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Review

Wind power forecasting technologies: A review

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Abstract: This study addresses the critical role of wind power forecasting in ensuring stable and reliable power system operations. Wind power forecasting is critical for the efficient operation of plants, time scheduling, and the balancing of power generation with grid integration systems. Due to its dependency on dynamic climatic conditions and associated factors, accurate wind power forecasting is challenging. The research delves into various aspects, including input data, input selection techniques, data pre-processing, and forecasting methods, with the aim of motivating researchers to design highly efficient online/offline models on weather-based data. The overarching goal is to enhance the reliability and stability of power systems while optimizing energy resource utilization. The analysis reveals that hybrid models offer more accurate results, highlighting their significance in the current era. This study investigates different Wind Power Forecasting (WPF) models from existing literature, focusing on input variables, time horizons, climatic conditions, pre-processing techniques, and sample sizes that affect model accuracy. It covers statistical models like ARMA and ARIMA, along with AI techniques including Deep Learning (DL), Machine Learning (ML), and neural networks, to estimate wind power.

Keywords: forecasting; neural networks; pre-processing; time series; wind power forecasting

1. Introduction

Rising demands for energy with a limited supply of fossil fuels have motivated the world to depend on renewable sources of energy, which include solar power, ocean power, geothermal power, biomass power, wind power, etc. These renewable energies act as an alternative solution to meet the huge demand of the world population [1]. Amongst which is wind power energy, which is highly rated as an as an encouraging and favorable power energy resource with abundant availability on the earth surface. In this current scenario, as demand for fossil fuels increases at a faster rate, there is a requirement to shift towards renewable energies. This leads to the use of the use of technology to find innovative solutions related to renewable energies. Hence Wind power forecasting has become one of the emerging research fields related primarily to electrical engineering. Several academicians and researchers are focused on the development of algorithms and related tools for forecasting wind power [2,3]. Ambitious goals are set by many nations to increase the generation of renewable energy to integrate into grid power, where a major contribution is expected from wind energy in order to reach these goals. But at the deeper levels, we can view uncertainty significantly and variability inherently in the generation of wind power, posing challenges in integrating wind power with grid power [4]. Generating wind energy is highly uncertain because it depends on the velocity of the wind, which is highly uncertain in nature. Also, wind farms are developing rapidly, creating the need for better forecasting methods of wind power generation. If these forecasting methods are accurate in computing the amount of wind power generated in the future, the cost incurred in balancing the system will be less. In the case of large windmill farms where wind power generation is on a large scale, substantial savings can be implied for the owners of the wind farm, increasing the overall efficiency of the system to a considerable level [2,5]. These power systems have a fundamental problem as the operators are unable to predict the schedule of generation of wind power due to its variability. Such inherent characteristics lead to commercial and technical implications for wind power systems and their effective planning and operation. Wind energy prediction power provides data on expected wind energy generation at specific time slots over a certain time interval. Hence, the critical aspect of the operation and integration of wind power totally depends on wind power forecasting [4]. **Figure 1** shows the way wind power forecasting takes place.

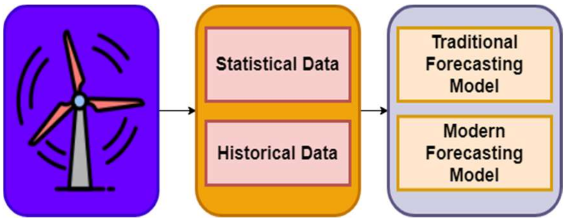

Figure 1. Wind power forecasting.

The necessity of forecasting for proper operation in power generation is part of planning for the future. However, the need for wind forecasting for wind power generation is given below:

- Wind power generation is variable in nature.
- The matching of supply and demand for power.
- The wind forecast system provides grid operators with a means to forecast and align electricity production and consumption.
- Operation planning decisions for the determination of the size, type, and economical location of wind power plants are to be planned in the future.
- Being able to predict wind output will make the electric grid work better under variable conditions.
- It is necessary for successful contract negotiations between suppliers and customers.
- Building of bidding strategies by the power suppliers and derivation of plans by the consumers in order to maximize the usage of utilities by purchasing electricity from pools [4].

