Chapter

Assessment and Analysis of Offshore Wind Energy Potential

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Abstract

Wind energy usage is increasing at fast rates due to significant technical advances, energy supply security and environmental concerns. Research is focusing among others areas on the development of reliable and accurate wind energy assessment methods. Offshore wind energy resources are usually larger than at geographically nearby onshore sites, which may offset in part higher installation, operation, and maintenance costs. Successful offshore wind energy development relies on accurate analysis and assessment of wind energy resource potential. Offshore wind assessment challenges are related to the wind turbine size, offshore installation challenges, lack of adequate and long-term wind and meteorological measurements, etc. Wind, a highly intermittent phenomenon has large spatiotemporal variability, being subject to sub-hourly, hourly, diurnal, seasonal, yearly, and climate variations in addition to their dependence on the geography and environment. Wind regime characteristics are critical to all aspect of a wind energy project, e.g. potential site identification, economic viability, equipment design, operation, management, or wind farm impacts on the electric grid. For a reliable wind energy assessment, measurements at rotor heights are required at least for one year. If such measurements are not available needs to be substituted by alternative approaches, e.g. measure-correlate-predict or numerical methods. Chapter objectives are to provide the reader with comprehensive reviews of the wind energy assessment and analysis methods.

Keywords: wind regime, offshore resource assessment, wind characteristics, wind profiles, turbulence intensity, wind statistics, measure-correlate-predict techniques

1. Introduction

Wind power is viewed as one of the most techno-economically viable renewable energy sources for electricity generation. In resource-ideal locations, the wind generated electricity costs are competitive with conventional power generation. Accurate estimates of the energy production together with good estimates of the uncertainties associated with any project are required to secure funds and hedge wind project risks. Wind energy resource assessment enters into the several project development phases: (1) suitable wind energy site prospecting, (2) site mapping and wind farm design, (3) wind turbine micro-siting, (4) risk assessment and performance analysis, (5) permitting and tower certification, and (6) wind farm operation and management [1–21]. Better knowledge, the smaller are the safety margins, therefore, the higher investment potential returns. An accurate prediction of the potential wind farm performance is therefore vital for the project success.

Electricity generation from wind can be economically achieved only where a significant wind resource exists. To maximize the wind form power output, the resource assessment at any prospective site is critical. Wind is highly variable, geographically and temporally, its variability persisting over a very wide range of spatiotemporal scales. Due to the cubic relationship between wind speed and energy output, sites with small differences in wind speeds can have substantial differences in available wind energy [2–10]. A wind power assessment is accurate, only if the wind speeds and directions are measured at the wind turbine hub height and for a significant time-period. Knowledge of the local wind regime is vital to the industry, yet commercially viable products that meet the wind industry needs are often questionable. Three main phase involved with project planning and operation, requiring accurate wind characterization are: (1) prospecting and siting, by using historical data, retrospective forecasts, and statistical methods to identify potential wind energy sites; (2) specific micro-siting assessment to determine the optimum wind energy project layout; and (3) operation using the wind prediction to determine available power output for specific time horizons. However, the most critical factor is the wind energy resource identification and characterization. Wind energy resources depend on the wind regime, varying in time and space due to large- and small-scale atmospheric circulations, surface energy fluxes, and geography. Ultimately, wind energy production is governed by factors such as: large-scale generation potential, grid supplied power predictability, and the expected investment returns. The various wind energy uncertainties impact the reliable determination of these viability factors.

Offshore wind power relates to the installation of wind turbines in large water bodies. On average, winds blow faster and more uniformly over the sea than on land, and a faster and steadier wind means less wear on the turbine components and more electricity generated per turbine [12–20]. Due to cubic relationship of the potential energy produced from wind and the wind speed, any wind speed marginal increase results in larger generated electricity. Notice that the offshore wind energy is also the most developed form of marine renewable energy in terms of technology, policy frameworks, and installed capacity. The offshore wind industry needs detailed wind regime information for proper structural design, e.g. wind shear and veer, across the rotor plane as well as between the water surface and hub height, turbulence, ideally at hub height, wind speed profile, wind velocity probability distributions, and extreme weather conditions. In addition to detailed wind information, other environmental data are also important during the design and operation, e.g. air and water temperature and gradients, tidal, storm surge, extreme waves, marine currents, atmospheric humidity, pressure, density, icing characteristics, hail and lightning frequency and severity, and seismic conditions [2–4, 9–22].

The most important activity in a site selection is to determine the wind energy resource potential, consisting in the estimated local wind velocity probability density function. Other important aspects in this context are estimating the turbulence levels and the resulting wind turbine loads at the concerned site, promoting better decision making, in selecting the most suitable site wind turbines and the project life cycle cost prediction. Higher wind loads result in higher maintenance and operation costs [1–27]. Other site selection criteria are: (1) local geography, (2) electric grid proximity, (3) permitting and land acquisition, and (4) site accessibility for transportation and maintenance. A planning strategy accounting for key engineering design factors and addressing the uncertainties in the wind energy project offers to the wind energy industry a powerful impetus. However, the wind energy resource itself is highly uncertain, while the wind conditions (wind speed and direction), turbulence intensity and air density are showing large temporal variations, varying significantly from season to season or from year to year.

Inaccuracies in wind velocity distributions can introduce significant errors in the estimated wind resource potential or in the wind farm performance prediction. Key measures of wind power plant performance include annual energy production, cost of energy, and payback period. Both parametric and nonparametric uncertainty models are formulated, which can be leveraged in conjunction with a wide variety of wind velocity distribution models [2–14].

Wind energy measurement campaigns have traditionally been conducted with mast-based instrumentation consisting of cup anemometers and wind vanes. Almost all field campaigns are also using temperature, pressure, and humidity sensors, besides the wind velocity sensors [2–16]. However, many wind energy developers and manufacturers stick to the standard mast configuration for long-term measurement campaigns. Notice that sonic anemometers and wind remote sensing instruments are still far from being standard instruments in wind energy assessment although they are being used more and more for detailed measurement campaigns or performance testing. Given the field campaign limited time span, it is often needed to extrapolate wind time series to periods of at least 5 years to better predict the long-term average energy yield. For this purpose, the measure-correlate-predict (MCP) methods are still the most used methods. Numerical models are especially used in wind resource assessment to spatially extrapolate the wind measurements to obtain wind maps, and vertically to estimate hub-height wind fields. Additionally, numerical weather prediction models are used to construct simulated historical time series that can be used to extend limited wind measurement time series to longer time spans in a similar way to the MCP methods. Usually measurement techniques are available for on-site measurement ranging from point measurements performed at different heights using anemometers or ultrasonic sensors to profiling techniques like sonic detection and ranging (SODAR) or light detection and ranging (LIDAR) systems. However, many measurement campaigns for commercial wind projects or even for wind energy research projects rely on cup anemometry and ultrasonic sensors, the latter being preferred in research projects. However, remote-sensing techniques (SODARs and LIDARs) are increasingly used as complementary techniques, providing high quality wind vertical profiles at higher sampling rates [1–20]. In wind projects the profiling instruments can be conveniently relocated within the project area for specific wind measurements. Remote sensed wind speed measurements are needed to supplement mast measurements, especially in off-shore, campaign to evaluate wind flow models for resource assessments, power curve measurements, or uncertainty evaluation.

The primary objectives of robust, accurate and optimal wind farm planning include: optimal site selection, based on the quality of the wind energy resource, maximization of the annual energy production, energy cost minimization, and reliability wind farm energy production maximization. Major activities in a site selection are accurately determining the wind energy potential at the candidate site, turbulence levels and the resulting wind loads at the wind farm site. Such activities are critical for selecting site optimum wind turbines and to predicting the life cycle cost of the project, higher wind loads usually implying higher costs. Other wind energy site selection criteria include, but not limited local geography, distance to electric grid connections, permitting, and site accessibility.

1.1 Issues and challenges of the offshore wind resource assessment

Developing any offshore wind energy project presents unique and specific challenges, different from the onshore wind energy counterparts. Offshore wind farms are subject to specific atmospheric conditions, the see atmosphere boundary layer dynamics are significantly different from the land ones, and in many regards, not fully understood [2–14]. Moreover, the atmospheric observations over the ocean or see are sparse compared to land, requiring an increasing reliance on numerical or MCP models to assess wind energy potential [2–4, 9–18]. Good wind energy potential is by far the most important factor, in any offshore wind energy project, considering relative merits of the potential sites. Wind energy resource assessment, covering a wide range of spatiotemporal scales, is playing a critical role in determining the wind energy project economic viability, described as a two-phase process: (a) regional wind energy resource assessment, and (b) site specific analyses of the energy resource quality. Successful offshore wind energy projects are relying on accurate estimate of the wind regime. However, since installing and operating offshore measurement equipment and meteorological masts are expensive and difficult to operate; prospective sites must be carefully evaluated through remote sensing, numerical model data or measure-correlate-predict approaches [2–4, 9, 14–18]. Relative paucity of comprehensive offshore wind velocity observations, with proper spatio-temporal resolution makes the offshore wind energy assessment more challenging than for the onshore sites. Notice also that the floating offshore wind technology is constrained by some practical installation depths (up to 1300 m depth), limiting the offshore wind energy availability and areas. The depth limits up to 1300 m are based on economic criteria, safety and installation issues for the electrical undersea power cables.

