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A Review on Wind Power Forecasting Models for improved Renewable Energy Integration

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Abstract— **This paper gives an overview of the research that has been done on wind power forecasting models, which may be used to aid in the optimum integration of Renewable Energy (RE) into electric power networks. Aside from the economic advantages, the variable nature of wind energy production has a variety of negative consequences for the electric grid system, including stability, reliability, and the capacity to plan for future operations, among other things. As a result, precise forecasting of wind power output is critical for grid stability and security, as well as for the promotion of large-scale wind power. To ensure the accuracy of wind energy forecasts, a variety of conventional, artificial intelligence, and hybrid methodologies have been developed. The simplicity and robustness of time-series-based methods have made them popular for forecasting applications. Artificial Neural Networks (ANNs) and Fuzzy Logic have recently been supported by several researchers for forecasting because of their flexibility. This review covers the performance of many wind power forecasting models that are classified according to their categories. It is also offered a critical examination of contemporary studies, which includes statistical model and machine learning models that are based on historical data. Aspects of this study that are taken into consideration include the advantages and disadvantages of various forecasting models, including hybrid models, as well as performance matrices used in assessing the forecasting model. In addition, the possible advantages of model optimization are examined in detail as well.**

Keywords— **Wind Power Forecasting, Renewable Energy Integration, Statistical Model, Machine Learning Model, Artificial Intelligence and Hybrid Model**

I. INTRODUCTION

The Variability of the wind is the most difficult challenge to implementing wind energy as a stable and self-sufficient source of electric power. For large-scale wind penetration to be successful solutions must be found to numerous problems including competitive market designs, real-time grid operations, standards of interconnection, ancillary service requirements and costs, quality of power, transmission system capacity and future upgrades, stability and reliability of the power system, and optimal reductions in greenhouse gas emissions of the entire power system, which is typically determined by the optimal amount of wind penetration into the system [1], [2]. Improved wind forecasting is widely recognized as a very effective approach for addressing many of these issues. Accurate wind forecasts, for example, are always appealing in competitive power markets, and this is true for a number of reasons. First and foremost, on the basis of market pricing, suitable incentives in the form of attractive market prices are supplied on energy imbalance charges. In addition, making an accurate prediction may aid in the development of well-functioning hour ahead or day-ahead markets. [4]-[7] go into more detail about some of the issues that were talked about. Getting better at predicting how much wind power there will be has big economic and technical benefits. [4] proposes a probabilistic method for figuring out how much energy wind generators will use if they make bad predictions. Case studies show that these costs can be as high as 10% of the total income from selling wind energy. a short-term probabilistic forecast of wind power is shown and discussed in [5]. There, an optimal bidding strategy is discussed that takes into account the uncertainty in the forecasts and how to make the best bids.

On a wide scale, the numeric weather predictor (NWP) model combined with a physical flow model and a statistical forecasting approach might save 15 to 25 percent of the fossil fuel now used compared to the persistence model[6]. A cost model is developed for the possibility of using a wind farm's output for ancillary services such as reactive power support, primary frequency support, power oscillation damping support, and so on, in the event that the wind farm's output remains unutilized due to forecast errors, as reported in [7]. In this model, the larger wind prediction error result in higher payments to wind farms for their reactive power supply, which is owing to the increased lost opportunity cost associated with higher wind forecast errors.

According to the most current accessible published studies, this paper presents an in-depth analysis of wind power and wind speed forecasting techniques. It is the primary contribution of this work that the literature on wind power/speed forecasting is classified based on the forecasting horizons and time-scales used in their forecasting is classified. A review article with this particular topic does not yet exist in the literature, despite the fact that there are multiple review papers accessible on wind power/speed forecasts (e.g., [8], [9]), to the best of the authors' knowledge. A significant contribution of this analysis is that it gives a clear comparison and assessment of each approach depending on the time horizon for which it is designed.

