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An overview of the wind forecasting techniques and resource assessment

Olurotimi Olakunle Awodiji [1,*] and Dauda Ishaya [2]

[1] *Department of Electrical & Electronics Engineering, University of Jos Plateau State, Nigeria.*
[2] *National Weather Forecasting and Climate Research Centre, Nigerian Meteorological Agency.*

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Abstract

With the increasing wind energy demand in the electricity grid, reliable, accurate, and precise wind energy prediction is necessary to manage and correctly operate the interconnected power systems. Therefore, wind energy forecasting plays a significant role in wind energy utilization, particularly wind speed forecasting. Given the importance of wind speed forecasting and its resource assessment, numerous forecasting methods have been proposed in the literature, each with its advantages and disadvantages. A search for effective wind speed forecasts in wind energy management and resource assessment poses a significant challenging task. This paper carried out an overview of the different methods of wind forecasting techniques and resource assessment parameters needed for accurate wind generation modeling in power systems planning, operation, and control. This is also useful in electricity market designing with high renewable penetration and provision of ancillary services.

Keywords: Forecasting; Seasonal; Variation; Weather

1. Introduction

The prevailing wind resource at a location varies continually with time and is dependent on seasonal variation. Availability of wind is very difficult to predict using all known weather parameters. This is partly due to the interactions between forcing mechanism such as the rotation of the earth, weather effect, and obstruction to the direction of wind flow, the topography of the earth's surface, hub height above the earth's surface, etc. [1]

For the purpose of siting a wind farm in a particular location, the information on the wind variation along with its influence on the power output of the wind energy conversion system is of great importance for optimal integration of the wind energy systems in the power network [2]. The adequate knowledge of the wind variation, wind direction, and wind turbulence are useful parameters to be considered for wind site selection and sizing. Prior to the development of a wind farm, large wind resource measurements are collected over an extended period of time at a proposed wind location. The wind measurements could be weather data consisting of the wind speed, wind direction, air temperature, atmospheric pressure, humidity, and gust readings. The wind speed measurement is then modeled using any of the established statistical techniques, from where wind speed distribution is obtained by determining the wind potential at that site. The analysis of the wind speed distribution obtained is often used in the wind energy industry for the evaluation of the wind resource potentials and for siting of wind energy conversion system (WECS) at different locations across the field [3].

2. Wind Speed and Forecasting Techniques

The prediction of the future occurrence of an event could either be through the estimation of some model or site parameters which are believed to influence the future event or through an inferred study of patterns or historical

* Corresponding author: Olurotimi Olakunle Awodiji

measurement of wind farm measurement taken over an extended period of time. In recent years, several forecast models have been proposed and developed in the literature for the short to long-term wind speed predictions. The accuracy of each forecast model depends on the modeling techniques and also its intended area of applications. The several forecast techniques can be summarized into the following: persistence-based; physical-based; statistical based which include the time series and artificial neural network based; and hybrid-based technique.

2.1. Persistence-Based Technique

The persistence-based technique widely used in industries (such as wind energy, weather stations, local airport, government agencies, etc.) as a benchmark for performance comparisons with other developed forecast models. The used of the persistence-based is usually aimed at very-short-term wind predictions. The persistence-based technique is the simplest forecast model being used to predict the future power outputs based on the present or the immediate past wind power [4] [5]. This model is developed on a general assumption that the future wind speed-power will be the same as the recently measured wind speed power over a past time period *t.*

One merit of the persistent-based technique is its forecast skill when utilized in predictions ranging from very short-term to short-term time horizon (minutes to less than 6-hour forecasts). However, its performance, accuracy decreases with the increasing time horizon. As a result, the applicability of this forecast model in wind prediction is often considered for a very short to short-term time horizons because of its remarkable forecast accuracy when used in a discrete time step.

