

Received November 29, 2021, accepted December 17, 2021, date of publication December 22, 2021, date of current version January 5, 2022.

Digital Object Identifier 10.1109/ACCESS.2021.3137419

Critical Review of Data, Models and Performance Metrics for Wind and Solar Power Forecast

V. PREMA¹, (Senior Member, IEEE), M. S. BHASKAR², (Senior Member, IEEE),
DHAIFER ALMAKHLES², (Senior Member, IEEE), N. GOWTHAM³, (Senior Member, IEEE),
AND K. UMA RAO⁴, (Senior Member, IEEE)

¹Department of Electrical and Electronics Engineering, B.M.S. College of Engineering, Bengaluru 560059, India

²Renewable Energy Laboratory, Department of Electrical Engineering, College of Engineering, Prince Sultan University, Riyadh 11586, Saudi Arabia

³Department of Electrical and Electronics Engineering, Vidyavardhaka College of Engineering, Mysuru 570002, India

⁴Department of Electrical and Electronics Engineering, R.V. College of Engineering, Bengaluru 560059, India

Corresponding authors: V. Prema (prema.v.eee@bmsce.ac.in) and M. S. Bhaskar (sagar25.mahajan@gmail.com)

This work was supported by the Renewable Energy Laboratory (REL), Department of Communications and Networks Engineering, College of Engineering, Prince Sultan University, Riyadh, Saudi Arabia. The Article Processing Charges (APC) of this publication is paid by Prince Sultan University, Riyadh, Saudi Arabia.

ABSTRACT Global climatic changes and increased carbon footprints provided the main impetus for the decrease in the use of fossil fuels for electricity generation and transportation. Matured manufacturing technologies of solar PV panels and on-shore and off-shore windmills have brought down the cost of generation of electricity using solar energy on par with conventional fossil fuel. Initially, solar and wind power generation was envisioned for microgrids, serving small local communities. However, advancements in power electronics have now facilitated large solar and wind farms to be integrated with main power grids. In this context, hosting capacity, which is the amount of distributed energy resources a grid can accommodate, without significant infrastructure up-gradation, has gained importance. In determining the hosting capacity at a particular location, the uncertainties of wind and solar power generation play a role. Effective forecasting models using time-series weather data can be built to predict wind and solar power generation. This forecast is essential to ensure proper grid operation and control when renewable energy sources are already installed. The forecast is also useful in the planning stages for investment decisions and distribution system planning. While long-term forecasts are rarely needed for the operation of integrated grids, accurate short-term predictive models are necessary for scheduling. This paper presents an extensive review of various forecast models available in the literature. The study mainly focuses on the short-term forecast, providing a critical review of the duration of data used in each model and a synoptic comparison of their performance indices.

INDEX TERMS Forecast techniques, forecast models, solar power, wind power.

NOMENCLATURE

<i>ACF</i>	Auto correlation function.	<i>DoE</i>	Design of Experiments.
<i>ANFIS</i>	Adaptive Network Based Fuzzy Inference System .	<i>EEMD – MLP</i>	Ensemble Empirical Mode Decomposition-Multi-layer Perceptron.
<i>ANN</i>	Artificial Neural Network.	<i>EEMGLSTM</i>	Ensemble Empirical Mode Decomposition-Long Short Term Memory Network.
<i>ARIMA</i>	Autoregressive Integrated Moving Average.	<i>EMD</i>	Empirical Mode Decomposition.
<i>ARMA</i>	Autoregressive Moving Average.	<i>FNN</i>	False Nearest Neighbour.
<i>AR</i>	Auto Regressive.	<i>GNN</i>	Generalized Neural Network.
<i>CART</i>	Classification and Regression Trees.	<i>GWe</i>	Gigawatt Electrical.
<i>CCRF</i>	Continuous Conditional Random Fields.	<i>LASSO</i>	Least Absolute Shrinkage and Selection Operator.
		<i>LM</i>	Levenberg-Marquardt.
		<i>LSSVM</i>	Least Square- Support Vector Machine.

The associate editor coordinating the review of this manuscript and approving it for publication was Akin Tascikaraoglu¹.

<i>MAE</i>	Mean Absolute Error.
<i>MAPE</i>	Mean Absolute Percentage Error.
<i>MA</i>	Moving Average.
<i>MOS</i>	Model Output Statistics.
<i>NARX</i>	Non-linear Autoregressive Network With Exogenous Inputs.
<i>NMAE</i>	Normalized Mean Absolute Error.
<i>NRMSE</i>	Normalized Root Mean Square Error.
<i>NWP</i>	Numerical Weather Prediction.
<i>PACF</i>	Partial Auto Correlation Function.
<i>PCA</i>	Principle Component Analysis.
<i>PSO</i>	Particle Swarm Optimization.
<i>PSO</i>	Particle Swam Optimization.
<i>PV</i>	Photo Voltaic.
<i>RBF</i>	Radial Basis Function.
<i>RF</i>	Random Forest.
<i>RMSE</i>	Root Mean Square Error.
<i>SAX</i>	Symbolic Aggregate Approximation.
<i>SA</i>	Simulated Annealing.
<i>SMAPE</i>	Symmetric Mean Absolute Percentage Error.
<i>SMA</i>	Seasonal Moving Average.
<i>SVM</i>	Support Vector Machine.
<i>VMD</i>	Variational Mode Decomposition.
<i>WNN</i>	Wavelet Neural Network.
<i>WRF</i>	Weather Research and Forecast.

I. INTRODUCTION

The energy demand of the earth's population is humongous and is expanding in mammoth proportions, with the current annual energy consumption being approximately 25 kTWh. The current trends indicate a doubling of this by 2050 and by the end of the century, it is expected to triple. Two scenarios may be considered easing this threat - carefully use the energy or find alternative energy sources [1]. Current dependencies on fossil fuels would lead the human population to an acute energy crisis. The continued use of the dwindling fossil fuels and their associated harmful effects like pollution and greenhouse gas emissions with resultant climate change, render them less acceptable and reliable as energy sources for the future. These factors pose some of the daunting challenges to humanity to identify and employ cleaner and greener energy sources that could satisfy and sustain the demand for the future [2], [3]. The prohibitive costs in consideration of the quantum of production limit the employment of the currently known sources of green energy as a viable alternative to conventional sources, though the gap is slowly diminishing. Among the renewable energy sources, solar and wind energy are immensely promising for electric power generation and have the potential to ensure a sizeable contribution to the electrical energy demand of the planet. Both these sources are practically inexhaustible, freely available, and involve no polluting residues or greenhouse gas emissions [4]. However, solar and wind energy are sources that depend on weather conditions, which carries an element of uncertainty. Though solar power production

has a fairly predictable pattern, wind power is intermittent, unreliable, [5], [6] and highly erratic [7]. This poses a major threat to the reliability of power dispatch. This causes high accuracy forecasts to be performed on multiple time horizons [8]. Forecasting tools help in the reduction of deviations between the schedule and the actual dispatch at the load dispatch centers [9]. The power produced by solar PV panels depends primarily on solar irradiance, which exhibits a specific pattern. The magnitude of irradiance is zero through the night and starts increasing with sunrise. It reaches its peak in the afternoon and then slopes down, reaching a near-zero with sunset, thus following a periodic pattern every day. The magnitude of irradiance may vary depending on the weather conditions while retaining the pattern [10]. There can also be variations due to the intervention of clouds. De Giorgi *et al.* [11], developed multi-regression and ANN models for solar irradiance prediction. A sensitivity analysis using regression models has been performed to estimate the impact of different input parameters, such as module temperature, ambient temperature, and irradiance on the modules for different tilt angles. The result showed a high impact of irradiance on PV power. Benganem and Joraid [12], estimated the relation between different parameters like global irradiance, diffuse irradiance, and temperature. This helped in evaluating the potential of solar energy in Medina, Saudi Arabia. The measured and estimated values are in good agreement. Ruiz Ariaz *et al.* [13], proposed a new regression model for the prediction of hourly solar irradiance. The model considers the clearness index and relative optical mass. Dong *et al.* [14], proposed a prediction of solar irradiance using a state-space exponential smoothing model. Before applying this model, the data is stationeries using the Fourier trend model. The performance is compared with other time series forecasting models, such as ARIMA, single exponential smoothing, random walk model, etc. [15].

Power generation from wind is highly susceptible to climatic variables viz. geographical location, wind speed and its direction, seasonal changes, time of the day, etc. A uniform efficiency cannot be warranted for a particular forecasting method across different geographies [16]. Hence it is critically essential to examine the seasonality and other influencing parameters to determine the best fit model for the location [17], [18] Literature provides a good number of options for forecast such as statistical models, intelligent models, etc. Reference [19]–[21] give a detailed review of diverse methods to forecast wind power. The authors have also enunciated the directions for developing forecast models. It is specified that a combination of physical and statistical models can be more effective in prediction. In [22], a model is proposed which integrates wind direction with other input parameters to form a mixed ARMA model. The inter-dependencies between wind speed and wind direction are investigated by K-Mean clustering. A hybrid model using ARIMA-GARCH and wavelet are proposed in [23]. The outliers in wind speed data are filtered out using wavelet decomposition, followed by modeling with the ARMA-GARCH model. In [24],

ANN and Bayesian algorithms are employed to propose a 2-step prediction. This methodology could achieve MAPE ranging from 14 to 18 percentage with the analysis done at two different sites.

Artificial Neural Networks (ANN) are gaining significant acceptance in recent times for renewable energy forecasts as they overcome certain shortfalls of time series models [25]–[27]. ANN is a self-learning network, which can learn from the given data during the process of training. A well-trained neural network can be made to behave as required. A network is formed with a set of neurons organized in different layers. The bottom layer has the predictors (inputs) and the top layer contains forecast (outputs). A series of known inputs and outputs are fed to the system. At each step, the output of the system is compared with the actual output and the error is propagated backward through the network. When the training is completed with a sufficient amount of data, the network will be capable of predicting the future. Thus ANN is a very good tool for prediction as it can be trained using historical data to predict future values [28], [29]. The input data set is split into three, each one for training, validation, and testing, while training recurrent networks. The network bias values and weights are corrected using the data set for training in the training algorithm, to minimize the error. The corrections are completed using the validation set. The trained network is finally evaluated for performance on the test data set.

In the past few decades, hundreds of models have been proposed in the literature to predict solar and wind power generation. An exhaustive comparison of all these models is limited in the literature. In this paper, the authors have attempted to analyze the existing models in renewable generation forecasts. A comprehensive comparison of the data, models, and their performances is presented. The paper is organized as follows. The installation capacity of solar and wind power is briefed in section II. Various forecasting techniques are illustrated in section III. A review of statistical models for solar and wind power forecast is discussed in sections IV and V respectively. Section VI summarizes machine learning techniques used for the short-term forecast. A review of machine learning models for wind and solar power forecast is discussed in sections VII and VIII respectively. Section IX comments on the concluding remarks and the future of short-term prediction for solar and wind power forecast.

II. SOLAR AND WIND ENERGY- INSTALLED CAPACITY

Solar energy is the biggest non-carbon energy source. The energy obtained from solar radiation that is incident on Earth per hour (4.3×10^{20} J) is much higher than the planet's consumption in one year (4.1×10^{20} J). Solar electrical production and supply is a 7.5-billion-dollar industry with an annual growth rate of 35-40% globally. The potential of solar power is clear from the fact that an energy equivalent to 20,000 GW nuclear mission plants, which is equivalent to twice the consumption of the world from fossil fuels, could be

supplied by coverage of 0.16% of the land on earth with solar conversion systems of 10% efficiency. Sun could virtually prove as an unlimited source of energy which dwarfs the capability of achievement by human technology.

Wind energy is another clean, eco-friendly source that is abundant. The advantage of wind energy is that power generation from it is easily scalable. Wind energy has an enormous offering to renewable power generation. This is clear from the studies that operating 20% rated capacity of 2.5 MW turbines restricted to warm, rural, and non-forested areas can exceed the cumulative global consumption of energy by 5-fold and that of electricity alone by 40 times. Off-shore wind capacity is also colossal. Studies indicate it could serve the energy demand of Europe seven times over and the energy demand of United States four times over.

A. GLOBAL SCENARIO

The installed capacity of solar PV globally has reached approximately 627 GW, which was 67 GW at the end of 2011, which was only 1.5 GW in 2000. The annual average growth rate of solar PV over the past five years is around 73%. The major contributors to this growth are only a few countries [30]. The top five countries with a cumulative installed PV capacity of 15 GW or above are China (207.4 GW), European Union (131.7 GW), the USA (75.9 GW), Japan (63 GW), and Germany (49.2 GW). 80% of the total global capacity is due to these countries as shown in Fig. 1. Country including Greece, India, Australia, France, Korea, and Portugal are gaining momentum due to economic support schemes and new policies. There has been tremendous growth in wind power production in the past 15 years [31]. According to the statistics provided by Global Wind Energy Council, the worldwide wind energy capacity was 17.4 GW in the year 2000. By the end of 2019, it became 650.5 GW. The top 5 countries in wind production at the end of the year 2019 are China (236.4 GW), European Union (192 GW), Germany (61.36 GW), USA (105.45 GW), and India (37.5 GW). Other countries emerging in wind generation are Brazil, France, United Kingdom, Spain, and Italy. Fig. 2 shows the wind generation capacity of different countries in the last 3 years.

B. INDIAN SCENARIO

Being a tropical country, India has a greater potential to tap solar energy. The PV industry in India is large and diversified. There are ten major solar cells, panels, and complete PV systems manufacturers, and around 50 different assemblers. These companies supply around 200 MW per year of 30 different types of PV systems in rural, remote areas, and industrial categories. The Ministry of New and Renewable Energy (MNRE) has started several new schemes and incentives which have provided new momentum to the growth of PV installations in India. The total PV installed capacity has quadrupled in the last four years. The total installed capacity from May 2014 to April 2017 is increased from 2.26 GW to 12.28 GW.

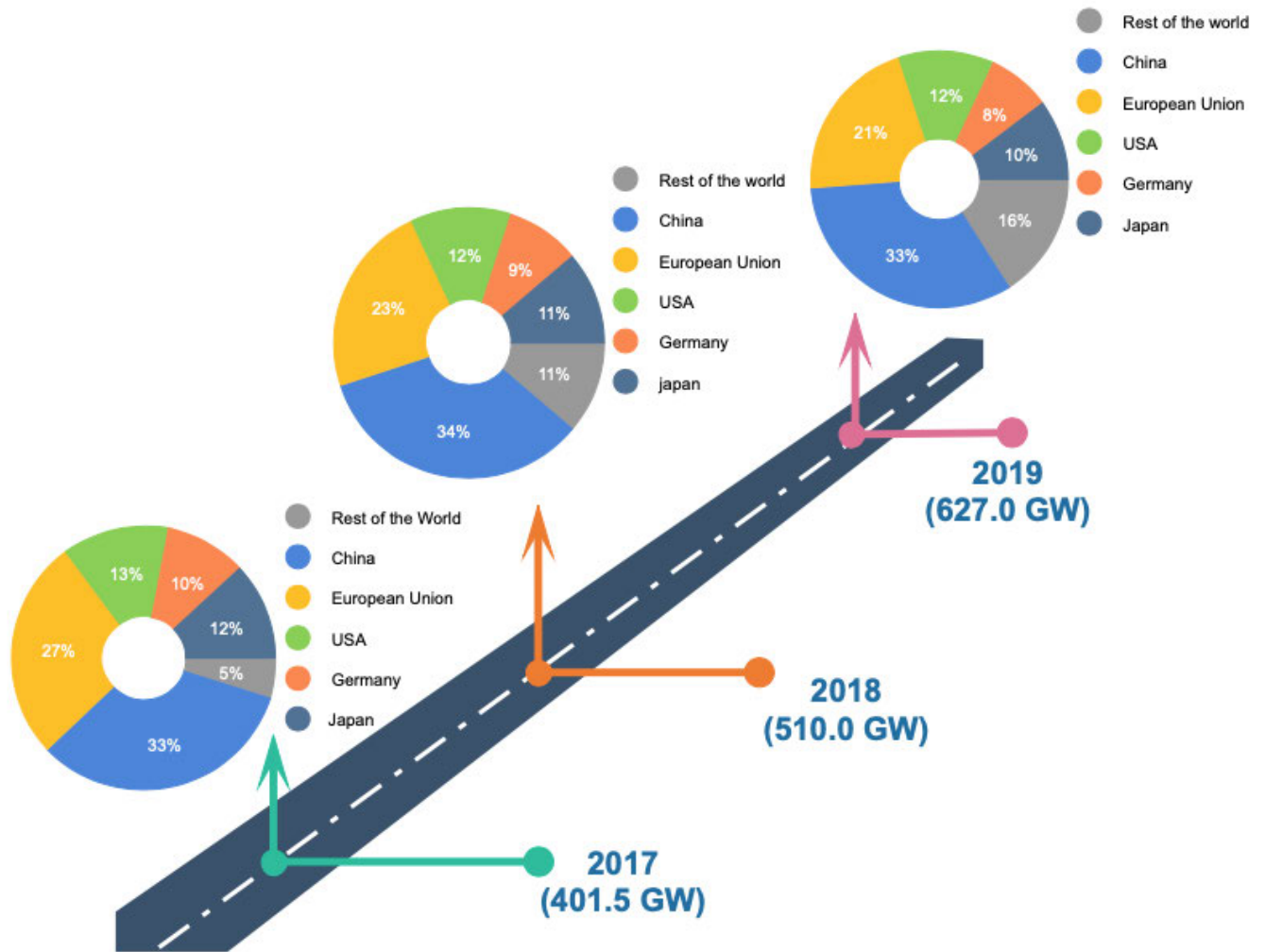


FIGURE 1. Solar PV installed capacities in leading countries.

