Wind Energy Facility Reliability and Maintenance

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Abstract The global wind power industry involves operations in highly stochastic environments and thus faces challenges in enhancing reliability and reducing maintenance costs. Earlier studies related to wind energy facility reliability and maintenance focused more on qualitative aspects, discussing the unique influencing factors in wind power operations and their effects on system performance. With operational experience accumulated for more than a decade, the most recent focus has shifted to a more structured approach using analytical and/or simulation methods. In this chapter, we provide a comprehensive account of the existing research regarding wind energy facility reliability and maintenance. We group the relevant studies into three major categories. The first category addresses the degradation and failure pattern of wind turbines, aiming at optimizing the operations and maintenance. The second and third categories discuss the reliability issues in a broader sense, focusing on reliability assessment at the wind farm level and at the overall power system level, respectively.

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1 Introduction

Wind power has become one of the fastest growing renewable energy sources around the world. Wind energy installed capacity increased from 31 GW in 2002 to 2082 GW in 2012 worldwide. According to the North American electric reliability corporation (NERC) [1], approximately 260 GW of new renewable nameplate capacity is projected in the US during 2009–2018. Roughly 96 % of this total is estimated to be wind energy. In fact, NERC predicts that wind power alone will account for 18 % of the U.S. total resource mix by 2018.

With operational experience accumulated for more than a decade, people have come to realize that operations and maintenance (O&M) costs constitute a substantial portion of the total costs of wind power production [2–4]. Field data from Germany [5] indicates approximately six failures per year and restoration times ranging from 60 hour to a few weeks. Overall, O&M costs account for 20–47.5 % of the wholesale market price [4]. Considering that most turbines in the U.S. were installed in the past 10–15 years, wind facilities are still operating in their relatively reliable period. In the decades to come, as turbine components are near the end of their designed life, the failure rates of wind power facilities can be expected to increase drastically, leading to higher costs of O&M.

The most common maintenance practice is to perform scheduled maintenance on a regular basis. Depending on a manufacturer's suggested guideline, scheduled maintenance is carried out usually once or twice a year for a turbine [6, 7]. Understandably, scheduled maintenance is usually incapable of addressing unexpected failures in a timely fashion, while, on the other hand, this strategy may also result in unnecessary visits. Wind farm operators have come to the consensus that more effective maintenance strategies are pressingly needed to reduce unnecessary service visits as well as turbine downtime.

Many studies have been conducted to examine effective maintenance strategies for conventional power systems, for example, [8–10] among others. However, the operating environment of wind turbines is different from that of traditional power plants in several ways. Wind turbines constantly operate under highly stochastic loading. The feasibility of both new repairs and the continuation of ongoing repairs is affected by uncertain weather conditions. The vast majority of wind turbines are installed in remote windy sites or offshore locations, hoping to harvest the maximum amount of wind energy. Due to the remote locations of the wind farms, access to turbines for maintenance can be restrictive during harsh weather seasons. For the same reason, repair actions, or even on-site observations, are very expensive. Compounded with these complexities, newly established wind farms usually house hundreds or more turbines that spread over a large geographical area. This makes O&M even more challenging and costly. We believe that wind farm operations call for new maintenance strategies that are specially tailored for handling the reliability and maintenance issues for wind energy facilities.

In this chapter, we discuss recent studies on wind energy facility reliability and maintenance. Earlier studies on wind power operations investigated unique but critical factors that have significant impact on the turbine's reliability and maintenance [6, 11–13]. Later, failure patterns and reliability trends of wind turbine were studied based on field data [2, 14, 15]. More recently, the focus has shifted towards developing a more structured model for reliability enhancement.

We group the existing research into three broad categories. The first category is degradation and failure pattern of an individual wind turbine (or, a wind turbine component) to assess its reliability over time. The major goal of these studies is to build a model for predicting the lifetime of a system, and further, to develop a cost-effective O&M decision strategy by quantifying risks and uncertainties based on the lifetime prediction. To fulfill this goal, several analytical models have been recently introduced in the wind power literature, including statistical-distribution based models [15–20], Markov process-based models [21–24] and physics-based structural load models [25–35]. Although renewal reward processes and regenerative processes have been extensively studied for general aging systems and power systems [36–38], we did not find them currently employed in the wind power literature. Concerning the question of testing, there is limited amount of literature which studies the appropriate testing procedures to certify wind turbine components [39–41].

The second category of research concerns the reliability of a wind farm with multiple turbines, and focuses on how the reliability of each wind turbine (or, turbine component) affects the performance of the whole wind farm. Many researchers have developed simulation models to represent the complex behavior of wind farm operations, as well as the interactions between wind turbines [6, 11, 16, 22, 42–46]. They investigate the effect of different maintenance strategies and evaluate the reliability of a wind farm using several performance indices [22, 45]. The effect on system performance coming from the environmental differences such as geographical terrain and wind farm sites (i.e., land-based or offshore) are also discussed in these studies [22, 46].

The third category extends the second category of studies to the overall power facilities, i.e., measure its capability to satisfy customer demands (or, loads) or system operational constraints [47]. This line of research is usually called "generation adequacy assessment". Both analytical and simulation models are used in this line of work, including multi-state models [47–52], correlation analysis [53, 54], Markov process [21, 55, 56], population-based stochastic search [57, 58], and Monte Carlo simulations [59–66]. One specific aspect these studies focus on is the effect of intermittent generation of wind energy on the power system reliability. The failure and repair rates of wind turbines are taken into account in the assessment. These studies provide practical implications about the reliability and cost issues of wind energy in the context of the entire electric power system. Table 1 provides a summary of the existing research.

The remainder of this chapter is organized as follows. We first discuss the O&M aspects of wind power operations in Sect. 2. In Sect. 3, we review the models that explore the reliability patterns of wind turbine components as well as the models that find optimal O&M strategies. Section 4 presents the reliability and maintenance studies at the wind farm level, while Sect. 5 discusses the same issue but for the entire power system (i.e., the generation adequacy assessment). Finally,

Table 1 Classification of literature at three operating levels

Level	Methodology	Literature
Wind turbine	Statistical approach	[15–20]
	Stochastic process[a]	[21–24]
	Structural load models	[25–35]
Wind farm	Simulation	[6, 11, 16, 22, 42–46]
Power system	Analytical approach	[21, 47–58]
	Simulation	[59–66]

[a] Only Markov processes are presented in this chapter because, to the best of our knowledge, other stochastic processes are not yet discussed in the wind power literature

we conclude the chapter in Sect. 6. We acknowledge that there are two other reviews on relevant literature: one is Alsyouf and El-Thalji [67], who reviewed the recent practices and studies focusing on maintenance issues, and the second is Wen et al. [47], who summarize the studies on adequacy assessment of power systems (wind power is one element of the power systems). This chapter provides a more comprehensive survey, including the literature in [67] and [47]. We also include new results from reports and papers since the last survey.