There are main issues regarding the offshore wind energy resources, e.g. atmospheric stability conditions, wind dynamics, the extrapolation of the wind speed at turbine hub heights due to the lack of adequate observations. For example, the influence of thermal stratification on vertical profiles of wind speed is believed to be larger than over land due to lower mechanically generated turbulence [9, 14]. Other issues affecting offshore wind energy resources are that many of the offshore wind farms are located in the coastal areas, the region extending from the coastline, where the wind velocity and turbulence profiles are not in equilibrium with the underlying sea surface, significantly affecting the wind shear, wind profiles and turbulence. Research works are suggesting that the distance from the coastline over which wind speed vertical profiles are not at equilibrium with the sea surface extends for about 20 km and possibly larger distance from the coastline [9, 12–14]. Several studies have demonstrated that careful area meteorology and climatology considerations, when determining the layout of an offshore wind farm can increase its power production, improving wind farm viability [9, 12–16]. It was shown by using a mesoscale model, incorporating a wind farm parameterization can improve wind energy resource assessment [9, 13–16]. Offshore wind energy assessments should also take into consideration the experience, technology advancements, and trends of the offshore wind industry over the past few decades to establish physical parameters for array power density and wind turbine height that are needed to accurate evaluate the power capacity and energy production [2–4, 9–19]. Notice that the assessment of availability for good offshore wind energy sites is dependent on meteorological see conditions, the service equipment availability, electric grid proximity and the land-based infrastructure.

2. Factors affecting wind power computation

Wind shear, turbulence intensity, and atmospheric stability effects on wind turbine production are not fully understood, and can introduce large uncertainties on wind energy assessment. The estimation of these uncertainties is related to empirical considerations rather than theoretical calculations. Several studies are suggesting that the natural variability of wind energy resources should include air density, surface roughness, associated probability distributions, and error for prediction of long-term wind velocity. Depending on atmospheric conditions, waking by upstream wind turbines and roughness interactions, wind turbines often operate far from the ideal conditions, field-deployed power curves being quite different from certified ones [2–12]. Better predictions of power output or loads require representative wind measurements and power estimates over the rotor-swept area for individual wind turbines. Depending on the flow properties and motion scales, the flow can become turbulent [2–4]. There are three approaches that can reduce the wind energy intermittency: spatial distribution of wind power facilities, accurate forecasting, and energy storage systems. Although wind generation is subject to large wind variations, if the facilities are spatially distributed, an overall output at any time is more uniform and reliable. The wind speed increases with height, higher elevation sites offering greater wind energy resources. However, the air density decrease with height reduces wind turbine power output. However, it is advantageous to locate turbines at higher elevations to take advantage of higher wind speeds. Power curves for various air density values must be accounted for better power output estimate accuracy. Air density is usually calculated from temperature and pressure measurements [2–4]. Depending on the wind turbine, either the wind velocity is normalized for power calculations. The wind speed is normalized with the reference air density ρ_0, as:

$$v_{norm} = \overline{v}\left(\frac{\overline{\rho}}{\rho_0}\right)^{1/3} \tag{1}$$

The usual hub-heights of 80 m or higher of the modern, the rotors may encounter large vertical gradients of wind speed and boundary layer turbulence. Wind turbine rotors are susceptible to turbulence fatigue damages. Understanding of the turbulence impact on the blades can help in better designing the operational and maintenance schedules for wind farms. Consequently, the full understanding can lead to advanced and improved control and management schemes and methods. Quantification of the turbulence effects on wind turbine is usually done by computing an equivalent fatigue load parameter, as a function of wind fluctuation amplitudes within the averaging period, blade material properties, and the size of measurement samples. It is found that the highest blade root flap bending moment equivalent fatigue load does not correspond to the greatest wind speeds, but to the class of wind speeds that has the highest amplitude of the fluctuations [2–4, 18–27]. Turbulent fluctuations are found to be the main source of the blade fatigue. The turbulence intensity (TI), a measure of the overall level of turbulence, is defined as:

$$TI = \frac{\sigma_v}{v} \tag{2}$$

where σ_v is the wind speed standard deviation (m/s) at the nacelle height over a specified averaging period (usually 10 min). In [21] was found that, from the power curves for different turbulence intensity classes and for low to moderate wind speeds (4 to 12 m/s), the high TIs are yielding the higher turbine power output. TI index is affected by the atmospheric stability, so the theoretical wind turbine power curves [2–4, 13–21]. A correction factor, common used, for the effect of turbulence intensity is given by:

$$v_{corr} = v_{norm}\left(1 + 3(TI)^2\right)^{1/3} \tag{3}$$

Vertical wind shear effects are important as the wind turbines become larger and larger. It is therefore quite questionable whether the hub height wind speed is representative. Various methods exist concerning the extrapolation of wind speed to the hub height of a wind turbine. The wind velocity varies as a disproportionate function of height. At low height levels surface friction and low level obstacles introduce turbulence and reduce the observed wind velocity. The velocity *u(z)* at low height levels over consistent terrain or see surfaces is conventionally approximated by the logarithmic function, of u^* is the scaling velocity, k is the Von Karman's constant, usually equal to 0.4, z is the desired height level and z_0 the roughness length, values lower than 0.01, while the roughness length or surface friction is the parameter of most influence in equation, defined as:

$$u(z) = \frac{u^*}{k} \ln\left(\frac{z}{z_0}\right) \tag{4}$$

There are several theoretical expressions used for determining the wind speed profile. However, the increase of wind speed with height should be considered for the installation of large wind turbines. Thus, the surveys must rely to simpler expressions and secure satisfactory results even when they are not theoretically accurate. For h_0 = 10 m and z_0 = 0.01 m, the parameter α = 1/7, which is consistent with the value of 0.147 used in the wind turbine design standards (IEC standard, 61400-3, 2005) to represent the change of wind speeds in the lowest levels of the atmosphere. Wind speed is usually recorded at the standard meteorological height of 10 m, while wind turbines usually have hub heights near 80 m. In cases which lack of elevated measurements, the hub-height wind velocity is estimated by applying a vertical extrapolation to the surface or reference measurements. However, the vertical extrapolation coefficient may contain errors and uncertainties due to terrain complexity, ground or see conditions, atmospheric stability, and turbulence [2–4, 17–36]. The wind speed *v(z)* at a height z can be calculated directly from the wind speed $v(z_{ref})$ at height zref (usually the standard measurement level) by using the logarithmic law (the so-called Hellmann exponential law) expressed by:

$$\frac{v(z)}{v_0} = \left(\frac{z}{z_{ref}}\right)^{\alpha} \tag{5}$$

where, *v(z)* is the wind speed at height z, v_0 is the speed at z_{ref} (usually 10 m height, the standard meteorological wind measurement level), and α is the power law index. This coefficient is a function of the site surface roughness and the thermal stability, frequently assumed to be 1/7 for open land. However, this parameter can vary diurnally, seasonally and spatially. It was found that a single power law is insufficient to adequately estimate the wind power at a given site, especially during nighttime and in presence of the low-level jets. Another formula, the logarithmic wind profile law, widely used in Europe, is:

$$\frac{v}{v_0} = \frac{\ln(z/z_0)}{\ln(z_{ref}/z_0)} \tag{6}$$

Here, z_0 is again the roughness length, expressed in meters, depending basically on the surface type, ranging from 0.0002 up to 1.6 or higher. In addition to the roughness, these values can vary during the day and at night, and even during the year. Once wind speeds have been calculated at other heights, Eq. (6) can be used for calculating the useful wind energy potential. Notice that the wind shear over the rotor area can also be significant. The standard procedure for power curve measurements is given by the IEC Standard, 6-1400-12-1, 2005 [19], where the wind speed at hub height is considered representative of the wind over the rotor area. This assumption can lead to large wind power estimate inaccuracies since inflow is often non-uniform and unsteady over the rotor-swept area. By integrating the wind profile over the rotor span, a corrected wind speed is obtained:

$$U_{avrg} = \frac{1}{D}\int_{H-\frac{D}{2}}^{H+\frac{D}{2}} v(z)dz = \quad v(H)\cdot\frac{1}{\alpha+1}\cdot\left(\left(\frac{3}{2}\right)^{\alpha+1} - \left(\frac{1}{2}\right)^{\alpha+1}\right) \tag{7}$$

where H is the nacelle height and D is the rotor diameter. It is observed these corrections have less significant effects. For wind speeds in the range 4 m/s to 20 m/s (the useful wind speed regime) the corrected power differs less than 5% from the uncorrected power. However, the corrected power is larger than the uncorrected turbine power.

An additional wind velocity property that can make the impact on wind turbine operations is the wind gustiness. Proper wind turbine design and operation requires knowledge of wind extremes and gustiness, defined by the wind gust factor. This is important in areas where wind climate shows strong gusty winds, e.g. downslope windstorms [3, 50, 51]. In sites with higher turbulent intensity and gusty winds, turbines are subject to extreme structural loading and fatigue. The gust factor (G) is defined as:

$$G = \frac{u_g}{U} - 1 \tag{8}$$

where ug is the gust speed and U is the mean daily wind speed. Higher gusts are usually associated with higher mean wind speeds; however, it also is expected that normalized gust speed ug/U and, consequently, the gust factor, G, decreases with the increasing mean speed. The following equation relates the gust factor to the mean daily wind speed:

$$G = AU^n \tag{9}$$

where the parameters A and n are obtained by using a least-square fit of the logarithm of G vs. the logarithm of the mean daily wind speed. While gusts generally decrease as wind speed increases, in extreme cases the wind gusts can easily reach over twice the strongest wind speeds ($v > 20\ ms^{-1}$) and damage a wind turbine. However, wind gusts over 25 m/s, the upper wind speed limit of a large wind turbine, are quite unlikely in many areas, occurring only about 2% of time [2–4, 23–25]. Gusts associated with stronger winds may cause considerable losses by reducing the energy production of the wind turbine which would otherwise operate at nominal output power. Another effect of wind gust is the additional stress on the wind turbine structure, which may reduce its lifespan.