The installed capacity of wind energy in India has considerably increased in the last few years. The potential of wind energy in India is about 400 GW as per the assessment in 2011 [32]. Major developments in wind energy production started with the formation of the National Program for Wind Energy Development in 1990. The total wind capacity of 1.9 GW in 2002-03 has escalated to 37 GW in 2019. Tamilnadu has a maximum capacity of 9.2 GW followed by Gujarat (7.2 GW) Maharashtra (4.79 GW), Rajasthan (3.3 GW), and Karnataka (4.73 GW) at the end of 2019 [33].

III. FORECASTING TECHNIQUES

Scheduling of electric power requires load forecasting and generation forecasting. Till the recent past, most of the power generation was from conventional sources of energy like thermal, hydel, and nuclear power plants, where the generation is easily controlled and limited by the ratings of the plant. Here, load forecasting is given more importance, and the generation is scheduled to meet the load demand. Hence, generation

forecasting is less. Generation forecasting is a vital factor in renewable power generation, where it is not easily controlled and depends on nature. In such a scenario, it is necessary to forecast the generation before the load schedule. Therefore, the research focus is shifting towards generation forecasting to enable greater renewable energy penetration. In generation forecasting [34], the period of the forecast is one of the main criteria to be considered. The different periods of forecast are primarily divided into the following [35]:

A. VERY SHORT TERM

The forecast horizon ranges from a few minutes to 1 hour. This forecast is useful for applications like electricity clearing, real-time grid operation, and regulatory actions [35].

B. SHORT TERM

The forecast horizon ranges from 1 hour to one or two days ahead [35]. This is useful in economic load dispatch planning, operational security in the electricity market, and decisions on load sharing.

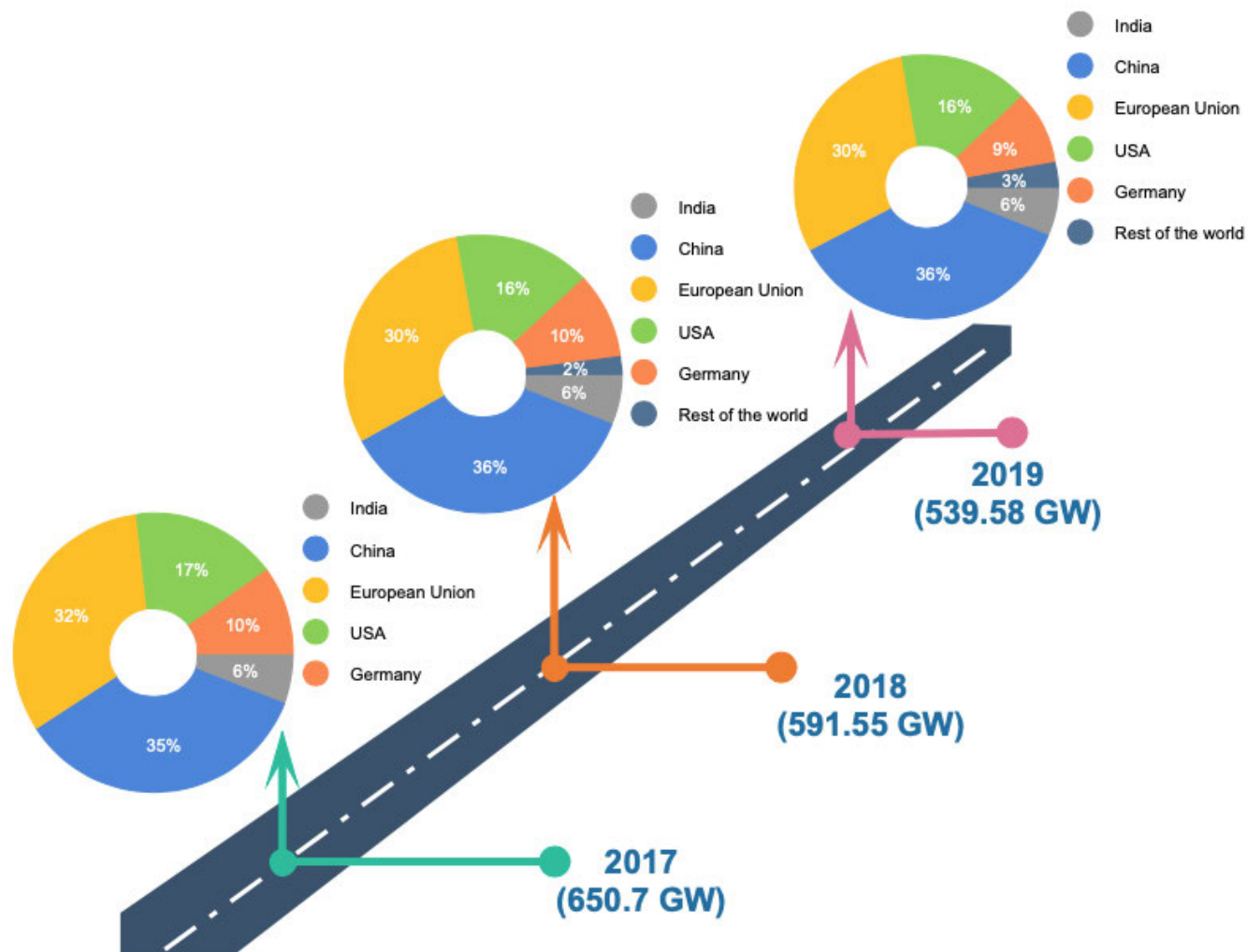


FIGURE 2. Wind installed capacities in leading countries.

C. MEDIUM TERM

The forecast horizon ranges from 5 to 7 days [35]. This is useful for situations like decisions on unit commitment or reserve requirements.

D. LONG TERM

Long-term forecast, whose duration is more than one week is useful for planning power plant maintenance, operation management, etc [35].

As the time of the forecast gets longer, the forecasting becomes more and more uncertain because of the erratic behavior of the predictors and the forecast variables. In this work, the emphasis is primarily on short-term forecasting. The predictions are done for 1 day ahead. Each forecasting process involves a set of basic steps enumerated as follows:

- 1) Identification of Problem
- 2) Data Acquisition
- 3) Exploratory analysis
- 4) Determine a suitable model to fit the data
- 5) Evaluation of the forecasting model

The problem of the prediction of solar or wind power generation is closely associated with the prediction weather parameters. This problem can be divided into two parts. First, solar irradiance or wind speed, or any other meteorological variable is predicted and then the amount of energy is estimated with the mathematical relations between the predicted parameter and power. Fig. 3 gives a classification of forecasting techniques.

E. PHYSICAL MODEL

The physical model starts with meteorological information such as NWP data and then model it to fit the local physical influences [36]. The adaptation of data is performed through the solar PV model with solar prediction and power curves of a wind turbine, provided by the wind turbine manufacturer, with wind forecast. This model may lead to systematic errors of the predicted power. This can be minimized by performing Model Output Statistics (MOS) applying the offline data from the site [37]. As this model needs high amount of

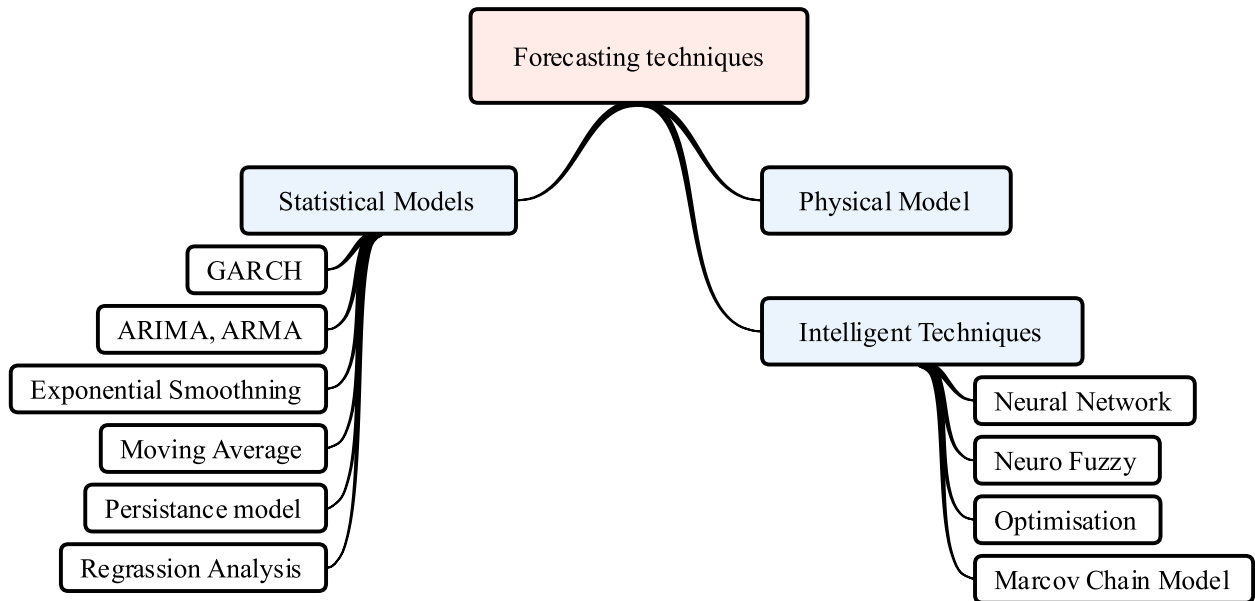


FIGURE 3. Classification of forecast techniques.

computations, this is normally performed with supercomputers and hence not very commonly used.

F. STATISTICAL MODELS

Statistical models are most appropriate for short-term forecasting [38]. This method uses historical data to predict solar irradiance and wind speed. The accuracy of prediction for these models is lower than that with a physical model, but the computational requirements are less. A very high level of accuracy is not demanded in the application of generation scheduling. Thus, statistical models have opted where time series models are developed with the past data and prediction of future is performed. A time-series data represents series of periodic measurements of a variable. The measurements can be hourly, daily, weekly, monthly, yearly, or at any other periodic interval. The primary information required to analyze the past behavior of time series data is the data pattern. The past pattern can be easily projected to predict the future using a suitable forecast model if data is expected to behave similarly. The two important classifications of time series models are Parametric and Non-Parametric models. It is assumed in the parametric model that the basic stationary data series is structured and can be characterized using a minimum number of parameters. In a non-parametric model, the model structure cannot be decided a priori and depends entirely on the amount of data [39]. Various types of statistical models are discussed below:

1) REGRESSION MODELS

In regression analysis, a trend line is fitted to statistical data points, and the line is projected to the future. Linear or non-linear trend equations can be developed [40]. By evaluating and analyzing a trend pattern, a historical pattern can

be determined which can then be projected to the future. The regression model also helps to separate the trend pattern from the data series. This method is normally used with decomposition techniques. In regression models, the mathematical relationship between two or more variables is evaluated from a plot of the historical data [41]. Multivariate linear regression model equation is as given in (1). For single varies regression, only coefficients β_0 and β_1 exist. All other coefficients β_n are zero.

$$y_i = \beta_0 + \beta_1 \chi_{i1} + \beta_2 \chi_{i2} + \dots + \beta_n \chi_{ip} \quad (1)$$

There are n number of dependent variable observations and p number of independent variable observations. Multivariate non-linear regression model equation is as given in (2).

$$y = b \times m_1^{x_1} \times m_2^{x_2} \quad (2)$$

In the equation, the dependent variable is y and independent variables are x_1, x_2 , etc. Linear and non-linear regression models are developed for prediction of solar irradiance and wind speed.

2) PERSISTENCE MODEL

This is the simplest forecasting technique. In most of the analysis, this method is considered as the baseline while evaluating the performance of other forecast models [42]. This model assumes tomorrow's conditions to be the same as today. The complete historical data is not considered for this model. Only the data pattern of the previous day is considered.

3) MOVING AVERAGE MODEL

These are elementary models to smooth historical data. Smoothing of data is required to evaluate the

trend component. There are many levels of moving average models such as simple moving average and weighted moving average [43]. In the simple moving average model of order k , the average of each observation is calculated by averaging that observation and m number of preceding and succeeding observations where $m = (k - 1)/2$. The expression is given in (3).

$$F_t = \sum_{j=-m}^m Y_{(t+j)} \quad (3)$$

where, F_t is predicted value of the current observation, Y_t is current observed value. The order of the moving average model has to be chosen carefully. It is a general observation that the trend is captured better with a large interval. The error in the forecasting model increases with the increase in order. The major drawback of moving average is that equal weight-age is given to all the past values which are considered for averaging. But in the actual case, the most recent data should have more relevance. The available past data is not fully used in this model. Rather, only the data which is considered for averaging is made use. The forecast result obtained through moving average may be misleading if the data contains seasonal variations as well.

4) EXPONENTIAL SMOOTHING

Forecasting by weighted moving average extends the moving average method. The simple moving average model attributes equal weight-age to all the k points. But it is obvious in any forecasting that the recent observations are the best guide to the future. Hence, it is prudent to use a weighting scheme that attributes lesser weight-age to older observations relative to the recent ones. In exponential smoothing models, the weights of older observations reduce exponentially [14]. There can be more than one smoothing parameter in exponential smoothing, which gives the classifications of exponential smoothing as single, double, and triple exponential smoothing. The determination of these parameters done with an iterative method and these values decide the weights assigned to the observations.

a: SINGLE EXPONENTIAL SMOOTHING

$$F_{(t+1)} = \alpha \times Y_t + (1 - \alpha) F_t \quad (4)$$

where F_{t+1} is predicted value of the subsequent sample, F_t is predicted value of the current observation, Y_t is current observed value, α is the smoothing parameter (varies between 0 and 1)

b: DOUBLE EXPONENTIAL SMOOTHING

$$Level \Rightarrow L_t = \alpha Y_t + (1 - \alpha) (L_{t-1} + b_{t-1}) \quad (5)$$

$$Trend \Rightarrow b_t = \beta (L_t - L_{t-1}) + (1 - \beta) b_{t-1} \quad (6)$$

where α and β are the trend smoothing constants respectively. Both lie between 0 and 1. and L_t and Y_t are the estimated and

actual values respectively if the time series at the time t . b_t is the slope.

c: TRIPLE EXPONENTIAL SMOOTHING:

$$Level \Rightarrow L_t = \alpha (Y_t - S_{t-s}) + (1 - \alpha) (L_{t-1} + b_{t-1}) \quad (7)$$

$$Trend \Rightarrow b_t = \beta (L_t - L_{t-1}) + (1 - \beta) b_{t-1} \quad (8)$$

$$Seasonal \Rightarrow S_t = \gamma (L_t - L_{t-1} - b_{t-1}) + (1 - \gamma) S_{t-s} \quad (9)$$

where γ is seasonal smoothing component (lies between 0 and 1), and S_t is seasonal component.