2 Understanding Current Status of Wind Turbine Operations

In this section, we examine the current O&M costs and key factors affecting wind turbine operations.

2.1 O&M Costs

Due to the relatively young history of the wind power industry, many turbines are still operating in their early age so that failure and maintenance data are not as ubiquitous as in a mature industry. Making the matter worse, modern turbines are much more diversified in terms of sizes and designs than earlier turbines. However, the current operational experience was built and accumulated based on earlier turbines. This means that evaluating O&M costs for this young industry is challenging and the results embed high uncertainty. Nevertheless, useful insights can be gained from the experience with the existing turbines.

2.1.1 Overall O&M Costs

Walford [2] evaluates how much O&M costs account for the total cost of energy (COE) by summarizing the results from Vachon [3], and Lemming et al. [68]. COE is a key metric to evaluate the marketability of wind energy. The current

COE is $0.06 - 0.08 k/kWh. According to the studies by Vachon [3] and Lemming and Morthorst [68], O&M costs are estimated to be $0.005–$0.006/kWh in the first few years of operations, but it escalates to $0.018–0.022/kWh after 20 years of operations. Based on these two studies, Walford [2] concluded that the overall O&M costs can account for 10–20 % of the total COE.

U.S. Department of Energy (DOE) [69] gives a similar estimate of $0.004–0.006/kWh in 2004 for new wind turbine projects in the Class 4 resource areas (at a Class 4 site, the wind speed is between 5.6 and 6.0 m/s at 10 m height [70]). But, according to a later report by DOE [71] in 2006, the actual O&M costs range from $0.008 to $0.018/kWh, depending on the wind farm size. Most recently, Asmus [72]'s study presents even higher O&M costs. Asmus [72] collected extensively O&M associating data from major wind turbine manufactures and wind energy operators. After compiling data from various sources, Asmus [72] concludes that the average O&M costs is $0.027/kWh (or, €0.019/kWh), which may account for half of the COE.

In summary, O&M costs are comparable to the $0.02/kWh federal production tax credit (PTC) offered in the U.S. as a subsidy. Although PTC was extended in 2012 in the U.S., the subsidy will eventually decrease or disappear in the future. Asmus [72] also notes that currently about 79 % of turbines are still under warranty, but their warranty phase will be over in the near future. The phase-out perspective of the PTC and the warranty calls for cost-effective O&M strategies for wind turbines in order to make the wind energy market competitive.

2.1.2 Cost Elements

Walford [2] identifies the cost elements associated with wind farm operations. They include the operational costs for daily activities such as scheduling site personnel, monitoring turbine operations, responding to failures, and coordinating with power utility companies. Other costs include those incurred from taking preventive maintenance actions to prevent failures in advance or taking corrective (or, unscheduled) maintenance after unanticipated failures. Krokoszinski [13] presents a mathematical model to quantify wind farm production losses in terms of the planned and unplanned downtime, and quality losses.

In general, expenses for daily operations are fairly stable over time, while repair costs fluctuate considerably, depending on the age, location, size of the turbine, and the maintenance strategy [73]. For example, offshore turbines have much higher corrective maintenance costs due to the logistic difficulties to access the turbines. Corrective maintenance cost can be more than twice the preventive maintenance cost [16, 43]. In general, corrective maintenance costs account for 30–60 % of the total O&M costs [2].

2.2 Factors Affecting O&M Costs

Many studies examine critical factors that affect the reliability and O&M costs of wind power facilities. Based on the findings, researchers suggest ways to reduce the impact of unplanned failures or minimize maintenance costs [2, 12]. Bussel [6] presents an expert system to determine the availability of wind turbines and O&M costs. The goal in this work is to find the most economical solution by striking a balance between the front-loading costs invested for reliability enhancement and the O&M costs. Pacot et al. [12] discuss key performance indicators in wind farm management, and analyze the effects of factors such as turbine age, size, and location. Here, we summarize the key factors, which we believe are the most critical in wind farm operations [22–24].

2.2.1 Stochastic Environmental Conditions

Stochastic operating conditions affect the reliability of wind turbines in several ways. First, maintenance activities can be constrained by the stochastic weather conditions. Harsh weather conditions may reduce the feasibility of maintenance. This is in contrast with traditional fuel-based power plants which operate under relatively stationary operating conditions. To maximize potential power generation, wind facilities are built at locations with high wind speeds. But climbing a turbine during wind speeds of more than 20 m/s is not allowed; when speeds are higher than 30 m/s, the site becomes inaccessible [22]. Moreover, some repair work takes days (and even weeks) to complete due to the physical difficulties of the job. The relatively long duration of a repair session increases the likelihood of disruption by adverse weather. A study using a Monte Carlo simulation [42] found that turbine availability was only 85–94 % in a 100-unit wind farm situated about 35 km off the Dutch coast. The relatively low turbine availability is in part due to the farm's poor accessibility, which is on average around 60 %. Another study [6] found that the availability of a wind farm was 76 %. The operational environments and their effect on maintenance feasibility are also discussed in our previous studies [23, 24, 45].

Weather conditions can affect the reliability of wind turbines substantially. Harsh weather events such as storms and gusts will generate non-stationary loading (or, stress) and reduce the life of key components. Tavner et al. [15] show that there is a strong relationship between the number of failures and wind speeds. Toward this claim, analysis of field data from Denmark and Germany confirms a clear 12-month periodicity of the number of failures, which coincides with annual weather seasonality.

Besides strong winds, other adverse weather conditions include temperature, icing and lightning strikes. According to Smolders et al. [74], the operating temperature for wind turbines could range from −25 to 40 °C. Wind turbines at very low temperature sites suffer from the icing problems, namely that icing decreases power generation and damages rotor blades significantly [75]. Lightning strikes can also cause serious damage to blades. Although modern turbines are equipped with lightning protection systems in blades, current technology cannot yet completely protect turbine blades from lightning damage [76].

Harsh weather conditions can cause high revenue losses during downtime. Lost productivity becomes more significant when turbine unavailability occurs during the windy periods [2]. With increasing application of wind turbines in different terrains, more research is pressingly needed to study how the adverse weather affects reliability and maintenance feasibility and to help practitioners make a better choice of farm locations [75].