Various approaches to forecasting wind power broadly fall into three main categories. The first categorization is based on a physical approach to meteorology, where various physical factors at the building of the model must be considered, which include humidity, roughness of the surface, temperature of the location, terrain quality, height of the hub, etc. The second approach is the statistical approach, which aims to find the relationship between the variables of the input of the wind power generation system and the output variables based on the data sets available in history. In this correlation, cross-correlation and auto-correlation functions are involved in wind power forecasting. In large-scale forecasting and long-term prediction, advantages are achieved by physical methods, whereas, in the short term, statistical methods are found to be good. Forecasting accuracy can be improved over time. To span the horizon, researchers focus on a hybrid method that combines both physical methods and statistical methods. Numerical prediction of weather, such as wind speed prediction, can be done by employing statistical methods/hybrid methods based on the input variables. Several approaches in the literature approve hybrid methods for forecasting in a better way. A training data set has to be selected that has great influence in establishing a model of statistical forecasting. In the approach of wind power forecasting, input variables that are non-linearly related to the output wind power can be easily constructed if the samples of training are the same as those of predicting the day [4–6].

In the wind forecasting models, they are categorized based on different technologies according to their accuracy. A comparative analysis of wind forecasting approaches is as follows in **Table 1**.

Table 1. Comparative analysis of wind forecasting approaches.

Wind forecast approach	Advantages	Features	Disadvantages
Physical approach	Focuses on how the wind flow flows around along with wind farm, their manufacturer's power curve and estimation over the wind power output range. Several sub-models are assigned together to translate the NWP forecast with the grid points	SCADA Data NWP Transformation to Hub Spatial refinement (Roughness)	Time-consuming Expensive Rebuilding is difficult
Statistical approach	Emulating the relation between each meteorological prediction where it attains the historical measurements and other generation output using the statistical models. Each parameter has their own estimated data without any phenomenon of physical medium into account.	NWP SCADA Data Statistical Model Kalman Filters ARMA	Misinterpretation in data Improper validation in data
Hybrid approach	In some of the WPF systems, they generally combine the two approaches along with other approaches to improve the forecast range.	Combination SCADA Data NWP	Diminished Type Divides between two categories Time-Series Losses Expensive
New casting model	Alternative way of forecasting based on the purpose. Tradeoff between the NWP costs and utility over the forecast.	Statistical Model	Only small scale in range Timescale for few hours
Regional forecasting	In some on-line information, the SCADA systems are measured mandatorily for the large farms. Up scaling approaches developed to forecast multiple farms	NWP Forecast Online SCADA Up scaling	Expensive Operation Time Limit

The objective of this review paper is to provide a comprehensive overview and critical analysis of the current state-of-the-art of WPF methodologies, techniques, challenges, and advancements. The contribution of the review aims to fulfill several objectives, including:

(1) Provide a comprehensive summary of existing literature and research findings in Wind Power Forecasting (WPF), covering historical developments, key concepts, and fundamental principles.

(2) Evaluate and categorize different methodological approaches used in WPF, including statistical methods, machine learning (ML), deep learning, and physical modeling techniques.

(3) Examine data sources for WPF, such as time series, meteorological data, turbine characteristics, and ancillary data, and explore data pre-processing techniques for cleaning, normalization, and feature engineering.

2. Background

In the literature technical survey, several techniques were applied to forecast wind power, i.e., hard (ARIMA-Autoregressive Integrated Moving Average, ARIMA-Wavelet & Mixed modeling approaches) and soft computing techniques (ANN). An appropriate model is adopted using algorithms that take physical phenomena into account to control the process. Therefore, in this section, we discuss the objectives and outcomes of wind power predictive models in existing literature, as shown in **Table 2**.

Table 2. Objective and outcomes of wind power predictive models.