5) AUTO REGRESSIVE (AR) MODELS

In AR Models, the present values of the variables are represented as a regressive function of the past values [44]. Thus, the model is said to be a regression of the past values. The combination of AR models and MA models leads to a powerful model named ARMA(p,q) model. Here p and q are orders of MA and AR models, respectively. Appropriate selection of the order of ARMA needs to be done for the effective forecast. These models can only be used if the data is stationary. The model can be expressed as given in (10).

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} \quad (10)$$

where Y_t is present observation, ϕ is AR coefficient, θ is MA coefficient, e_t is error, p is order of AR, q is order of MA.

Three steps are required to model a practical time series using the above equation. First is the transformation of the original series Y_t to be stationary about its mean and variance. The second is the selection of suitable order of p and q . Third, the estimation is parameters $\phi_1, \phi_2, \dots, \phi_p$ and $\theta_1, \theta_2, \dots, \theta_p$. Generally, this is achieved using some non-linear optimization procedure that minimizes the sum of square errors. If the data has seasonal variations, it can be modeled as seasonal ARMA, which is expressed as ARMA(p,q)(P,Q).

AR: p is order of the auto regressive part, MA: q is order the moving average part, SAR: P is order of seasonal auto regressive part, SMA: Q is order of seasonal moving average part. The order of the ARMA model is obtained by analyzing the auto-correlations and partial auto-correlations of the stationary series. Both auto-correlation and partial auto-correlation functions should not have any abrupt cut-offs. Box and Jenkins (1976) presented set of rules to determine suitable values for p, q, P and Q . According to Box-Jenkins's methodology, any model is pertinent if it results in random residuals. If more than one such model is found to be well fitting, the model with fewer parameters need to be selected.

6) ARIMA MODEL

ARIMA model considers the irregular component of a time series. The model allows nonzero auto-correlations in the

irregular component, which can cause a better model for the data [45]. In AR, the variables usually have a built-in dependence relationship which violates the assumption that the error is independent. And the choice of the number of past values to be considered alters the efficiency (effectiveness) or goodness of fit of the model [46]. In the ARIMA model, the disadvantage of the seasonal error component that was experienced in the ARMA model is eliminated by regressing the dependent variable against the past errors. The Integrative (I) part of the ARIMA model includes the elimination of non-stationary in a time series by difference the time series as in (11).

$$Y'_t = Y_t + Y_{t-1} \quad (11)$$

G. INTELLIGENT TECHNIQUES

Intelligent techniques for forecasting are appropriate when the time series data are non-stationary and erratic. The advantage of these methods is the reduced computational complexity compared to statistical models [25], [27]. These methods can be categorized into two methods.

- 1) Based on Neural Networks (NN)
- 2) Based on Evolutionary Algorithms like Genetic Algorithm (GA)

The various methods based on NN solve the problem by mimicking the human brain. The designed network is trained with the historic data. The trained network is then validated and tested with the known data. In evolutionary algorithms, the problem is solved by imitating the process of biological evolution. Some hybrid models combine the advantages of two or more models [26].

H. ERROR MEASURES

It is essential to perform a comparative analysis to determine the accuracy of individual models when different models are employed for the test data. The right choice of the error measures is pivotal in determining the accuracy of the predictive model. Three error measures are used primarily to compare different models: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (SMAPE).

1) MEAN ABSOLUTE ERROR (MAE)

MAE is defined as given as,

$$MAE = \frac{\sum |X_t - F_t|}{N} \times 100 \quad (12)$$

where X_t is input data at time t , F_t is predicted value at time t , N is number of samples used in computing the error, MAE is an absolute measure. MAE can range from zero to infinity. MAE cannot be considered a final guideline to judge the accuracy of the model as the actual value decides the extent of the error. For example, an error of 10 becomes negligible when the actual value is 2000 but turns out to be significant for an actual value of 50.

2) MEAN ABSOLUTE PERCENTAGE ERROR (MAPE)

MAPE can be defined as given as,

$$MAPE = \frac{1}{N} \times \frac{\sum |X_t - F_t|}{X_t} \times 100 \quad (13)$$

MAPE represents the quantum of error relative to the actual data expressed as a percentage, thereby directly indicating the accuracy of the model. Considering an error value of 10, MAPE is 1% for an actual value of 10 and 20% for an actual value of 50. This enhances the choice of MAPE as an effective pointer to the accuracy of forecasting techniques. While MAPE considers the absolute value of the error, it cannot provide information on the deviation of the predicted values towards positive or negative. Outlets also may affect MAPE.

I. SYMMETRIC MEAN AVERAGE PERCENTAGE ERROR (SMAPE)

The disadvantages of MAPE can be overcome by taking the ratio of error and the mean of actual and predicted values. This is defined as Symmetric MAPE as given as,

$$SMAPE = \frac{1}{N} \times \frac{\sum |X_t - F_t|}{(X_t + F_t)/2} \times 100 \quad (14)$$

When taken the same example as is MAPE, SMAPE gives an error of 28.57% in either case.

IV. REVIEW OF STATISTICAL MODELS FOR SOLAR FORECAST

In [47] Peder Bacher *et al.*, have proposed a method for online short-term solar power forecasting. The data used for this work is the hourly solar power from a PV system and NWP (Numerical Weather Prediction) global irradiance. Three different models are developed in this paper. The reference model is taken as the persistence model. Then, a simple auto-regressive model is developed. The third model is the conditional parametric model, where both observed power and NWP power are the inputs. The coefficients chosen for the model are conditional on the time of the day and time of the year. The developed models are compared and Root Mean Square Error (RMSE) for 10-hour ahead prediction is compared.

In [48] S. Kaplanis *et al.* propose a novel method to predict solar irradiance for any hour of a day based on only one measurement in the morning. 5 years of measured data is used for model development. Hourly global solar radiation is determined based on the day of the year and site location. A correction factor is introduced which accounts for the air mass difference during the penetration of solar irradiance. The results obtained are within the limits of standard deviation. In [39], the solar irradiance data is classified by different seasons. Each seasonal series is decomposed into trends and random components. Trend component is modeled with the least square method and random series with the ARMA model. The prediction of solar irradiance in the superimposition of individual prediction. The solar irradiance data of the duration 1998 to 2005 is used for model

building and testing. The average error obtained is between 15 to 21%. Finally, the predicted solar irradiance is used to predict the power output from the solar panel.

In [49], a data mining approach is used to implement solar irradiance forecasts. The historical data for 5 years is classified into different clusters like a cloudy sky, clear sky, etc. using a k -means clustering algorithm. This is done to obtain rainfall probability patterns. These patterns are later used to predict solar irradiance. In [50], the CART (Classification and Regression Trees) algorithm of data mining is chosen to analyze the data. The results indicated that the prediction model has great importance on the seasonal parameters. In [51], the multiplicative ARMA model is used to predict solar irradiance. Four years of data are considered for model development. Annual periodicity and seasonal variations were removed. The order of the ARMA model is determined by observing the ACF and PACF plots. In [13], a new regressive model with predictors for the sigmoid function as clearness index and relative optical mass is proposed. 21 weather stations in different locations are considered for model building. The model is compared with two other similar models in the literature and the proposed model is found better. Other models are concisely tabulated in Table 1.

V. REVIEW OF STATISTICAL MODELS FOR WIND FORECAST

Forecast models are highly data dependent when the data is erratic like wind speed. The existing time series models like exponential smoothing, ARIMA, etc. may not give the best expected results with the data available from the region of study. Hence it is required to deploy various models to the data to understand the behavior pattern of the wind and to zero in on a model and develop a custom-made solution for the region of study. The first step towards developing the best forecast model is to test the basic-existing statistical time series models such as persistence, regression [62], moving average, exponential smoothing, and ARIMA as these are the basic and simple models available.

References [19], [20] give a detailed review on diverse methods to forecast wind power. The authors have also enunciated the directions for developing forecast models. It is specified that a combination of physical and statistical models is more effective for prediction. Reference [22], proposes a model which integrates wind direction with other input parameters to form a mixed ARMA model. The inter-dependencies between wind speed and wind direction are investigated by k -Mean clustering. The outliers in wind speed data are filtered out using wavelet decomposition, followed by modeling a hybrid model with ARMA-GARCH [23]. In [63], ANN and Bayesian algorithms are employed to propose a 2-step prediction. This methodology could achieve MAPE ranging from 14 to 18% with the analysis done at two different sites.

Decomposition of time series data is one of the oldest methods to analyze and characterize time series data. The idea of decomposing the time series data was introduced in the

early 1950s. Since then, extensive studies were carried out by various researchers in this area. Initial works were focused on seasonal decomposition and the effect of using forecasting to reduce the complexity of seasonal adjustments [64]. Some researchers were working on forecast effects of trend variance [65]. A decomposition method based on seasonally adjusted data was proposed by Miller and Williams [66]. Later, the concept of empirically combining distinct seasonal models was proposed [67]–[69]. In [70], Chen analyzed the strength of various models like regression, ARIMA, and Holt-Winters' and found that Holt-Winters' gave better results. In [71], the performance of forecast of various seasonal models with different types of real-time data was analyzed. The performance of each model varies mainly depending on the data. Thus, there is no accord yet as to the situations under which each model is preferred. Some of the recent works include [72], [73]. In [72], the authors proposed a generic method to identify and characterize different types of changes occurring in time series data. The algorithm integrates the decomposed components with methods to detect multiple changes. In [73], the authors focus on separating trends and growth cycles. The complexity of the separation of trends arises due to the interaction of trends and business cycles. Thus, a piece-wise linear approach termed as Phase Average Trend (PAT) was developed. In [74], a day-ahead prediction of wind speed is performed by developing a multiplicative Decomposition Model. Analysis indicates that the decomposition model is promising in terms of better results and lesser errors in comparison with the existent basic forecasting methods built on time series models. A concise framework of other statistical models for wind forecast is presented in Table 2.

It can be observed from the results of decomposition models presented that the percentage errors are between 10 to 15% in the solar forecast and 10 to 25% in the wind forecast. Even though the models gave reasonable accuracy in the solar forecast, they did not effectively capture the outlets in the wind data. As wind data is too erratic to be modeled by a time series model, non-linear models such as Machine Learning would be more effective.

VI. OVERVIEW OF MACHINE LEARNING BASED MODELS

Machine learning models are extensively used in various forecasting applications as they can predict the behavior of the data sets and also, they can predict the output based on historical information. Some of the machine learning-based models extensively used in solar and wind power prediction are SVM, ELM, BA-BP, EANN, PSO-SVM model, ARMA and SVM, ARMA, and PSO-SVM, Clustered hybrid, deep learning, swarm intelligence, ensemble and hybrid ensemble learning, and hybrid ensemble learning methods. Classification of machine learning techniques is depicted in Fig. 4.

The brief description of few models is described as,

A. SVM

This is a popular type of statistical learning technique that is based on structural risk reduction [86]. This technique is

TABLE 1. Review of statistical models for solar forecast.

Ref.	Model Used	Data duration	Error	Brief Description
[52]	Solar Time-based analog ensemble method	Data for 1 day from various web servers	NMAE=4.659%, NRMSE=7.356	This model gives a forecast technique which does not require long-term past data. For a day ahead prediction, data from previous day is collected from online data available freely through an automated web crawler. Data pre-processing is carried out by clustering. Day ahead solar power is predicted by comparing data from each cluster with the previous day data with similar solar irradiance and earth inclination angle.
[53]	Combination of several decomposition and transposition models	5 years	RMSE=14.9, MAE=10.4%	In this work, models combining several decomposition and transposition models are proposed. Diffused horizontal irradiance is estimated with decomposition models and PV irradiance is found from transposition models. Based on this, a physical model is developed to improve the performance.
[54]	Least Absolute Shrinkage and Selection Operator (LASSO)	7 years	RMSE=14.336, MAPE=3.3357	LASSO is a widely accepted method for regression-based analysis. As solar power depends upon several weather parameters, it is important to figure out the parameter which is more significant. The penalty factor generated by LASSO approach eliminates the less important parameters. An increased accuracy is observed with the proposed approach.
[55]	Chaos Theory, False Nearest Neighbor method (FNN)	1 Year	—	Erratic nature of solar irradiance makes chaos analysis best for prediction. False Nearest Neighborhood (FNN) Method is the most prevalent method used in chaos analysis. This method is helpful to study non-linear system dynamics. The experiment was conducted on data sampled at 60 minutes and 30 minutes intervals. The results reveal that the prediction can be accurate.
[56]	Continuous conditional random fields	4 months	RMSE=8.92	Continuous Conditional Random Fields (CCRF) combines the advantages of relationship learning, optimization, and probabilistic forecast. Furthermore, over-fitting of the data is avoided by adding weight regularization. It was observed from the results that this method improves prediction accuracy.
[57]	Probabilistic Forecast	—	nMSE<1	A model is developed by joining two models, one to derive a relationship between solar power and cloud stochastic and another model to get relationship between solar power and temperature. Predictions are done separately for 3 different conditions, viz. sunny, partly cloudy and overcast. The strength of the model is verified by testing it on a few real-time data-sets. It was observed that the proposed model outperformed many standard models.
[58]	Triple Exponential Smoothing	2000 samples	RMSE=29.28	Triple exponential smoothing is adopted in this paper. Weather sensors are used to study the behavior of incident solar irradiance on earth's surface. The prediction error is found to be lesser than the benchmark models.
[59]	Multivariate spatio-temporal model	1 year	nRMSE=0.15	Spatio-temporal analysis is an effective technique for prediction of incomplete time series data. A tensor learning scheme is proposed. In this, a relationship is developed between the missing and their neighbouring values. A statistical Design of Experiments (DoE) framework is developed to implement the algorithm.
[60]	Ensemble Model	—	Relative Forecast improvement=19.51%	A novel residual compensation with adaptive algorithm is proposed. The algorithm is based on probabilistic forecast, thereby providing a perfect input-output mapping for missing data. The algorithm is run as an optimization algorithm where the objective function is to minimize the root-mean-square error. It was observed that the forecast accuracy improved by 19.51 %.
[61]	Symbolic Aggregate Approximation (SAX)	4 months	RMSE=2.57, MAE=1.86	Spatial and temporal characteristics of data are considered in this model to get a forecast independent of location. SAX approach speeds up the calculations for larger sets of data. Three different models are proposed based on amount of data classified as small, medium, or large data sets. The authors claim that the proposed algorithm is superior to ANN and SVM forecast as this algorithm give more accurate forecast for any weather conditions.

very popular amongst the other machine learning techniques. Given a data-set $\{b_i, a_i\}_i^N = 1$, here N represents the data-set length, $a_i \in X^n$ represents the input vector and $b_i \in X^n$ is the i th label of A. The main aim of this function is to set up a classifier function $f(a) = W_a^T + Y$, this function will in turn map the input values 'a' to labels b; W in the function, $W = [w_1, w_2, w_3, \dots, w_R]^T$ denotes weight-vector. Y is a scalar quantity, $f(a)$ is a mathematical function which reflects the mapping of the input variables to higher order dimensional space. Since SVM performs minimization of structural risk, the optimization can be transformed further as,

$$\frac{1}{2} \|W\|^2 + B \sum_{i=1}^n u_i \delta_i \tag{15}$$

(15) is subjected to

$$b_i (w a_i + y) \geq 1 - \delta_i \text{ and } \delta_i \geq 0, \quad i = 1, 2, \dots, n \tag{16}$$

where, b is penalty number and δ_i is the marginal distance.