It should also be noted that weather forecasting can play an important role on reliability assessment and maintenance decision-making. The benefits from weather forecasts depend on the accuracy of the forecasts. Thanks to today's sophisticated weather forecast technology, the near-future weather information is usually deemed reliable [77]. Considering the possible long repair time which can take up to several weeks, reliable forecast techniques for medium- or long-term is much needed but not yet available.

2.2.2 Logistic Difficulty

Recently established wind farms tend to house larger and larger wind turbines, in a great number and spreading over a broad area. The sheer size of wind turbine components makes it difficult to store spare parts in a warehouse waiting for repairs or replacements. Rather, they are likely ordered and shipped directly from a manufacturer when needed. Doing so often leads to long lead time in obtaining parts and can result in costly delays in performing repairs. Pacot et al. [12] point out that it may take several weeks for critical parts, such as a gearbox, to be delivered. Another aspect of the logistic difficulty is caused by the long distances of wind farms from their operation centers, and that major repairs require heavy duty equipment such as a crane or a helicopter to access the turbine. It certainly takes quite an effort to assemble the maintenance crews and prepare for a major repair. Logistic costs may escalate substantially, depending on accessibility to the turbine site, maintenance strategy, and equipment availability.

2.2.3 Different Failure Modes and Effects

A wind turbine consists of several critical components such as a drive train, gearbox, generator and electrical system, each of which has different failure frequencies and effects. Each single component may also have different failure modes. The occurring failure mode determines what type of parts/crew is required, which in turn determines the costs, lead time and repair time. Accordingly, the maintenance costs and the downtime due to the occurrence of a failure could vary significantly for different failure modes.

Arabian-Hoseynabadi et al. [78] perform a failure modes and effects analysis for the major components in various types of wind turbines and study their failure effects on the overall turbine performance. Ribrant [14] and Ribrant and Bertling [79] review the different failure modes of turbine components and the corresponding consequences. For example, a failing gearbox can lead to bearing failures, sealing problems, and oil system problems. According to Ribrant [14], it can take several weeks to fix the problems associated with bearing failures, partly because of the long lead time needed to have labor and heavy-duty equipment in place. On the other hand, oil system problems can be fixed within hours.

According to a recent industry survey [72], most serious failures are associated with the gearbox. As an alternative, direct-drive (gearbox free) turbines in which generators rotate at the same speed as the rotor were introduced. Echavarria et al. [75] show, however, that the failure rate in “generator” of direct drive turbines is higher than the failure rates in “generator” and “gearbox” combined during the first ten operational years. This implies that direct-drive may resolve the frequent failure issues of the gearbox, but cause new problems that have not been encountered in other designs. Yet, we should be cautious to conclude which design is better in terms of reliability since the reliability results of direct-drive turbines in Echavarria et al.’s study are based on a small number of direct-drive turbines. More time and efforts would be required to assess the reliability of each different design.

2.2.4 Condition-Based Maintenance

Condition-based maintenance (CBM) has become an important method to reduce the O&M costs [80]. CBM involves two processes. The first process is to diagnose the current condition through condition monitoring equipment. Sensors installed inside turbines can provide diagnostic information about the health condition of turbine components. Such data help wind farm operators estimate the deterioration level and make real-time reliability evaluation. Based on this reliability update, the next step is to establish appropriate maintenance policies before the actual occurrence of major failures to avoid consequential damages.

Comprehensive review of the recent monitoring techniques is provided by Hameed et al. [81]. In general, vibration analysis is the primary monitoring technique used for gearbox fault detection [82]. Other common monitoring systems include: measuring the temperature of bearings, analyzing the lubrication oil particulate content, and optical measurements of strains in wind turbine structures. Caselitz and Giebhardt [83] discuss the integration of a condition monitoring system into offshore wind turbines for improved operational safety.

A few studies attempt to quantify the benefits of CBM in the wind power industry [7, 22, 45]. Nilsson and Bertling [7] present an asset life-cycle cost analysis by breaking the total maintenance cost into several cost components. They analyze the benefits of CBM with case studies of two wind farms in Sweden and the UK, respectively. They conclude that CBM can benefit the maintenance management of wind power systems. The economic advantage becomes more clear when an entire wind farm rather than a single wind turbine is considered. For offshore wind farms, a condition monitoring system could provide a greater help by making maintenance planning more efficient.

McMillan and Ault [22] evaluate the cost-effectiveness of CBM via Monte Carlo simulations. They compare a six-month periodic maintenance policy with CBM with respect to the annual yield of power production, capacity factor, availability, annual revenue and failure rates. Through simulating various scenarios with different weather patterns, down-time durations, and repair costs, they show for land-based turbines that a CBM strategy could provide the operators remarkable economic benefits. For example, with an average wind speed of 6.590 m/s and cost factors obtained from [84], CBM can have operational savings of £225,000 (or, equivalently, $350,280 with an exchange rate of 1 pound = 1.5668 dollar) per turbine, when considering 15 years as a turbine life. Sensitivity analysis with relatively large ranges in parameter values indicate that the contribution of CBM is highly dependent on replacement costs, wind regime and downtime durations. Obviously, one would expect more benefits for offshore wind turbines since the repairs of those turbines are more costly and taking maintenance actions at an offshore location faces more constraints.

McMillan and Ault [22] assume that the condition monitoring equipment reveals exactly the degradation status of each turbine component. However, condition monitoring equipment cannot in general solve the uncertainty issue [85]. Estimations rarely reveal perfectly the system's health status due to a wide variety of reasons, such as imperfect models linking measurements to specific faults, as well as noises and contaminations in sensor signals. More importantly, fault diagnosis based on sensor measurements is nontrivial, because wind turbines operate under non-steady and irregular operating conditions.

Considering these sensor uncertainties, the authors of this chapter consider two types of measurements to estimate the internal condition of each turbine component in our previous work [23, 24]: (1) inexpensive, but less reliable, real-time remote sensing and diagnosis from general condition monitoring equipment, and (2) expensive, but more certain, on-site visit/observation (OB). OB is fulfilled by either dispatching a maintenance crew or, if technologically feasible, invoking more advanced smart sensors. Both options are generally costly, but can presumably depict system conditions with a high confidence. It should be noted that the co-existence of real-time monitoring and on-site visit/observation is a unique aspect in the wind energy industry. The information uncertainty from the condition monitoring equipment must be handled with caution, and on-site observations must be integrated with planning maintenance actions. Considering the different observation options, Byon et al. propose two CBM models in [23, 24]. Their results show that OB should be taken when the estimated system conditions from condition monitoring equipment are not clear. The optimal observation actions also depend on the weather conditions. For example, OB should be taken more often under harsh weather conditions to decide the most suitable maintenance tasks than under mild weather conditions.

