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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 plant, time scheduling, and it's 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 of energy with limited supply of fossil fuel has motivated the world to depend on renewable source of energies which includes such as: solar power, ocean power, geothermal power, biomass power, wind power etc. These renewable energies act as an alternative solution in meeting the huge demand of the world population [1]. Amongst which wind power energy is highly rated encouraging and favorable power energy resource with abundance availability on the earth surface. In this current scenario demand of fossil fuels increase at a faster rate, there is requirement of shifting towards renewable energies. This leads to technology to find innovative solutions related to renewable energies. Hence Wind power forecasting has become one of the emerging research fields related majorly to electrical engineering. Several academicians and researchers are focused in the development of algorithms and the related tools for forecasting of wind power [2,3]. Ambitious goals are set by many nations to increase the generation of renewable energy to integrate in grid power where 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 the grid power [4]. Generating wind energy is highly uncertain because it depends on the velocity of wind which is highly uncertain in nature. Also, the wind farms are developing rapidly creating the need for better forecasting methods of wind power generation. If these forecasting methods are accurate in computing amount of wind power generated is mere in future, lesser will the cost incurred in balancing the system. In case of large wind mills farms where wind power generation is in 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 to technical implications of wind power system and its effective planning and operation. Wind energy predictions power provides data of expected wind energy generation at specific time slots of certain time interval. Hence the critical aspect in operation and integration of wind power totally depends on wind power forecasting [4]. **Figure 1** shows the way the wind power forecasting takes place.

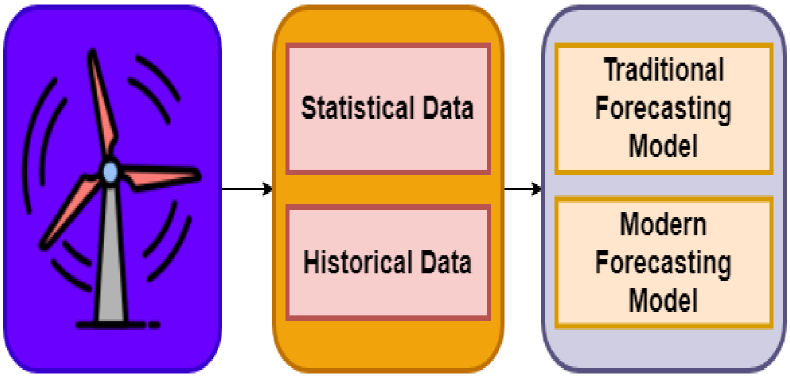

Figure 1. Wind power forecasting.

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

(1) Wind power generation is variable in nature.
(2) The matching of supply and demand of power.
(3) Wind forecast system provides grid operators with means to the forecast & align electricity production and consumption.
(4) Operation planning decision for determination of size, type and economical location of wind power plants to be planned in the future.
(5) Being able to predict wind output will make the electric grid work better under variable conditions.
(6) Necessary for successful contract negotiations between the suppliers & customers.
(7) 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 pool [4].

Various approaches to forecast wind power broadly falls into three main categories. The first categorization is based on physical approach meteorologically where various physical factors at the building of the model must be considered which includes 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 in finding the relationship between the variable of the input of the wind power generation system with the output variables based on the data sets available in the history. In this correlation, cross correlation and auto correlation function are involved in wind power forecasting. In large scale forecasting and long term prediction, advantages are achieved by physical methods, whereas, in short term, statistical methods are found to be good forecasting accuracy can be improved in time span horizon, researchers focus on a hybrid method which combines both physical methods along with statistical method. Numerical prediction of weather such as prediction of wind speed can be done by employing statistical methods/hybrid methods based on the input variables. Several approaches in literature approve hybrid methods for forecasting in a better way. Training data set has to be selected which has great influencing power in establishing model of statistical forecasting. In the approach of wind power forecasting, input variables are non-linearly related to the output wind power can be constructed easily if the samples of training are same as that of predicting day [4–6].

