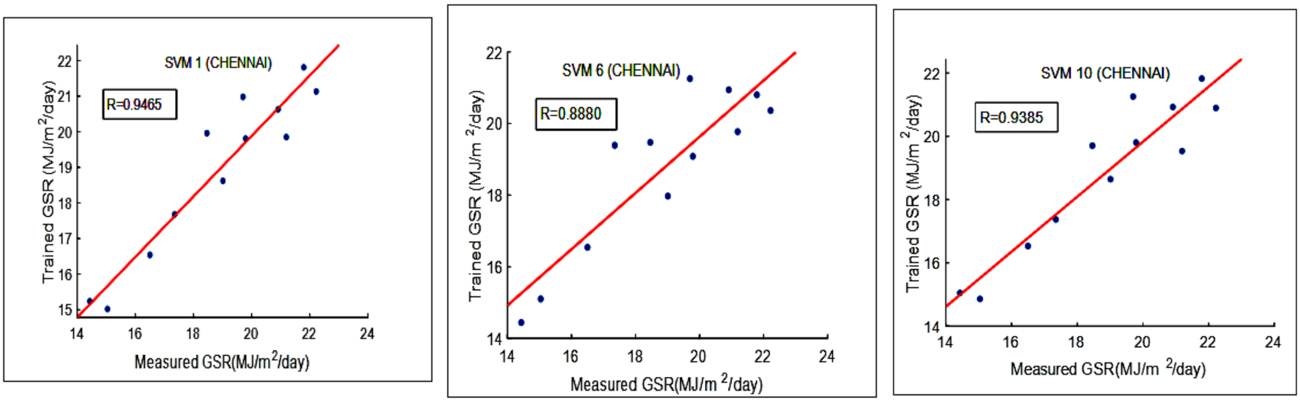

Fig. 14 Scatter plots presents the comparison between the actual and predicted solar radiation using SVM ML technique [21]

Table 3 Comparison of various weather prediction models [20]

Forecasting model/location Chennai	R	RMSE
Statistical model $\frac{H}{H_0} = \left(a + b\left(\frac{T_{min}}{T_{max}}\right)\right)\left(\frac{T_{min}}{T_{max}}\right)^c$	0.8078	1.58
Artificial Neural network	0.9043	1.12
Machine learning models		
Simple linear regression	0.7011	1.76
M5 model tree ML algorithm	0.7987	1.52
Support Vector Machine	0.9706	1.16
Random forest ML algorithm	0.9700	0.75

forest algorithm produced higher accuracy. Solar radiation is predicted for all Indian states using random forest machine learning algorithm without using the costly pyranometer. The correlation coefficient value approaches one (0.9700) in both SVM and random forest machine learning models. The RMSE value is very less in RF ML model.

4.5 Deep Learning Models

Currently, another solution for estimating the solar energy with better accuracy is possible by adapting the models using deep learning techniques. Deep learning models are used for various applications like stock predictions, forecasting and other fields like medical, banking and other government applications [76–79]. The model using deep learning techniques are applicable for managing time-series data and are addressed in various literatures is discussed here. Recurrent Neural Network (RNN) [80–86], Long Short-Term Memory (LSTM) [87, 88], and Convolutional Neural Network (CNN) [89], hybrid models such as CNN–LSTM models are distinctive [90–94]. The deep learning models are applied for solar and wind forecasting. Many researchers utilized the wind speed data set of the NREL sites for the forecasting of wind speed and power. Regressive model, artificial intelligence and LSTM models are evaluated for long term 1 month wind speed forecasting for various NREL sites [33]. Figure 15 shows the wind speed data for the NREL site at 80 m and 100 m hub heights. Long-term forecasting of wind speed using LSTM is shown in Fig. 16. It is proved that the LSTM outperforms the ARIMA and ANN based log term forecasting of wind speed. Convolutional networks are more suitable to high-dimensional data sets. In order to eliminate the redundancy and to get the real features using the CNN, the input data set are compressed. Amongst the three mentioned deep learning models, with regard of performance metrics such as root-mean-square error (RMSE), LSTM based forecasting gives the outstanding prediction results. Figure 17 shows the block diagram of CNN–LSTM based forecasting model [92]. The hybrid model (CNN–LSTM) gives more accurate forecasting compared to the three standalone models namely RNN, CNN and LSTM. Thus, the inference is that the deep learning neural networks are more appropriate for forecasting solar radiation and wind speed compared to the other existing machine learning algorithm based models.