The authors of this chapter also develop a discrete event simulation model for wind farm operations that can evaluate different O&M strategies [45]. The current version implements two different O&M strategies: scheduled maintenance and a CBM strategy. In the CBM strategy, preventive repairs are carried out when sensors send alarm signals. The implementation results indicate that the CBM strategy provides appreciable benefits over the scheduled maintenance in terms of failure frequency, O&M costs and power generation. For example, the failure frequency is reduced by 11.7 %, when CBM instead of scheduled maintenance is used.

3 Models to Assess Reliability of a Wind Turbine and to Find Optimal O&M Strategies

In this section, we review existing studies that evaluate the reliability of a wind turbine and find a cost-effective O&M strategy. We discuss three different approaches: the first one is the statistical approach to assess the reliability level and identify the optimal repair (or, replacement) time based on the failure statistics; the second approach uses Markov models to analyze the stochastic aging behavior of wind turbine components; and the third approach is based on physical fatigue analysis.

3.1 Statistical Distribution-Based Analysis

3.1.1 Life-Time Analysis Using the Weibull Distribution

In reliability engineering, one of the most commonly used distributions to represent the life-time of a system is a Weibull distribution. This distribution has been applied in many applications to model a great variety of data and life characteristics. In wind facility modeling, several studies apply the Weibull distribution in determining the lifetime reliability of a population of wind turbines (or, turbine components).

Let T be a random variable representing the life-time of a system. The probability density function (pdf) of the Weibull distribution is given as follows:

$$f(t) = \begin{cases} \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1}\left(e^{-\frac{t}{\eta}}\right)^{\beta}, & t \geq 0 \\ 0, & t < 0, \end{cases} \quad (1)$$

where $\beta > 0$ is the shape parameter and $\eta > 0$ is the scale parameter. $\beta < 1$ denotes a decreasing failure rate, usually known as the "infant mortality". This happens when failures occur in an early period of operation. As the defective items are taken out of the population, failure rates decrease over time. On the other hand,

$\beta > 1$ indicates an increasing failure pattern, often found in an aging system. When $\beta = 1$, the pdf in (1) is exactly the same as the pdf of an exponential distribution. As such, $\beta = 1$ indicates a constant failure rate, or random failure pattern, implying that any maintenance activity to improve the system condition is unnecessary. For detailed discussions to assess reliability using the Weibull distribution, please refer to [86].

Andrawus et al. [16] employ the Weibull distribution to model the failure patterns of several critical components in a wind turbine such as the main shaft, main bearings, gearbox and generator. For one type of 600 kW horizontal axis turbines, they collect historical failure data from the turbine's supervisory control and data acquisition (SCADA) system over a period of 9 years. The data include the date and time of failure occurrences and the (possible) causes of the failures. They estimate the parameter values in the Weibull distribution using a maximum likelihood estimation (MLE). According to their case studies, the estimated shape parameters for the main bearing, gearbox and generator are close to "one", indicating a random failure pattern. Only the main shafts exhibit a wear-out (or, aging) failure pattern. After conducting these life-time analyses and also considering the cost factors (such as planned and unplanned maintenance costs), they made suggestions for the optimal replacement time for each component. For example, they recommend that a gearbox should be replaced every six years and a generator every three years to minimize the total maintenance costs.

Remark The results of the constant failure rates of the three components in Andrawus et al.'s study [16] are counter-intuitive, contradicting the results from other studies [19, 22]. It is commonly accepted that most wind turbine components deteriorate over time. On the other hand, electrical systems in a turbine show random failure patterns in general. We conjecture that the maintenance practices, which might have been performed while the field data were collected, may need to be considered in Andrawus et al.'s study. If the failure data used in the study are obtained from the turbines under scheduled maintenance, the random failure patterns may be because the scheduled maintenance restores the turbines back to their renewed states from time to time. If this maintenance effect is taken out, Andrawus et al.'s data may confirm the result from [19, 22], and show turbine deterioration patterns instead.

Wind turbines at different locations undergo different degradation, depending on the climate characteristics under which a turbine is operating. Vittal and Teboul [20] use a Weibull proportional hazard model to incorporate the weather climate effects on the lifetime of wind turbines. They express the scale parameter, η in (1), as a function of weather factors such as wind speed, capacity factor, and temperature. In this way, site-specific climate characteristics are combined with the general aging behavior of a population of wind turbines to derive a turbine lifetime.

Wen et al. [47] and Basumatary et al. [87] summarize different methods to estimate the parameters of the Weibull distribution. They use these methods in the wind regime analysis to represent the wind speeds model. Nonetheless, we believe that these methods can be applied to reliability analysis as well.

3.1.2 Assessing Reliability Patterns Using Homogeneous/Non-Homogeneous Poisson Process

Oftentimes, the time to failure information (which was used in Andrawus et al. [16]) may not be available in the public domain. Instead, a few survey reports and newsletters provide "grouped" data with little information on individual turbines or maintenance activities [19, 88]. In the grouped data, only is provided the number of failures occurring in a population of turbines during a specific period, whereas the actual time when a failure takes place is missing [17]. For example, Windstats [88], a quarterly newsletter issued by Haymarket Business Media Limited (Haymarket), provides a monthly or quarterly survey including the number of failures for each subsystem of wind turbines. Table 2 presents an illustrative example of the failure statistics from one Windstats newsletter [18].

To utilize the failure statistics over time, several studies use modeling tools such as homogeneous or non-homogeneous Poisson processes [15, 17–19]. Homogeneous Poisson process (HPP) is a typical Poisson process with constant occurrence rate λ per unit time, while, understandably, a non-homogeneous Poisson process (NHPP) has a time-varying failure rate, represented by an intensity function $\lambda(t)$ at time (or, age) t. NHPP was used to model the failure patterns in the repairable systems. It is assumed that a repair returns the system condition to its original state immediately prior to the failure; this repair is called *minimal repair* [89]. In NHPP, the probability of n failures occurring in the time interval (a, b] is given by [90],

$$P(N(a,b] = n) = \frac{\left[\int_a^b \lambda(t)dt\right]^n e^{-\int_a^b \lambda(t)dt}}{n!}, \tag{2}$$

for $n = 0, 1, \ldots$. For a detailed discussion of NHPP, we refer the interested reader to [90–93].