Ref.	Objective	Outcome
[1]	Different ANN models are used to improve the WPF accuracy for short & very short-term time span basis. For the selection of inputs of the reference wind power station of the concerned wind farm meteorological information is considered.	New ANN models were proposed by varying the number of prior hours at input layer of ANN model. Achieve better accuracy in terms of mean absolute relative error (MARE) up to 7.5%. Further for long time span forecasting more degree of improvement is required.
[2]	The random fluctuations in the wind a natural process will cause challenges to the electrical system designers. It is necessary to forecast wind power with higher accuracy on short term basis.	In this, least square fitting & batch normalization (BN) techniques has been used to pre-process the input data.
[3]	The integration of wind farms output generation with electricity grid is a tough challenge for the continuous and proper functioning of electricity supply system. So, a precise and highly accurate wind power prediction system is required for the efficient operation of wind farm with electricity grid integrated system.	The proper forecasting performance was compared with the other neural networks (NN) based models such as: back propagation & Gaussian regression.
[7]	For improving the prediction accuracy, a hybrid model using variational mode decomposition (VMD), long & short memory network (LSTM) is used. In this, data has been pre-processed through VMD algorithm and forecasting has been carried out using LSTM.	The proposed model achieved forecasting accuracy in terms of mean absolute error of 1534.5 KW and RMSE of 2345.89 KW on 1hours a-head basis.
[8]	In this WT is used for input data pre- processing, PSO is used for optimal tuning of neural network model for WPF.	The proposed model outperformed and have accuracy of 6.378 in terms of NAPE which is far better from other NN based model
[9]	To forecast the wind power SVM and gray based model have been implemented for suitable and efficient forecast with higher accuracy. The gray model can work efficiently using small data at input level.	As compare to other bench mark and statistical models the accuracy is better.
[10]	The proposed paper was on literature in which different input selection and neural network models with pre-processing have been analyzed.	The hybrid model is most accurate and efficient one but they take more time to forecast.
[11]	In the particular, seasonal proper weather predictions of wind data have proven useful for the wind power generation for industry.	Electricity production depends on the many factors in addition to the wind conditions; the capacity factor is a suitable indicator to quantify the effects of wind fluctuations on production.
[12]	On the basis of Euclidean distance and angle cosine algorithms a novel clustering methodology has been proposed for short term WPF. The forecasting has been performed using neural network model.	The results in terms of accuracy proved the superiority of proposed model as compare to others.
[13]	The Markov chain model is implemented to forecast accurately the time series data of wind collected from wind farm on short term time span basis.	In an Indian geographical location of Jodhpur city in Rajasthan has been taken into consideration and achieve better forecast error.

3. Wind power forecasting techniques

During the wind energy power forecasting process, data such as wind pace (speed), historical data, wind direction in the farm with respect to speed of the wind, and data on historical production of power in the wind farm are utilized. Wind power system output is composed of output values of generated power at different horizons of forecasting. But there is variation in the prior hours before the hour of forecasting, along with the forecasting horizon length. In the literature, various methods of wind forecasting have been discussed, which are classified broadly based on the structure of the model, their operation, and the data sets. In a few other models that are subsequently explained, further reference station wind farm data, historical data on wind speed, and data on direction of wind are utilized. In this section, we categorize power forecasting and wind speed based on the input data variables, time-scaling, generated output power, and the method of forecasting.

3.1. Input data

According to input data, we can classify deterministic wind speed forecasting into two subclasses: the NWP model, i.e., numerical weather prediction models working on a time series basis, and the purely time-based series model. NWP models are developed by meteorologists for predicting weather based on the simulation of the Earth's atmosphere. This model of NWP is an approximate numerical solution depending on the equations of the atmospheric processes and the changes occurring in them [14–17]. The related primary equations utilized in this model are energy conservation, water conservation, mass conservation, momentum conservation, and the state equation. The NWP model divides the Earth's atmosphere into three-dimensional cubes with horizontal model resolution and vertical model resolution, respectively. Orography is represented by the horizontal resolution, whereas the phenomenon of weather is represented by the vertical resolution [18]. The resolution size is influenced profoundly by the model. For example, only limited details will be available in coarse resolution from the heights and valleys of the mountain. Better resolution is obtained by higher resolution, but it involves more computation. Both at the regional and global levels, NWP models are applicable. Less time and low computational resources are required by time series data compared to NWP data for modeling and operation. Traditionally, forecasting in the long term utilizes the approach of Measure Correlate Predict (MCP) [19]. This approach to MCP considers the measured value of wind speed at the wind farm, which is then correlated with the meteorological station data taken for the long term utilizing the technique of linear regression. But there are so many problems related to time series data, meteorological data planning, the measurement of precise data from meteorological stations, and the availability of calibrated weather stations. In many countries, the number of meteorological weather stations is limited as the management of these stations is considerably high. Thus, for input selection, some of the statistical tools can be utilized, like correlation, auto-correlation, cross-correlation, and partial auto-correlation [20,21].

3.2. Time-scales

In forecasting, the time scale involved depends on the requirements of the end user, the conditions involved technically, and situations of regularity. In the literature, there is limited data on the forecasting time scales. However, considering the literature, we can categorize the time scale into four divisions from very short to long-term forecasting, i.e., VST, ST, MT, and LT forecasting. The time scale for VST forecasting ranges from a few seconds to 30 min. The generation of wind power can be forecasted at various time scales based on the application intended. Wind power forecasting for active turbine control typically ranges from milliseconds to minutes, which is generally referred to as Very Short-Term (VST) forecasting. Trading of energy or management of power systems requires forecasting ranging from 48 to 72 h, such that decisions on conventional power plants are taken to provide commitment for a particular power unit and for optimizing power dispatch from these plants. These kinds of forecasting are termed short-term forecasting [19,22].