5 Conclusion

This paper presented an overview of current and new development of weather forecasting such as solar and wind forecasting techniques for renewable energy system in smart grid. Many forecasting methods like physical models, statistical models, artificial intelligence based models, machine learning and deep learning based models were discussed. Also hybrid models like CNN–LSTM models were discussed which have their unique feature and performance. Artificial Intelligence and Machine learning based techniques are widely used for renewable energy forecasting. As the renewable energy sources are highly intermittent, all weather forecasting models contain errors. Artificial intelligence based model outperforms the statistical and physical

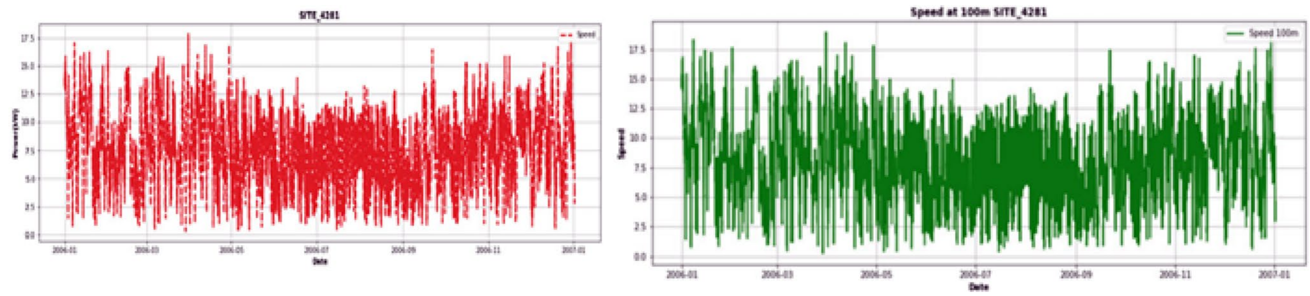

Fig. 15 Wind speed data set for the NREL Site_4281 at 80 m and 100 m hub heights [19]