In the wind forecasting models, they are categorized based upon different technologies according to the accuracy within it. 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 review aims to fulfill the 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 applying to forecast the wind power forecasting have been reported i.e. hard (ARIMA-Autoregressive Integrated Moving Average, ARIMA-Wavelet & Mixed modeling approaches) & 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 objective and outcomes of wind power predictive models in the 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, 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 structure of model, their operation and on data sets. In few other models, that are subsequently explained, further more 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 namely NWP model i.e. Numerical Weather Prediction models working on time series basis and purely time based series model. NWP models are developed by meteorologists for predicting the 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 it [14–17]. The related primary equations utilized in this model are energy conservation, water conversation, mass conservation, momentum conversation and state equation. 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 vertical resolution [18]. The resolution size is influenced profoundly by the model. For example, only limited details will be available from coarse resolution from heights and valleys of the mountain. Better resolution is obtained by higher resolution but it involves more time of computation. Both in the regional and global level, NWP models are applicable. Less time and low computational resource is required by time series data compared to NWP data for modeling and operation. Traditionally, forecasting in long term utilizes the approach of Measure Correlate Predict (MCP) [19]. This approach of MCP considers the measured value of wind speed at the wind farm which is then correlated with the meteorological station data taken for long term utilizing the technique of linear regression. But there are so many problem related with the time series data, meteorological data planning; measurement of precise data from meteorological station and availability of calibrated weather station. In many countries, the number of meteorological weather stations is limited as the management of these weather 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, time scale involved depends on the requirements of the end user, 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 few seconds-30 minutes. 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 require forecasting ranging between 48 hours to 72 hours such that decisions on conventional power plants are taken to provide commitment for a particular power unit and for optimizing power dispatch of these plants. These kinds of forecasting are termed as short-term forecasting [19,22].

Maintenance of conventional power plants with wind farms can be planned by forecasting 5 days to 7 days ahead which is termed as long-term forecasting. Offshore wind farm maintenance is expensive hence importance is provided to maintenance under optimal planning. Prediction of wind power based on temporal resolution can range between 10 minutes to few hours based on the length of forecasting. Wind power (energy) forecasting can be improved using involving more input values with provision of uncertain estimates with conventional predictions [22].

3.3. Power output

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

3.4. Forecasting methods

These are the following forecasting techniques at present:

Persistence Method: Persistence Method also known as the Native Predictor, working depends on the high correlation between current wind speed and future wind speed values. It is assumed that at ‘t’ time, current wind speed is 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 local surface, pressure, power curves of wind turbine and obstacles involved in prediction. This physical method is categorized into two different categories which includes D (Diagnostic) model and CFD model i.e. computational fluid dynamic model. The CFD model does simulation of fields of wind flow dynamically whereas diagnostic model utilizes the boundary layer parameterization. These diagnostic models are ideally appropriate for wind flow on areas such as flat landscape but computational fluid dynamics model 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 mesoscale model or micro scale model for obtaining the wind farm hub height. The resolution attained along with the domain size range differentiates whether it is mesoscale (meso) model or a microscale (micro) model. The power is estimated using forecasted wind flow or speed. Easy 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 of physical behavior is enabled by the physical models by incorporating orography. Complex numerical systems can be solved by these models, using initial conditions generated using regional forecasting and global forecasting. In such models, the historical data are less important. But for wind prediction to be done accurately, extensive information is required on the wind farm characteristics and on the roughness of the surface [23].

3.4.2. Statistical method

In statistical methods, recursive techniques are utilized to obtain the 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 increase in time, there is degradation in the accuracy obtained from statistical model. Predefined mathematical models are not involved, hence these models depend on the patterns.

3.4.3. Artificial intelligence/machine learning method

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

Artificial neural network (ANN)

ANN i.e. artificial neutral network model was proposed in 1934 by Mc Cullloch and Pits. Working of this network is identical to that of human brain, hence able to make decision by biological neuron. In a human brain, 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 layer namely Input, hidden and Output layer. This network working is based on two different algorithms i.e. LM (Levenberg Marquardt) algorithm and Pola-ribiere to predict output value. Its basic idea is represented in **Figure 2**.

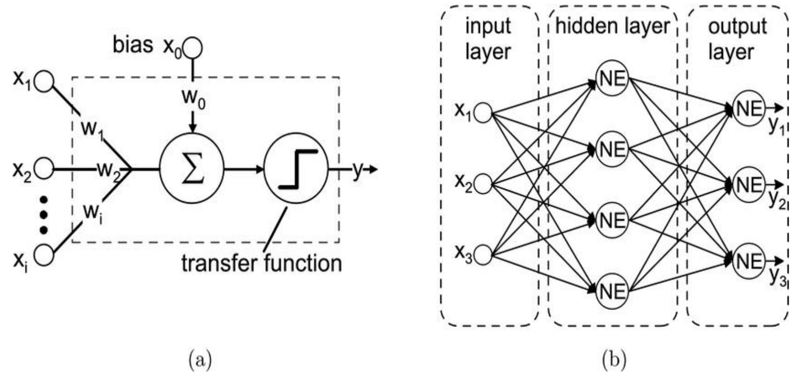

Figure 2. ANN (Artificial Neural Network).