B. EXTREME LEARNING MACHINE (ELM) MODEL

It is a method that is primarily developed to solve the complication of simple hidden layer NN [87]. The main advantage of ELM is accuracy and also the single layer NN is computationally faster than conventional learning frameworks [88], [89]. Consider a single hidden layer NN, inputs weight w_i and offsets Y are initialized randomly after which the output weights are obtained. The input weights and the hidden layer bias of the neural network are randomly obtained to get a

TABLE 2. Review of statistical models for wind forecast.

Ref.	Model Used	Data duration	Error	Brief Description
[75]	Gaussian Process	2 Days	RMSE improvement 10%.	Authors proposed a new prediction model using Gaussian Process. The proposed model reduced the computational complexity. In comparison with the standard Gaussian model, the error reported is drastically reduced. A comparison is made of RMSE for each proposed model. 12 hours ahead prediction in an interval of 15min has been carried out.
[76]	Grubb's Test	24 hours	MAPE=7.12%.	The power measurements received from a wind farm is pre-processed by applying Grubb's test. This eliminated outliers in wind data and smoothed out the measurement errors. Wind power that lie outside a defined boundary are eliminated. The range of MAPE is between 7 to 23% and is dependent on the number of out-samples predicted.
[23]	ARIMA-ARCH	240 data values	MRE=0.09	The non-linearity and non-stationarity of wind speed is addressed by pre-processing the data using wavelet transformation. The combination of ARIMA and ARCH models is applied.
[77]	WRF, WindSim	1 Year	Error Histogram	Wind power forecast for Soma wind farm in Turkey is performed by combining WRF (Weather Research and Forecast) model and WindSim models. The wind farm has 36 turbines which are classified into 6 groups for simplicity in determining the model parameters. It is found that daily generated wind power varies between 90kW and 350kW.
[78]	Marcov chain	28 Months	nRMSE=8%	Wind power forecast is performed using Marcov chain model, which comes under probabilistic forecasting method, thus giving a probability distribution associated with the point forecast. The results are compared with persistence model. It is found that for a forecast horizon of 12 hour, the error of the proposed model is 8 smaller than persistence model.
[79]	ARMA	3 Years	Absolute Error	Wind power forecast is done using a simple window based adaptive-parameter regression model. It is basically a best fit ARMA model. The predicted wind power is applied to an economic dispatch problem solved by genetic algorithm.
[80]	Seasonal ARIMA	72 mean monthly data for 5 years	MAPE=6%.	Extreme Learning Machine and Seasonal ARIMA methods are used for wind speed prediction. The lowest MAPE obtained is 6%.
[81]	Combined Probability Prediction	3 Months	RMSE=0.322MW, MAPE=2.712%	The raw wind data is pre-processed by energy optimized variational mode decomposition. The methodology used for prediction is regression models based on Gaussian process. Ten GPR models are implemented to reduce prediction errors.
[82]	ARMA, PSO-SVM, Clustering	2 years	RMSE=4.75MW, MAPE=7.19%	A combination of ARMA, PSO and SVM models is implemented. Clustering technique is used to determine the effective data-set to carryout prediction.
[83]	NWP, Persistence, Neural Network	Previous day from NWP	Prediction accuracy=88.95%	This method is an improvisation to wind power forecasting with NWP data. As an initial stage, wind power is predicted with persistence method. These values are compared with NWP data and the points with low prediction accuracy are identified. Neural network is used for prediction of such points. It was observed that the prediction accuracy improves significantly.
[84]	Time Series AR model	A few days	Minimum MAPE=4.2%	A combination of Weather Research and Forecast (WRF) and Auto-Regressive time series model is proposed. Different data consisting of smooth and erratic wind patterns are tested. The results reveal the fact that AR models give better results for erratic patterns when compared to steady wind speeds.
[85]	ARIMA-GARCH and Elman	A few samples	MAPE=9.79%	A prediction model based on ARIMA, GARCH and Elman models is proposed. Initially, these models are run for the same data individually. Then a combined optimized algorithm taking into consideration of weights of errors from each model is developed.

unique value $NN(H)$ for the hidden layer output matrix. Single hidden layer NN is transformed into a linear system $H\gamma = T$, with the identification of its output weight [90].

$$\hat{H} = H'T \quad (17)$$

Here \hat{H} represents the inverse of the matrix H .

C. BAT ALGORITHM- BACK PROPAGATION MODEL

This technique is an amalgam of methods. Back Propagation (BP) is a multi-layer feed-forward NN. In this technique, the error is back-propagated, and the signal is forward propagated. This technique is most popular in machine learning to perform function approximation, pattern recognition, and classification. The network framework of this technique is highly complex [91]. BA is developed based on its echolocation behavior [92]. BA is applied to classify and design many

engineering applications [93], [94]. The combined BA-BP framework has better accuracy in terms of its prediction capability. The initial weights are optimized with BA and channelized to the BPNN.

D. ELMAN ANN

This type of NN is a simple recurrent NN [95] which consists of four structural layers. The four structural layers are input layer, middle layer, receiving layer and an output layer. The main function of the receiving layer is to properly comprehend the output information of the hidden layer [96], [97]. The function of hidden layer neuron is given by,

$$F_i(t) = a \left\{ \sum_{k=1}^k V_{ik} F_k(t-1) + \sum_{n=1}^N W_{ij} J_j(t-1) \right\} \quad (18)$$

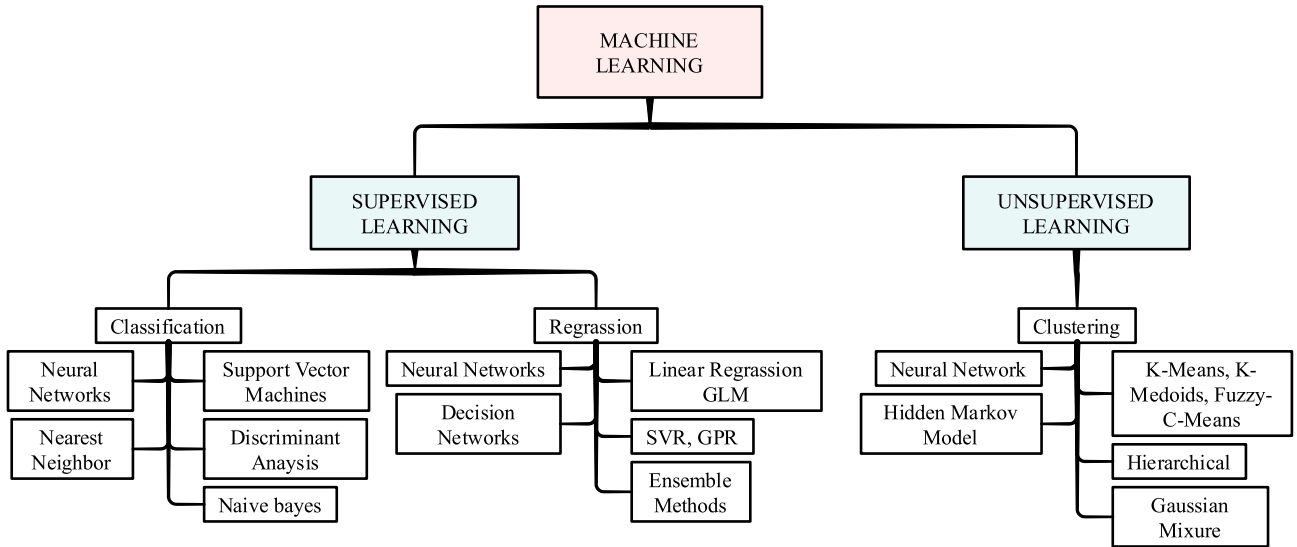


FIGURE 4. Classification of machine learning models.

where $F_k(t)$ and $I_j(t)$ denote output of the receiving layer, and input neurons. V_{ik} and W_{ij} are the weights. This model is most preferred for its use in dynamic modelling. It has the capability of self-correlation and can process dynamic information. BP based NN is robust in terms of learning and adaptability. However, these models are prone to minor optimization problems and lack convergence speed [98]. SVM can lessen the complexity of solving high dimensional space problems. When compared to NN, they have greater generalization and extension capability [99]. In the case of the ELM, algorithm to obtain better prediction accuracy only hidden layers neurons need to be set. The learning and generalization capability of ELM are superior when compared to other learning machine models. However, they are prone to regularization problems. EANN model has enhanced model fitting capability. In this model, the output of the hidden layer is memorized in the last iteration with a surplus layer called the receiving layer. This model is complex as it has number of hidden layers in the framework when compared to other network frameworks. Owing to the above-mentioned features, combination models are more helpful and are noteworthy in enhancing the prediction accuracy by overcoming the shortfalls of the individual models.

1) LINEAR COMBINATION

This methodology is usually preferred for time series prediction. In order to find out the weights of this linear combination, VMD-IPN and RBF framework is used. This forecasting model has the capability of reducing the problems of prediction accuracy of the single models [100]. In a combination model, $Z = [Z_1, Z_2, \dots, Z_N]^T$, where the equation represents an array of target values and $\hat{Z}(j) = [\hat{Z}_1(j), \hat{Z}_2(j), \dots, \hat{Z}_N(j)]^T, j = 1, 2, \dots, n$ is an array of predicted values to the j^{th} single model. Therefore the forecasted values

can be found by,

$$\hat{Z} = \sum_{j=1}^n W_j \hat{Z}(j) \tag{19}$$

where n denotes the total number of n single models of the linear combination and N is array of values predicted W_j is the weight of the model. Also to enhance the efficacy of the linear combination model, the final predictive value \hat{Z} and the single predictive value $\hat{Z}(j)$ should comply to inequalities [101]. $\gamma(Z, \hat{Z}) \leq \gamma(Z, \hat{Z}(j)), \forall j(j = 1, 2, 3 \dots, n)$, where γ is forecasting error. The linear combinational model can find the corresponding weight considering the predicting capability of the model components and later the combinational weights are predicted by NN. The model works initially by developing the in-sample training validation pairs and then finds the combination weights by Variational Mode decomposition; in-sample training validation pair based neural network weighting and radial bias function.

2) ARMA AND SVM

It is a hybrid model developed for wind power prediction. ARMA model fetches the time series information [82]. After fetching the relevant information, the model can predict the values with the help of historical data. Consider a time series $f(t)$; the ARMA (a, b) model is given by

$$f(t) = \sum_{i=1}^x a_i f_{t-i} - \sum_{j=1}^y b_j \gamma_{t-j} + \gamma_t \tag{20}$$

Here a_i is autoregressive value; b_j is the moving average value which is determined using LSE. γ_t is Gaussian noise and x is the order of AR and y is the order of MA.

3) PSO-SVM

This framework is an amalgam of optimization technique and learning mechanism. This combinational model can solve problems related to regression and classification [82]. SVM has greater generalization capability when compared to other ML techniques. The parameter of RBF and the penalty factor are important in determining the performance of the SVM technique. PSO is used to find the best value of the two parameters.

4) ARMA AND PSO-SVM MODEL

To enhance the prediction capability, it is necessary to combine two or more models with rational weights. These combinational models outperform when compared to single prediction models. However, it is very difficult to rate the prediction accuracy of individual models arbitrarily. In this model, time series and an intelligent technique is used. The main advantage of this technique is that it can store more information and enhance prediction accuracy [82]. The combined ARMA and PSO-SVM model can be written as,

$$G_{com} = \delta_1 G_{ARMA} + \delta_2 G_{SVM} \quad (21)$$

where δ_1 and δ_2 denotes weights of the ARMA and PSO-SVM model and it should satisfy the condition $\delta_1 + \delta_2 = 1$. GCOM denotes combinational model that predicts the results of the combined ARMA and PSO-SVM model.

5) CLUSTERED COMBINATIONAL MODEL

In order to explore the prediction accuracy of the wind power, proper investigations need to be conducted on the historical data. The main advantage of clustering is to encapsulate the characteristics of wind speed, power and temperature and can also verify the effective data-set. Some of the other combination models are (Ensemble Empirical Mode Decomposition-Long Short-Term Memory Network) EEMD-LSTM, EEMD-ARIMA, and EEMD-MLP (Multi-layer perceptron) is tested for different data sets and the results are validated under different conditions [82].

VII. REVIEW OF VARIOUS MACHINE LEARNING METHODS FOR WIND FORECAST

Wind speed forecasting ensures stabilization of regulatory markets in terms of proper power dispatch, thereby leading to structured planning of reserve power capacity. Due to the extensive use of BESS in modern wind power plants as a reserve, the shelf life of BESS units gets deteriorated due to frequent charging and discharging. The capacity of the BESS is predicted by the charging and discharging schedules. An accurate wind power forecasting technique enables a wind farm operator to determine the capacity of battery units with reserve power mode [102]. Deep learning techniques are widely used in applications like regression, clustering, classification, and pattern recognition. Also, ANN based methodologies [35] are in used to predict solar radiation and wind speed. With wind farms, the data sets can be obtained from failure history, SCADA, maintenance, and CMS data.

Deep Mind, based on NN, a forecasting tool developed by Google. Some of the common reasons for the failure of a wind turbine are fluctuations in the rotor blades and the tower of the wind turbine. Machine learning based methodologies can be used to detect the fault and monitor the performance of the wind turbine [103]. Wind turbines are usually subjected to wear and tear; ML based techniques can be used to prevent such events by analyzing some parameters like yaw angle, pitch angle, and rotor speed. Some of the most commonly used AI techniques are feature based algorithms. These algorithms fetch information like acoustics, temperature, torque, and rotor speed from the sensors housed on the turbine equipment [104].

The flow of wind primarily depends on atmospheric parameters like pressure, humidity, height, and surface irregularities. These parameters are of utmost importance for short-term predictions. In solar power prediction, levels of irradiance, humidity, temperature have to be given more priority. To solve the issues with non-linearity ML methods are the prime choice. For accurate wind speed forecasting, a large amount of data sets is necessary. These data sets are in turn used to train a supervised machine learning regression technique. Extreme learning machines, SVM, and ANN are the most frequently used machine learning regression techniques [105]. For a duration ranging from three minutes to six hours, multilayer perceptron based NN techniques is used to forecast wind power. A hybrid model consisting of wavelet transform and NN is used for short-term wind speed forecasting in Portugal [106]. In this framework, the data of wind speed is divided into series through a discrete wavelet. The series of these data-sets is later fed to the neural network for training. Once the data sets pass through the training algorithm, they are trained for learning where minimization of error is performed. The learning algorithm generally used is backpropagation [107]. This technique lacks speed and as a result, it is replaced by Levenberg-Marquardt (LM). The NN based wavelet technique is compared with ARIMA and NN with the use of data-sets. The value of MAPE is around 6.97%. Physical algorithms are usually preferred to map the data of the wind turbine into numerical weather prediction (NWP) systems [108]. This technique is preferred to enhance the prediction of wind speed. However, this method is not preferred for short-term wind forecasting. An enhanced auto-regressive integrated moving average (ARIMA) model is developed to forecast the wind speed; the obtained results are marginally acceptable in terms of its accuracy and efficacy. Single statistical models are not significant in extracting the wind speed information. Generally, SVM and ANN techniques are used for wind speed forecasting in such cases. These techniques are highly expensive in terms of training the model. Conventional single models, namely physical, statistical and NN are not effective in terms of accuracy of predicting wind speed. These models have acoustic noise and result in reduced forecasting accuracy. It is, therefore, necessary to combine forecasting models to enhance the robustness of the multiple single models [109].

TABLE 3. Review of machine learning models for wind forecast-1.