Maintenance of conventional power plants with wind farms can be planned by forecasting 5 to 7 days ahead, which is termed long-term forecasting. Offshore wind farm maintenance is expensive; hence, importance is given to maintenance under optimal planning. The prediction of wind power based on temporal resolution can range from 10 min to a few hours, depending on the length of the forecast. Wind power (energy) forecasting can be improved by involving more input values and providing uncertain estimates with conventional predictions [22].

3.3. Power output

Forecasted output can be obtained in two ways. The first is the direct method, by which we can obtain the forecasted wind power through supervisory control and data acquisition; hence, this method is called the direct method. Another method involves wind speed forecasting, based on which a power curve is drawn for converting this forecasting into output wind power. This method is termed the indirect method.

3.4. Forecasting methods

These are the following forecasting techniques at present:

Persistence Method: Persistence Method also known as the Native Predictor, depends on the high correlation between current wind speed and future wind speed values. It is assumed that at ‘t’ time, the current wind speed is the same at ‘$t + \Delta t$’ time, such that the equation is $v\ (t + \Delta t) = v(t)$. This method is known for providing good accuracy even at very short levels of forecasting [23].

3.4.1. Physical method

This method indeed requires physical meteorological data such as temperature, roughness of the local surface, pressure, power curves of wind turbines, and obstacles involved in prediction. This physical method is categorized into two different categories, which include the D (diagnostic) model and the CFD model, i.e., the computational fluid dynamic model. The CFD model simulates fields of wind flow dynamically, whereas the diagnostic model utilizes boundary layer parameterization. These diagnostic models are ideally appropriate for wind flow in areas such as flat landscapes, but computational fluid dynamics models are suitable for areas where wind speed is considered over complex terrains. Commercially, wind power forecasting (WPF) utilizes the NWP model for providing input data for the forecasting, which is then refined accordingly to obtain the forecasted output wind speed for the onsite conditions. The interpolation of wind speed can be downscaled based on the physical methods that utilize a mesoscale or microscale model for obtaining the wind farm hub height. The resolution attained along with the domain size range differentiates whether it is a mesoscale (meso) model or a microscale (micro) model. The power is estimated using forecasted wind flow or speed. The easiest way is to apply and use the power curve from the manufacturer. The scaling errors can be corrected by the approach of Model Output Statistics (MOS). Understanding physical behavior is enabled by the physical models incorporated into orography. Complex numerical systems can be solved by these models using initial conditions generated using regional forecasting and global forecasting. In such models, historical data are less important. But for wind prediction to be done accurately, extensive information is required on the wind farm's characteristics and the roughness of the surface [23].

3.4.2. Statistical method

In statistical methods, recursive techniques are utilized to obtain relations based on the time series data. Precise prediction is obtained by these models in a cheaper and easier way for short-term forecasting. As there is an increase in time, there is a degradation in the accuracy obtained from the statistical model. Predefined mathematical models are not involved; hence, these models depend on the patterns.

3.4.3. Artificial intelligence/machine learning method

The inputs for the statistical model are historical data; hence, these models are independent of the model's internal state. A statistical time series method for wind energy forecasting may be developed based on various techniques like SVM, ANN models, regression models, etc.

Artificial neural network (ANN)

ANN, i.e., the artificial neutral network model, was proposed in 1934 by McCullloch and Pits. The workings of this network are identical to those of the human brain; hence, it is able to make decisions by biological neurons. In the human brain, a neuron is able to perform various processes in parallel and analyses various patterns. This similar technique can be utilized for solving non-linear mathematical problems such as image processing, wind forecasting, etc. In this ANN model, training is provided continuously for obtaining the best weight value to plot input to output. ANN involves three layers, namely the input, hidden, and output layers. This network is based on two different algorithms, i.e., the LM (Levenberg Marquardt) algorithm and the Pola-Ribiere algorithm, to predict the output value. Its basic idea is represented in **Figure 2**.