II. Wind Speed Versus Wind Power

Wind turbine output power is dependent on wind speed, which fluctuates over time and is affected by regional landscape type, weather patterns, and seasonal fluctuations. The amount of wind power available and realistically wind power travelling across the rotor blades per unit sweep area is defined as[10]

$$P_{av}(\upsilon) = \frac{1}{2}\rho(t)A\upsilon^3 \quad (1)$$

$$P_{real}(\upsilon) = \frac{1}{2}\rho(t)A\upsilon^3 C_p(\upsilon) \quad (2)$$

Where $P_{av}(v)$ denotes the ideal available wind power and $P_{real}(v)$ denotes the wind turbines realistic power output in Watts (W), $\rho(t)$ denotes the time-varying air density, which varies in response to the surrounding atmospheric pressure and temperature. A is the sweep area of the blades in square metres (m^2), and v is the wind speed in m/s. power coefficient (C_p) is the ratio of wind turbines realistic power $P_{real}(v)$ divided by ideal available wind power $P_{av}(v)$ at specific wind speed. C_p is governed by the turbine's tip angle, blade design and wind speed-to-rotor speed relationship. 0.593 is the greatest power coefficient (Betz limit). However, in reality, this value is not possible. An estimate of the power coefficient under different circumstances of operation was not provided. All three models were compared using a power coefficient of 0.5.

As seen in equation 1 and 2, air density is a critical element impacting the quantity of wind energy produced by a wind turbine. The connection between the temperature, air density and barometric pressure at the place is as follows:

$$\rho(t) = \left(\frac{P}{RT}\right) e^{-\left(\frac{gh}{RT}\right)} \quad (3)$$

Where $\rho(t)$ is the time variable air density in kg/m^3, T is the air temperature in K, P is barometric pressure in Pa, g is the gravity of Earth in $9.81 m/s^2$, R is the specific gas constant for dry air in 287.058 J/(kg.K) and h is the hub height above ground level in m.

III. Time Scale Classification of Forecasting & It's Applications

The categorization of wind forecasting technologies according to their time scale is vague. However, as shown in Table I, wind forecasting can be separated into four categories:

TABLE I

Time-Scale Classification and It's Applications

Time Horizon	**Range**	**Applications**
Very short term	Few seconds to 30 minutes ahead	Grid stability operations and voltage regulation actions
Short-term	30 minutes to 72 hours ahead	Maintenance planning of network lines, Congestion management, Day-ahead reserve setting, Unit commitment & economic dispatch
Medium term	72 hours to 7 Days ahead	Generator Online/Offline Decisions, Operational Security in Day-Ahead Electricity Market
Long-term	7 Days to 2 week or more ahead	Planning of the electricity generation, transmission and distribution

IV. Classification of wind power forecasting models

A large number of researchers have studied the many approaches for predicting the output of wind energy. A number of strategies and models for forecast wind energy output were suggested and developed. The following are the most widely used and important forecasting techniques, in order of popularity.

*A. **Persistence model***

The forecasted wind power output is assumed to remain constant at the same time the previous or following day in this model. The expected forecasted wind energy output over the next 24 hours is as follows:

$$P_f(t) = P_{pd}(t) \quad (4)$$

At the time t, P_f is the forecasted wind power output and P_{pd} is the previous day wind power output at the same time[11]. When it comes to short-term forecasting, this model is most often utilised for wind power and speed forecasts, particularly for one-hour forward forecasting. The accuracy of this forecasting model is dependent on the stability of the meteorological conditions.