2.2. Physical -Based Technique

The physical-based technique also known as the numeric weather prediction (NWP) technique was first developed and implemented in the 1920s and was later modified in the 1950s for prediction of the future state of the atmosphere based on the present weather conditions at a location [6] [7]. The NWP model was developed by meteorologists and widely accepted as the most accurate technique for long-term weather forecast [8] [9]. This model is based on the mathematical model that solves complex non-linear relationship of the present weather conditions to predict the future state of atmospheric conditions. The model uses information such as the mass of air, temperature, pressure, relative humidity, surface terrain information, air (wind) velocity etc. to produce the future meteorological information. Due to the complexity of this model in acquiring weather predictions in short time horizon, the computations (simulation programs) are run 1-2 times per day. Hence, this limits the use of NWP model for short-term weather forecasts. The short-term weather forecasts require the incorporation of an accurate digital elevation model to the NWP model to denote the pattern of the wind flow over the considered terrain structure [10]. For long-term weather forecasts, the accuracy of the prediction depends on the NWP model and it performs well if the raw weather conditions information over a relatively large area is known [11] [12]

2.3. Statistical -Based Technique

The statistical-based technique is the most widely used forecasting models for the prediction of future events based on historical events or measurement. The use of the statistical technique is aimed at predicting the availability of wind ranging between very short and short-term predictions. Unlike the physical based method that uses complex mathematical equations for its predictions, the statistical technique is based on the pattern recognition between historical measurements taken over an extended time period. This technique adopts the differences (errors) between the predicted and the real (actual) measurements to adjust its model parameters [13]. The statistical-based technique is grouped into the time series based and the artificial neural network

2.4. Time Series Technique

The aim of the time series technique is for the development of a forecast model that can tune the forecast parameters such that the forecast error between the predicted and the actual values are small. The time series-best known as the conventional statistical technique is based on the auto-recursive algorithm. The time series technique is aimed at the prediction of future value based on historical measurements taken at successive time intervals. The forecast skills and accuracy of this technique, decrease with increasing time steps, especially when seasonal components exist in the time series. As a result, the time series model performs well using uniformly spaced time series as compared to its use with stochastic time series [14]. The various time series techniques which have been adopted in predictions of the time series data include the following: Auto-Regressive (AR), Moving Average (MA), Auto-Regressive Moving Average (ARMA), Auto-Regressive Integrated Moving Average (ARIMA), Exponential Smoothening (ES), Grey Predictor, and Kalman filters etc.

2.5. Moving Average (MA)

The moving average technique is the simplest and the most popular statistical technique used for prediction of a univariate time series. The moving average technique is considered as an accurate forecast tool for short-term prediction where there were no trends in the past time series (events). However, where trends are in past data, the use of MA technique will perform poorly because of the residual error in past data which is propagated into the future predictions. The MA model technique usually fits with the time series by replacing past measurement with an average of past data that moves by a forward time step.

If $P_1, P_2, P_3 ......P_m$ is the successive past power measurement at a successive time t; $\alpha_t, \alpha_{t-1}, \alpha_{t-2}, ... \alpha_{t-m}$ is the white noise errors at time $t, t-1, ...t-m$; $\theta_1, \theta_2, ... \theta_m$ is the moving average of parameters: the m^{th} order of the moving average with parameters $\varphi_1, \varphi_2, ... \varphi_m$ is defined as:

$$M_{ma}(m) = \mu + \alpha_t + \theta_1\alpha_{t-1} + \theta_2\alpha_{t-2} + \theta_3\alpha_{t-3} \dots \dots .. + \theta_m\alpha_{t-m} \dots\dots\dots \quad (1)$$

$$= \alpha_t + \sum_{j=1}^{m} \theta_1\alpha_{(t-1)} \dots\dots\dots\dots \quad (2)$$

where $M_{ma}(m)$ is the moving average forecast for successive future events beyond time t, μ is the mean of the time series (often assumed to be zero).