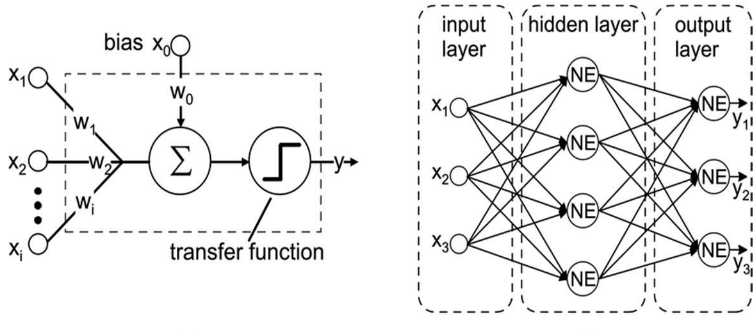

Figure 2. ANN (Artificial Neural Network).

Regression model

In this model, dependent and independent variables are related to each other. This model involves fitting a straight line to the data. Assumption is made that the mean wind speed, being the dependent variable, has a normal distribution. The direction of wind, pressure, temperature, and precipitation are considered independent variables. The values of the dependent variables and independent variables are associated together. As the number of independent variables influences the dependent variables, in this case, multivariate regression is applicable instead of univariate regression [24].

Support vector machine

This technique was introduced in 1995 by Vapnik and Cortes using statistical learning. Initially, this approach was developed for the process of pattern recognition, but now this technique is utilized in several processes such as diagnosis of faults, retrieval of images, computation of regression, forecasting, etc. This model is trained based on time series, which is similar to a neural network model, and overfitting curves or local minima are not required in this technique. The basic SVM architecture is shown in **Figure 3**.

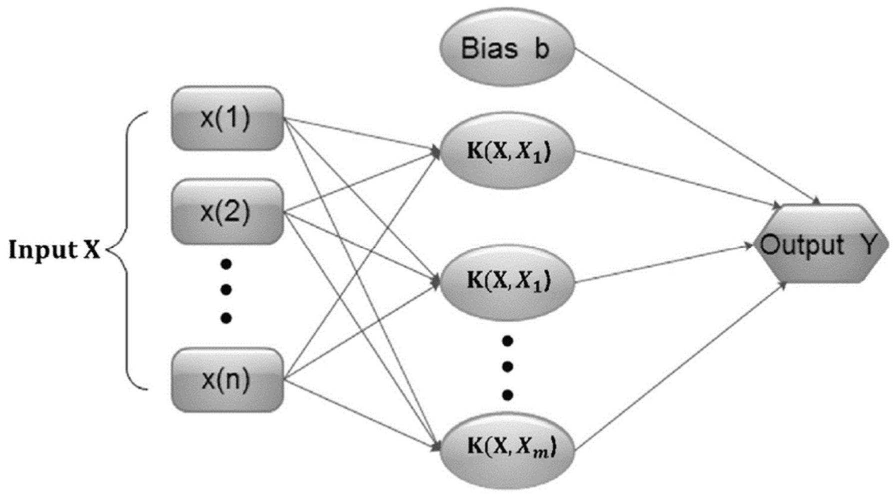

Figure 3. SVM (Support Vector Machine).

Where Y: Output function, b: bias [25].

Forecasting models based on physical method

This method interacts between geographical and meteorological data sets. The relationship between the dynamic motion of the wind due to the solar radiation in the atmosphere and the physical state is obtained by utilizing statistical equations and functions [26].

Numerical weather prediction

This study represents the current measurement of weather practiced to forecast the future weather state. The perfect solution is to utilize the NWP model, where the forecast horizon ranges from one day to several days. Hence, this technique is valuable for forecasting in several applications, e.g., PV (solar) forecasting, wind forecasting, etc. This model is also able to predict the cloud transient variation, which is the greatest obstacle to the solar irradiance of the ground. The future conditions are predicted using the NWP model after assimilation of the existing findings.

Empirical model

The first empirical model was proposed by Hargreaves and Samani in 1982 and is used to represent the activities for creating models both through experiments and observation. The evolution of several other models is based on variations in factors such as sunshine hours, content of water vapor, minimum and maximum temperature, temperature, pressure, wind direction, guest speed of the wind, humidity, etc. Wind power is the key parameter measured for most of the empirical models. Future values of wind power forecasting can be determined by an empirical model, which is the technique that establishes the relationship between linear and non-linear wind power and meteorological variables.

Forecasting technique based on the ensemble method

The method commonly used for solar irradiation forecasting is the ensemble method, which predicts with greater precision than the isolated method. In an individual model, several factors are considered in order to model it accurately. Integrating two or more methods for the forecasting process is termed a hybrid approach. A hybrid model combines two or more linear or non-linear models for forecasting. Based on the literature, hybrid models involve several techniques, such as preprocessing, postprocessing, and optimization.

