Evolution of Wind Power Forecasting Techniques

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Abstract- *Wind Energy is variable in nature as it depends on sun, temperature, pressure variations and geography. Wind Energy based power generation poses problems in grid integration due to its fluctuating nature. Hence, it becomes necessary to forecast the wind power generation which is necessary for generation scheduling. The wind power forecasting helps the wind farm operator to convey reliable generation data to the load dispatch centre to facilitate generation scheduling needed for stable operation of Grid. This paper summarises some of the developments in the field of Wind power forecasting which may help researchers in formulation of a wind power forecasting model. Increasing wind energy penetration avoids carbon emission whereas wind power forecasting facilitates optimum utilization of wind resource.*

Keywords: Wind Power Forecasting, Artificial Neural Network, Generation Scheduling

I. INTRODUCTION

Electrical Energy plays an important role in the development of any nation, as it helps in increasing the industrial, transportation and agricultural activities. To fulfil these energy needs and to reduce the carbon emissions, the renewable energy dominated by solar and wind energy, are playing important role but both these resources of renewable energy are variable in nature. India is an emerging economic powerhouse. It is also the world's third largest energy consumer and emitter of the greenhouse gas which are responsible for global warming resulting in climate change. India has voluntarily committed to achieve about 40% energy needs from non-fossil fuels by 2030 [1-3]. According to Ministry of New and Renewable Energy, already non-fossil fuel energy electricity capacity was 38% of India's total installed electricity, from that almost 25% is from renewable energy sources as of May 2021. As of Feb 2021 the total installed wind power capacity of India was 38.789 GW, i.e., about 10% of India's total installed power capacity. India has the fourth largest installed wind power capacity in the world. Wind Power Forecasting becomes necessary for generation scheduling and also for optimum utilization of wind resource.

i. Wind Power Forecasting

Wind power forecasting is a technique which estimates the power production of a wind turbine in the future. Usually these are carried out in two steps:

Step 1: To predict the wind speed and direction for a given location.

Step 2: To convert the predicted wind parameters to wind power and on this basis electrical output of generator.

Due to the variability of the wind, there can be seasonal changes, daily cycles and fluctuations at a few minutes scale. The variability is mainly due to temperature changes, altitude change and pressure changes. An efficient forecasting algorithm plays key role in minimising the error in wind power forecasting which in-turn helps in maximizing the use of wind resource.

While modelling a wind power forecasting modelling, some factors are to be kept in mind:

(a) Winds are uncertain in nature hence,

i. They pose a revenue risk as compared to conventional power plants which means higher cost.
ii. Due to global climatic changes, as wind power plants operate for decades. Forecasts should have high accuracy in predicted values.

(b) The decisions for the operation of the wind power generation in accordance with the grid has to be based on,

i. The forecast of wind resources over the course of next several minutes or hours should have minimum error.
ii. Forecasts should be accurate enough to aid in the smooth integration of wind power with the grid.

(c) Improvement in the technology of turbine, converters, and structure extends the lifetime of wind power generation projects.

In the Indian scenario, NIWE (National Institute of Wind Energy) directly or through empanelled organisations has been providing high quality forecasting and scheduling of wind power in India forecasting [4].

(d) Classification of wind power forecasting based on time scale:

Forecasting algorithms are normally classified on the basis of time. Forecasting time limits are not strictly defined and it varies depending on the application for which the forecasting model is designed. They can be classified as follows based on the time period:

i. Short Term Forecasting (Few Minutes to Few Hours Ahead) [16]

This is needed for Load based planning (like decisions for increment or decrement of loads). It is also useful for turbine active control and for buying and selling of electricity-based decisions in combination with the grid.

ii. Medium Term Forecasting (Few Hours to 1 Day Ahead) [9][11][20][31][37][28][25]

This is needed for Base Load Generators based decisions (like whether it has to be online or offline), for energy trading and for operational security of the grid one day ahead.

iii. Long Term Forecasting (1 Day Ahead to 1 Week or more) [29]

This is needed for reserve-based decisions (like procurement or processing of coal), and for carrying out maintenance activities (like scheduling maintenance for wind farms, transmission lines or other power plants connected with the grid), and to obtain the optimum operational costs for a grid.