There are several techniques to estimate the intensity function $\lambda(t)$. One of the commonly used models is a power law process, or Weibull process [89, 93], where the intensity function has the following form:

$$\lambda(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1}. \tag{3}$$

Table 2 The number of failures in Danish wind turbines in 1994

	October	November	December
Number of total turbines reporting	2,036	2,083	2,164
Subassembly failure			
Blade	15	6	6
Gearbox	5	2	4
…		…	
Total number of failures	158	130	175

Note: The data are obtained from the study of Guo et al. [18]

Here, $\beta > 0$ is the shape parameter and $\eta > 0$ is the scale parameter. Similar to the Weibull distribution discussed above, $\beta < 1$ represents early failure patterns, whereas $\beta > 1$ indicates a deteriorating (or, aging) process, and $\beta = 1$ denotes a constant failure rate.

Tavner et al. [17] establish an HPP model using the failure statistics data obtained from Windstats over the 10-year period from 1994 to 2004. They analyze the failure data from two countries, Germany and Denmark, both of which hold a large wind energy production capacity. Tavner et al. [17] assume that failures occur randomly and their HPP model has $\beta = 1$ and $\lambda = 1/\eta$ (i.e., $\lambda(t)$ is constant) because they consider the deterioration phase has not yet arrived for the wind turbines under study due to the turbine's young age. In another study, Tavner et al. [15] quantify how the wind speeds affect turbine reliability and which components are affected the most, also using the Windstats data.

Later, Guo et al. [18] extend Tavner et al.'s study [17] by considering a NHPP model. They also use the data extracted from Windstats [88]. For handling the "grouped data", they suppose that there are $n_1, n_2, \ldots, n_k$ failures during the time intervals of $(t_0, t_1]$, $(t_1, t_2]$, $\ldots$, $(t_{k-1}, t_k]$, respectively, and assume that individual groups are independent of each other. Then, the joint probability for the k group events is:

$$\begin{aligned} P(N(t_0,t_1] = n_1, N(t_1,t_2] = n_2, \ldots, N(t_{k-1},t_k] = n_k) \\ = \prod_{i=1}^{k} P(N(t_{i-1},t_i] = n_i) \\ = \prod_{i=1}^{k} \frac{\left[\int_{t_{i-1}}^{t_i} \lambda(t)dt\right]^{n_i} e^{-\int_{t_{i-1}}^{t_i} \lambda(t)dt}}{n_i!}, \end{aligned} \tag{4}$$

where $\lambda(t)$ is given in (3). One additional complexity Guo et al. [18] need to handle is the uncertain running time of the turbines since their installation. This is because the data collected in Windstats does not necessarily (and usually do not) coincide with the exact date when the wind turbines started their first operations. For example, even though the Danish turbine data in Windstats start from October 1994 in Windstats, it is more likely that the reported wind turbines started their operations earlier than October 1994. For handling this problem, Guo et al. [18] introduce an additional parameter into the Weibull process and argue for using a three-parameter Weibull distribution, rather than the typical two-parameter one as discussed above. Like the two-parameter Weibull distribution, the parameter estimation part in the three-parameter model is still done through either the MLE or the least-squares (LS) methods. After analyzing the Danish and German data in Windstat, respectively, Guo et al. [18] conclude that the three-parameter model has advantages over the two-parameters model in terms of predicting the reliability trend more accurately.

The studies by Tavner et al. [17] and Guo et al. [18] make an initial attempt in utilizing grouped failure data for reliability assessment. However, their models do not consider the changing population of turbines. Apparently, individual turbines with different sizes and structural designs are added at different times. This is evident in Table 2, where the number of turbines reported in Windstats increases over time, possibly with variations in turbine sizes and designs. Consequently, turbines may be at different operating ages and have different intensity function $\lambda(t)$ in (3) during a given time interval $(t_{i-1}, t_i]$. But because of the lack of detailed information in Windstats, Guo et al. [18] do not consider the difference in turbines coming from an evolving turbine population. Rather, Guo et al. [18]'s NHHP model treats the operation time of all turbines the same. Future work will need to account for the evolving nature of turbine population for more accurate reliability assessment of the wind power facilities.

Coolen et al. [19] study the grouped failure statistics data published in LWK [94] regarding turbines in Germany. Unlike the Windstats data, LWK provides the models of wind turbines associated with their data. Coolen et al. [19] attempt to build a NHPP model for wind turbine Model *V*39/500. Unfortunately, the Chi squared test rejects the hypothesis that the NHPP model fits the data for the whole wind turbine system and the gearbox. Coolen et al. [19] argue that the rejection is due to the lack of the actual turbine operation time, which in turn makes the probability calculation in (4) inconsistent with data. This explanation appears to be in line with our concerns expressed in the previous paragraph.

3.2 Markov Process-Based Analysis

3.2.1 Reliability Assessment Using a Markov Process

Markov process-based models are widely used in reliability assessment for the conventional power systems [8–10, 95, 96]. Not surprisingly, it has become one of the most popular modeling tools for wind turbine reliability assessment as well.

Let us consider a discrete time Markov process with a finite number of states. Suppose that the deterioration levels of an operating system are classified into a finite number of conditions 1, …, M and that there are L different types of failures. Then, the system condition can be categorized into a series of states, 1, …, $M + L$. State 1 denotes the best condition like "new", and state M denotes the most deteriorated operating condition before a system fails. State $M + l$ reflects the lth failed mode, $l = 1, \ldots, L$. When a system undergoes Markovian deterioration, the transition probability from one state to another only depends on the immediate past state rather than the entire state history.

Figure 1 illustrates the state transitions for a repairable system. In the figure, p_{ij}, $i \le j$, $i, j = 1, \ldots, M$, above a solid line denotes a transition probability from an operating state to another operating state, and λ_{ij} is the failure rate from an operating state i to the failure state j. Because an operating system cannot improve on its own in general, only transitions to more degraded or failed states are