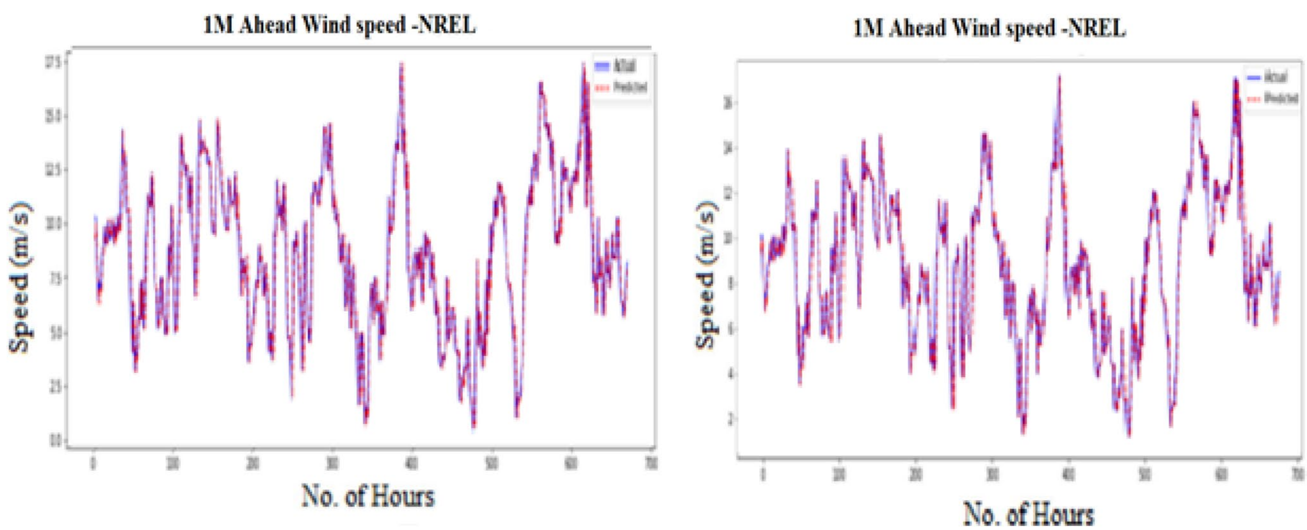

Fig. 16 Long-term forecasting of wind speed using LSTM–NREL Site at 80 m and 100 m hub heights [19]

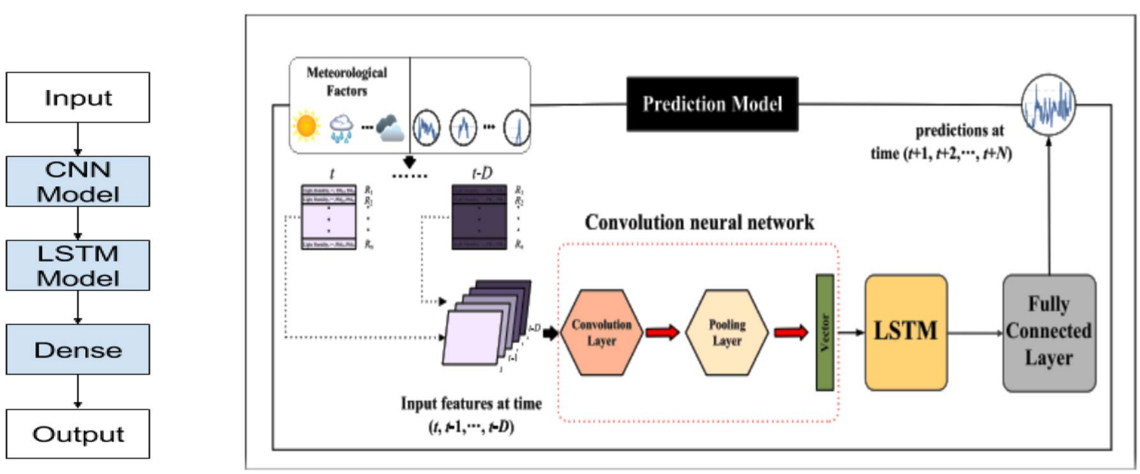

Fig. 17 Block diagram of CNN–LSTM based forecasting model [92]

forecasting models. But artificial intelligence based models require huge training time for a large data set. Also ANN gives different prediction result for each and every simulation. Compared to artificial intelligence based models, machine learning model like SVM gives a unique solution because of the convex optimality problem. This is the significance of machine learning model, when compared with ANN. Ensemble methods helps improve machine learning results by combining multiple models. Using ensemble methods allows producing better predictions compared to a single model. Deep learning networks such as CNN are more suitable to high-dimensional data sets and can produce accurate forecasts. Another big advantage of the CNN is that the complexity of this prediction model was very much reduced, because the convolutional neural networks use shared weights, LSTM can learn meaningful information from the past historical data by using the memory cell, while the useless unnecessary information will be forgotten by using the forget gate. LSTM outperform traditional-based algorithms such as ARIMA model and also artificial intelligence based model. Deep learning methods based forecasting model can replace the traditional climate models with significant reduction of simulation time without adjusting the predictive accuracy. To conclude, machine learning and deep learning methods based climate model with MSE ranges from 0.075 to 0.7 can replace the traditional methods to drastically decrease the simulation time without compromising the reliability and predictive accuracy. Also the deep learning neural networks produce reasonable weather forecasts despite having no clear understanding of atmospheric physics. This review paper will give hopefully a new research direction in weather forecasting using machine learning techniques.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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