The moving average technique is accurate for stationary time series data without cyclic or seasonal trends. Another disadvantage of the simple moving average model is that the forecast accuracy decreases when there is a strong trend in the historical time series data. But, to handle the problem associated with seasonal trends, the historical time series with the trend is transformed from the non-stationary time series into stationary series data by using modeling techniques such as differential transformation as well as the iterative non-linear fitting, etc. This will enhance the minimization of the forecast error that may occur when using the MA model for seasonal or non-stationary time series data.

2.6. Auto-Regressive (AR)

The autoregressive (AR) technique is another time series forecast technique which has been used for the modeling and prediction of time series based on its previous pattern or successive past data. The autoregressive technique is often described by a weighted sum of its previous values and the presence of white noise error.

If $P_1, P_2, P_3 ......P_m$ is the successive past power measurement at a successive time t; the autoregressive model of n^{th} order at which the model will go backward to predict the future value is defined as:

$$M_{ar}(n) = \varphi_1 P_{t-1} + \varphi_2 P_{t-2} + \varphi_3 P_{t-3} \dots\dots + \varphi_n P_{t-n} + \alpha_t \dots\dots\dots\dots (3)$$

$$= \sum_{i=1}^{n} \varphi_i P_{t-i} + \alpha_t \dots\dots\dots\dots\dots\dots (4)$$

where φ_i is the auto-regressive parameter, α_t is the white noise error, and $M_{ar}(n)$ is the auto- regressive forecasts for period beyond time t.

2.7. Auto-Regressive Moving Average (ARMA)

The Auto-Regressive Moving Average (ARMA) is a stationary time series model which is made up of the autoregressive and the moving average. The ARMA model is often used for the modeling of stationary time series, which takes into account the past event, forecast error, and the lagged term (random white noise) [15] [16]

The ARMA (n, m) order of the model is defined as the past time steps the model will go to predict the future value as illustrated by:

$$M_A(n, m) = \sum_{i=1}^{n} \varphi_i P_{t-1} + \alpha_t - \sum_{j=1}^{m} \theta_j \alpha_{t-j} \dots\dots\dots\dots (5)$$

where φ_i is the auto-regressive parameter, α_t is the white noise error, θ_j is the moving average parameter, P_t is the past power value at a time t, n is the autoregressive order and m is the moving-average order. The ARMA technique is suitable for short term forecasts, but forecast accuracy drops with increasing time horizon (that is, the performance of the ARMA differs with time horizons). One advantage of the ARMA technique is its performance when utilized for short term forecasts, where the time series is stationary with no seasonal trends. For a non-stationary time series, the ARMA model performs poorly when used for forecasts of time series events.

2.8. Auto-Regressive Integrated Moving Average (ARIMA)

The Auto-Regressive Integrated Moving Average (ARIMA) is a time series technique used for the filtering of seasonal trends in non-stationary time series as compared with the ARMA which is used for modeling of the stationary time series. For non-stationary time series, the trend can be decomposed (by applying one or more differential transformation to the non-stationary data to achieve stationary time series). Thereafter, the ARMA model applies to the transformation, and this technique is defined as the ARIMA modeling [60].

2.9. Exponential Smoothening (ES)

Exponential smoothening (ES) is a technique used for cyclic and seasonal trend time series. This technique is often used for smoothing the irregularities or seasonal variation in a time series because the seasonal variation in the time series cannot be easily removed. The exponential smoothing technique is a weighted averaging forecast technique that is based on an unequal allocation of weights to time series with a smoothing constant. The use of the exponential smoothening technique is more complicated than the simple moving average (MA) technique because greater weights are given to the recent data while lesser weights are given to past data as compared to the equal weight allocation given to the past data in the MA technique. In addition, the weights allocated to the past data declines in an exponential manner with increasing forecast time (i.e. greater weight is given to the more recent forecasts and takes less consideration of the long past events or forecasts) [17]. With an unequal assignment of weights to the recent value, it is easier to adjust the noise or forecast errors in the past values or data to tune the ES model for future forecasts.