The low-level jet, observed worldwide is a mesoscale phenomenon associated with the nighttime very stable boundary layer that can have a width of hundreds of kilometers and a length of a thousand kilometers. During nighttime and over land, ground surface cools at a faster rate than the adjacent air and stable stratification forms near the surface and propagates upward. Downward mixing of the winds is reduced, and winds aloft become decoupled from the surface and accelerate. The maximum wind speeds are usually 10 m/s to 20 m/s or even higher at elevations 100 m to 300 m. Consequently, it is not possible to accurately estimate winds aloft at hub and blade tip heights from routine surface measurements [4]. Additionally, a strong wind shear and associated turbulence are developing at the bottom and top of the jet layer. After the wind velocity field data are collected and transferred to the computing environment, the next steps are to validate and process data, and generate reports. Data validation is defined as the inspection of all the collected data for completeness and reasonableness, and the elimination of erroneous values. Data validation transforms raw data into validated data. The validated data are then processed to produce the summary reports required for analysis, step crucial in maintaining high rates of data completeness. Therefore, data must be validated as soon as possible, after they are transferred. The sooner the site operator is notified of a potential measurement problem, the lower the risk of data loss. Data can be validated either manually or by using computer-based data analysis [2–4]. The latter is preferred to take advantage of the computer power and speed, although some manual reviews are always required. Data validation implies visual inspection, editing, missing data interpolation, outliers and questionable data rejection, and finally saving data in appropriate format.

3. Wind energy statistical analysis

The wind is characterized by its speed and direction which is affected by several factors, including: geographic location, climate characteristics, height above ground, vegetation and surface topography. Wind turbines interact with the wind capturing part of its kinetic energy and converting it into usable energy. Wind availability, the influence of the turbine height installation above ground, the wind gusting effect and the wind turbine micro-sitting are the main influences of the annual energy output and are the theoretical basis for the wind energy assessment [2–9, 14, 32–60]. There main aspects of the wind resource assessment are the wind power potential estimate, and the prediction of the wind plant energy production. The measured wind velocity data were usually available at 10 m standard meteorological height. However, sometimes the anemometers are installed on top of buildings or airport control towers, or at meteorological masts. The wind energy classes were developed for 10 m height because that was the standard for meteorological data, and then the wind power potential is extrapolated at 50 m, assuming that the wind shear exponent was 1/7 for all locations. Global wind patterns, upper air wind data, and boundary layer meteorology were routinely used to obtain estimates of the wind energy resource [2–4]. The knowledge of the quasi-steady mean wind speeds that can be expected at a potential site is critical to determine the wind economic viability of a wind energy project. Such information is essential in the wind turbine selection in order to maximize efficiency and durability. The wind frequency distributions, used in wind energy assessment are predicted from wind measurements collected during several years. If such information is not available, wind speed probability distributions, constructed from limited field campaigns, e.g. Weibull or Rayleigh probability distributions are used to estimate the wind power potential. The highly dependent nature of energy production on wind speed needs accurate predictions of the distribution of wind speeds for a prospecting wind farm location and for accurate energy production calculations.

The wind probability distribution (PDF) functions have been investigated, employed and explained by many researchers and engineers involved in the wind energy [2–12, 42–68]. In wind power studies such probability distributions are used for assessment and analysis of wind energy resources, wind power plant operation, as well as for turbine design. Both analytical and numerical methods can be carried out. However, a planning from a different point of view can be performed, while similar distribution functions can be used for wind power, if wind velocity distribution functions are taken into account, together with WT features, provided by the manufacturers. Usually the wind velocity time series are rather large, differences among parameter estimation methods is not as important as differences among distributions. There are several estimators of PDF parameters, such as Method of Moment (MOM), Maximum Likelihood Estimators (MLE), Least-Square (LS), and Percentile Estimators Methods [2–72]. These estimators are unbiased, so there is no reason to give preference to any of them. The choice of specific estimators is based on the existing wind speed data, computing availability and user preference. The rule-of-thumb is to select a number of estimators of the PDF parameters, while the parameters are usually computed by taking the averages of the estimates found by these methods. We preferentially use MLE, MOM and LS estimators for the large samples, and the averages are the PDF parameters [45–70]. However, when using MOM, we calculate the sample mean standard deviation (s), and skewness (G) as:

$$\overline{v} = \frac{1}{N}\sum_{i=1}^{N} v_i \tag{10}$$

$$s = \sqrt{\frac{1}{N-1}\sum\nolimits_{i=1}^{N}(v_i - \overline{v})^2} \tag{11}$$

and

$$G = \frac{1}{N}\cdot\frac{\sum_{i=1}^{N}(v_i - \overline{v})^3}{S^3} \tag{12}$$

where N is the number of observations in v, the wind speed. Once the wind power distribution function is obtained, the mean power available is deduced. So as not to depend on the type of wind turbine, this will be shown per unit of surface (mean power density). This process is performed in four different ways: (1) obtaining of the wind power; (2) Betz' law considerations; (3) consideration of realistic values, remembering that Betz' law is an upper limit; and (4) consideration of WT parameters such as Cut-In and Cut-Out wind speed, rated speed, and rated power. The goal of any wind energy assessment and analysis is to give response to questions about statistical distribution of the maximum power obtainable from the wind, regardless of the WT chosen, and also taking into account its features, when the only input value is the mean wind speed.

3.1 Weibull probability distribution

The Weibull density distribution is a commonly applied statistical distribution to model wind speed regime. The use of probability distribution functions in order to define and to characterize the field data has a long history of use. It has been established, in the literature [2–4, 41–70] that the Weibull probability distribution is very well fitted to characterize wind speed regimes, being commonly used to estimate and to assess wind energy potential. However, efforts have been made over the years to fit the wind data to other distributions, e.g. exponential distribution, gamma distribution, or logistic distribution. The Weibull probability distribution is given by:

$$f_{WB} = k\frac{v^{k-1}}{c^k}\exp\left(-\left(\frac{v}{c}\right)^k\right) \tag{13}$$

The Weibull distribution is a function of two parameters: k, the shape parameter, and c, the scale factor. These parameters are defining the shape or steepness of the curve and the mean value of the distribution. These coefficients are adjusted to match the wind data at a particular site. For wind modeling, typical k values range from 1 to 2.5 and can vary drastically form site to site, as well as during years and/or seasons. The scale parameter, c, corresponds to the average wind speed for the site. The main inaccuracy of the Weibull distribution is that it always has a zero probability of zero wind speed, which is not the case since there are frequently times in which no wind is blowing. The higher the k value, the sharper the increasing part of the curve is. The higher c values correspond to a shorter and fatter distribution, with a higher mean value. Ideally the mean value would correlate with the rated wind speed of the turbine: producing rated power for the extended time annually. The cumulative probability function for Weibull distribution is given by:

$$F(v) = 1 - \exp\left[-\left(\frac{v}{c}\right)^k\right] \tag{14}$$

The availability of high quality wind speed distributions is crucial to accurate forecasts of annual energy production for a wind turbine. Statistical distributions suffice for early estimations, while the actual wind speed measurements are necessary for accurate predictions. The factors k and c featuring in Eq. (13) are determined for each measurement site. There are several estimators of Weibull parameters, such as the Moment (MOM), Maximum Likelihood (MLE), Least-Square, and Percentile Estimators. These estimators are unbiased, although some of them, such as the Method of Moments, may have large variances, so there is no reason to prefer any of them. The choice of specific estimators is based on the existing wind speed observations, computing availability and user preference. The rule-of-thumb is to select estimators of the Weibull parameters, such as: standard least-square, maximum likelihood or MLE variants, while the shape and scale parameters are computed taking the averages [2–4]. If sufficient wind speed observations are available, one of the most used is the MOM methods or its variants. It is based on the numerical iteration of the following two equations while the mean ($\overline{v}$) and standard deviation (s) of the wind speeds are determined from:

$$\overline{v} = c \cdot \Gamma\left(1 + \frac{1}{k}\right) \tag{15}$$

and

$$s = c\left[\Gamma\left(1 + \frac{2}{k}\right) - \Gamma^2\left(1 + \frac{1}{k}\right)\right]^{1/2} \tag{16}$$

where $\overline{v}$ is the wind speed data set (sample) mean, as defined in Eq. (11), s is the wind speed data set (sample) standard deviation, and $\Gamma()$ is the Gamma function:

$$\Gamma(x) = \int_0^\infty t^{x-1} \exp(-t) dt \tag{17}$$

A special case of the moment method is the so-called empirical method, where the Weibull shape parameter k is estimated by following relationship:

$$k = \left(\frac{s}{\overline{v}}\right)^{-1.086} \tag{18}$$

Then the scale parameter, c is computed by using the following relationship:

$$c = \frac{\overline{v}}{\Gamma(1 + 1/k)} \tag{19}$$

Both, the moment and empirical method require a reasonable wind speed observations data set to be available. Another Weibull parameter estimator, based on the least squares, is the graphical method. In which a straight line is fitted to the wind speed data using lease squares, where the time-series data must be sorted into bins. Taking a double logarithmic transformation, the cumulative distribution function is rewritten as:

$$ln\left\{-ln\left[1 - F(v)\right]\right\} = kln(v) - kln(c)$$

Plotting ln(v) against ln{−ln[1 - F(v)]}, the slope of the best fitted line to data pairs is the shape parameter, and the scale parameter is then obtained by the intercept with y-axis. The graphical method requires that the wind speed data be in cumulative frequency distribution format. Time-series data must therefore first sort into bins. In essence the graphical method is a variant of the moment method, consisting of the calculation from the time series of the observations of statistical estimators, such as wind speed means and of the square wind speeds. Then the Weibull parameters are calculated as:

$$\overline{v} = \frac{c}{k}\Gamma\left(\frac{1}{k}\right) \tag{20}$$

and

$$\overline{v^2} = \frac{2c^2}{k}\Gamma\left(\frac{2}{k}\right) \tag{21}$$

Then computing the means from the wind observations (Eq. (20) and Eq. (21)), the Weibull parameters are estimated. The Weibull distribution can also be fitted to time-series wind data using the maximum likelihood method. The shape factor k and the scale factor c are estimated, numerically using the following two equations:

$$k = \left(\frac{\sum_{i=1}^{N} v_i^k\, ln\,(v_i)}{\sum_{i=1}^{N} v_i^k} - \frac{\sum_{i=1}^{N} ln\,(v_i)}{N}\right)^{-1} \tag{22}$$

$$c = \left(\frac{1}{N}\sum_{i=1}^{N} v_i^k P(v_i)\right)^{1/k} \tag{23}$$

where v_i is the wind speed in the bin i and N is the number of nonzero wind speeds (the actual wind speed observations). Eq. (22) is solved numerical, usually through iterative methods, with k equal to 2 as initial guess, and then Eq. (23) is solved explicitly. When wind speed data are available in frequency distribution format, a MLE variant can be applied. In this cans, the Weibull parameters are then estimated through:

$$k = \left(\frac{\sum_{i=1}^{N} v_i^k\, ln\,(v_i)P(v_i)}{\sum_{i=1}^{N} v_i^k P(v_i)} - \frac{\sum_{i=1}^{N} ln\,(v_i)P(v_i)}{P(v \geq 0)}\right)^{-1} \tag{24}$$

$$c = \left(\frac{1}{P(v \geq 0)} \sum_{i=1}^{N} v_i^k P(v_i) \right)^{1/k} \tag{25}$$

where, $P(v_i)$ is the frequency with which the wind speed falls within bin i, $P(v \geq 0)$ is the probability that the wind speed equals or exceeds zero. Eq. (23) must be solved iteratively, after which Eq. (25) is solved explicitly to determine the Weibull parameters. One of the parameter estimator not very often used is the energy pattern factor method. In this approach, the energy pattern factor for a given wind speed data is defined as:

$$E_{pf} = \frac{\overline{v^3}}{\overline{v}^3} \tag{26}$$

here $(\overline{v^3})$ is the mean of the cubes of the wind speed. Notice that the factors in Eq. (26) are related to the wind energy estimates. Weibull shape parameter can be estimated with the following equation:

$$k = 1 + \frac{3.69}{E_{pf}} \tag{27}$$

Scale parameter is estimated by using Eq. (19), for example. Often isw necessary to estimate the Weibull parameters in the absence of suitable information about the distribution of wind speeds. For example, if only annual or monthly averages may be available, the value of k must be estimated by Eq. (27). The value of k is usually from 1.5 and 3, depending on the wind variability. Smaller k values correspond to variable winds.

To analyze the accuracy of the aforementioned methods, the following tests are used, RMSE (root mean square error), χ^2 (chi-square), R^2 (variance analysis or method efficiency) and the Kolmogorov–Smirnov test. These tests are examining whether a PDF is suitable to describe the wind speed data or not. The RMSE test is defined by:

$$RMSE = \left[\frac{1}{N} \sum_{i=1}^{N} \left(y_i - x_i\right)^2 \right]^{1/2} \tag{28}$$

where y_i is the actual values at time stage i, x_i is the value computed from correlation for the same stage, and N is the number of data. The next two tests are defined by:

$$\chi^2 = \frac{\sum_{i=1}^{N} \left(y_i - x_i\right)^2}{N - n} \tag{29}$$

and

$$R^2 = \frac{\sum_{i=1}^{N} \left(y_i - z_i\right)^2 - \sum_{i=1}^{N} \left(y_i - x_i\right)^2}{\sum_{i=1}^{N} \left(y_i - z_i\right)^2} \tag{30}$$

where N is the number of observations, y_i is the frequency of observations, x_i is the Weibull frequency, and z_i is the mean wind speed. The Kolmogorov–Smirnov test is defined as the max-error between two cumulative distribution functions:

$$Q = max \left| F_T(v) - F_O(v) \right| \tag{31}$$

where $F_T(v)$ and $F_O(v)$ are the cumulative distributions functions for wind speed not exceeding v computed by using estimated Weibull parameters and by observed (or randomly generated) time-series, respectively. The critical value for the Kolmogorov–Smirnov test at 95% confident level is given by:

$$Q_{95} = \frac{1.36}{\sqrt{N}} \tag{32}$$

If Q value exceeds the critical value, then there is significant difference between the theoretical and the time-series data under the given confident level. **Figure 1** shows the fitted Weibull probability distributions with long-term observations, for two locations [4, 51, 52], exhibiting a good agreement between fitted PDF and actual data. The energy that a wind turbine generates depends on both on its power curve, a nonlinear relationship between the wind speed and turbine power output and the wind speed frequency distribution. If derived from long-term (multi-annual) wind speed data sets the histograms shape of the PDFs that are characterizing the wind speed at a specific site or for a region.

3.2 Other probability distribution function used in wind energy

Another used probability distribution is the Rayleigh distribution, which is a special case of the Weibull distribution where k = 2. The Rayleigh distribution is simpler because it depends only on the mean wind speed, and is given by:

$$f_{RL}(v) = \frac{\pi}{2}\frac{v}{c^2}\,exp\left[-\frac{\pi}{4}\left(\frac{v}{c}\right)^2\right] \tag{33}$$

These two probability distribution functions, Weibull and Rayleigh [2–4, 9, 41–72] are the most commonly used for wind energy analysis and assessment. The Rayleigh PDF is a special case of the Weibull distribution with k = 2. Notice that for both distributions, V_{min} = 0 and V_{max} = ∞. The cumulative Rayleigh distribution is expressed as:

$$F(v) = 1 - e^{-(v/c)^2} \tag{34}$$

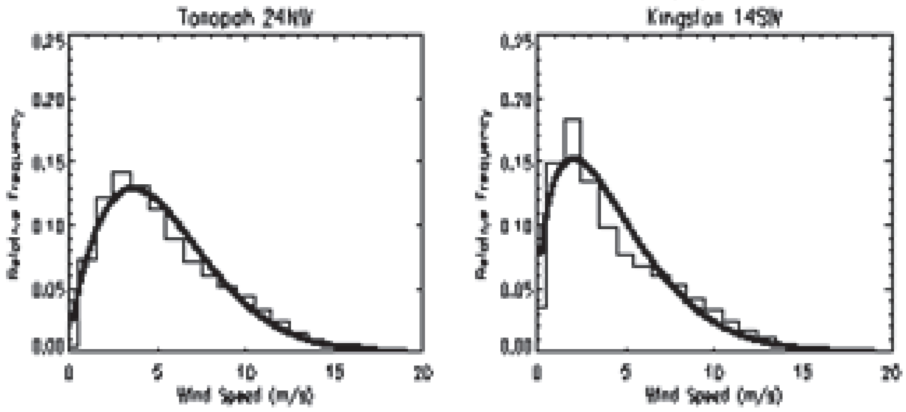

Figure 1.
Experimental wind speed probability density functions, at 50 m level, using the composite 2003–2008 data sets, for two 50 m instrumented towers [4, 51, 52].

For the Rayleigh distribution the single parameter, c, relates the following three properties:

$$c = V_{mp}\sqrt{2} = \frac{2\mu}{\sqrt{\pi}} = \sigma\sqrt{\frac{4}{8-\pi}} \tag{35}$$

The Rayleigh distribution can be written using V_{mp} or the mean velocity, μ. Determination of the mean and standard deviation from experimental data for the normal distribution are well known. The MLE estimate of the normal distribution en is the arithmetic mean. The parameter c in the Rayleigh distribution can be evaluated from N wind velocities, V_i. If experimental data are used to determine distribution parameters, the computed result is called an estimate of the true parameter. Here, the symbol used to indicate that the equation gives only an estimate of the true distribution parameter, c.

$$\hat{c} = \sqrt{\frac{1}{2N}\sum_{i=1}^{N} V_i^2} \tag{36}$$

The 3-parameter Weibull (W3) is a generalization of the 2-paramter Weibull distribution, where the location parameter s establishes a lower bound (assumed to be zero in the case of 2-parameter Weibull distribution). It was found that for some areas the W3 fits wind speed data better than the 2-parameter Weibull model [4, 40–72]. The W3 probability distribution and cumulative distribution functions are expressed as:

$$f(v,k,c,\tau) = \frac{kv^{k-1}}{c^k}\exp\left[-\left(\frac{v-\tau}{c}\right)^k\right] \tag{37}$$

and

$$F(v,k,c,\tau) = 1 - \exp\left[-\left(\frac{v-\tau}{c}\right)^k\right] \tag{38}$$

Respectively, for $v \geq \tau$, and τ is the location parameter, locating the probability distribution along the abscissa (v axis). Changing the value of τ has the effect of sliding the distribution and its associated function either to the right (if τ > 0) or to the left (if τ < 0). The MLE estimators for the W3 PDF parameter calculation are:

$$\frac{\sum_{i=1}^{N}(v_i-\widehat{\tau})^{\widehat{k}}\ln(v-\widehat{\tau})}{\sum_{i=1}^{N}(v_i-\widehat{\tau})^{\widehat{k}}} - \frac{1}{\widehat{k}} - \frac{1}{N}\sum_{i=1}^{N}\ln(v_i-\widehat{\tau}) = 0 \tag{39}$$

and

$$\widehat{c} = \left(\frac{1}{N}\sum_{i=1}^{N}(v_i-\widehat{\tau})^{\widehat{k}}\right) \tag{40}$$

$$\widehat{\tau} + \frac{\widehat{c}}{N^{1/\widehat{k}}}\Gamma\left(1+\frac{1}{\widehat{k}}\right) = U_{\min} \tag{41}$$

where N is the number of observations in the sample v, and U_{min} indicates the minimum values in the v time series. Parameters of the W3 distributions are then found iteratively.