II. DESIGN OF A WIND FORECAST MODEL

There are certain steps which are to be followed for the design of a Wind Forecasting model, there cannot be a generalised approach as the model designed will be for a specific location or specific site. The steps listed below showcase a generalised format in which any wind forecasting model can be designed and optimised from scratch.

(a) Data Selection

Depending on the interval for which forecasting is to be made and the model selection, the data required would change. The selection and processing of data to be fed, plays the most important role for designing any forecasting model. This has to be achieved by the researcher after careful considerations and depending on the availability of data.

(b) Selection of input parameters

Before starting with any wind power forecasting model so on this the optimised model will function and forecast the selected parameter.

Some of the commonly used inputs for wind power forecasting are temperature [12][19][31][33][5], peak wind speed[5], wind power[me inputs are to be fed to the model which is going to be designed and based [4][7][9][10][11][13][14][15] [19][20] [31][33][25], metrological parameters[11][13], wind speed [9][12][13][14][19][31][33][28][25][27], average wind speed[22], wind direction [13][19][31][33][5], fan blade angle [9], relative humidity [12][31][33][5], numerical weather prediction data(NWP) [10][14][25], Global horizontal irradiance GHI [5], air pressure[12][19][5][27], vapour pressure[12].

(c) Selection of output

The main aim of designing any model for wind power forecasting is to find out the output power that will be produced by the wind power plant in consideration. Depending on the type of model used the outputs for wind power forecasting can be predicted wind speed [7], wind power [9][27].

(d) Implementation and Validation of forecast model

There are a variety of models that can be used for wind power forecasting to determine its energy output. The selection of a model depends on various factors like the selection of input variables, the application. They are classified as follows

i. Persistence Method/ Naive Predictor

It assumes that the wind power to be forecasted at a certain interval will be the same and it will depend on the last measured value. Some of the researchers have used Naive predictors or Persistence Method [6][8][9][15][25][34][35] as these prove to be accurate for short term predictions

ii. Physical Approach / Numeric Weather Predictors

This depends on the Numerical Weather prediction models and uses them as the inputs. These models are based on the equations of motions and forces affecting fluids. Based on the data from atmospheric variables the system of equations will allow the estimation of wind power. Some of the models are Global Forecasting System [4][19], Prediktor [19], Numerical Weather Predictor (NWP) [34][37], Physical Approach [34][35].

iii. Statistical Approaches [34][35][37]

These are based on one or more methods. They basically establish a relation between the past values of power generated as well as the past and forecasted meteorological parameters. These are further classified as

iv. Artificial Intelligence Models

These are models which use artificial intelligence which mimic the operation of a human brain to learn from the data given. This tries to generalise a pattern and apply the learning to estimate the future values based on past performance. Some of the models are Feed-forward Neural Networks [5] [12], Recurrent Neural Networks[36], Multilayer Perceptron Network[36], Radial Basis Function based Neural Network[8][31], Back Propagation Neural Networks [5][17][22][28], Support Vector Machines [5][9][33][35], Fuzzy Logic [35], Wavelet Transform [11], Ensemble Predictions [14][18], Genetic Algorithm[35], Particle Swarm Optimization (PSO)[23]

v. Time-series Models [34]

These models have the involvement of a time component. A time series is a sequence of observations taken sequentially in time. Forecasting is done by modelling based on past data and using them to predict the actual outcome which may not be known till the future date. Some of the models are Auto Regressive Moving Average with Exogenous Input (ARX)[34][15], Auto-Regressive Moving Average(ARMA)[6][8]34][35], Auto Regressive Integrated Moving Average (ARIMA) [26][31][34], Grey Predictors[34], Linear Predictions[34], Exponential Smoothing[25][34], Probabilistic forecasting [7][8][10][14][18][20][21][24][25][26], Gaussian process [8][21][24][35]

vi. Hybrid Models

These models try to combine one or more of the previously described methods, in doing so they combine the benefits of each model and hence obtain a better forecasting performance. Some of the models are ANN + Fuzzy logic =

ANFIS [27][34][35], Elman Neural Network (ENN) algorithm trained by PSO [11], Cooperative Co-evolution Genetic Algorithm (CC-GABP) based on Back Propagation (GABP) Neural Network [12], Least-Squares Boosted Regression Tree Method (LSBRT) + Cost-Oriented Boosted Regression Tree Method (COBRT) [13], Lasso-Type Estimation of Autoregressive Models [15], Non Linear Regression Model +Machine Learning [4], Bootstrap Based Extreme Learning Machine (BELM)[20], Input Parameters Selection-Particle Swarm Optimization Algorithm-BP Neural Network (IS-PSO-BP)[22], Enhanced Particle Swarm Optimization Technique (EPSO) and Modified Hybrid Neural Network (MHNN) [31], Hybrid Intelligent Algorithm (HIA) approach+ Extreme Learning Machine(ELM) and Particle Swarm Optimization[25], Back-Propagation NN and Chaotic Shark Smell Optimization Algorithm (CSSO) [17].