*B. **Autoregressive moving average (ARMA) model***

According to Karakus et al[21], statistical procedures for wind forecasting are based on historical data and meteorological conditions and need just a single step. In Shukur and Lee[22] created a time-series prediction model based on the autoregressive moving average (ARMA) and the Kalman filter (KF) techniques. According to Li and Hu[23], statistical models provide the greatest outcomes for situations involving short-term forecasting. In Equation 5, we see how the ARMA-based technique is expressed.

$$x_t = \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{j=1}^{q} \theta_j e_{t-i} + k + e_t \quad (5)$$

where x_t represents the forecasting parameter at time instant t, φ denotes the Auto Regression (AR) parameter, θ denotes the Moving Average parameter, k is the constant and e_t represents the random white noise. p and q are the orders of Auto Regression(AR) and Moving Average(MA) respectively[12].

The capability of the ARMA model to extract statistical characteristics, as well as its use of the Box-Jenkins technique, are the primary reasons for its widespread use and acceptance. This model is commonly utilised for various forecasting models with an acceptable degree of accuracy, and an extension of it known as the AR integrated MA is often used for these models (ARIMA). When using the ARIMA model, an integrated portion is used to eliminate any nonstationary information from the data. The most significant drawback of the ARMA model is that the time series data must be stationary nature.

The next step is to utilise the autocorrelation function (ACF) and the partial autocorrelation function (PACF) to determine an ARMA model that is appropriate for the data. The ACF is defined as the proportion of X_t and X_{t-1} autocovariance to the variance of a dependent variable as indicated in

$$ACF(k) = \frac{\operatorname{cov}(X_t, X_{t-k})}{Var(X_t)} \tag{6}$$

where Cov denotes the covariance and Var denotes the variance. To assess the degree of association between X_t and X_{t-k} are associated when the effects of additional time lags $X_{t-1},\ldots,X_{t-k-1}$ are eliminated, the partial autocorrelation function (PACF) was utilised.

TABLE II
Properties Of ACF And PACF

	AR(p)	MA(q)	ARMA(p,q)
ACF	Tails off	Cuts off after lag *q*	Tails off
PACF	Cuts off after lag *p*	Tails off	Tails off

For AR and MA, the number of orders was determined by examining the attributes of the ACF and PACF (Katchova, 2017). The next stage is to identify the most suitable models based on the results of the white noise test and the quality of fit. The next stage was to plot the ACF of residuals to see whether the residuals resembled white noise.

C. *Artificial neural network (ANN)*

Because of the non-linearity of meteorological data, artificial neural networks (ANNs) are frequently employed in most studies to forecasting wind power production. When a non-linear and complicated bonding between the data occurs between the data without any previous assumptions, ANN is more appropriate than statistical approaches. The input, hidden, and output layers, as well as the neurons and connections, are the primary components of an ANN. According to the illustration, the neuron cell is divided into two sections. The first component is the "combination function," which generates a value by adding all of the inputs together. The second section is referred to as the "activation function"[13].

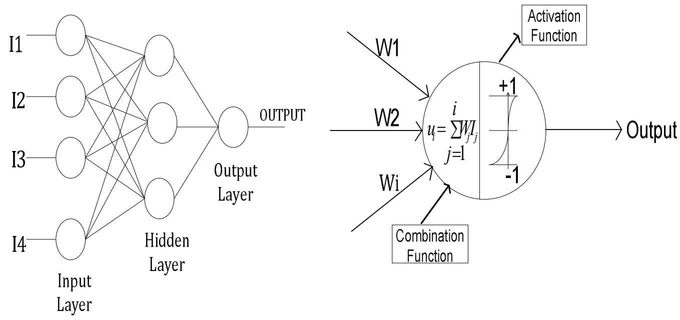

Fig.1: (a) Schematic diagram of an ANN structure, which consists of an input, hidden, and output layers. (b) A mathematical model of an ANN cell.