Regression model

In this model dependent and independent variables are related with each other. This model involves fitting of straight line on the data. Assumption is made that the mean wind speed being the dependent variable has normal distribution. Direction of wind, pressure, temperature, precipitation is considered as the 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 fault, retrieval of images, computation of regression, forecasting etc. This model is trained based on time series which is similar to neural network model and over fitting curve or local minima is not required in this technique. The basic SVM architecture is shown in **Figure 3**.

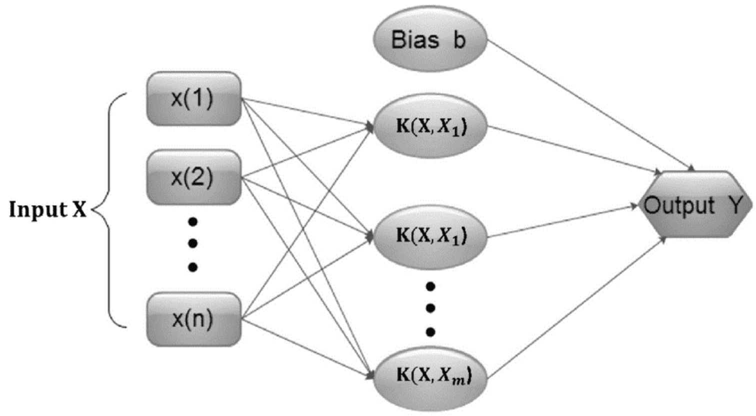

Figure 3. SVM (Support Vector Machine).

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

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 by experiments and observation. Evolution of several other models are based on variation of 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 model. Future values of Wind power forecasting can be done by empirical model which is the techniques that establishes the relationship between the linear and non-linear, wind power and meteorological variables.

Forecasting technique based on ensemble method

The method used commonly for solar irradiation forecasting is the ensemble method to predict with greater precision compared to isolate one. In individual model, several factors are considered in order to model it accurately. Integrating of two or more methods for forecasting process is termed as hybrid approach. A hybrid model combines two or more linear or non-linear models for forecasting. Based on the literature, hybrid models involves several techniques such as preprocessing, post processing and optimization.

Deep learning

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

4. Factor affecting wind power forecasting

There is so many other factor/parameter that ensures model forecasting accuracy directly/indirectly. These factors affecting the wind power generation. The wind power forecasting (WPF) depends on forecast horizons, geographical condition, climatic variability, Testing period, normalization & pre-processing technique

4.1. Forecast horizon

Time horizon issue is related to the future period for which model is forecasting. This period may be from 1 minute to several hours or days. According to review of literature forecast horizon can be broadly classified in 4 different categories [27]:

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

Short-term forecasting (1 hour to several hours/days ahead). Encompassing forecasts from 1 hour 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 parameter different model behave differently. In most studies ANN provide importance to meteorological and geographical variables. The increased numbers of the irrelevant meteorological parameters/data's degrades the performance and accuracy of the model. Therefore, the appropriate & suitable parameters have to select to increases the performance & accuracy of a model.

4.3. Preprocessing techniques

The model's accuracy can be increased using the pre-processing technique to 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 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 important factor which affect the accuracy of the model. Various studies have shown that the large collection of training data set enhance the learning capacity and also improves the accuracy [26].

4.5. Geographical location

The model behavior changes according to the geographical location and different wind locations affects 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 forecasting issues in various domains which include planning stage, executing operational stage and balancing a power system at real time. Hence, in order to take care of the efficient forecasting issues which 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 on numerous factors despite of wind flowing conditions. In order to quantify wind speed variability impact capacity factor is an important indicator to take care of.

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

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

As ANN is one of the most viable means to 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 is also proposed an ANN model which is emerged by using assorted 1h time intervals elected for the input value using layer parameters and output layer with hidden layers of neural networks along with wind farm references stations.

6. Conclusion

The wind power forecasting plays an important and crucial role for the reliable, stable & efficient power systems operations. Currently, number of researches is going in the file 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 their parameters characterized on the basis of forecasting horizon. In this, a review has been done on wind power forecasting at an intermediate stage, also it requires more reliable data clustering/pre-processing tool to obtain more accurate results. From the review analysis, it has been analyzed that hybrid models which involves data pre-processing and learning tool present more accurate results and are the need of present era. Hence, using the outcomes of this research it will be very easy for power system researchers to design new model for forecasting wind power.

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