Another PDF used in wind energy assessment, especially in offshore applications is the lognormal distribution [4, 66–68]. The 2-parameter lognormal PDF is given by:

$$\hat{\tau} + \frac{\hat{c}}{N^{1/\hat{k}}}\Gamma\left(1 + \frac{1}{\hat{k}}\right) = U_{\min} \tag{42}$$

And its cumulative distribution function is expressed as:

$$F(v, \mu, \sigma) = \frac{1}{2} + \frac{1}{2} erf\left[\frac{\ln(v) - \mu}{\sigma\sqrt{2}}\right] \tag{43}$$

where $erf(x) = \frac{2}{\sqrt{\pi}}\int_0^x \exp(-t^2) \cdot dt$ is the error function from the Normal distribution, and the parameters μ and σ are the mean and standard deviation of the natural logarithm of v. The parameter estimators are given by:

$$\hat{\mu} = \ln\left(\frac{\bar{v}}{\sqrt{1 + \frac{s^2}{\bar{v}^2}}}\right)$$

$$\hat{\sigma} = \sqrt{\ln\left(\frac{s^2}{\bar{v}^2}\right)}$$

The truncated normal distribution is the probability distribution function of a normally distributed random variable whose values are either bounded at lower end, higher end or at both. Since the wind speed is only positive, the most common is the single truncated normal distribution, suitable for nonnegative case:

$$n(v, \mu, \sigma) = \frac{1}{I(\mu, \sigma)\sigma\sqrt{2\pi}} \exp\left[-\frac{(v - \mu)^2}{2\sigma^2}\right], \ for\ v > 0 \tag{44}$$

where μ and σ are the date mean and standard deviation, and I(μ, σ) is the normalized factor, making the integral of this distribution equal to one, the cumulative distribution function is evaluated in its domain de definition. The normalized factor is given by:

$$I(\mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \int_0^\infty \exp\left[-\frac{(v - \mu)^2}{2\sigma^2}\right] dv \tag{45}$$

The distribution function parameters can be determine using graphical, moment or maximum likelihood methods or a combination of them. The maximum entropy probability (MEP) concept has commonly been applied in many engineering and science areas. The entropy of PDF, f(x) is defined [54–72] by:

$$S(x) = -\int f(x) \ln(f(x)) dx$$

Maximizing the entropy subject to specific constrains enables to find the most likely probability distribution function if the information available is provided by moment functions. The classical MEP solution applied to wind distribution case is given by:

$$f(v) = \exp\left[-\sum_{k=0}^{N} a_k v^k\right] \tag{46}$$

and solution, Lagrange multipliers are given by the following nonlinear system of equations:

$$Z_n(a) = \int v^n \exp\left[-\sum_{k=0}^{n} a_k v^k\right] dv = \lambda_n \, for \; n = 1, 2, \dots, N$$

The λ_n, n = 0,1, … , N, with λ_0 = 1, are the distribution moments, representing the mean values of n wind speed powers, calculated from observations. MEP probability density functions of third or fourth order with three or four moment constrains.

Gamma PDF can be expressed with the following function:

$$g(v; x; \beta) = \frac{v^{x-1}}{\beta^2 \Gamma(x)} \exp\left[-\frac{v}{\beta}\right], \; for \; v, x, \beta > 0 \tag{47}$$

where x and β are the shape and scale parameter, respectively. The parameters of the Gamma distribution can be estimated using graphical, moment or maximum likelihood methods, similar to one presented above in the Weibull case. However, the Gamma PDF is usually employed in a mixture of distributions in connection with Weibull PDF.

In recent years, in order to improve the accuracy of wind statistics, mixtures of PDFs were employed [4, 50–72]. Distribution function mixed with Gamma, Weibull, or Normal distribution functions can be used to describe the wind statistics. For example, Gamma and Weibull mixture applied to wind energy assessment is given by:

$$h(v; w; x, \beta, k, c) = wg(v, x, \beta) + (1 - w)f(v, k, c) \tag{48}$$

where $0 \le w \le 1$ is the weight parameter indicating the mixed proportion of each probability distribution included in the PDF mixture relationship. Again, the five parameters, in the Eq. (48) can be estimated using graphical, moment, maximum likelihood methods or any combination them, as discussed in the Weibull case.

3.3 Wind turbine power and energy estimates

The average power of a wind turbine, over a specific time period (e.g. one month) is determined by multiplying the wind speed probability density function $f_{PDF}(v)$ and the power curve of the turbine, $CP(v)$. The power curve represents the wind turbine output power vs. wind speed diagram [2–4, 68–72]. The power curve depends on the wind speed, air density and turbulence intensity, being usually provided by the manufacturers or can be constructed from the field measurements. However, the manufacturers do not usually are providing the information on the power curves of their wind turbines in a continuous (analytic) form, but rather in a discrete form with N nodes ($P_{WT\text{-}i}$, v_i). Wind power density, a measure of the energy flux through an area perpendicular to the direction of motion, it is extensively used in wind energy assessment. It is also varying not only with the cube of wind speed, but also with the air density and turbulence. The monthly average energy produced by a wind turbine is obtained from the monthly average output power by multiplying it with the hours of that month. The prediction of the wind speed variation with height, the variation in wind speed over the wind farm area, air density and the wake interaction between the wind turbines are usually calculated by using a computer programs, specifically designed to facilitate accurate predictions of wind farm energy production. Such computing applications allow fast computations of the energy production for different layouts, turbine type and hub height to determine the optimum setting. In the statistic approaches, based on an estimate of the wind velocity probability distribution function, for the location wind regime, $f_{PDF}(v)$, extrapolated at the hub height and a known WT power curve $P_{WT}(v)$, the mean power output of a wind turbine (assuming 100% of its availability) is given in the following equation:

$$\overline{P}_{WT} = \int_{V_{ci}}^{V_{co}} f_{PDF}(v) \cdot CP(v) \cdot dv \tag{49}$$

Generally, the integral of Eq. (49) has no analytic solution and must be resolved numerically. For example, if the Weibull probability distribution is determined the wind power density, *WPD* is estimated, function of the Weibull parameters by:

$$WPD = 0.5 \cdot \rho c^3 \left(1 + \frac{3}{k}\right)$$

The relationship between the power output of a turbine and the incoming wind speed is usually simplified by a generic power curve model, as expressed in practical application by the following relationship:

$$P_{WTG}(v) = \begin{cases} 0, & \mathrm{v} \le \mathrm{V_{ci}} \ \text{ or } \ \mathrm{V_{co}} \le \mathrm{v} \\ P_{WT-Rated}\left(\frac{v}{V_R}\right)^3, & \mathrm{V_{ci}} \le \mathrm{v} \le \mathrm{V}_R \\ P_{\text{WT-Rated}}, & \mathrm{V}_R \le \mathrm{v} \le \mathrm{V_{co}} \end{cases} \tag{50}$$

Here, $P_{WT\text{-}Rated}$ is the wind turbine rated power, V_{ci}, V_R, and V_{co} are the wind turbine cut-in, rated, and cut-off speeds. These values are also provided by the manufacturer. The total power yield of the wind farm is the sum of the power output of each wind farm turbine. For a number of wind turbines taking into consideration of the generator efficiency, the total output power can be extracted as follows:

$$P_{WT-tot} = N_{WT} \times \eta_{WTG} \times P_{WT} \tag{51}$$

Where: η_{WTG} and N_{WT} are the wind generator efficiency and number of wind turbine generators in the wind farm, respectively. Wind turbine output power is estimated, as adapted from the Eq. (49), by a relationship such as:

$$P_{WT}(v) = \begin{cases} 0, & \mathrm{v} \le \mathrm{V_{ci}} \ \text{ or } \ \mathrm{V_{co}} \le \mathrm{v} \\ 0.5 \cdot \rho \cdot \mathrm{A} \cdot \mathrm{C}_P(\lambda, \beta) v^3, & \mathrm{V_{ci}} \le \mathrm{v} \le \mathrm{V}_R \\ P_{\text{WT-Rated}}, & \mathrm{V}_R \le \mathrm{v} \le \mathrm{V_{co}} \end{cases} \tag{52}$$