(e) Activation Functions

Artificial Intelligence and Machine learning based models are being developed and widely used nowadays for Wind power forecasting, these models use Activation Functions to determine the output of a neural network. An artificial neuron estimates the weight of its input and adds a bias to it and gives an output, based on this output the neuron decides whether it should be activated or not.

$$Y = \sum (Weight * Input) + \ Bias \cdots\cdots (1)$$

The activation function is usually used to limit the amplitude of output of a neuron. It maps the resulting values in between 0 to 1 or -1 to 1 etc. (depending upon the function). The Commonly used activation functions are:

i. Step Function [37]

This is basically a threshold-based activation function, when the value of the output from a neuron is above a certain value it is declared as activated. If it's less than the threshold, then it is not activated.

$$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases} \cdots\cdots (2)$$

ii. Linear Function [37]

This is a straight line function where the activation is proportional to the inputs to the neuron which is the weighted sum from neuron.

$$f(x) = x \cdots\cdots (3)$$

iii. Sigmoid Function [37]

This is a non-linear function and has a fixed output range. Sigmoid takes a real value as input and outputs another value between 0 and 1.

$$A = \frac{1}{1 + e^{-x}} \cdots\cdots (4)$$

iv. Tanh Function

This is also a non-linear function, but more preferred than Sigmoid. Tabs fits a real-value number to the range [-1, 1], its output is zero-centered.

$$tanh = \frac{e^x - e^{-x}}{e^x + e^{-x}} \cdots\cdots (5)$$

v. ELU (Exponential Linear Unit) Function

This function tends to converge to zero faster and produce more accurate results. Different to other activation functions, it has extra alpha constant which should be positive number.

$$R(x) = \begin{cases} x \text{ for } x > 0 \\ \alpha(e^x - 1) \quad \text{for } x \leq 0 \end{cases} \cdots\cdots (6)$$

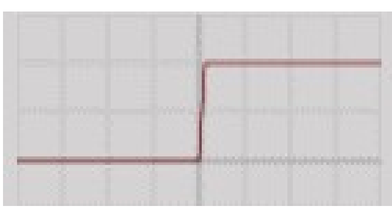

Fig. 1a Step Function

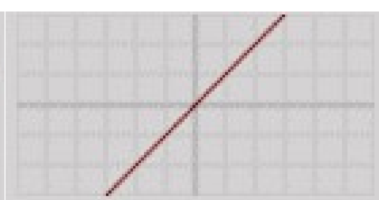

Fig. 1b Linear Function

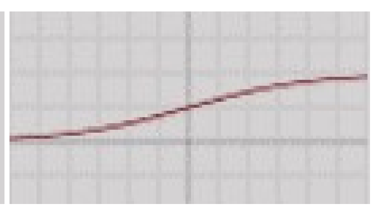

Fig. 1c Sigmoid Function

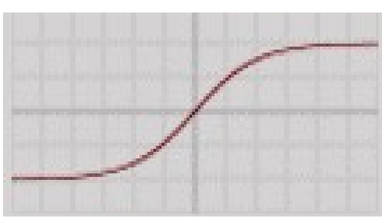

Fig. 1d Tanh Function

Fig. 1e ELU Function

Fig. 1f ReLU Function

vi. ReLU (Rectified Linear Units) Function

This is also a non-linear function and most widely used nowadays and provides the same benefits as Sigmoid but with better performance.

$$R(x) = \begin{cases} x & for\ x > 0 \\ 0 & for\ x \leq 0 \end{cases} \cdots\cdots (7)$$

(f) Comparative Evaluation

The models designed are to be compared with already existing models so that it can be ensured that the designed model is more accurate, efficient and optimised. There can be a comparison between any two or more models which are applicable in a certain area of wind forecasting. Another important tool for comparison can be the errors, there are a variety of errors that can be compared, let us look into various errors considered by researchers for wind forecasting.