Utilizing the activation function, the network output is formed by adding up the weighted inputs. So the network's activation function serves as a squeeze function, transferring the input in the form of an output. The fundamental ANN mathematical formula is represented as

$$U_N = b + \sum_{j=1}^{N} \left(W_j \times \mathrm{I_j}\right) \tag{7}$$

There are many types of activation functions that may be used to forecast wind power output. The most generally utilised are the sigmoid, hyperbolic tangent sigmoid and Gaussian radial basis functions since they are continuous, differentiable, and provide non-linearity to the network. The two fundamental processes of a neural network are training and testing. The network is taught during the training stage utilising the training input data set and learning algorithm. The learning algorithm of the NN attempts to map the input-output relationship by updating the synaptic weight values. It is necessary to compare the output generated by the network with the desired output in order to compute the error. Because of this, the weight and bias values of NN (which serve as a compensator) are adjusted in response to the error. After that, the process is repeated till the desired output result is obtained. As a result, during the testing stage, the network produces the final output depending on the testing input data set and the model weight value that was used. Several kinds of neural networks (NNs) have been developed, each with a different architectures and a different set of input-output mapping techniques. The multilayer perceptron NN(MLPNN), multilayer feed-forward NN (MLFFNN), radial basis function NN (RBFNN), recurrent NN (RNN), and general regression NN (GRNN) are the most often utilised neural networks. The primary disadvantages of ANN are that they need a large amount of data during the training phase and overfitting[14].

D. *Adaptive network based Fuzzy Inference System(ANFIS)*

In the adaptive neuro-fuzzy inference system (ANFIS), the fuzzy logic approach is combined with the neuro network technology, which allows the fuzzy inference system to benefit from the learning capabilities of neural networks. The parameters of the membership function in an ANFIS are adjusted using neuro-adaptive learning techniques, which are implemented in the ANFIS. The parameters have an effect on the form of the membership functions. When it comes to wind energy forecasting, the structure of the neuro-fuzzy model may be represented as a particular multilayer feedforward neural network.

Mamdani and Sugeno-type fuzzy inference techniques are two of the most often utilised fuzzy inference methods. It is recommended that the Sugeno-type approach be employed in the ANFIS in the review article since it is effective when used in adaptive techniques and optimization (Sugeno-type fuzzy inference, 2017)[15]. As a result, the output membership functions are restricted to constants and linear functions. The maximum, minimum, and average wind speeds observed at an elevation above ground were used as inputs to the model. ANFIS is the most generally used method because it is computationally less costly, transparent, and delivers results that are as robust as statistical models.

*E. **Support Vector Machine(SVM)***

SVM is a supervised machine-learning approach that is based on principle of structural risk minimization (SRM). SRM reduces the expected risk of a upper bound to low value as possible. As a result, SVM may reduce the amount of error in the training data. Vapnik developed the SVM algorithm in order to solve the classification problem. SVM, on the other hand, has been extended to the area of regression issues. Support vector regression is the term used to describe the use of SVM in time series regression (SVR). SVR is an appropriate method in this situation since wind power generation forecasting is a typical time series analysis issue.

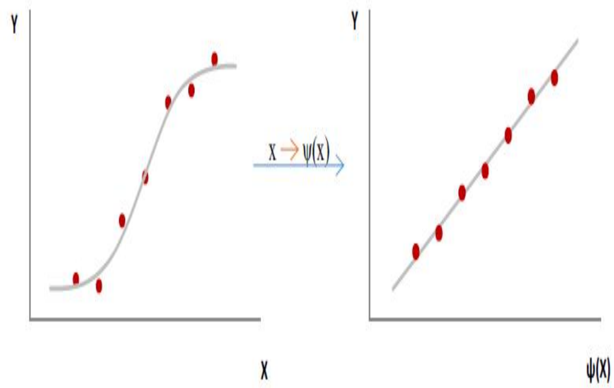

Fig.2. Changing nonlinear regression into linear regression.