Ref.	Model Used	Data duration	Error	Brief Description
[110]	SVM	24 hours from 144 wind speed data samples with sampling interval 10 min	RMSE(m/s)=0.45, MAE(m/s)=0.34, MAPE (%)=7.07	The combinational method VMD-IPN-RBF outperforms with the best results. The combinational method has reduced values of RMSE, MAE, and MAPE. Amongst the individual models, the order in which the models have obtained the reduced values of RMSE, MAE and MAPE is SVM, EANN, BA-BP and ELM. From the results, we can infer that the combinational model has the best prediction accuracy for a data set. The model can also predict the non-stationary characteristics of the wind speed sequences with high accuracy. As a result, we can conclude that the model is more suitable than the other individual models for wind speed forecasting.
	ELM		RMSE(m/s)=0.47, MAE(m/s)=0.36, MAPE(%)=7.58	
	BA-BP		RMSE=0.48, MAE=0.36, MAPE=7.58	
	EANN		RMSE=0.45, MAE=0.34, MAPE=7.11	
	VMD-IPN-RBF		RMSE=0.23, MAE=0.18, MAPE=3.71	
	SVM	24 hours from 144 wind speed data samples with sampling interval 30 min	RMSE=0.94, MAE=0.73, MAPE=11.89	The combinational method VMD-IPN-RBF outperforms with the best results. The combinational method has reduced values of RMSE, MAE, and MAPE. The prediction error of the individual models is less and their accuracy is less when compared to individual model.
	ELM		RMSE=0.91, MAE=0.71, MAPE=11.57	
	BA-BP		RMSE=0.92, MAE=0.72, MAPE=11.72	
	EANN		RMSE=0.93, MAE=0.72, MAPE=11.89	
	VMD-IPN-RBF		RMSE=0.64, MAE=0.50, MAPE=8.47	
[82]	ARMA	24 hour with 96 prediction points with a sampling frequency of 15 minute	RMSE=5.5, MAPE=10.57, MAE=3.94	The combinational model has the lowest values of RMSE, MAPE and MAE, therefore the model has better prediction accuracy. Also, the model has reduced prediction error and can circumvent the error of ARMA and PSO-SVM.
	PSO-SVM		RMSE=5.38, MAPE=10.38, MAE=3.69	
	PSO-SVM-ARMA		RMSE(%)=5.38, MAPE(%)=10.31, MAE(%)=3.63	
	C-PSO-SVM-ARMA	24 hour with 96 prediction points with a sampling frequency of 15 minute	RMSE(%)=4.88, MAPE(%)=7.68, MAE(%)=3.5	The results of the three models suggest that I-PSO-SVM-ARMA and C-PSO-SVM-ARMA have better results when compared to PSO-SVM-ARMA. However, all the three models show better prediction accuracy. The C-PSO-SVM-ARMA is effective because of the clustering technique involved in training the data-set. The computation capability of I-PSO-SVM-ARMA is greater than C-PSO-SVM-ARMA. Therefore, we can conclude that the clustered model is workable and can also ensure better prediction accuracy.
	I-PSO-SVM-ARMA		RMSE=4.75, MAPE=7.19, MAE=3.31	
	PSO-SVM-ARMA		RMSE(%)=5.25, MAPE(%)=8.77, MAE(%)=3.94	

These combined models for wind forecast are classified into model variables and structure optimization weighted and error correction based [106]. In model variables and structure based optimization methods, a modified optimization technique [114], [115] is applied to a model during the training phase to obtain greater accuracy. In [116], to forecast short-term wind speed, PSO based optimization technique is applied to LSSVM [117]. To optimize the requisite

parameters in an RBF technique, the ordinary least square method is used instead of the conventional gradient search method. Also, many optimization techniques like Grey Wolf, Whale, Bat, GA, and so on have been used for parameter optimization. To increase the accuracy of wind power forecasting, error correction-based models are usually preferred. In this methodology, the data present in the system error is extracted to ensure greater accuracy of forecasting.

TABLE 4. Review of machine learning models for wind forecast-2.

Ref.	Model Used	Data duration	Error	Brief Description
[111]	EEMD-LSTM	24 hours with scanning rate 144 times and the average sampling time is ten minutes.	RMSE(%)=0.36, MAPE(%)=4.23, MAE(%)=0.25	The results of Ensemble empirical mode decomposition (EEMD)-Long short term memory (LSTM), EEMD-Multi layer perceptron (MLP) EEMD-ARIMA and combination model shows that the combination model has better prediction accuracy when compared to other models. The combination's model can also minimize the redundancy of the dynamic information and can improve the optimal value.
	EEMD-MLP		RMSE(%)=0.32, MAPE(%)=3.73, MAE(%)=0.23	
	EEMD-ARIMA		RMSE=0.46, MAPE(%)=5.55, MAE=0.33	
	Comb. model		RMSE=0.31, MAPE(%)=3.52, MAE=0.22	
[112]	BPNN	Hourly based	MAE=0.21, RMSE=0.32	The error results suggest that the deep learning and PCA approach has better efficacy and prediction accuracy. The error values of deep learning and PCA is less when compared to other methodologies. Ensemble selection technique also has reduced error values. These models were tested on large scale wind turbine data. Initially PCA is applied to extract information from the data sets and later desirable patterns are obtained in a minimized dimensional space. Later deep learning is applied to principle components for wind power forecasting. The errors result validates that the deep learning and PCA method is noteworthy for its applications in short term wind power forecasting.
	Ensemble selection		MAE=0.17, RMSE=0.29	
	CNN		MAE=0.35, RMSE=0.40	
	AR		MAE=0.24, RMSE=0.35	
	Deep learning and principle component analysis(PCA)		MAE=0.15, RMSE=0.05	
[113]	LASSO	Daily wind speed	RMSE =186.1, MAE = 94.67 $R^2 = 0.823$	The error results show that the ML algorithms provide acceptable results except LASSO as the value of R2 is above 0.9. SVR algorithm has better results. RF has decreased value of 0.921 when compared to k NN, xGBoost, SVR. The increase in efficacy of RF algorithm is mainly due to its enhanced features.
	NN		RMSE = 105.76, MAE = 42.47, $R^2 = 0.943$	
	xGBoost		RMSE = 115.47, MAE = 41.58, $R^2 = 0.932$	
	SVR		RMSE = 93.13, MAE = 32.63, $R^2 = 0.955$	
	RF		RMSE = 123.88, MAE = 42.76, $R^2 = 0.921$	

To establish enhanced accuracy of the forecast, a combined grey and Markov model is implemented to ensure greater precision [118], [119]. In this combined methodology, the errors forecasted by the grey model are categorized into different conditions using the Markov model and for each conditions the probability is estimated. The most frequently used model amongst the weighted combination is the linear combination model. In this model, the approach used is the average of the components. In [120]–[122], results suggest that a single naïve average can achieve acceptable correctness. But this method has lesser accuracy. These methods cannot recognize the fact that the prediction values depend on past information. The weights of the backpropagation neural network and statistical models are identified by the error propagation of the wind speed forecasting [123]. To prevent the shortfalls of the single model prediction methods, a multi-objective Bat algorithm is applied to determine the coefficients of optimal weight [105]. The aforementioned prediction methods have certain shortfalls. Model variables and structure optimization combination models are complex in terms of computation.

Also, in AI-based optimization techniques, training time is too long, and they are subjected to over-fitting problems. Error correction-based models can reduce the prediction error and are extremely expensive in terms of designing a model. The weight-based model is not preferred over the first model, but they have greater adaptability to information and can ensure stabilized predictive performance. Even though the models are not capable of optimal prediction, the results are within the prediction sequence. Therefore, it is necessary to combine an additional model for the identification of the weight of every single model. Studies suggest many methods to find the correct weights but, in most cases, predicting the optimal weights will always be a nightmare. Therefore, because of the aforesaid shortfalls, it is necessary to use a combination model for wind speed forecasting. A combination model can combine the strengths of the individual components to achieve greater accuracy. Support Vector Machine (SVM) is a popular regression model that maps the predicted values to actual values of wind speed. A,ultivariate least square SVM is proposed in [124]. The method is tested

on data collected over a year from wind farms in different locations. A MAPE 10.06% is the best obtained.

Hybrid Models using fuzzy logic and AI techniques are proposed for forecasting in [125]. NWP is used to do a preliminary forecast and the quality of NWP is estimated with fuzzy rules. One hour ahead forecast is done using a neural network with wind speed measurements from a wind farm and NWP data as inputs. The worst case error is in the range of 40 to 50%. With a second model, quality of NWP is estimated by using the output of the first model as input to the second model. The rule sets of the fuzzy model are decided by comparison of wind power obtained from power curve of a wind turbine with NWP data. The fuzzy model output yields and NWP quality index. With a third model, separate forecast is done for each class of wind speed. The error obtained in the range of 5 and 14%. A combined hybrid approach using ANFIS, PSO and wavelet is proposed in [75]. Wavelet Transform is used to decompose the measured values of wind power. The prediction of this data is performed using ANFIS. PSO technique is used to improve the performance. The accuracy of the model is increased by training the parameters of the membership function of ANFIS using PSO. The best MAPE reported using the proposed model is 4.98%. In [126], wind speed prediction is performed with a novel ANN model, ICA-NN. The inputs to the prediction model are measured data from a SCADA system and NWP data. This data set contained temperature, humidity, and wind speed. Imperialist Competitive algorithm is used to adjust the weights. The Mean Square Error is found to be less than 20%. In [127], Wavelet Neural Network (WNN) is used to predict wind power. WNN is an ANN where the activation function is a wavelet function. A new training strategy is proposed based on Clonal Search Algorithm (CSA). The proposed model is compared with existing models such as Simulated Annealing (SA), Particle Swarm Optimization (PSO), CSA, and Differential Evolution (DE). The proposed method has an error of 9.7%, which is the lowest. In [128], the hybrid model is developed to predict wind speed where wind speed is decomposed into several sub-layers using empirical mode decomposition. Each decomposed series is predicted with a neural network optimized by genetic algorithm and mind evolutionary algorithm. The lowest MAPE obtained was 2.5%. In [129], lifting wavelet transform and Support Vector Machine (SVM) are used for model building. Wavelet transform characterizes the original wind speed and SVM improves the prediction accuracy. Each decomposed data is predicted separately and superimposed to obtain the final prediction. The prediction error is found to be 14.9%. In [130], SVM enhanced Markov Chain model is chosen for wind power forecast. Markov chain is used to capture the normal variations in wind speed, whereas SVM identifies the wind ramp dynamics. Several methods for wind power forecast have been proposed by Jing Shi, *et al.* In [24], [25], ANN techniques are used. One method is a technique employing two steps based on neural network and Bayesian algorithm. The algorithm was tested for data collected from two sites

and the MAPE is between 14 to 18%. Prediction models with ANN are compared with auto-regressive models and seasonal ARIMA models in [26], [27], [80], [131]. A new training algorithm is proposed by applying the Lyapunov stability approach to ANFIS. The results are compared with common training algorithms like GD and RLS. In [132], an entropy based neural network learning algorithm is proposed.

Wind speed depends on many inputs such as temperature, humidity, wind direction, atmospheric pressure, etc. In the literature, algorithm using wavelet transform are extensively reported [133]–[137]. The technique is used to smoothen the data prior to prediction. Time series data is effectively decomposed in the time frequency domain. Interest on wavelet transform application for forecasting began in 1990's. The percentage error obtained is 14.9% using lifting wavelet for characterization of the signal and SVM technique to obtain better accuracy [138]–[144]. In [144], [145], hybrid wavelet-neuro algorithms with novel training strategies are proposed to reduce prediction error. Recent works include application of empirical mode decomposition and principal component reconstruction technique with multilayer ANN. The authors of the reported literature have used data specific to a particular geographic location, hence dependent on local atmospheric and weather conditions. This makes it difficult to compare the accuracy of the various models. However, from the results presented, a general conclusion can be drawn that hybrid models using machine learning algorithms have better accuracy. To ensure better performance and forecasting accuracy, hybrid or combinations models are of prime choice. In the combinations models, the diversity of the combination is given more importance rather than the optimality of each model [146]. In the study of these combinations models, different types of NN combinations are considered. A comparison of various single and combinations models used for wind power forecasting is presented in Tables 3 and 4.

VIII. REVIEW OF MACHINE LEARNING TECHNIQUES FOR SOLAR FORECAST

In [147], a forecasting technique is proposed that uses a neural network and fuzzy theory. Fuzzy rules are determined to predict solar insolation from humidity and the amount of cloud. Fuzzy rules are set using min-max theory, based on the measured values of cloud amount and humidity. A correction method is also proposed to reduce forecast errors. The output of solar power obtained using fuzzy logic and correction method is used to train the neural network.

In [154], one-day ahead solar forecast using ANN is proposed. The novelty of the proposed method is that the operator of the PV panel could appropriately select the model parameters of the ANN such as the number of hidden layers, number of delay elements, etc. NARX network with back-propagation LM algorithm is chosen for the model development. The absolute percentage error is between 1 to 5%. In [155], ANN and GNN (Generalized Neural Network) models are compared. The first stage in modeling with GNN is an offline process called the model structuring phase, where

TABLE 5. Review of machine learning models for solar forecast.

Ref.	Model Used	Data duration	Error	Brief Description
[148]-[150]	GB	24 ahead hourly data from 1 may 2014 to 8 November 2015	nRMSE(%)=7.36, nMAE(%)=3.2	It is easy to understand from the error findings that ENS is outperforming amongst the various models. ENS, QRF, and kNN offer the three best results, while SVR, NN, and GB give less reliable forecasts. Also, the results suggest ENS model is the best algorithm, and the model validates the error results obtained with the theoretical results indicating that ENS is the best framework for solar power forecasting.
	NN		nRMSE(%)=7.41, nMAE(%)=3.24	
	Knn		nRMSE(%)=7.21, nMAE(%)=3.13	
	QRF		nRMSE(%)=7.32, nMAE(%)=3.11	
	SVR		nRMSE(%)=7.40, nMAE(%)=3.19	
	ENS		nRMSE(%)=7.16, nMAE(%)=3.07	
[151]	SVM	April 2011 to November 2012. Data is recorded for every 30 min.	RMSE=54.29, RMSE reduction with LASSO=73.41(%) MAPE=19.01, MAPE reduction with LASSO=82.46(%)	The level of solar intensities varies from country to country due to the changes in the weather pattern. From the values, all the three methods have much closer values of RMSE. But there is a slight difference in the values of MAPE. The LASSO based method can provide reduced values of MAPE and RMSE over SVM and TLLE. As a result, this model provides better prediction accuracy in contrast to other models. The main advantages of LASSO based model is that the data requires less training and can handle irregularities in data points.
	TLLE		RMSE=43.13, RMSE reduction with LASSO=63.53(%) MAPE=17.71, MAPE reduction with LASSO=81.16(%)	
	LSSO		RMSE=14.43, MAPE=3.33	
[54]	SVM	One year	NMAE=5.64%, NRMSE=8.53%	The error results show that HDC based blended method has reduced error when compared to SVM model. The blended technique has greater accuracy, ease of data acquisition with the help of web crawlers and can be applied to various locations globally.
	HDC, Blended NWP models		NMAE =4.65%, NRMSE =7.35%	
[52]	MLP model	5 years	RMAE=46(%), RRMSE=16.25(%)	In NN based model, selection of input data is of high priority. The prediction accuracy depends on input data, hidden layers, activation function and learning algorithm. From the results obtained, we can infer that the NN with 20 neurons exhibits the best performance and is more effective during sunny day.
	N5		RMAE=46(%),RRMSE=16.25(%)	
	N10		RMAE=46, RRMSE=19.89	
	N15		RMAE=43(%), RRMSE=22.71(%)	
	N20		RMAE=45(%), RRMSE=4.38(%)	
	N25		RMAE=43(%), RRMSE=23.55(%)	
[152]-[153]	FCN	5 years	MAPE=0.13, NMAE=0.12 NRMSE=0.16	From the error results, we can conclude that the HDNN-Fusion model exhibits the best results when compared to other models. These model error results have the lowest values of MAPE, NMAE and NRMSE when compared to other models. This hybrid deep learning NN fusion model can be applied to various forecasting frameworks and for larger PV models.
	RNN		MAPE=2.93, NMAE=1.12 NRMSE=1.41	
	LSTM		MAPE=7.06, NMAE=2.80 NRMSE=3.42	
	MLPN		MAPE=1.97, NMAE=0.78 NRMSE=0.97	
	HDNN-FUSION		MAPE=0.2, NMAE=0.08 NRMSE=0.09	

the aggregation function is fixed. The second stage is testing which is an online process. GNN model performed better than the normal ANN. In [135], a novel ANN-based model for the prediction of solar irradiance is proposed. Instead of considering solar irradiance as the only parameter in training ANN, an input vector that consists of statistical feature parameters is constructed. To obtain this, the relationship between surface solar irradiance and extra-terrestrial irradiance is found out. LM algorithm is chosen for training the ANN. The MAPE obtained for sunny and cloudy days are 9 and 26%, respectively. In [11], short-term solar forecasting system is implemented using Elmann ANN. An initial investigation on the relationship between different input parameters is carried out using multivariate regression. The ANN is trained with different sets of input vectors. The first vector was with only measured PV power, the second vector was formed by combining PV power and irradiance on the plane of the

PV module. The third vector was formed by combing PV power and ambient temperature. The forecast error for the day ahead prediction was found to be between 26.2 to 19.5%. In [49], a data mining approach is used to implement solar irradiance forecasts. The historical data for 5 years is classified into different clusters like a cloudy sky, clear sky, etc. using a k-means clustering algorithm. This is done to obtain rainfall probability patterns. These patterns are later used to predict solar irradiance. In [50], the CART (Classification and Regression Trees) algorithm of data mining is chosen to analyze the data. The results indicated that the prediction model has great importance on the seasonal parameters. In [156], solar prediction models are developed with two multiple regression models, the least-square algorithm, and the Support Vector Machine (SVM) technique. In the least square method, parameters like dew point, temperature, wind speed, sky cover, precipitation, and humidity are considered.