(g) Errors in Wind Forecasting

The error measurement between the forecasted value and actual value is useful in order to evaluate the performance of the model. And it is also necessary to understand these forecasting errors in order to provide the necessary feedbacks required to improve the forecast accuracy.

i. Mean Absolute error (MAE) [8][11][12][16][19][20][21][22][23][34][35]

The Mean Absolute Error is a simple measure of error value. This is simply the mean or average of the value of absolute error.

$$MAE = \frac{1}{n}\sum |forecast_t - actual_t| \cdots\cdots (8)$$

ii. Mean Absolute Percentage Error (MAPE) [22][34][17]

The Mean Absolute Percentage Error is the absolute error normalized over the actual value, this is computed for every data values and then averaged.

$$MAPE = \frac{1}{n}\sum \left|\frac{forecast_t - actual_t}{actual_t}\right| \cdots\cdots (9)$$

iii. Normalized Mean Absolute Error (NMAE) [9][31][8][17]

The Normalized Mean Absolute Error is the average of mean absolute error normalized over the average of all the actual values

$$NMAE = \frac{\sum |forecast_t - actual_t|}{\sum |actual_t|} \cdots\cdots (10)$$

iv. Mean Square Error (MSE) [12][21][22][34][35][28]

The Mean Squared Error is a measure of the closeness of a fitted line to the given data values.

$$MSE = \frac{1}{N}\left(\sum (forecast_t - actual_t)\right)^2$$

v. Root Mean Square Error (RMSE) [8][12][15][20][21][23][31][34][5][35][18]

The Root Mean Square Error is the square root of the mean square error

$$RMSE = \sqrt{\frac{1}{N}\left(\sum (forecast_t - actual_t)\right)^2} \cdots\cdots (11)$$

vi. Normalized Root Mean Squared Error (NRMSE) [9][8][17]

The Normalized Root Mean Square Error is the average of the root mean square error normalized over the average of all actual values. It is useful to compare models with different scale.

$$NRMSE = \frac{RMSE}{\sum actual} \cdots\cdots (12)$$

vii. Mean Absolute Scaled Error (MASE) [8]

The Mean Absolute Scaled Error (MASE) is a scale-free error metric that gives each error as a ratio compared to a baseline's average error.

$$MASE = \frac{1}{N}\left[\sum_{t=1}^{N} \frac{actual_t - forecast_t}{\frac{1}{N-1}\sum_{t=2}^{N}|actual_t - actual_{t-1}|}\right] \cdots\cdots (13)$$

viii. Average Relative Error (ARE) [23]

The Average Relative Error is a traditional performance index which is used for the measure of prediction accuracy.

$$ARE = \frac{1}{N}\sum_{t=1}^{n} \frac{|forecast_t - actual_t|}{actual_t} \cdots\cdots (14)$$

ix. Absolute Relative Error (RAE) [27]

The Absolute Relative Error is a metric comparing actual forecast error to the forecast error of a simplistic model.

$$RAE = \frac{\left[\sum_{t=1}^{n}\{forecast_t - actual_t\}^2\right]^{\frac{1}{2}}}{\left[\sum_{t=1}^{n} actual_t^2\right]^{\frac{1}{2}}} \cdots\cdots (15)$$

x. Coefficient of Determination (COD) criteria [34]

The Coefficient of Determination is used to analyze how differences in one variable can be explained by a difference in a second variable. It is a measure of the degree of relationship between two individuals.

$$(R)^2 = 1 - \frac{\sum_{t=1}^{n}(\text{actual(t)} - \text{forecast(t)})}{\sum_{t=1}^{m}(\text{actual(t)} - \text{meanof actual values})} \cdots\cdots (16)$$

III. CONCLUSION

Wind power forecasting techniques have seen a drastic change in the past decades. It has shown improvement from a mere prediction-based model to Artificial Intelligence based models nowadays. Based on the survey some points can be highlighted as follows:

i. The wind power forecasting techniques should be combined with the grid management system for low cost and reliable operation of the grid.

ii. Work has to be carried out for reduction of the uncertainty prevailing in wind energy forecasting, which will make it more reliable and more risk free from the view point of investors.

iii. Models should be developed which can work in the short-term forecasting and can be used as effective tools for increasing the reliability of a wind power plant.

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