The wind generator power output is best estimated through interpolation of the values of the data provided by the manufacturers with wind velocity observations. As the power curves are quite smooth, they can be approximated using a cubic spline interpolation. The fitting equation of the output characteristic of wind generator can be expressed as:

$$\mathrm{P_{WTG}(v)} = \begin{cases} 0 & v \le V_{ci} \quad or \quad v \ge V_{co} \\ \mathrm{a_1}v^3 + \mathrm{b_1}v^2 + \ \mathrm{c_1}v + \ d_1 & V_{ci} < v < V_1 \\ \mathrm{a_2}v^3 + \mathrm{b_2}v^2 + \ \mathrm{c_2}v + \ d_2 & V_1 < v < V_2 \\ \cdots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots & \\ \mathrm{a_n}v^3 + \mathrm{b_n}v^2 + \ \mathrm{c_n}v + \ d_n & V_{n-1} < v < V_r \\ P_{rated} & V_r \le v < V_{co} \end{cases} \tag{53}$$

Where P_{WTG} is the output power of wind generator at wind speed v, is the wind turbine rated power; v is the wind speed at the hub height, n is the number of cubic spline interpolation functions corresponding to $n + 1$ values, couples of the wind speed and the wind turbine output power. These data are provided by the manufacturers, a, b, c and d are the polynomial coefficients of the cubic spline interpolation functions, depending on the wind turbine type and are estimated from measurements. Simplified versions of the wind turbine power output calculations, usually used in practice and design are:

$$P_{WT} = \begin{cases} P_{WT-Rated}\dfrac{(v(t) - V_{ci})}{(V_r - V_{ci})}, & for \ \ V_{ci} \le v(t) < V_R \\ P_{WT-Rated}, & for \ \ V_R \le v(t) \le V_{co} \\ \\ 0, & for \ \ v(t) < V_{ci}, or \ v(t) > V_{co} \end{cases}$$

Or

$$P_{WT} = \begin{cases} a \cdot (v(t))^3 - b \cdot P_{WT-Rated}, & for \ \ V_{ci} \le v(t) < V_R \\ P_{WT-Rated}, & for \ \ V_R \le v(t) \le V_{co} \\ 0, & for \ \ v(t) < V_{ci}, or \ v(t) > V_{co} \end{cases}$$

where $P_{WT}(v)$ is the output power of WT units with an ambient wind speed v, $\mathrm{P_{WT\text{-}Rated}}$ is the rated power of the WT, Vci, Vco and VR are the cut-in wind speed, cut-out wind speed, and rated wind speed, respectively. Based on the wind speed data, the output power of WT units is calculated according to one of these relationships. The parameters a, and b, of the last WT power output relationship are calculated by these expressions:

$$a = \frac{P_{WT-rated}}{V_r^3 - V_{ci}^3}, \ \text{ and } \ b = \frac{V_{ci}^3}{V_r^3 - V_{ci}^3}$$

Calculation of energy output requires knowledge of the wind speed probability distribution and the wind turbine power curve. Once, the wind speed probability distribution and turbine power curve are determined, the output energy of a wind turbine or for a wind farm can be easy determined. The wind energy (EWT) that can be extracted by a wind turbine, over a T time period is defined by this relationship:

$$E_{WTG} = \int_0^{\infty} CP(v) \cdot f_{PDF}(v) \cdot dv \tag{54}$$

3.4 Wind direction

To ensure the most effective use of a wind turbine it should be exposed to the most energetic wind. Though the wind may blow more frequently from the west more wind energy may come from a different direction if those winds are stronger. It is important to find out which directions have the best winds for electricity production. The distribution of wind direction is crucially important for the evaluation of the possibilities of utilizing wind power. The distributions of wind speed and direction are conventionally given by wind roses. A wind rose, generated from your wind resource assessment, is a helpful tool to determine wind direction and distribution. Traditionally, wind direction changes are illustrated by a graph, which indicates percent of winds from that direction, or the wind rose diagram [2, 4, 52, 61, 62, 66–70]. The wind rose diagrams and wind direction frequency histograms provide useful information on the prevailing wind direction and availability in different wind speed bin. A vane points toward the wind source. Wind direction is reported as the direction from which the wind blows, not the direction toward which the wind blows, e.g. a North wind blows from the North toward the South. The wind direction varies from station to station due to different local features (topography, altitude, distance from the shore, vegetation, etc.). There are usually changes in the wind directions on diurnal, seasonal or annual basis. The wind direction can also be analyzed using continuous probability models to represent distributions of directional winds, e.g. von Mises circular statistics, usually comprised of a mixture of von Mises distributions.

The wind rose diagrams and wind direction frequency histograms provide useful information on the prevailing wind direction and availability of directional wind speed in different wind speed bins. The wind roses were constructed using the composite data sets of measurements of wind velocities. The wind direction is analyzed using a continuous variable probability model to represent distributions of directional winds, comprising of a finite mixture of the von Mises distributions (vM – PDF) [2–4, 52, 61, 62, 60–66]. The model parameters are estimated using the least square method. The range of integration to compute the mean angle and standard deviation of the wind direction is adjusted to minimum variance requirements. For example, the proposed probability model mvM(θ) is comprised of a sum of N von Mises probability density functions, vMj(θ), as:

$$mvM(\theta) = \sum_{j=1}^{N} w_j vM_j(\theta) \tag{55}$$

where w_j are non-negative weighting factors that sum to one [2–4, 52, 61, 62, 66]:

$$0 \le w_j \le 1, \quad \text{for } j = 1, \dots, N, \text{and } \sum_{j=1}^{N} w_j = 1$$

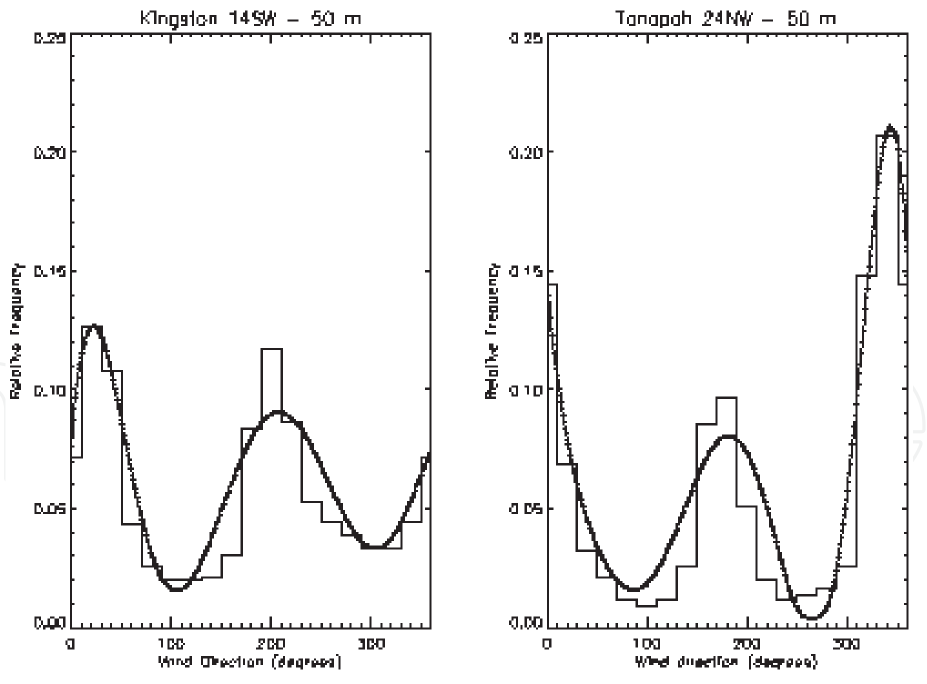

Figure 2.
Frequency histograms of wind directions and the fitted von Mises distribution functions at (a) Kingston 14SW tower and 50 m level, and (b) Tonopah 24NW and 50 m level using the composite 2003–2008 data sets [4, 51, 52].

A von Mises distribution vM-PDF if its probability is defined by the equation:

$$vM_j\left(\theta; k_j, \mu_j\right) = \frac{1}{2\pi I_0\left(k_j\right)} \exp\left[k_j \cos\left(\theta - \mu_j\right)\right], \text{and } 0 \le \theta \le 2\pi \tag{56}$$

where $k_j \geq 0$ and $0 \leq \mu_j \leq 2\pi$ are the concentration and mean direction parameters. The angle corresponding to the northerly direction is taken as 0°. Note that in meteorology, the angle is measured clockwise from North. Here, $I_0(k_j)$ is a modified Bessel function of the first kind and order zero and is given by:

$$I_0\left(k_j\right) = \frac{1}{2\sqrt{\pi}} \int_0^{2\pi} \exp\left[k_j \cos\theta\right] d\theta \approx \sum_{p=0}^{\infty} \frac{1}{(p!)^2} \left(\frac{k_j}{2}\right)^{2p} \tag{57}$$

The distribution law mvM(θ), given by Eq. (49) is numerically integrated between two given values of θ to obtain the probability that wind direction is within a particular angle sector. Various methods are employed to compute the 3 N parameters on of the mixture of von Mises distribution. **Figure 2** is showing fitted von Mise distributions to two long-term wind direction time series for two locations [4, 52, 53, 66].

4. Measure-correlate-predict methods

Measure-correlate-predict (MCP) algorithms are used to predict the wind energy resource at target sites, by using relatively long-term measurements at reference locations. MCP methods model the relationship between wind velocity data measured at the target site, usually over a short period, up to a year, and concurrent data at a nearby reference site. The model is then used with long-term data from the reference site to predict the long-term wind speed and direction distributions at the target sites [4, 73–76]. Typical wind energy assessments last anywhere from one to three years, with important decisions to be taken often after only few months, there is an obvious need for a prediction of the performance of a planned wind energy project for expected life time (20 years or more). Such an assessment is an important part of the financing process. While the measurement campaign may correspond to an untypically high or low period, correlations with nearby reference stations help to detect such trends and provide accurate long-term estimate of the wind velocity at the development site and its inter-annual variations. Moreover, since the wind turbine power output depends on the wind speed in a non-linear way, the distribution of the wind speeds should be predicted accurately. MCP methods proceed by measuring the winds at a target site, correlating with winds from reference sites, then by applying these correlations to historical data from the reference site, to predict the long term wind resource of the target site [2–4, 72–77].