2.10. Time Scale Wind Prediction Techniques

The time step or an interval between the current and future values of a forecast model has been defined as the forecast time horizon. The future value of an unknown event can be predicted at different time horizons such as seconds to few minutes ahead, minutes to a few hours ahead, hours to 1-day ahead; one day to a week or more etc. Several forecast wind models have been proposed in the literature for prediction of wind speed and power output of a WECS at different locations over a wide range of forecast time. However, the accuracy of various forecast models considered differ with the quality of the available wind measurement, the atmospheric stability of the considered sites, forecast skills of the developed models, as well as its intended applications (such as electricity market bidding and clearing, economic load dispatch planning, operational security in day ahead marketing, maintenance scheduling and resource planning etc. In addition, the choice of a wind forecast model (such as the persistent-based, physical-based, statistical-based, ANN or the hybrid model etc.) depends on the intended forecast time horizons, as well as the computation speed requirement for acquisition of the forecast results.

2.11. Very Short-Term Forecasting

The very short-term forecasting has received a wide attention in deregulated electricity markets and trading applications. Often times, the very short-term forecast usually refers to as persistence-based technique because the forecast time ranges from a few seconds to 30-minutes ahead. The very short time wind forecasts are used in applications such as; electricity market settlements; regulatory actions such as in the response to a fault tackling, quick load changes in turbine control etc. [18]. The persistence-based technique, time series-based technique and hybrid technique (e.g. the ANN and fuzzy logic) are examples of the very short-term forecast models that have been utilized within this forecast time range.

2.12. Short-Term Forecasting

The short-term forecasting is based on the time series prediction ranging from 30 minutes to a day ahead. The short-term power forecast is useful for determining an incremental cost that a varying wind power generation can incur for power network instability. It is worth mentioning that the varying power generation at a given wind farm can change the scheduling of other power plants in order to stabilize the net imbalance between the wind farm outputs and the loads on the network. The short-term forecasts are useful in applications such as; the power system management (e.g. economic load dispatch decisions, unit commitment), security, purpose in day-ahead electricity trading, generator offline or online decisions etc [19].

2.13. Long-Term Forecasting

The long-term forecasts are usually based on the prediction of regional atmospheric patterns, ranging from 1 day to 1 week ahead. For this forecast horizon, a large meteorological data is required for developing the forecast model to produce an accurate forecast [20]. For wind power forecasts, the prediction is aimed at maintenance and planning of wind farm operations, conventional power plant decisions such as unit commitment and electricity markets, etc. In addition, the long-term power forecast is aimed at providing stability support to the power grid, especially during peak load demand.

3. Wind Resource Assessment

3.1. Mean Wind Speed

The mean wind speed is an important site parameter that is considered in the wind profile determination at any given site. The mean wind speed (MWS) is used to measure the wind potential at a known site for small-scale to large-scale energy project. The mean wind speed (m/s) at wind sites was obtained using the equation:

$$V = \frac{1}{N}\sum_{i}^{N} v_i \text{..............}(6)$$

Where v_i is the wind speed sampling at t^{th} time, and N is wind speed data points number.

3.2. Air Density Variation with Height(s)

The air density is a site parameter considered when measuring the wind potentials at a site. The air density at a site affects the operation and performance of the WECS. The wind power generation of the WECS is directly proportional to the air density at given height (h), as a function of the atmospheric pressure and air temperature. As the air temperature of 15 °C above the ground level, the density of dry air has a constantly approximated value of 1.225 kg/m3. The use of constant air density usually underestimates or overestimates the actual air density value at a wind site. Some of the mathematical models available for modeling of the prevailing air temperature and atmospheric pressure are discussed below:

- For a known air temperature and atmospheric pressure readings at a hub height h, the air density at the site can be obtained using:

$$\rho = \frac{P}{RT} \text{.............}(7)$$

where ρ is the time varying air density (kg/m^3) at the site, P is the atmospheric pressure (hPa.), and T is the air temperature (K) and R is the molar gas constant (287.05J/(K.mol.)).