Deep learning

Deep prediction can be done in an accurate way using a deep neural network. It provides a good result as it involves a number of hidden units, and the learning of this model is based on continuous training. The passing of information occurs from one layer to the next. Initially, weights are assigned; finally, the result is obtained by summing the weights obtained.

4. Factor affecting wind power forecasting

There are so many other factor/parameter that ensure model forecasting accuracy, either directly/indirectly. These factors affect wind power generation. Wind power forecasting (WPF) depends on forecast horizons, geographical conditions, climatic variability, testing period, normalization, and pre-processing technique.

4.1. Forecast horizon

The time horizon issue is related to the future period for which the model is forecasting. This period may be from 1 minute to several hours or days. According to a review of the literature, forecast horizons can be broadly classified into four different categories [27]:

Very-short-term forecasting (1 min to several minutes ahead). This category includes forecasts ranging from 1 min to several minutes ahead, typically used for immediate decision-making and operational planning.

Short-term forecasting (1 h to several hours/days ahead). Encompassing forecasts from 1 h to several hours or days ahead, this category is vital for short-range planning, energy scheduling, and grid management.

Mid-term forecasting (1 month to 12 months ahead). Covering forecasts from 1 month to 12 months ahead, this horizon is crucial for medium-range planning, resource allocation, and market analysis.

Long-term forecasting (12 months to several years ahead). Extending from 12 months to several years ahead, this category is essential for strategic planning, policy formulation, and investment decisions in the energy sector.

4.2. Climatic variability

The variables in the input data may be systemic, endogenous, and exogenous. On various combinations of input parameters, different models behave differently. In most studies, ANN gives importance to meteorological and geographical variables. The increased number of irrelevant meteorological parameters/data's degrades the performance and accuracy of the model. Therefore, the appropriate and suitable parameters have to be selected to increase the performance and accuracy of a model.

4.3. Preprocessing techniques

The model's accuracy can be increased using the pre-processing technique for input data sets. The input data sets for a particular targeted site obtained from every entity are extremely unpredictable and abnormal. The preprocessing techniques used on the data were used to increase or scale down the data element. Many researchers have used wavelet transform (WT) to pre-process the input time series into different constituents, while EMD further dissects the input series into various constituent parts. This combined use of WT and EMD algorithms allows for a more comprehensive decomposition of the input series, aiding in the improvement of model accuracy [28].

4.4. Training and testing period

The training and testing cycle is also an important factor that affects the accuracy of the model. Various studies have shown that the large collection of training data sets enhances learning capacity and also improves accuracy [26].

4.5. Geographical location

The model behavior changes according to the geographical location, and different wind locations affect its performance [4–6,29–35].

5. Outcomes of the literature survey

The typical wind forecasting has forced the researchers to treat the problem as a forecasting issue in various domains, which include the planning stage, executing the operational stage, and balancing a power system in real time. Hence, in order to take care of the efficient forecasting issues that are related to wind power forecasting techniques, these are some outcomes after a deep study:

Much research is also focused on seasonal wind energy generation, which is affected by numerous factors despite wind-flowing conditions. In order to quantify wind speed variability, the impact capacity factor is an important indicator to take care of.

The pre-processing of data, which involves classification, plays an important role in accurate forecasting.

Identification of the forecasting issues with different time series and scales using a different hybrid model for accurate and efficient forecasting.

As ANN is one of the most viable means, conventional algorithms have the ability to get proper and efficient forecasting of wind power.

Various developed hybrid models can be effectively compared with some other forecasting models for predicting their performance and evaluation in predicting the efficient forecasting of the power system.

Much research has also proposed an ANN model that emerged by using assorted 1-hour time intervals elected for the input value using layer parameters and an output layer with hidden layers of neural networks along with wind farm reference stations.

6. Conclusion

Wind power forecasting plays an important and crucial role in reliable, stable, and efficient power system operations. Currently, a number of studies are going into the field of wind power forecasting to develop methodologies in order to achieve better forecasting accuracy levels. Each model/technique developed has its own characteristics as per the available input data used, along with its parameters characterized on the basis of forecasting horizons. In this, a review has been done on wind power forecasting at an intermediate stage, and it also requires more reliable data clustering/pre-processing tools to obtain more accurate results. From the review analysis, it has been analyzed that hybrid models, which involve data pre-processing and learning tools, present more accurate results and are the need of the present era. Hence, using the outcomes of this research, it will be very easy for power system researchers to design new models for forecasting wind power.

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