Several MCP algorithms have been studied using wind data from potential wind energy sites. Some of the algorithms and methods have been improved using probabilistic methods, and have then been implemented into software packages, such as the WindPRO or WAsP for planning and projecting of wind power plants. MCP process methods [72–77] consist of: (1) collect wind data at the predictor site for extended possible time period; (2) identify reference sites, for which high quality, long term records exist, ideally located in the predictor site proximity, with similar climate; (3) obtain reference site wind data for the same time period as for the predictor site, the concurrent period; (4) determine the relationship between the reference and predictor site wind data for the concurrent period; (5) obtain wind data from the reference site for a historic period of over 10 years duration or the longest possible, the historic period; and (6) apply the relationship determined in step (4) to the historic data from the reference site to "predict" what the winds would have been at the predictor site over that period. These are the wind predictions that would have been observed and the measurements were made at the predictor site for the same period as the historic data, rather than a wind velocity prediction. The MCP key factor is the algorithm or relationship used in step (4). Most MCP techniques use direction sectored regression analysis to establish relationships of the wind speed and direction at the reference site and the ones at the potential wind farm site. The long-term wind data may be taken from nearby meteorological stations or data from the NCEP/NCAR reanalysis dataset. The general approach is to look for a relationship between the wind speed variables vsite and v_{met} of the site under development and a suitable reference station:

$$v_{site} = f(v_{met}) \tag{58}$$

Often, it may be suitable to consider several reference stations with concurrent data sets for a given development site; Eq. (57) can be then generalized to:

$$v_{site} = g\left(v_{met}^{1}, v_{met}^{2}, \dots, v_{met}^{N}\right) \tag{59}$$

Currently different MCP variants are implemented in the WindPRO, WAsP or other wind energy software packages. However, many researchers developed own MCP applications. Notice that the wind speed time series can be analyzed irrespective of wind direction, while usually, the wind direction is binned into a certain number of sectors and the wind speed subsets for each direction bin are analyzed separately for their MCP correlations. Since wind direction observations may not always coincide, binning may be based either on the wind direction measured at the reference station (usually) or at the prospect site. When a systematic veer occurs (e.g., in response to the topography), the relationship between the site and the meteorological station direction may be fitted, and the fit curve may be used to predict the long-term site wind direction. A deeper objective, requiring a more insightful analysis of the statistical behavior is to achieve an estimation of the probability density function $f_{Y,long}\ (v_{sim},\ v_{me}t,\ \alpha)$, which best describes the long-term wind speed distribution at a given location and height above ground level based on the knowledge of the density in the reference site. Here α is a vector of parameters for each one of the distributions; the number and type of parameters here depend on the particular distributions. The knowledge of $f_{Y,long}\ (v_{sim},\ v_{me}t,\ \alpha)$, allows to calculate the average wind speed and power density and, most importantly, the average energy yield of a given wind turbine [4, 72–77]. Additionally, intra- or inter-annual fluctuations of the wind resource at the prospective site need to be studied, although the present study does not consider such variations. The models employed in practical applications fall into two classes, linear and non-linear and can be described mathematically, adapting previous equations, as:

$$v_{pred} = f\left(v_{ref}, \theta_{ref}\right) \tag{60}$$

$$\theta_{pred} = g\left(v_{ref}, \theta_{ref}\right) \tag{61}$$

Here, f and g are the functional relationships between two concurrent data, target and reference sites. Subscripts denote the data set, the reference as ref., or predictor as pred. There are several variants of these models, each with advantages and disadvantages.

4.1 Linear and regression models

The regression MCP method holds the traditional linear regression MCP analysis as a specialized subset of regression models using polynomials of other orders. Polynomial fitting methods are included, as suggested in literature [73–77]. In the simplest linear models the wind speed and direction at the target/predictor site is expressed as:

$$v_{h,pred} = f\left(v_{h,ref}\right) \tag{62}$$

and

$$f\left(v_{h,ref}\right) = \frac{\overline{v}_{c,pred}}{\overline{v}_{c,pred}} v_{h,ref} \tag{63}$$

Here the over bar refers to average, while c and h to the concurrent and historic data. Regression, with one independent (x) and one dependent (Y) variable is expressed as:

$$Y = f(x) + e \tag{64}$$

Here, Y is the dependent variable, x is the independent variable, f(x) is the regression model, and e is a random error (residual). The regression model could be polynomials of any order or other models, but traditionally a linear model is assumed, as this model has been found to give reasonable fits for wind energy estimation. In the case of a regression MCP analysis, the independent variable could be the wind speed measured at the reference site. The dependent variable, Y is then the wind speed at the local WT site. The regression parameters are estimated through a least square algorithm. The distributions of the random errors may, reasonably be assumed to follow a zero mean Gaussian distribution, $e \sim N(0,\sigma)$. However, the distribution of the residuals should be visually checked, so that the assumption is verified as reasonable. This is needed, as the random variable model for the residuals is included in the MCP model to give the right energy levels in the new MCP-corrected time series. Note, that currently the distribution of residuals is conditioned on the reference wind direction only. Thus, conditioned on the reference wind direction, the residuals are independent on the reference wind speed.

4.2 Matrix method

In the matrix methods the changes in the wind speed and direction (wind veer) are modelled through joint distributions fitted on the 'matrix' of wind speed bins and wind direction bins. The concurrent periods of the measured wind data are used to calculate the set of non-linear transfer functions, used for estimating wind speeds and directions from the reference site to the prospect site. Since real measurements suffer from data missing in bins in the dataset, this method needs a way to substitute the missing input bins. A basic assumption of the matrix method is that the long-term site data (wind speed and direction) can be expressed through the simultaneous measurements of on-site data and reference site data. How this joint distribution is modelled should actually depend on the data in question, suggesting that a combination of binned sample distributions and modelled joint Gaussian distributions are working well [73–77]. The transfer model, given as a conditional distribution, is actually the key distribution in the matrix method. When applying the matrix method this conditional distribution is stipulated to hold regardless of the time frame considered. Thus, for each measured sample it is necessary to calculate/measure pairs of the two quantities (a pair is data with identical timestamps):

$$\Delta v = v_{site} - v_{ref} \tag{65}$$

$$\Delta \theta = \theta_{site} - \theta_{ref} \tag{66}$$

These parameters refer to the wind speeds and directions at the wind project site and the meteorological site, respectively. The joint distribution of $f(\Delta u, \Delta\theta)$ is modelled conditioned on the wind speed and the wind direction on the reference site. The joint distributions are represented as either through the samples (bootstrap model) or often through a joint Gaussian distribution. When the data has been measured and a match between the short-term data and the short-term reference data has been established, then the samples are sorted into bins with specific resolutions, such as 1 m/s and 10 degrees. The result from this binning is a set of joint sample distributions of wind veer and wind speeds. Since the data is binned with wind speed and wind direction, these sample distributions are conditioned on the mean wind speed at the reference position and the wind direction on the reference position. The calculated distributions are used directly in a bootstrapping technique when doing matrix MCP calculations. Based on the sample distributions, the statistics, calculated for the wind veer are the mean, the standard deviation, and the correlation coefficients. To enable interpolations and extrapolations into bins where no data is present, a spline is fitted to the sample distributions. This parametric distribution is represented by the two moments and the correlation, assuming that a joint Gaussian distribution. Note, that even if the Gaussian distribution assumption may seem a bit crude, then the parametric model can be applied in cases where limited or no sample data is available. Thus, the influence of this assumption is limited, as most long-term corrected samples are typically based on the resampling approach. The mean, standard deviation and correlation are now modelled as 'slices' of polynomial surfaces:

$$P(v, \theta) = \sum_{i=0}^{N} a_i(v_i, \theta_i) v_{ref}^1 \tag{67}$$

where P denotes the sample statistical moment (or correlation) considered, N is the order of the polynomial is the polynomial coefficients, depending on the wind velocities. As in the case of regression MCP, the long-term corrected meteorological data is calculated using Bootstrap and Monte-Carlo techniques, i.e. probabilistic methods enabling generation of the long-term corrected wind distribution through an *artificial* time series.

4.3 Hybrid MCP and the wind index MCP methods

The hybrid MCP method [72–77] correlates the wind data at the targeted wind plant site with that at multiple reference stations. The strategy accounts for the local climate and the topography information. In the original hybrid MCP method, all component MCP estimations between the targeted wind plant site and each reference station use a single MCP method (e.g., linear regression, variance ratio, Weibull scale, or neural networks). The weight of each reference station in the hybrid strategy is determined based on: (i) the distance and (ii) the elevation differences between the target wind plant site and each reference station. The hypothesis here is that the weight of a reference station is larger when the reference station is closer (shorter distance and smaller elevation difference) to the target wind plant site. The weight of each reference station, w_i, is determined by:

$$w_j = F\left(n_{ref}, \Delta d_j, \Delta h_j\right) \tag{68}$$

where n_{ref} is the number of reference stations; and Δd_j and Δh_j represent the distance and the elevation difference between the target site and *jth* reference station, respectively. Each wind data point is allocated to a bin according to the wind direction sector at the target wind plant site. Within each sector, the long-term wind speed is predicted by a hybrid MCP strategy based on the concurrent short-term wind speed data within that specific sector. By setting the wind speed data in each sector together, the long-term wind data at the target wind plant site can be obtained. The predicted long-term wind data quality is usually evaluated using the performance metrics. ANNs are used to correlate and predict wind conditions because of their ability to recognize patterns in noisy or complex data. A neural network contains an input layer, one or more hidden layers, and an output layer, being defined the following parameters: input and output connections, number of neuron layers, the weights, and transfer functions, the interconnection pattern between different neuron layers, the learning process for updating the weights of the interconnections, and the activation function that converts the input into outputs. The Levenberg–Marquardt algorithm is usually used for neural network training.