Consider the following set of training data:; $\{(x_1,y_1), (x_2,y_2) ....(x_l,y_l)\}$ where $x_l \varepsilon R^n$ in the input vector (meteorological variables data), and $y_l \varepsilon R^n$ is the corresponding to the output value (wind power output). The estimation function f (x) is represented as

$$Y_f = f(x) = w \times \psi(x) + b \qquad (8)$$

where ψ (x) is the feature vector of inputs x; $w \in R^n$ is a weight vector, and $b \in R$ is the bias term, which are estimated by minimizing the regularized risk function [16,17]

$$R(C) = C\frac{1}{N}\sum_{i=1}^{N} L_e(y_i, f_i) + \frac{1}{2}\|w\|^2 \qquad (9)$$

$$L_e(y_i, f_i) = \begin{Bmatrix} |y_i - f_i| - \varepsilon, \text{if } |y_i - f_i| \geq \varepsilon \\ 0 \text{ otherwise} \end{Bmatrix} \qquad (10)$$

Where ε-insensitive loss function, C and ε are the user-determined prescribed parameters, y_i is the actual value at period i, and f_i is the forecasted value at period i. The loss will be equal to zero if the forecasted value is within the ε-tube. The second term, ½ $\|w\|^2$ measures the flatness of the function.

*F. **HYBRID MODEL***

When it comes to forecasting wind power generation in different scenarios, the performance of a single model is not accurate. This issue may be attributed to the limitations of a stand-alone technique. As a hybrid model, it's best to use two or more different techniques together. In some forecasting applications, these models have been used to get better results because they have a better chance of accuracy. One of the main goals of these models is to look at how different topologies can work together to improve the accuracy of forecasts.

The use of a fuzzy inference model with RNN in wind power forecasting has been shown effective. It has been decided to apply a fuzzy inference model in this instance in order to smooth out the meteorological data, which will be used to forecasting wind energy production. Wind power forecasting using a hybrid fuzzy-Genetic Algorithm(GA) forecasting model [18] has also shown promising results. [18] In numerous hybrid forecasting models, the wavelet transform (WT) is employed with conventional or artificial intelligence approaches in the prediction of wind power. In this scenario, WT is used to de-noise the input data, which is then processed further. The meteorological data collected after WT was utilised as input for ANN and SVM-based forecasting models, which accurately forecasting wind power generation with the least amount of error.

Comparisons of forecasting methodologies employed in various forecasting horizons are shown in Table-III. Although several approaches are acceptable for short-term and medium-term wind forecasting, only a handful have been tested for long-term forecasting.

Table-III
Forecasting method/ model used in different forecasting horizon

Method / Model	Short Term	Medium Term	Long Term
Physical (Numeric Weather Predictors (NWP))	Applicable	Applicable	Not Applicable
ARMA	Applicable	Applicable	Not Applicable
ARIMA	Applicable	Applicable	Not Applicable
Support vector machine	Applicable	Applicable	Not Applicable
Multiple Regression	Applicable	Applicable	Not Applicable
Exponential Smoothing	Applicable	Applicable	Not Applicable
Fuzzy Inference system	Applicable	Not Applicable	Not Applicable
Genetic algorithm	Applicable	Applicable	Not Applicable
Neural Network	Applicable	Applicable	Not Applicable
Machine Learning	Applicable	Applicable	Applicable
Persistence	Not Applicable	Applicable	Applicable
Wavelet Based Model	Not Applicable	Applicable	Applicable
Fuzzy+ Neural Network model	Applicable	Not Applicable	Not Applicable
Fuzzy+GA model	Applicable	Not Applicable	Not Applicable
WT+ANN	Applicable	Not Applicable	Not Applicable

V. Performance Evaluation of Wind forecasting Models

Today's power grid system receives an increasing quantity of electricity from wind energy systems, and this number is growing on a regular basis. A consequence has been a significant reliance on the unit commitment of wind power systems for the stability of grid networks. If the wind system fails to provide the agreed energy, the grid system will have issues in terms of supplying an acceptable amount of power. It is thus critical to accurately forecasting the production of wind energy in order to maintain grid stability and encourage further wind energy installations. As a result, the accuracy assessment of the wind power forecasting model is an extremely important aspect of the forecasting process itself. When evaluating the accuracy of wind power forecasting models, many assessment matrices have been applied. In the forecasting model review and benchmarking process, standardised performance metrics would be useful. According to the table below, the mean square error [MSE], root mean square error [RMSE], normalised root mean square error [nRMSE], mean absolute error [MAE], mean absolute percentage error [MAPE], mean relative error [MRE] and mean bias error [MBE] are all commonly used in evaluating the accuracy of wind power forecasting models[19-20].