In the SVM technique, three different kernel functions like Linear Kernel, a Polynomial Kernel, and a Radial Basis Function (RBF) kernel are used for model building. RBF kernel is found to be the best. Comparison of various models for solar forecast and brief analysis is presented in Table 5.

IX. CONCLUSION

An exhaustive review of the short-term predictive models for solar and wind power is carried out in this paper. The models can broadly be classified into two categories, statistical models, and machine learning models. The most commonly proposed statistical models are Auto-regressive models, decomposition models, classification and regression tree models, Spatio-temporal models, Gaussian models, combination's probability models, etc. It is observed from the results of various basic time series models like ARIMA and ARMA, etc. that it is required to develop more sophisticated predictive models to improve the accuracy of forecasting. The models should be capable of capturing abrupt changes in the solar irradiates and wind speed data. Thus, decomposition models, Spatio-temporal models, etc. give better results. It is also observed that even though the models gave reasonable accuracy in the solar forecast; they did not effectively capture the outlets in the wind data. As wind data is too erratic to be modeled by a time series model, non-linear models such as machine learning algorithms. Despite the intermittent nature of wind and solar energy resources, they have been used for energy production on a larger scale. The study of various machine learning models is presented in the paper. The comparative analysis of various models suggests some of the noteworthy characteristics of the models. Wind power forecast was performed daily with certain data sets and the requisite samples were also considered for proper forecasting. These models were applied to different locations. The combinations models, deep learning, and principle component analysis (PCA) based models, Random forest (RF) algorithm have performed better in terms of prediction accuracy and stability. Also, LASSO based model used for wind power forecasting exhibited poor performance due to its linear behavior. Support Vector Regression (SVR) algorithm could provide better prediction accuracy if its standard deviation is not considered in the data set. Also, VMD based technique can decompose the sequence of raw wind speed data and can generate a new sequence. The clustered PSO-SVM-ARMA model provided better results and it can ensure safe operation of power system even during large scale integration of wind power. With solar power forecasting models, EMS, LASSO, HDC-blended, and MLP techniques outperformed the other models. These models have exhibited better prediction accuracy. Also, the LASSO model in solar power forecast requires less training and can handle irregularities in data points.

Some improvements that can be suggested to enhance the prediction accuracy of wind speed forecasting and also to predict the in-sample weights, is to investigate other data pre-processing methods. Most of the ensemble-based models have not considered Spatio-temporal information; this

information can be considered in designing the learning models to enhance prediction accuracy. Optimal methods can be explored, individually for each of the components of the time series data and then the predicted values of the components combined to obtain the forecast.

ACKNOWLEDGMENT

This work was supported by the Renewable Energy Laboratory (REL), Department of Communications and Networks Engineering, College of Engineering, Prince Sultan University, Riyadh, Saudi Arabia. The Article Processing Charges (APC) of this publication is paid by Prince Sultan University, Riyadh, Saudi Arabia.

REFERENCES

- [1] R. M. Elavarasan, G. Shafiullah, S. Padmanaban, N. M. Kumar, A. Annam, A. M. Vetrichelvan, L. Mihet-Popa, and J. B. Holm-Nielsen, "A comprehensive review on renewable energy development, challenges, and policies of leading Indian states with an international perspective," *IEEE Access*, vol. 8, pp. 74432–74457, 2020.
- [2] B. Kroposki, B. Johnson, Y. Zhang, V. Gevorgian, P. Denholm, B.-M. Hodge, and B. Hannegan, "Achieving a 100% renewable grid: Operating electric power systems with extremely high levels of variable renewable energy," *IEEE Power Energy Mag.*, vol. 15, no. 2, pp. 61–73, Mar. 2017.
- [3] L. A. Wong, V. K. Ramachandaramurthy, P. Taylor, J. B. Ekanayake, S. L. Walker, and S. Padmanaban, "Review on the optimal placement, sizing and control of an energy storage system in the distribution network," *J. Energy Storage*, vol. 21, pp. 489–504, Feb. 2019.
- [4] J. R. Andrade and R. J. Bessa, "Improving renewable energy forecasting with a grid of numerical weather predictions," *IEEE Trans. Sustain. Energy*, vol. 8, no. 4, pp. 1571–1580, Oct. 2017.
- [5] S. Kumar, R. K. Saket, D. K. Dheer, P. Sanjeevikumar, J. B. Holm-Nielsen, and F. Blaabjerg, "Layout optimisation algorithms and reliability assessment of wind farm for microgrid integration: A comprehensive review," *IET Renew. Power Gener.*, vol. 15, no. 10, pp. 2063–2084, Jul. 2021.
- [6] O. P. Mahela, A. G. Shaik, N. Gupta, M. Khosravy, B. Khan, H. H. Alhelou, and S. Padmanaban, "Recognition of power quality issues associated with grid integrated solar photovoltaic plant in experimental framework," *IEEE Syst. J.*, vol. 15, no. 3, pp. 3740–3748, Sep. 2021.
- [7] F. Meng, Q. Zou, Z. Zhang, B. Wang, H. Ma, H. M. Abdullah, A. Almalaq, and M. A. Mohamed, "An intelligent hybrid wavelet-adversarial deep model for accurate prediction of solar power generation," *Energy Rep.*, vol. 7, pp. 2155–2164, Nov. 2021.
- [8] N. Mbuli, M. Mathonsi, M. Seitshiro, and J.-H.-C. Pretorius, "Decomposition forecasting methods: A review of applications in power systems," *Energy Rep.*, vol. 6, pp. 298–306, Dec. 2020.
- [9] K. Murugaperumal, S. Srinivasn, and G. R. K. D. S. Prasad, "Optimum design of hybrid renewable energy system through load forecasting and different operating strategies for rural electrification," *Sustain. Energy Technol. Assessments*, vol. 37, Feb. 2020, Art. no. 100613.
- [10] G. de Freitas Viscondi and S. N. Alves-Souza, "A systematic literature review on big data for solar photovoltaic electricity generation forecasting," *Sustain. Energy Technol. Assessments*, vol. 31, pp. 54–63, Feb. 2019.
- [11] M. G. De Giorgi, P. M. Congedo, and M. Malvoni, "Photovoltaic power forecasting using statistical methods: Impact of weather data," *IET Sci. Meas. Technol.*, vol. 8, no. 3, pp. 90–97, May 2014.
- [12] M. Benganem and A. A. Joraid, "A multiple correlation between different solar parameters in medina, Saudi Arabia," *Renew. Energy*, vol. 32, no. 14, pp. 2424–2435, Nov. 2007.
- [13] J. A. Ruiz-Arias, H. Alsamamra, J. Tovar-Pescador, and D. Pozo-Vázquez, "Proposal of a regressive model for the hourly diffuse solar radiation under all sky conditions," *Energy Convers. Manage.*, vol. 51, no. 5, pp. 881–893, May 2010.
- [14] Z. Dong, D. Yang, T. Reindl, and W. M. Walsh, "Short-term solar irradiance forecasting using exponential smoothing state space model," *Energy*, vol. 55, pp. 1104–1113, Jun. 2013.

- [15] M. Louzazni, H. Mosalam, A. Khouya, and K. Amechnoue, "A non-linear auto-regressive exogenous method to forecast the photovoltaic power output," *Sustain. Energy Technol. Assessments*, vol. 38, Apr. 2020, Art. no. 100670.
- [16] L. Zhang, J. Wang, and X. Niu, "Wind speed prediction system based on data pre-processing strategy and multi-objective dragonfly optimization algorithm," *Sustain. Energy Technol. Assessments*, vol. 47, Oct. 2021, Art. no. 101346.
- [17] M. Ferreira, A. Santos, and P. Lucio, "Short-term forecast of wind speed through mathematical models," *Energy Rep.*, vol. 5, pp. 1172–1184, Nov. 2019.
- [18] X. Guo, Q. Zhao, D. Zheng, Y. Ning, and Y. Gao, "A short-term load forecasting model of multi-scale CNN-LSTM hybrid neural network considering the real-time electricity price," *Energy Rep.*, vol. 6, pp. 1046–1053, Dec. 2020.
- [19] X. Zhao, S. Wang, and T. Li, "Review of evaluation criteria and main methods of wind power forecasting," *Energy Proc.*, vol. 12, pp. 761–769, Jan. 2011. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S187661021101928X>
- [20] X. Wang, P. Guo, and X. Huang, "A review of wind power forecasting models," *Energy Proc.*, vol. 12, pp. 770–778, Dec. 2011. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1876610211019291>
- [21] M. S. Nazir, F. Alturise, S. Alshmrany, H. M. J. Nazir, M. Bilal, A. N. Abdalla, P. Sanjeevikumar, and Z. M. Ali, "Wind generation forecasting methods and proliferation of artificial neural network: A review of five years research trend," *Sustainability*, vol. 12, no. 9, p. 3778, May 2020.
- [22] E. Erdem, J. Shi, and Y. Peng, "Short-term forecasting of wind speed and power—A clustering approach," in *Proc. IIE Annu. Conf.*, Jan. 2014, pp. 3501–3508.
- [23] P. Lv and L. Yue, "Short-term wind speed forecasting based on non-stationary time series analysis and ARCH model," in *Proc. Int. Conf. Multimedia Technol.*, Jul. 2011, pp. 2549–2553.
- [24] G. Li, J. Shi, and J. Zhou, "Bayesian adaptive combination of short-term wind speed forecasts from neural network models," *Renew. Energy*, vol. 36, pp. 352–359, Jan. 2011. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0960148110003228>
- [25] G. Li and J. Shi, "On comparing three artificial neural networks for wind speed forecasting," *Appl. Energy*, vol. 87, no. 7, pp. 2313–2320, 2010.
- [26] M. A. Mohandes, S. Rehman, and T. O. Halawani, "A neural networks approach for wind speed prediction," *Renew. Energy*, vol. 13, no. 3, pp. 345–354, Mar. 1998.
- [27] M. A. Shoorehdeli, M. Teshnehlab, A. K. Sedigh, and M. A. Khanesar, "Identification using ANFIS with intelligent hybrid stable learning algorithm approaches and stability analysis of training methods," *Appl. Soft Comput.*, vol. 9, no. 2, pp. 833–850, Mar. 2009.
- [28] M. Negnevitsky, P. Johnson, and S. Santoso, "Short term wind power forecasting using hybrid intelligent systems," in *Proc. IEEE Power Eng. Soc. Gen. Meeting*, Jun. 2007, pp. 1–4.
- [29] Z. O. Olaofe, "A 5-day wind speed & power forecasts using a layer recurrent neural network (LRNN)," *Sustain. Energy Technol. Assessments*, vol. 6, pp. 1–24, Jun. 2014.
- [30] A. Jäger-Waldau, *PV Status Report 2019*. Luxembourg, Germany: Publications Office European Union Headquarters, 2019.
- [31] I. Khan, H. Chowdhury, R. Rasjidin, F. Alam, T. Islam, and S. Islam, "Review of wind energy utilization in South Asia," *Proc. Eng.*, vol. 49, pp. 213–220, Jan. 2012.
- [32] R. Satharthan and M. Geethanjali, "Wind energy utilization in India: A review," *Middle-East J. Sci. Res.*, vol. 22, vol. 6, pp. 796–801, 2014.
- [33] D. Sangroya and J. K. Nayak, "Development of wind energy in India," *Int. J. Renew. Energy Res.*, vol. 5, no. 1, pp. 1–13, 2015.
- [34] B. Espinarm, J. L. Aznarte, R. Girard, A. M. Moussa, and G. Kariniotakis, "Photovoltaic forecasting: A state of the art," in *Proc. 5th Eur. PV-Hybrid Mini-Grid Conf.*, 2010, pp. 250–255.
- [35] S. S. Soman, H. Zareipour, O. Malik, and P. Mandal, "A review of wind power and wind speed forecasting methods with different time horizons," in *Proc. North Amer. Power Symp.*, Sep. 2010, pp. 1–8.
- [36] E. Lorenz, J. Hurka, and M. Schneider, "Qualified forecast of ensemble power production by spatially dispersed grid-connected PV systems," in *Proc. 23rd Eur. Photovolt. Sol. Energy Conf.*, 2008, pp. 3285–3291.
- [37] H. R. Glahn and D. A. Lowry, "The use of model output statistics (MOS) in objective weather forecasting," *J. Appl. Meteorol.*, vol. 11, no. 8, pp. 1203–1211, Dec. 1972.
- [38] B. Abraham and J. Ledolter, *Statistical Methods for Forecasting*, vol. 234. Hoboken, NJ, USA: Wiley, 2009.
- [39] H. Cheng, W.-S. Cao, and P.-J. Ge, "Forecasting research of long-term solar irradiance and output power for photovoltaic generation system," in *Proc. 4th Int. Conf. Comput. Inf. Sci.*, Aug. 2012, pp. 1224–1227.
- [40] T. Fang and R. Lahdelma, "Evaluation of a multiple linear regression model and SARIMA model in forecasting heat demand for district heating system," *Appl. Energy*, vol. 179, pp. 544–552, Oct. 2016.
- [41] C.-C. Chou, C.-W. Chu, and G.-S. Liang, "A modified regression model for forecasting the volumes of Taiwan's import containers," *Math. Comput. Model.*, vol. 47, nos. 9–10, pp. 797–807, May 2008.
- [42] G. Notton and C. Voyant, "Forecasting of intermittent solar energy resource," in *Advances in Renewable Energies and Power Technologies*, I. Yahyaoui, Ed. Amsterdam, The Netherlands: Elsevier, 2018, ch. 3, pp. 77–114. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/B9780128129593000034>
- [43] N. Tripathy, "Forecasting gold price with auto regressive integrated moving average model," *Int. J. Econ. Financial Issues*, vol. 7, no. 4, pp. 1–6, 2017.
- [44] J.-F. Chen, W.-M. Wang, and C.-M. Huang, "Analysis of an adaptive time-series autoregressive moving-average (ARMA) model for short-term load forecasting," *Electr. Power Syst. Res.*, vol. 34, no. 3, pp. 187–196, Sep. 1995.
- [45] R. Nochai and T. Nochai, "ARIMA model for forecasting oil palm price," in *Proc. 2nd IMT-GT Regional Conf. Math., Statist. Appl.*, 2006, pp. 13–15.
- [46] G. Yu and C. Zhang, "Switching ARIMA model based forecasting for traffic flow," in *Proc. IEEE Int. Conf. Acoust., Speech, Signal Process.*, vol. 2, May 2004, pp. 1–4.
- [47] P. Bacher, H. Madsen, and H. A. Nielsen, "Online short-term solar power forecasting," *Sol. Energy*, vol. 83, no. 10, pp. 1772–1783, 2009.
- [48] S. Kaplanis and E. Kaplani, "A model to predict expected mean and stochastic hourly global solar radiation $I(h; n_j)$ values," *Renew. Energy*, vol. 32, no. 8, pp. 1414–1425, Jul. 2007.
- [49] M.-C. Kang, J.-M. Sohn, J.-Y. Park, S.-K. Lee, and Y.-T. Yoon, "Development of algorithm for day ahead PV generation forecasting using data mining method," in *Proc. IEEE 54th Int. Midwest Symp. Circuits Syst. (MWSCAS)*, Aug. 2011, pp. 1–4.
- [50] H. Mori and A. Takahashi, "A data mining method for selecting input variables for forecasting model of global solar radiation," in *Proc. PES T&D*, May 2012, pp. 1–6.
- [51] A. Moreno-Munoz, J. J. G. de la Rosa, R. Posadillo, and V. Pallares, "Short term forecasting of solar radiation," in *Proc. IEEE Int. Symp. Ind. Electron.*, Jun. 2008, pp. 1537–1541.
- [52] X. Zhang, Y. Li, S. Lu, H. F. Hamann, B.-M. Hodge, and B. Lehman, "A solar time based analog ensemble method for regional solar power forecasting," *IEEE Trans. Sustain. Energy*, vol. 10, no. 1, pp. 268–279, Jan. 2019.
- [53] C. Cui, Y. Zou, L. Wei, and Y. Wang, "Evaluating combination models of solar irradiance on inclined surfaces and forecasting photovoltaic power generation," *IET Smart Grid*, vol. 2, no. 1, pp. 123–130, Mar. 2019.
- [54] N. Tang, S. Mao, Y. Wang, and R. M. Nelms, "Solar power generation forecasting with a LASSO-based approach," *IEEE Internet Things J.*, vol. 5, no. 2, pp. 1090–1099, Apr. 2018.
- [55] T. A. Fathima, V. Nedumpozhimana, Y. H. Lee, S. Winkler, and S. Dev, "A chaotic approach on solar irradiance forecasting," in *Proc. Photon. Electromagn. Res. Symp.-Fall (PIERS-Fall)*, Dec. 2019, pp. 2724–2728.
- [56] C. Pan, J. Tan, and D. Feng, "Short-term solar power generation forecasting via continuous conditional random fields," in *Proc. IEEE 5th Int. Conf. Comput. Commun. (ICCC)*, Dec. 2019, pp. 251–256.
- [57] R. Ramakrishna, A. Scaglione, V. Vittal, E. Dall'Anese, and A. Bernstein, "A model for joint probabilistic forecast of solar photovoltaic power and outdoor temperature," *IEEE Trans. Signal Process.*, vol. 67, no. 24, pp. 6368–6383, Dec. 2019.
- [58] T. A. Fathima, V. Nedumpozhimana, Y. H. Lee, S. Winkler, and S. Dev, "Predicting solar irradiance in Singapore," in *Proc. Photon. Electromagn. Res. Symp.-Fall (PIERS-Fall)*, Dec. 2019, pp. 3164–3167.
- [59] M. H. Kapourchali, M. Sepehry, and V. Aravinthan, "Multivariate spatio-temporal solar generation forecasting: A unified approach to deal with communication failure and invisible sites," *IEEE Syst. J.*, vol. 13, no. 2, pp. 1804–1812, Jun. 2019.
- [60] H.-Y. Su, T.-Y. Liu, and H.-H. Hong, "Adaptive residual compensation ensemble models for improving solar energy generation forecasting," *IEEE Trans. Sustain. Energy*, vol. 11, no. 2, pp. 1103–1105, Apr. 2020.