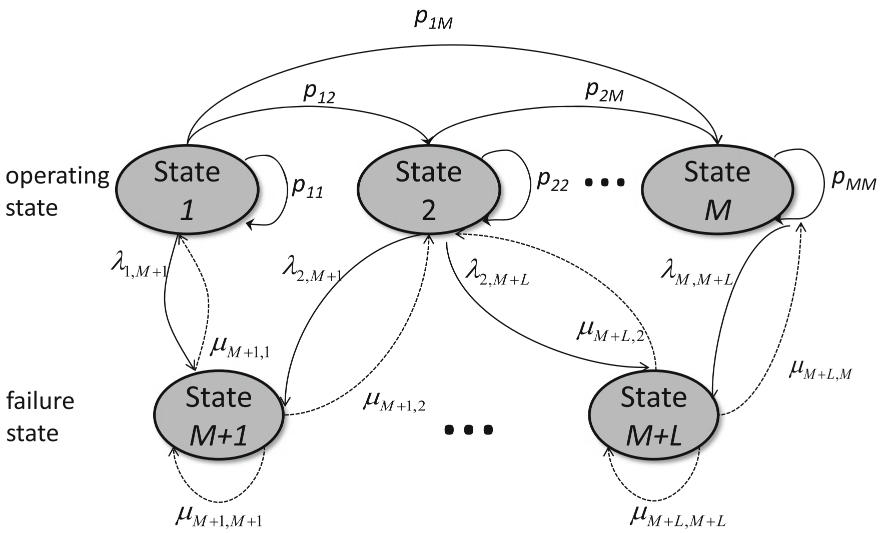

Fig. 1 State transition diagram for Markovian deterioration system

considered in the figure, denoted by the solid lines. μ_{ij} near the dashed line is the repair rate from a failure state i, improving the system to an operating state j for $j \leq i$, whereas μ_{ii}, $i = M + 1, \ldots, M + L$, is the non-repair rate. With repair, the system can be returned from a failure state back to operation.

For simplicity, suppose that $M = 1$ and $L = 1$. That is, the system condition is categorized by two simple states: up or down. Let us also assume that operators repair the system whenever it fails. Then, the transition probability matrix $P_{2\times2}$ consists of the following four elements [24]:

$$P = \begin{bmatrix} 1 - \lambda & \lambda \\ \mu & 1 - \mu \end{bmatrix}, \tag{5}$$

where λ denotes a failure rate which is the probability that the system fails until the next period. μ is a transition probability with which the system can be restored to the operating state. People call this probability as the repair rate of the system [21]. In this simple case, the mean time to failure (MTTF) is $1/\lambda$, and the mean time to repair (MTTR) is $1/\mu$. The mean time between failure (MTBF) is simply the sum of MTTF and MTTR. By applying the limit distribution of an ergodic Markov chain [97], the limiting average availability (i.e., the limiting expected proportion of time when the system is up) becomes $\mu/\lambda + \mu$. For a more complicated system with multiple deteriorating states (i.e., $M > 1$) and/or multiple failure states (i.e., $L > 1$), similar analysis can be done.

Initial efforts using a Markov model in wind power systems can be found in Sayas and Allan's study [21]. They evaluate the generation adequacy of wind farms, in which the wind turbine condition is divided into two binary states (i.e., up and down) using the transition matrix in (5). They also model wind speeds using a Markov process with four different categories. They recognize that the failure rates and repair rates of a turbine are affected by wind regimes. The failure rate of a turbine increases under extremely high wind speeds, whereas the repair rate decreases with wind speed. Considering this weather effect, they propose a combined Markov model for a wind farm. The transition probabilities between the states are obtained using historical data. Then using the limit distribution, the average frequency and duration per year for each combined state, i.e., turbine conditions *plus* wind regimes, are calculated. The results are used for assessing a wind farm's performance, including a turbine's availability and expected generation of wind energy.

Markov processes are also employed in simulation studies [22, 45]. McMillan and Ault [22] consider an intermediate state "degraded" for each component, in addition to the "up" and "down" states. They estimate the state transition probability for four critical components, including gearbox, generator, rotor blade, and electronic device, but do so by combining the operational data and expert judgments. Then, state transitions are simulated given those transition probabilities during the simulation runs. Byon et al. [45] take a similar approach, but consider more refined component states (namely, "normal", "alert", "alarm", and "failed"). In both simulation studies, Markov processes are not used as a standalone tool, but they are embedded within simulation models to capture the evolving characteristics of component deterioration and failures.

3.2.2 Optimization Models Using Markov Decision Processes

A Markov decision process (MDP) is a sequential decision making process used to control a stochastic system based on the knowledge of system states [98–100]. This modeling method is popular in the literature of optimal preventive maintenance [99–104]. Most of the above-cited studies are not specific to wind turbine maintenance; rather they are intended for general aging systems. However, we can gain useful insights from those studies. For this reason, we first discuss the MDP studies for general aging systems and then we present the studies specialized for wind turbine maintenance.

Let S denote the state space of a Markov decision process and $V_t(s)$ be the total cost from the current period t to the terminal period (so $V_t(s)$ is also known as the total cost-to-go). When the system state is $s_t \in S$, decision makers want to find the best action to minimize $V_t(s)$ as follows:

$$V_t(s) = \min_{a_t \in A_{s_t}} \left\{ c_t(s_t, a_t) + \gamma \sum_{s_{t+1} \in S} P_t(s_{t+1} | s_t, a_t) V_{t+1}(s_{t+1}) \right\}. \tag{6}$$

In (6), A_{s_t} is a set of possible actions at state s_t, which may include an inspection, major/minor maintenance, and taking no action. $c_t(s_t, a_t)$ is an immediate cost incurred by decision a_t. $P_t(s_{t+1}|s_t, a_t)$ is the transition probability from s_t to s_{t+1} as a result of taking the action a_t. $\gamma \leq 1$ is a discount factor. A model with $\gamma < 1$ is called a discounted cost model, whereas the model with $\gamma = 1$ is called an average cost model. Equation (6) is referred to as an "optimality equation" or "Bellman equation". Understandably, the optimal maintenance actions are found by solving the above optimality equation.

Several mathematical models have been introduced, incorporating information from condition monitoring equipment for general aging systems [99–104]. Since sensors in condition monitoring equipment provide uncertain data, most of these studies use a partially observed MDP (POMDP) to reflect the incomplete understanding about the current system state. In a POMDP setting, the system condition cannot be observed directly, so that the condition is estimated in a probabilistic sense [103, 104]. Suppose that a system condition can be categorized into $M + L$ states as explained in Sect. 3.2.1. Under a POMDP setting, a system state is defined as a probability distribution, representing one's belief over the corresponding true state. As such, the state of the system can be defined as the following probability distribution:

$$\pi = [\pi_1, \pi_2, \ldots, \pi_{M+L}], \tag{7}$$

where π_i, $i = 1, \ldots, M + L$, is the probability that the system is in deterioration level i. π is commonly known in the literature as an information state [104]. Then, the state space under the POMDP setting becomes

$$S = \left\{ [\pi_1, \pi_2, \ldots, \pi_{M+L}]; \sum_{i=1}^{M+L} \pi_i = 1, 0 \leq \pi_i \leq 1, \quad i = 1, \ldots, M + L \right\}. \tag{8}$$

Maillart [103] uses a POMDP to adaptively schedule observations and to decide the appropriate maintenance actions based on the state information. In her study, the system is assumed to undergo a multi-state Markovian deterioration process with a known and fixed transition probability matrix. Similarly, Ghasemi et al. [105] represent a system's deterioration process using the average aging behavior, provided by the manufacturer (or, from survival data), and the system utilization, diagnosed by using CBM data. They formulate the maintenance decision problem using a POMDP and derive optimal policies using dynamic programming.