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(W_{forecasted} - W_{true}\right)^2$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(W_{forecasted} - W_{true}\right)^2}$$

$$nRMSE = \left(\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(W_{forecasted} - W_{true}\right)^2}\right)\times 100 \Big/ W_{true(\max)}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|W_{forecasted} - W_{true}\right|$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|W_{forecasted} - W_{true}\right|}{W_{true}}\times 100\%$$

$$MRE = \frac{1}{N}\sum_{i=1}^{N}\frac{W_{forecasted} - W_{true}}{W_{total}}\times 100\%$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N}\left(W_{forecasted} - W_{true}\right)$$

Where

$W_{forecasting}$ = The forecasted wind power at each time point,
W_{true} = The observed/measured wind power at each time point,
$W_{true(max)}$ = The maximum observed wind power of this scale,
W_{total} = The wind installation capacity,
N = The number of data sample for the time scale.

VI. Conclusion

Due to the climate change and global warming, the integration of renewable energy source like wind energy into the electricity grid has risen in recent years as a study area of concern. Since there is a pressing need to fulfil rising energy demand while also mitigating climate change and stabilising electric grid systems, precise forecasting of wind energy output has become vital. Because of this, a plethora of research have been undertaken on the subject from various angles. The current research presents the results of a thorough and complete evaluation of the literature on direct wind power forecasting models and approaches. This review paper begins with an overview of wind energy production and the importance of wind power forecasting. It has also been taken into account the significance of the correlation of meteorological and wind power output data, as well as the value of pre-processing model input data. It has been discovered that when the inputs of a model have a high correlation factor with the output, the accuracy of a model is improved. Additionally, when pre-processed input data is employed, the accuracy of the predicting output is improved. Following a discussion of input selection, a critical analysis of wind power forecasting was carried out, which was based on the categorization of the models from several viewpoints. The findings demonstrate that the outcomes of forecasting models are dependent on the forecasting horizon, the amount of data provided, and the technique used for the forecasting. A short-term forecasting horizon was used in the development of the wind power forecasting model in the vast majority of the situations studied. Even though the forecast model parameters are the same, the accuracy of the wind power forecasting model changes depending on the forecasting horizon used to make the prediction. Future researchers in this subject will benefit from the literature evaluations of current works on direct forecasting of wind power output in this article, which will include the strengths and limits of the models as well as recommendations for future studies in this field. It was studied and compared the performance of numerous modern forecasting approaches against various parameters, including accuracy, dependability, computing cost, and complexity, and the results were conclusive. According to recent research, ANN and SVM-based forecasting models performed admirably under rapidly changing and varied environmental circumstances. Furthermore, the majority of the research used a variety of methodologies to create the forecasting model, which resulted in higher accuracy. A significant number of studies divided the anticipated day into distinct groups depending on the weather conditions using a variety of methodologies and then constructed a forecasting model to account for this classification. However, the range of the error that was found was very wide because of different weather conditions. To avoid making mistakes, the separate model for each weather condition must work well. However, the cost and complexity of the model should be taken into account in this case. Furthermore, the performance matrices that are used to evaluate the forecasting models have been added. Results show that RMSE was used more often than other things. Furthermore, the benefits of model optimization were also talked about. Findings show that the optimised algorithm made the model a lot more accurate at predicting the future. In this process, GA is one of the best ways to improve things in this field.

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