- When information about the atmospheric pressure and the air temperature readings of the wind site are unavailable, the air density can be determined using the experiential formula proposed. The mathematical relationship that exists between the air density for a reference height h is defined as:

$$\rho(h) = 1.225e^{-0.001h} \quad \text{..........}(3)$$

where $\rho(h)$ is the varied air density (kg/m^3) at the considered hub height (m) h. Thus, the determination of the wind profile at a new height h_2 is crucial because it influences the turbine performance at that height, as well as reduce the lifespan of the turbine rotor blades due to fatigue. The hub height is related to the wind speed by the mathematical relationship below:

$$\frac{v_2}{v_1} = \left(\frac{h_2}{h_1}\right)^{\alpha} \text{.............}(9)$$

where v_1 is the reference wind speed at a 10 m hub height h_1; v_2 is the new wind speed at hub heights h_2; and α is the exponent which depends on the site surface roughness:

- When the information about air temperature and atmospheric pressure readings of the sites are available, the moisture content in the air is taken into consideration.

The site's varying air densities at the considered hub heights were obtained using [67].

$$\rho(h) = \frac{P}{RT} e^{-\left(\frac{gh}{RT}\right)} \text{...............}(10)$$

where ρ(h) is the time varying air density as a function of hub height (kg/m^3), R is the molar gas constant (287.05J/(K.mol.)), P is the atmospheric pressure (hPa.), T is the air temperature (K), g is the gravitational constant ($9.81 m/s^2$), and h, the height.

3.3. Wind Turbulence Intensity

High wind turbulence intensity often affects the performance of the energy output of the WECS, thereby causing great stress on the wind energy system components. The speed and direction of the wind flow often change rapidly while passing through the terrain surface or obstacles such as vegetation, hills, trees, buildings, and mountains. The standard deviation of the wind speed is the most common indicator of the turbulence intensity of a site. Turbulence is defined as the rapid disturbances or irregularities in the flow of the wind speed and direction at any given site. In addition, turbulence intensity is often defined as the ratio of wind speed standard deviation to the mean wind speed, typically measured over some time t. Other reasons for high turbulence intensity at a windy location are due to the weather effects, as well as non-uniformity of the terrain surface which varies significantly from one wind site to another.

$$T = \left(\frac{v}{\delta}\right) \ldots\ldots\ldots\ldots\ldots(11)$$

where δ is the standard deviation of wind speed and v is the wind speed.

Using the Maximum Likelihood Estimator (MLE), the standard deviation in terms of the sampled wind speed (vi) and the mean wind speed (v) is defined by:

$$\delta = \sqrt{\left(\frac{1}{N}\sum_{i=1}^{1}(v_i - v)^2\right)} \ldots\ldots\ldots\ldots(12)$$

where N is a number of wind data points, and δ is the standard deviation of the wind speed.

3.4. Shape and Scale Parameters

The statistical shape and scale parameters are crucial site parameters that are often considered in wind resource assessment at any given site. The estimated shape and scale parameters of the site are essential for the development of the statistical distribution model, as well as in the evaluation of the wind resources for wind energy projects. The estimated values of shape and scale parameters are important for the selection of a suitable site for wind farm development. The various shape and scale parameters available in wind resources assessment include the Weibull, Rayleigh, Gamma, lognormal, and Inverse Gaussian.

3.5. Shape Parameter

The shape parameter of a given site is a dimensionless entity used in wind site assessment to denote the nature of prevailing wind. The shape parameter value of a given site is generally used to denote the nature of the prevailing wind such as gusty, moderate, or steadier wind. A value of $k<1.50$ corresponds to a highly variable or gusty wind, $k = 2$ corresponds to a moderately gusty wind, and $k=3$ indicates a regular and steadier wind.