Most maintenance studies in the literature to date only consider static environmental conditions. Very few quantitative studies examine systems operating under stochastic environments. Thomas et al. [106] investigate the repair strategies to maximize the expected survival time until a catastrophic event occurs in an uncertain environment. They consider the situation where a system should be stopped during inspection or maintenance action. If specific events, termed "initiating events", take place when a system is down or being replaced, they are noted as catastrophic events; examples given are military equipment or hospital systems. Kim and Thomas [107] extend the problem where the multiple environmental situations are assumed to follow a Markovian process. The criteria in both studies are to maximize the expected time until a catastrophe occurs. In other words, these studies focus on short-term availability.

There are a few relevant studies using a MDP or POMDP for wind turbine maintenances. The authors of this chapter present two optimization models and their solutions using POMDPs in [23, 24]. The presented models extend the model introduced in [103] by incorporating the unique characteristics of turbine operations. For example, to represent stochastic weather conditions, Byon et al. [23, 24] apply the initiating events idea described in [106]. Other characteristics included are long lead times after unplanned failures and the accompanying production losses.

The model presented in [23] is a static, time-independent model with homogeneous parameters in its optimality equation. The homogeneous parameters imply that the characteristics of weather conditions remain constant period by period. This relatively simple model allows us to characterize the solution structures and develop efficient solution techniques. Byon et al. [23] analytically derive the optimal control limits for each action in a set of closed-form expressions, and provide the necessary and sufficient conditions under which the preventive maintenance will be optimal and the sufficient conditions for other actions to be optimal. The second model in [24] extends the first model and is a dynamic, time-dependent model with non-homogeneous parameters. The time-varying parameters depend on prevailing weather conditions and exhibit considerable seasonal differences. Therefore, the resulting strategy is adaptive to the operating environments. The optimal policy is constructed from the evolution of the deterioration states of individual wind turbine components. A backward dynamic programming algorithm is used to solve the second problem.

In both models [23, 24], three major actions (or, polices, controls) are considered at each decision point. The first action is to continue the operation without any maintenance interruption. When this action is selected, the system would undergo Markovian deterioration with a given transition probability matrix. The second action is to perform preventive maintenance to improve the system condition and thus avoid failures. Lastly, wind farm operators can dispatch a maintenance crew for on-site observation/inspection to evaluate the exact deterioration level. Optimal action at every decision point is derived based on the system state and weather conditions.

In these studies, a season-independent degradation process is assumed. That is, the constant transition matrix is considered over the whole decision horizon. However, the degradation process can be accelerated, and consequently, more frequent failures are expected during harsh weather seasons than during mild seasons, as discussed in previous sections. Reflecting these seasonal aspects, there is a need in future research to extend the models in [23, 24] to incorporate weather impact on turbine reliability and model a season-dependent deterioration process.

3.3 Structural Load-Based Reliability Analysis

The approaches reviewed in categories of Sects. 3.1 and 3.2, namely the statistical distribution-based and Markov process-based analyses, are considered cumulative degradation modeling approaches. The influence of environmental factors on the turbine reliability and O&M costs are already examined by several lines of work [15, 22–24], falling into either category of the two previously reviewed approaches. Nevertheless, the direct relationship between structural loads (or, stresses) and physical damage is not investigated in detail in those studies. In this section, we review another category of analytical models which address the structural loads and its effect on damage.

Assuring a desired level of structural performance (in blade and tower) requires the characterization of the variability in material's resistance and stress. International Electrotechnical Commission (IEC) standards (IEC 61400-1) [108] formalized design requirements for wind turbines to ensure its structural integrity. There are two design requirements for wind turbine structures; fatigue loads and extreme loads. Fatigue load analysis focuses on the progressive structural damage that occurs when a system is subjected to cyclic loading, whereas the extreme load (or, ultimate design load) is a maximum load level that can be encountered during a turbine life [108]. In this section, we focus on the fatigue load analysis. For detailed discussions to estimate the extreme load, please refer to [109–111].

One of the initial studies on structural reliability analysis can be found in Ronold et al.'s study [25]. They derive a probabilistic model for assessing the cumulative fatigue damage of turbine blades. They first perform regression analysis to understand how weather factors, including the average wind speed and turbulence intensity, affect the bending moment at the blade root. Then, a fatigue model is developed based on an SN-curve, which is an empirical curve representing the relationship between the fatigue load stress and the number of stress cycles to failure. For example, a simple SN-curve is $N = BS^{-m}$ where N is the number of stress cycles to failure for a given S, S is the fatigue load stress, and B and m are material parameters [25]. Since there are multiple stress levels due to various wind speeds and turbulence, Ronold et al. apply a Miner's rule approach which extends the conventional SN-curve as follows:

$$D = \sum_{i=1}^{K} \frac{\Delta n(S_i)}{N(S_i)}, \tag{9}$$

where $\Delta n(S_i)$ is the number of load cycles at stress range S_i, and $N(S_i)$ is the number of cycles to failure at this stress level as determined from the SN-curve. Consequently, D denotes the weighted sum of damage from various stress ranges, $\forall S_i,\ i = 1, \ldots, K$. In Ronold et al.'s study [25], considering a 20-year design lifetime, a first-order reliability method is used to calculate the structural reliability against fatigue failure.

Manuel et al. [26] also applied parametric models to estimate wind turbine fatigue loads for turbine lifetime. In a later study, Manuel et al. [27] consider extra weather parameters including the Reynolds stresses and vertical shear exponent, in addition to the average wind speed and turbulence intensity.

Many studies on structural reliability analysis rely on a cycle counting technique over multiple stress ranges, called the "rainflow counting method" [25, 26]. However, this method is computationally extensive and requires data over the whole range of weather profiles for accurate prediction. In reality, many data sets do not include the rarely occurring (but, arguably more important) weather profiles such as the high wind speeds and turbulent inflow. To overcome these limitations, Ragan and Manuel [30] suggested using the power spectrum to estimate the stress range probability distributions. The major advantages of power spectrum analysis is that the load power spectrum may be estimated with less statistical uncertainty and a stress range probability density function can be obtained with a small number of simulations, or limited amount of field data. Ragan and Manuel [30] evaluate the advantage of this method in terms of accuracy, statistical reliability, and efficiency of calculation using field data from a utility-scale 1.5 MW turbine. Early studies making use of power spectral density can be also found in [28, 29].