- [61] G. Shi and S. Eftekharij, "Data-driven solar generation forecast considering temporal characteristics of data," in *Proc. IEEE Texas Power Energy Conf. (TPEC)*, Feb. 2020, pp. 1–6.
- [62] N. N. Arjun, V. Prema, D. K. Kumar, P. Prashanth, V. S. Preeksht, and K. U. Rao, "Multivariate regression models for prediction of wind speed," in *Proc. Int. Conf. Data Sci. Eng. (ICDSE)*, Aug. 2014, pp. 171–176.
- [63] G. Li, J. Shi, and J. Zhou, "Bayesian adaptive combination of short-term wind speed forecasts from neural network models," *Renew. Energy*, vol. 36, pp. 352–359, Jan. 2011. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0960148110003228>
- [64] E. B. Dagum, "Revisions of time varying seasonal filters," *J. Forecasting*, vol. 1, no. 2, pp. 173–187, Apr. 1982.
- [65] D. Pfeiffermann, M. Morry, and P. Wong, "Estimation of the variances of X-11 ARIMA seasonally adjusted estimators for a multiplicative decomposition and heteroscedastic variances," *Int. J. Forecasting*, vol. 11, no. 2, pp. 271–283, Jun. 1995.
- [66] D. M. Miller and D. Williams, "Shrinkage estimators of time series seasonal factors and their effect on forecasting accuracy," *Int. J. Forecasting*, vol. 19, no. 4, pp. 669–684, 2003. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0169207002000778>
- [67] C. Chen, "Robustness properties of some forecasting methods for seasonal time series: A Monte Carlo study," *Int. J. Forecasting*, vol. 13, no. 2, pp. 269–280, Jun. 1997. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0169207097000149>
- [68] D. J. Noakes, A. I. McLeod, and K. W. Hipel, "Forecasting monthly riverflow time series," *Int. J. Forecasting*, vol. 1, no. 2, pp. 179–190, Jan. 1985.
- [69] B.-L. Zhang, R. Coggins, M. A. Jabri, D. Dersch, and B. Flower, "Multiresolution forecasting for futures trading using wavelet decompositions," *IEEE Trans. Neural Netw.*, vol. 12, no. 4, pp. 765–775, Jul. 2001.
- [70] P. H. Franses and D. van Dijk, "The forecasting performance of various models for seasonality and nonlinearity for quarterly industrial production," *Int. J. Forecasting*, vol. 21, no. 1, pp. 87–102, Jan. 2005. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0169207004000524>
- [71] N. Kulendran and M. L. King, "Forecasting international quarterly tourist flows using error-correction and time-series models," *Int. J. Forecasting*, vol. 13, no. 3, pp. 319–327, Sep. 1997. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0169207097000204>
- [72] J. Verbesselt, R. Hyndman, G. Newnham, and D. Culvenor, "Detecting trend and seasonal changes in satellite image time series," *Remote Sens. Environ.*, vol. 114, no. 1, pp. 106–115, 2010.
- [73] V. Zarnowitz and A. Ozyildirim, "Time series decomposition and measurement of business cycles, trends and growth cycles," *J. Monetary Econ.*, vol. 53, no. 7, pp. 1717–1739, Oct. 2006.
- [74] V. Prema and K. U. Rao, "Time series decomposition model for accurate wind speed forecast," *Renewables, Wind, Water, Sol.*, vol. 2, no. 1, pp. 1–11, Dec. 2015.
- [75] J. Yan, K. Li, and E.-W. Bai, "Prediction error adjusted Gaussian process for short-term wind power forecasting," in *Proc. IEEE Int. Workshop Intelligent Energy Syst. (IWIES)*, Nov. 2013, pp. 173–178.
- [76] X. Wu, B. Hong, X. Peng, F. Wen, and J. Huang, "Radial basis function neural network based short-term wind power forecasting with Grubbs test," in *Proc. 4th Int. Conf. Electric Utility Deregulation Restructuring Power Technol. (DRPT)*, Jul. 2011, pp. 1879–1882.
- [77] B. Efe, S. Menten, Y. Unal, E. Tan, E. Unal, T. Ozdemir, B. Barutcu, B. Onol, and S. Topcu, "72 hr forecast of wind power in Mani'sa, Turkey by using the WRF model coupled to WindSim," in *Proc. Int. Conf. Renew. Energy Res. Appl. (ICRERA)*, Nov. 2012, pp. 1–6.
- [78] A. Carpinon, R. Langella, A. Testa, and M. Giorgio, "Very short-term probabilistic wind power forecasting based on Markov chain models," in *Proc. IEEE 11th Int. Conf. Probabilistic Methods Appl. Power Syst.*, Jun. 2010, pp. 107–112.
- [79] F. Marzbani, A. Osman, M. Hassan, and T. Landolsi, "Short-term wind power forecast for economic dispatch," in *Proc. 5th Int. Conf. Modeling, Simulation Appl. Optim. (ICMSAO)*, Apr. 2013, pp. 1–6.
- [80] J. Wang, J. Hu, K. Ma, and Y. Zhang, "A self-adaptive hybrid approach for wind speed forecasting," *Renew. Energy*, vol. 78, pp. 374–385, Jun. 2015.
- [81] N. Huang, Y. Wu, G. Lu, W. Wang, and X. Cao, "Combined probability prediction of wind power considering the conflict of evaluation indicators," *IEEE Access*, vol. 7, pp. 174709–174724, 2019.
- [82] Y. Wang, D. Wang, and Y. Tang, "Clustered hybrid wind power prediction model based on ARMA, PSO-SVM, and clustering methods," *IEEE Access*, vol. 8, pp. 17071–17079, 2020.
- [83] Y. Sun, Z. Li, X. Yu, B. Li, and M. Yang, "Research on ultra-short-term wind power prediction considering source relevance," *IEEE Access*, vol. 8, pp. 147703–147710, 2020.
- [84] S. Lu, "Multi-step ahead ultra-short-term wind power forecasting based on time series analysis," in *Proc. Int. Conf. Comput. Inf. Big Data Appl. (CIBDA)*, Apr. 2020, pp. 430–434.
- [85] H. Xiao, H. Tang, and J. Zhou, "Short-term wind speed combined prediction model based on ARIMA-GARCH and Elman," in *Proc. Asia-Pacific Conf. Image Process., Electron. Comput. (IPEC)*, Apr. 2020, pp. 73–76.
- [86] V. Vapnik, *The Nature of Statistical Learning Theory*. New York, NY, USA: Springer, 2000.
- [87] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, "Extreme learning machine: Theory and applications," *Neurocomputing*, vol. 70, nos. 1–3, pp. 489–501, 2006.
- [88] L. Lazić, G. Pejanović, and M. Živković, "Wind forecasts for wind power generation using the eta model," *Renew. Energy*, vol. 35, no. 6, pp. 1236–1243, Jun. 2010.
- [89] G. B. Huang, H. Zhou, X. Ding, and R. Zhang, "Extreme learning machine for regression and multiclass classification," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 42, no. 2, pp. 513–529, Feb. 2012.
- [90] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, "Extreme learning machine: A new learning scheme of feedforward neural networks," in *Proc. IEEE Int. Joint Conf. Neural Netw.*, vol. 2, Jul. 2004, pp. 985–990.
- [91] L. Hui, "Target threat estimation based on BP neural network optimized by BA," *Shanxi Electron. Technol.*, vol. 1, p. 3, Oct. 2016.
- [92] T. L. Best, "Bats: Biology and behaviour," *J. Mammal.*, vol. 78, no. 3, p. 986, 1997.
- [93] X. Yang and A. H. Gandomi, "Bat algorithm: A novel approach for global engineering optimization," *Eng. Comput.*, vol. 29, no. 5, pp. 464–483, Jul. 2012.
- [94] S. Mishra, K. Shaw, and D. Mishra, "A new meta-heuristic bat inspired classification approach for microarray data," *Proc. Technol.*, vol. 4, pp. 802–806, Jan. 2012.
- [95] J. L. Elman, "Finding structure in time," *Cognit. Sci.*, vol. 14, no. 2, pp. 179–211, Mar. 1990.
- [96] R. Chandra and M. Zhang, "Cooperative coevolution of Elman recurrent neural networks for chaotic time series prediction," *Neurocomputing*, vol. 86, pp. 116–123, Jun. 2012.
- [97] M. Cacciola, G. Megali, D. Pellicano, and F. C. Morabito, "Elman neural networks for characterizing voids in welded strips: A study," *Neural Comput. Appl.*, vol. 21, no. 5, pp. 869–875, Jul. 2012.
- [98] W. Chen and W. Ma, "Applications based on genetic neural network model of Lianyungang marine water quality optimization techniques and algorithms technology," in *Proc. Int. Conf. Inf. Sci. Manage. Eng.*, vol. 1, Aug. 2010, pp. 526–529.
- [99] G. D. Gao, W. X. Zhang, J. H. Sui, and G. Y. Mu, "Research on diesel engine fault diagnosis modeling based on Elman neural network," in *Advanced Materials Research*, vol. 361. Stafa-Zurich, Switzerland: Trans Tech Publication, 2012, pp. 1506–1509.
- [100] A. Timmermann, G. Elliott, and C. Granger, "Forecast combinations," in *Handbook of Economic Forecasting*, vol. 1. Amsterdam, The Netherlands: Elsevier, 2006, ch. 4, pp. 135–196. [Online]. Available: <https://EconPapers.repec.org/RePEc:eee:ecofch:1-04>
- [101] R. Adhikari, "A neural network based linear ensemble framework for time series forecasting," *Neurocomputing*, vol. 157, pp. 231–242, Jun. 2015.
- [102] A. Botterud, Z. Zhi, J. Wang, R. J. Bessa, H. Keko, J. Mendes, J. Sumaili, and V. Miranda, "Use of wind power forecasting in operational decisions," Argonne Nat. Lab., Argonne, IL, USA, Tech. Rep. ANL-DIS-11-08, 2011.
- [103] A. Stetco, F. Dinmohammadi, X. Zhao, V. Robu, D. Flynn, M. Barnes, J. Keane, and G. Nenadic, "Machine learning methods for wind turbine condition monitoring: A review," *Renew. Energy*, vol. 133, pp. 620–635, Apr. 2019.
- [104] M. Lydia and S. Suresh Kumar, "A comprehensive overview on wind power forecasting," in *Proc. Conf. IPEC*, Oct. 2010, pp. 268–273.
- [105] L. Xiao, J. Wang, Y. Dong, and J. Wu, "Combined forecasting models for wind energy forecasting: A case study in China," *Renew. Sustain. Energy Rev.*, vol. 44, pp. 271–288, Apr. 2015.
- [106] J. Shi, J. Guo, and S. Zheng, "Evaluation of hybrid forecasting approaches for wind speed and power generation time series," *Renew. Sustain. Energy Rev.*, vol. 16, no. 5, pp. 3471–3480, 2012.
- [107] P. Jiang, F. Liu, and Y. Song, "A hybrid forecasting model based on date-framework strategy and improved feature selection technology for short-term load forecasting," *Energy*, vol. 119, pp. 694–709, Jan. 2017.