There is a wide range of techniques available for the estimation of the site shape parameter. The available estimation techniques for estimating the most widely used Weibull parameter are the Maximum Likelihood Estimator (MLE), Modified Maximum Likelihood Estimator (MMLE), Method of Moments (MOM) [71]. Analytical or Standard Deviation Method. Graphical Method (Least Square), Energy Pattern Factor etc. The Graphical Method (Least Square) is a technique used in engineering and mathematical problems for estimating the Weibull parameter when modeling experimental data with a linear relationship. For time series data, the appropriate Weibull techniques often utilized for estimation are the standard deviation method and the MLE. The choices of the listed techniques are dependent mainly on its simplicity and accuracy. To use other estimation methods, the applications required the transformation of the time series wind speed data into bins or cumulative frequency distribution. When the wind speed data are available in time series format, the analytical method and the MLE can be applied for estimating the Weibull distribution for wind energy analysis. The analytical method has found its applicability in this study due to its simplicity and flexibility. However, the analytical technique does not give an accurate estimate of the Weibull parameter values when used for the different wind measurements. Rather, it gives an approximate value based on the standard deviation and means of the wind speed.

The shape parameter of a Weibull distribution function using the MLE is defined as:

$$k = \left(\frac{\sum_{i=1}^{N} \ln{(v_i)} v_i^k}{\sum_{i=1}^{N} v_i^k} - \frac{\sum_{i=1}^{N} \ln{(v_i)}}{N}\right)^{-1} \ldots\ldots\ldots (13)$$

Where k is the Weibull shape parameter using an iterative procedure, N is the number of non-zero wind speed data points.

The shape parameter of a gamma distribution function is defined as:

$$k_g = \left(\frac{v^2}{\delta^2}\right) \ldots\ldots\ldots\ldots (14)$$

where k_g, δ are the gamma shape parameter and the standard deviation

The shape parameter of the lognormal distribution k_l was estimated as:

$$k_l = \mu = ln\left(\frac{v^{-2}}{\sqrt{var + v^{-2}}}\right) \ldots\ldots\ldots\ldots (15)$$

3.6. Scale Parameter

The scale parameter is used in wind resource assessment to denote the strength of the prevailing wind at a given site. The scale parameter of the Weibull distribution c was estimated using the MLE defined in Eqn. (16):

$$c = \left(\frac{\sum_{i=1}^{N} {v_i}^k}{N}\right)^{\frac{1}{k}} \ldots\ldots\ldots\ldots (16)$$

where c is the scale parameter of the Weibull distribution, and k is the value of the Weibull shape parameter.

The scale parameter of the Rayleigh distribution c_r was estimated using the MLE defined as:

$$c_r = \sqrt{\left(\frac{1}{2N} \sum_{i=1}^{N} {v_i}^2\right)} \ldots\ldots\ldots\ldots (17)$$

where c_r is the scale parameter of the Rayleigh distribution and v_i is the wind speed observations at ith time step(s).

distribution

The scale parameter of the Gamma c_g was estimated as:

$$c_g = \left(\frac{\delta^2}{v}\right) \ldots\ldots\ldots\ldots (18)$$

where c_g is the scale parameter of the Gamma distribution.

The scale parameter (sigma) of the lognormal distribution c_l was estimated as [77]

$$c_l = \sqrt{ln\left(1 + \frac{var}{v^2}\right)} \ldots\ldots\ldots\ldots (19)$$

where c_l is the scale parameter of the lognormal distribution.

4. Conclusion

This paper gives an overview of the different forecasting techniques useful for wind speed forecasting and resource assessment. A concise description of the different methods was highlighted and their usefulness and applicability can be easily identified. The paper suggests quick parameter identification and the necessary selection of the desirable methods for faster implementation.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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