The index correlation method is a method creating the MCP analysis by means of monthly averages of the energy yield, disregarding the wind directional distributions [72–77]. Even though this method may seem rather crude and primitive when comparing to other more advanced MCP methods, which takes the wind veer into account; this method has the advantages in stability and performance as it may even succeed in the cases where other MCP methods may fail. This is due to the fact, that the wind indexes are related directly to WTG energy yield and that the method allows the production calculation to be completed using actual measured data before applying the correction. The Wind Index MCP method offers the opportunity to calculate the wind indexes using real power curves of the wind turbines. A generic power curve based on a truncated squared wind speed approach may be chosen. When the wind indexes are calculated, the MCP correction is done on the estimated WTG energy yield, i.e. by multiplying the production estimated with a correction factor based on the difference in the wind index from the short-term site data to the long-term site estimated data. However, since the power curve of a WTG is a non-linear function of the wind speed the wind index is typically modelled using power curve common models. For the power output, calculated for the target site and the reference to be comparable they must be based on a similar mean wind speed. This is done by assuming a sector uniform shear that can be applied so that both concurrent mean wind speeds are set to a fixed user-inferred wind speed, typically the expected mean wind speed at hub height. The individual wind speed measurements are thus multiplied with the relevant factor. Full time series wind speeds are adjusted with the same ratio as the one applied to the respective concurrent time series. The argument for this operation is that the variations in wind speed will only be interpreted correctly in terms of wind energy if a comparable section of the power curve is considered.

As discussed in [4, 9, 14, 72–77], once a regression equation has been conditioned based on the measurement overlap period, the regression parameters can then be used to derive an extended data record for the site of interest. MCP methods are generally applied using some sort of regression analysis for each wind direction sector. An issue of using MCP methods based on wind velocity data from the land sites, due to the scarcity of offshore wind velocity observations is that most applications use linear regression which cannot account for observed differences in the wind speed distribution between the land site and the offshore sites. In [9, 14] was proposed in such cases to apply wind velocity corrections of the probability distribution functions, e.g. Weibull parameter corrections. In this method, the Weibull parameters of the short-term data series are modified to characterize longer data sampling periods. It compares sector-based wind speed distributions at the onshore and the off-shore sites considering the on-shore long-term time series as representative of the area of interests. Weibull scale (c) and shape (k) factors are determined for each of several wind sectors and for the mean values in each point of the grid, for data sets from overlapping periods. The differences between the two datasets are expressed in terms of the ratios of Eq. (69). These correction factors are applied to the Weibull factors estimated for the short-term data sets.

$$Corr_{Scale} = \frac{c(\text{off-shore})}{c(\text{on-shore})}, \text{and } Corr_{Shape} = \frac{k(\text{off-shore})}{k(\text{on-shore})} \tag{69}$$

The Weibull correction method, as discussed in [9, 14] gave better wind velocity estimated for both onshore and offshore flow where the wind speeds were overestimated.

5. Wind energy resources in climate projections

Just as with the other aspects of climate, wind statistics are subject to natural variability on a wide range of time scales. Like other meteorological parameters, such as temperature, rainfall, or other climate variables, wind speeds and directions change on time scales of minutes, hours, months, years, and decades. Future climate change is expected to alter the spatio-temporal distribution of surface wind speeds and directions, with impacts on wind-based electricity generation. Long term trends in wind speeds are difficult to quantify and large historical data sets are required to accurately capture and describe such variations. This is a more evident in the case of the offshore wind energy resources. Wind energy resources at any location vary on a range of time scales, and hence any resource assessment should address issues of climate variability and change. However, due to scarcity of complete datasets offshore, comparisons have generally been performed with the hypothesis that local wind regimes have not changed during the last 10–20 years. The assumption validity is questionable, being likely to be regionally variable [78–81]. Even in the absence of climate non-stationarity, wind energy measurement sites typically have data periods up to 3 years and hence are not representative of wind climates over the 20–30 year lifetime of the wind farms. A further confounding influence is that homogeneous wind speed time series are rarely available for long periods because many monitoring locations have undergone change in land use and instrumentation. Accordingly, one can conceptualize the wind resource assessment as a two-step process: (1) an evaluation of wind resources at the regional scale to locate promising wind farm sites and (2) a site specific evaluation of wind climatology and vertical profiles of wind and atmospheric turbulence, in addition to an assessment of historical and possibly future changes due to climate variability.

In the context of wind energy generation, even small changes in the wind speed magnitude can have major impacts on the productivity of wind power plants, as the wind power relationship is directly proportional to the cube of the wind speed. However, the predictions for the direction and magnitude of these changes hinge critically on the assessment methods used. Decadal and multi-decadal variability in wind speed statistics currently introduce an element of risk into the decision process for siting new wind power generation facilities. Recent findings from the atmospheric science community suggest that climate change may introduce an added risk to this process. Many climate change impact analyses, including those focused on wind energy, use individual climate models and/or statistical downscaling methods rooted in historical observations. Wind speed and direction vary on small scales and respond in complex ways to changes in large-scale circulation, surface energy fluxes, and topography. Thus, whereas multiple climate models often agree qualitatively on temperature projections, wind estimates are less robust. The spatial variability of wind and its sensitivity to model structure suggest that higher resolution models and multi-model comparisons are particularly valuable for wind energy projections. For long-term planning of wind resources, it is imperative to analyze historical datasets and establish monitoring at hub-height using meteorological towers and remote sensing. A comprehensive review of climate change impacts on wind energy is shown in [78–81], discussing the main changes in the wind resources due to climate evolution, focused on northern Europe, with significant wind energy installations.

According to the analysis, until the middle of the current century natural variability will exceed the effect of climate change in the wind energy resources [78–81]. They conclude that there is no detectable trend in the wind resources that would impact future planning and development of wind industry in northern Europe. Pryor et al. (2006) down-scaled winds from ten global climate models at locations in northern Europe and found no evidence of significant changes in the 21st century wind regime compared to the 20th century. Predicted changes are found to be small and comparable to the variability associated with different global climate models. Using another approach, Ren [79] proposed a power-law relationship between global warming and the usable wind energy. The power-law exponent was calibrated using results from eight global climate models. He found that reduction of wind power scales with the degree of warming according to method and estimated that about 4 Celsius degrees increase in the temperatures in mid to high latitudes would result in up to 12% decrease in wind speeds in northern latitudes. Ren [79] suggested that an early maximized harvesting is beneficial and should be carried out. However, more studies are needed to solve all uncertainties in climate projections of wind resources under various future climate scenarios [4].

6. Chapter summary

Several factors are influencing the accurate assessment and prediction of wind energy production. A primary issue is adequate understanding of the effects of wind variability, atmospheric stability, turbulence and air density variability on the wind turbine energy production. Non-negligible and quite often significant error is incurred when the effects of shear, TI, and atmospheric stability on the wind turbine power performance are ignored, as in the IEC standard, 61400-12-1 (2005). The standard procedures are valid only for ideal neutral conditions and a small wind turbine. Besides the dominant cubic dependence of the wind speed on the wind power density, there are smaller but still important corrections to the air density that are important to harvesting wind energy at high-elevation sites. Corrections that account for these factors must be included in the power output estimates, and more accurate predictions will help alleviate production-consumption imbalances. These imbalances can also be ameliorated through the use of storage devices. The field of wind resource assessment is evolving rapidly, responding to the increasingly stringent requirements of large-scale wind farm projects often involving investments of several hundred million dollars. Traditional cup anemometry is being complemented with ultrasonic sensors providing information on all three components of the wind velocity vector and enabling a better assessment of turbulence. Remote sensing devices like sodar and lidar are becoming more popular as turbine hub heights and rotor diameters increase, often placing the upper edge of the swept rotor area at heights of 130 m or more. While the traditional, conventional approaches of measuring the wind speed and direction at a few heights below hub height and extrapolating based on a logarithmic profile is still very common, the use of both vertical profiling devices and more accurate modeling tools considering the full terrain complexity and atmospheric stability is quickly moving into the mainstream. Measure-correlate-predict (MCP) methods are used to estimate wind speeds and directions at a target site where wind power is assessed for development. These methods use two sets of in-data. To begin with a series of measured speeds and directions from the target site during a period of time (usually one year) is needed. In addition to this, a reference series from a much longer period needs to be obtained. On the other hand, the advanced hybrid MCP method uses the recorded data of multiple reference stations to estimate the long-term wind condition at a target plant site. Because each reference station has the flexibility to use any of the available MCP techniques, the multiple reference weather stations were combined into the hybrid MCP strategy with the best suitable MCP algorithm for each reference station. Climate projections of wind resources in changing climate are a topic of a debate in the literature, requiring a thorough investigation of uncertainties and understanding the complex interaction of atmospheric dynamics. This will contribute to understanding the extent to which some of the predicted trends are the result of the weather and climate variability or the result of inadequate physical parameterizations in global and regional climate models.

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