- [108] W. Y. Y. Cheng, Y. B. Liu, A. J. Bourgeois, Y. H. Wu, and S. E. Haupt, "Short-term wind forecast of a data assimilation/weather forecasting system with wind turbine anemometer measurement assimilation," *Renew. Energy*, vol. 107, pp. 340–351, Jul. 2017.
- [109] B.-M. Hodge, A. Zeiler, D. Brooks, G. Blau, J. Pekny, and G. Reklatis, "Improved wind power forecasting with ARIMA models," *Comput. Aided Chem. Eng.*, vol. 29, pp. 1789–1793, Jan. 2011.
- [110] J. Wang, N. Zhang, and H. Lu, "A novel system based on neural networks with linear combination framework for wind speed forecasting," *Energy Convers. Manage.*, vol. 181, pp. 425–442, Feb. 2019.
- [111] X. He, Y. Nie, H. Guo, and J. Wang, "Research on a novel combination system on the basis of deep learning and swarm intelligence optimization algorithm for wind speed forecasting," *IEEE Access*, vol. 8, pp. 51482–51499, 2020.
- [112] M. Khan, T. Liu, and F. Ullah, "A new hybrid approach to forecast wind power for large scale wind turbine data using deep learning with TensorFlow framework and principal component analysis," *Energies*, vol. 12, no. 12, p. 2229, Jun. 2019.
- [113] H. Demolli, A. S. Dokuz, A. Ecemis, and M. Gokcek, "Wind power forecasting based on daily wind speed data using machine learning algorithms," *Energy Convers. Manage.*, vol. 198, Oct. 2019, Art. no. 111823.
- [114] P. Du, J. Wang, W. Yang, and T. Niu, "Multi-step ahead forecasting in electrical power system using a hybrid forecasting system," *Renew. Energy*, vol. 122, pp. 533–550, Jul. 2018.
- [115] P. Jiang, H. Yang, and J. Heng, "A hybrid forecasting system based on fuzzy time series and multi-objective optimization for wind speed forecasting," *Appl. Energy*, vol. 235, pp. 786–801, Feb. 2019.
- [116] B. Sun and H.-T. Yao, "The short-term wind speed forecast analysis based on the PSO-LSSVM predict model," *Power Syst. Protection Control*, vol. 40, no. 5, pp. 85–89, 2012.
- [117] B. Chen, L. Zhao, and J. Hong Lu, "Wind power forecast using RBF network and culture algorithm," in *Proc. Int. Conf. Sustain. Power Gener. Supply*, Apr. 2009, pp. 1–6.
- [118] S. Chen, L. Ye, G. Zhang, C. Zeng, S. Dong, and C. Dai, "Short-term wind power prediction based on combined grey-Markov model," in *Proc. Int. Conf. Adv. Power Syst. Autom. Protection*, Oct. 2011, pp. 1705–1711.
- [119] J. G. D. Gooijer and R. J. Hyndman, "25 years of time series forecasting," *Int. J. Forecasting*, vol. 22, no. 3, pp. 443–473, 2006.
- [120] V. R. R. Jose and R. L. Winkler, "Simple robust averages of forecasts: Some empirical results," *Int. J. Forecasting*, vol. 24, no. 1, pp. 163–169, 2008.
- [121] R. R. Andrawis, A. F. Atiya, and H. El-Shishiny, "Forecast combinations of computational intelligence and linear models for the NN5 time series forecasting competition," *Int. J. Forecasting*, vol. 27, no. 3, pp. 672–688, Sep. 2011.
- [122] X. Nan, Q. Li, D. Qiu, Y. Zhao, and X. Guo, "Short-term wind speed syntheses correcting forecasting model and its application," *Int. J. Electr. Power Energy Syst.*, vol. 49, pp. 264–268, Jul. 2013.
- [123] J. Wang, J. Heng, L. Xiao, and C. Wang, "Research and application of a combined model based on multi-objective optimization for multi-step ahead wind speed forecasting," *Energy*, vol. 125, pp. 591–613, Apr. 2017.
- [124] Q. Wang, K. K. Lai, D. Niu, and Q. Zhang, "A multivariate wind power forecasting model based on LS-SVM," in *Proc. 5th Int. Joint Conf. Comput. Sci. Optim.*, Jun. 2012, pp. 127–131.
- [125] J. P. S. Catalão, H. M. I. Pousinho, and V. M. F. Mendes, "Hybrid wavelet-PSO-ANFIS approach for short-term wind power forecasting in Portugal," *IEEE Trans. Sustainable Energy*, vol. 2, no. 1, pp. 50–59, Jan. 2011.
- [126] M. J. Ghadi, S. H. Gilani, A. Sharifiyan, and H. Afrakhteh, "A new method for short-term wind power forecasting," in *Proc. 17th Conf. Electr. Power Distrib.*, May 2012, pp. 1–6.
- [127] H. Chitsaz, N. Amjadi, and H. Zareipour, "Wind power forecast using wavelet neural network trained by improved Clonal selection algorithm," *Energy Convers. Manage.*, vol. 89, pp. 588–598, Jan. 2015.
- [128] H. Liu, H. Tian, X. Liang, and Y. Li, "New wind speed forecasting approaches using fast ensemble empirical model decomposition, genetic algorithm, mind evolutionary algorithm and artificial neural networks," *Renew. Energy*, vol. 83, pp. 1066–1075, Nov. 2015.
- [129] J. Wen, X. Wang, Y. Zheng, L. Li, L. Zhou, G. Yao, and H. Chen, "Short-term wind power forecasting based on lifting wavelet transform and SVM," in *Proc. Power Eng. Autom. Conf.*, Sep. 2012, pp. 1–4.
- [130] L. Yang, M. He, J. Zhang, and V. Vittal, "Support-vector-machine-enhanced Markov model for short-term wind power forecast," *IEEE Trans. Sustain. Energy*, vol. 6, no. 3, pp. 791–799, Jul. 2015.
- [131] R. J. Bessa, V. Miranda, and J. Gama, "Entropy and correntropy against minimum square error in offline and online three-day ahead wind power forecasting," *IEEE Trans. Power Syst.*, vol. 24, no. 4, pp. 1657–1666, Nov. 2009.
- [132] I. J. Ramirez-Rosado, L. A. Fernandez-Jimenez, C. Monteiro, J. Sousa, and R. Bessa, "Comparison of two new short-term wind-power forecasting systems," *Renew. Energy*, vol. 34, no. 7, pp. 1848–1854, 2009.
- [133] M. Sifuzzaman, M. R. Islam, and M. Z. Ali, "Application of wavelet transform and its advantages compared to Fourier transform," *J. Phys. Sci.*, vol. 13, pp. 121–134, 2009.
- [134] I. Daubechies, *The Wavelet Transform, Time-Frequency Localization and Signal Analysis*. Princeton, NJ, USA: Princeton Univ. Press, 2009.
- [135] X. Wang, Y. Zheng, L. Li, L. Zhou, G. Yao, and T. Huang, "Short-term wind power prediction based on wavelet decomposition and extreme learning machine," in *Proc. Int. Symp. Neural Netw.* Springer, 2012, pp. 645–653.
- [136] P. L. Johnson, M. Negnevitsky, and K. M. Muttaqi, "Short term wind power forecasting using adaptive neuro-fuzzy inference systems," in *Proc. Australas. Univ. Power Eng. Conf.*, Dec. 2007, pp. 1–6.
- [137] Z. J. Hou, P. V. Etingov, Y. V. Makarov, and N. A. Samaan, "Uncertainty reduction in power generation forecast using coupled wavelet-ARIMA," in *Proc. IEEE PES Gen. Meeting Conf. Exposit.*, Jul. 2014, pp. 1–5.
- [138] P. Mandal, A. Ul Haque, J. Meng, A. K. Srivastava, and R. Martinez, "A novel hybrid approach using wavelet, firefly algorithm, and fuzzy ARTMAP for day-ahead electricity price forecasting," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 1041–1051, May 2013.
- [139] K. Albertson and J. Aylene, "Modelling the great lakes freeze: Forecasting and seasonality in the market for ferrous scrap," *Int. J. Forecasting*, vol. 12, no. 3, pp. 345–359, Sep. 1996.
- [140] L. Wu and M. Shahidehpour, "A hybrid model for day-ahead price forecasting," *IEEE Trans. Power Syst.*, vol. 25, no. 3, pp. 1519–1530, Aug. 2010.
- [141] P. C. Chang and C. Y. Fan, "A hybrid system integrating a wavelet and TSK fuzzy rules for stock price forecasting," *IEEE Trans. Syst., Man, C.*, vol. 38, no. 6, pp. 802–815, Nov. 2008.
- [142] G. Osório, J. C. O. Matias, and J. Catalão, "Short-term wind power forecasting using adaptive neuro-fuzzy inference system combined with evolutionary particle swarm optimization, wavelet transform and mutual information," *Renew. Energy*, vol. 75, pp. 301–307, Mar. 2015.
- [143] V. Prema and K. U. Rao, "Interactive graphical user interface (GUI) for wind speed prediction using wavelet and artificial neural network," *J. Inst. Eng. India, B*, vol. 99, no. 5, pp. 467–477, Oct. 2018.
- [144] V. Prema, K. U. Rao, B. Jnaneswar, C. A. Badarish, P. S. Ashok, and S. Agarwal, "Application of hybrid neuro-wavelet models for effective prediction of wind speed," in *Intelligent Systems Technologies and Applications*. Springer, 2016, pp. 345–354.
- [145] V. Prema, B. S. Jnaneswar, C. A. Badarish, P. S. Ashok, S. Agarwal, and U. Rao, "Novel training strategies for wavelet-neuro models for wind speed prediction," in *Proc. IEEE Region Conf. (TENCON)*, Nov. 2015, pp. 1–4.
- [146] L. Han, C. E. Romero, and Z. Yao, "Wind power forecasting based on principle component phase space reconstruction," *Renew. Energy*, vol. 81, pp. 737–744, Sep. 2015.
- [147] A. Yona, T. Senjyu, T. Funabashi, and C.-H. Kim, "Determination method of insolation prediction with fuzzy and applying neural network for long-term ahead PV power output correction," *IEEE Trans. Sustain. Energy*, vol. 4, no. 2, pp. 527–533, Apr. 2013.
- [148] D. A. Snegirev, S. A. Eroshenko, A. I. Khalyasmaa, V. V. Dubailova, and A. I. Stepanova, "Day-ahead solar power plant forecasting accuracy improvement on the hourly basis," in *Proc. IEEE Conf. Russian Young Researchers Electr. Electron. Eng. (EIConRus)*, Jan. 2019, pp. 1088–1091.
- [149] R. Varga, S. M. Matheson, and A. Hamilton-Wright, "Aggregate features in multisample classification problems," *IEEE J. Biomed. Health Inform.*, vol. 19, no. 2, pp. 486–492, Mar. 2015.
- [150] Y. Ren, P. Suganthan, and N. Srikanth, "Ensemble methods for wind and solar power forecasting—a state-of-the-art review," *Renew. Sustain. Energy Rev.*, vol. 50, pp. 82–91, 2015.
- [151] A. W. Bowman and A. Azzalini, *Applied Smoothing Techniques for Data Analysis: The Kernel Approach With S-Plus Illustrations*, vol. 18. Oxford, U.K.: OUP Oxford, 1997.
- [152] Z. Zarkov, L. Stoyanov, I. Draganovska, and V. Lazarov, "Application of ANN for solar radiation forecasting—case study of Oryahovo," in *Proc. 11th Electr. Eng. Fac. Conf. (BulEF)*, Sep. 2019, pp. 1–5.

- [153] D. A. R. De Jesus, P. Mandal, M. Velez-Reyes, S. Chakraborty, and T. Senjyu, "Data fusion based hybrid deep neural network method for solar PV power forecasting," in *Proc. North Amer. Power Symp. (NAPS)*, Oct. 2019, pp. 1–6.
- [154] M. Cococcioni, E. D'Andrea, and B. Lazzerini, "24-hour-ahead forecasting of energy production in solar PV systems," in *Proc. 11th Int. Conf. Intell. Syst. Design Appl.*, Nov. 2011, pp. 1276–1281.
- [155] V. P. Singh, K. Vaibhav, and D. K. Chaturvedi, "Solar power forecasting modeling using soft computing approach," in *Proc. Nirma Univ. Int. Conf. Eng. (NUiCONE)*, Dec. 2012, pp. 1–5.
- [156] N. Sharma, P. Sharma, D. Irwin, and P. Shenoy, "Predicting solar generation from weather forecasts using machine learning," in *Proc. IEEE Int. Conf. Smart Grid Commun. (SmartGridComm)*, Oct. 2011, pp. 528–533.



V. PREMA (Senior Member, IEEE) was born in Thiruvananthapuram, Kerala, India, in 1979. She received the B.Tech. degree in electrical engineering from Calicut University, in 2001, and the M.Tech. degree in power electronics and the Ph.D. degree in electrical engineering from Visvesvaraya Technological University, in 2005 and 2018, respectively. She has 16 years of teaching and industry experience. She is currently working as an Associate Professor with the B.M.S. College of Engineering, Bengaluru. She has authored more than 25 papers in various journals and conferences. Her research interests include renewable energy, forecasting, and power electronics.



M. S. BHASKAR (Senior Member, IEEE) received the bachelor's degree in electronics and telecommunication engineering from the University of Mumbai, Mumbai, India, in 2011, the master's degree in power electronics and drives from the Vellore Institute of Technology, VIT University, India, in 2014, and the Ph.D. degree in electrical and electronic engineering from the University of Johannesburg, South Africa, in 2019. He is currently with Renewable Energy Laboratory, Department of Electrical Engineering, College of Engineering, Prince Sultan University, Riyadh, Saudi Arabia. He has authored 150 plus scientific articles with particular reference to dc/dc and dc/ac converter, and high gain converter. He is also a reviewer member of various international journals and conferences, including IEEE and IET. He is also a Senior Member of IEEE Industrial Electronics, Power Electronics, Industrial Application, Power and Energy, Robotics and Automation, Vehicular Technology Societies, and Young Professionals, various IEEE Councils, and Technical Communities. He received IEEE ACCESS Award "Reviewer of Month" in January 2019 for his valuable and thorough feedback on manuscripts, and for his quick turnaround on reviews. He received the Best Paper Research Paper Award from IEEE-GPECOM'20, IEEE-CENCON'19, IEEE-ICCPCT'14, and IET-CEAT'16. He is also an Associate Editor of *IET Power Electronics* and the Topic Editor of *MDPI Electronics*, Switzerland.



DHAFER ALMAKHLES (Senior Member, IEEE) received the B.E. degree in electrical engineering from the King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia, in 2006, and the master's (Hons.) and Ph.D. degrees from The University of Auckland, New Zealand, in 2011 and 2016, respectively. Since 2016, he has been with Prince Sultan University, Saudi Arabia. He is currently the Leader of the Renewable Energy Research Team and Laboratory. His research interests include power electronics, control theory, unmanned aerial vehicles, renewable energy systems, and FPGA applications.



N. GOWTHAM (Senior Member, IEEE) received the bachelor's degree in electrical and electronics engineering from the Vidyavardhaka College of Engineering, Mysuru, in 2011, the M.Tech. degree in microelectronics and control systems from the Dayananda Sagar College of Engineering, Bengaluru, in 2013, and the Ph.D. degree in power quality, in 2020. He was a Research Fellow with IIT Delhi. He is currently working as an Assistant Professor with the Department of Electrical and Electronics Engineering, Vidyavardhaka College of Engineering. He has published books and book chapters. He has authored more than 20 research papers in reputed conferences and journals. His research interests include applications of power electronics to power systems, power quality, integration of RE into LV/MV grid, and engineering education.



K. UMA RAO (Senior Member, IEEE) was born in India, in March 1963. She received the B.E. degree in electrical engineering and the M.E. degree in power systems from the University Visvesvaraya College of Engineering, Bengaluru, in 1984 and 1987, respectively, and the Ph.D. degree from the Indian Institute of Science, Bengaluru, in 1997. She has 30 years of teaching experience and currently working as a Professor with the Department of Electrical and Electronics Engineering, R.V. College of Engineering[®], Bengaluru. She has published 11 technical books and more than 170 technical publications in national and international journals and conferences. Her research interests include FACTS, custom power, power quality, renewable energy, and technical education. She received 11 awards of excellence from various technical societies.

...