Moan [31] summarizes operational experiences with respect to degradation of various types of offshore structures, and presents a reliability model focusing on fatigue failures and corrosion. Rangel-Ramírez and Sørensen [32] apply similar techniques to wind turbines, considering time-varying fatigue degradation for offshore turbines with jacket and tripod types of support structures. Especially, they analyze the "wake effect" on the performance of neighboring wind turbines. Here, wake effect implies an increased turbulence intensity, coming from the decrease of wind velocity behind a turbine. In the example of offshore wind turbines with a steel jacket support, Rangel-Ramírez and Sørensen [32] investigate the inspection schedules that are meant to achieve a prescribed reliability level. They show that earlier inspections are very beneficial and thus must be performed for wind turbines in a wind farm. This is different from the practice on those standalone, isolated wind turbines, and is primarily due to the increase of fatigue coming from the wake turbulence.

Sørensen et al. [33] take an analogous approach to model the fatigue-related reliability of main components of wind turbines, including welded details in the tower, cast steel details in the nacelle, and fiber reinforced details in the blades. Later, Sørensen [34] presents an overall decision making framework that may help decide the design for robustness, the choice of inspection methods, and scheduling and repair strategies. Sørensen [33] argues that multiple inspection techniques should be used for decision making. For instance, to assess the deterioration level of a gearbox, several techniques are available including visual inspection, oil analysis, particle counting and vibration analysis, but their abilities to detect and quantify degradation differ drastically from one another. They may provide complementary information to produce a more accurate reflection of the actual degradation. Sørensen [34] also suggests taking a Bayesian approach to update a degradation model based on inspection results. Sørensen illustrates, through an example, that inspections, scheduled for maintaining the turbine operation at an acceptable risk (e.g., in terms of the number of failures per year) can be very different, depending on inspection quality as well as the operating environment.

Bhardawaj et al. [35] illustrate a probabilistic damage model for general corrosion of the tower structure. They present a risk-based decision making methodology for undertaking the run-repair-replace actions with the ultimate goal of maximizing the net present value of the investment in maintenance.

4 Simulation Studies for Wind Farm Operations

Due to the complicated nature of wind farm operations, it is quite challenging to model wind farm operations entirely using analytical approaches. For example, wind power generation from individual turbines are not independent of each other because wind speeds at turbine sites are correlated. A failure of one component might affect the operating conditions of other components, which is known as the "cascading effect". Few analytical models have been proposed to analyze the reliability at the wind farm level. Sayas and Allan [21] extend their analysis of wind turbines (discussed in Sect. 3.2.1) to a wind farm level with multiple turbines. But the number of turbines is limited due to the curse of dimensionality.

With these reasons, simulations have been utilized to evaluate the performance of current or future wind farms with the metrics of interest such as the average number of failures per year in a wind farm, O&M costs, and availability. Most of the simulation models presented in the literature belong to the category of Monte Carlo simulation in the sense that they use random number generators to reflect the stochastic aspects of wind farm operations. To accommodate uncertainties, several probabilistic models are embedded within a simulation, and maintenance constraints under different operating environments are implemented [22, 42, 45].

Rademakers et al. [42] describe a Monte Carlo simulation model, developed by Delft University of Technology (TU-Delft), for maintaining offshore wind farms. They illustrate the features and benefits of the model using a case study of a 100 MW wind farm. The model simulates the operation aspects over a period of time, considering multiple critical factors for performing repair actions, such as turbine failures and weather conditions. The failures of turbine components are generated stochastically, based on the relevant statistics such as MTTF and reliability distributions. Weather conditions are realized using the historical summer and winter storm occurrences at specific sites. The model further categorizes different failure modes and the corresponding repair actions. For example, the first category of failure modes requires replacement of rotor and nacelle using an external crane; the second failure mode requires replacement of large components using an internal crane, and so on. The failure rates of the individual components are distributed over four maintenance categories. Please note that Rademakers et al. [42]'s model only considers corrective maintenance, and their simulation results indicate that the revenue losses during such corrective repairing account for

55 % of the total maintenance costs, largely due to the long lead time to prepare parts and the long waiting time until favorable weather conditions are met. Similar studies appear in [6, 11, 43].

Foley and Gutowski [46] investigate the energy loss associated with component failures using a simulator named TurbSim. They assume random failures and estimate the MTBF and MTTR using data obtained from [17] and [112]. In addition, they consider degraded outputs of a turbine upon a component's failure, meaning that they decrease the power output of a turbine by a certain percentage point, depending upon the impact of a broken subsystem. They use wind speed data from the national oceanic and atmospheric administration (NOAA)'s weather stations [113] and fit a Weibull distribution to simulate wind speeds. The wind speed at the ground level is adjusted to the hub height speed while considering the roughness of the surrounding terrain. Their simulation results of an artificial wind farm in Massachusetts for a 20-year period (the presumed turbine life) show that the energy loss from component failures is 1.24 % of the total generation of a wind farm with no wind turbine failures. For off-shore turbines, the simulation produces a more noticeable 2.38 % loss of power generation, still compared with the circumstance of no failure. Foley and Gutowski [46] stress that these results represent a significant loss of energy generation over the lifetime of turbines.

Negra et al. [44] describe a set of approaches to be used for wind farm reliability calculations. They especially consider unique aspects that influence the *offshore* wind farm reliability including grid connection configuration and offshore environment. Factors that are common to land-based turbines such as wake effect and correlation of power output are also considered. A Monte Carlo simulation shows how some of these factors influence the reliability evaluation. For example, the inclusion of cable and connector failures has a substantial impact on the power generation from the off-shore wind farms.

Simulations are also used for the purpose of validating various O&M approaches [16, 22, 45]. In [16], the suggested strategy resulting from the statistical model is evaluated by using Monte Carlo simulation. They assess the reliability, availability, and maintenance costs by simulating a wind farm with turbines over a period of four years. The simulation is conducted using a commercial software called ReliaSoft BlockSim-7 [114]. McMillan and Ault [22] implement a simulation model to quantify the cost-effectiveness of CBM by comparing the performance of different maintenance polices. They use an autoregressive time series analysis to generate wind speeds and consider weather constraints when performing repair actions.

The authors of this chapter develop a discrete event simulation model to characterize the dynamic operations of wind power systems, as discussed in Sect. 2.2.4 [45]. The discrete event simulation model tracks each event going from a state to another. A major difference between this model and previously discussed models is that time evolution in the latter is unimportant, and the focus is to obtain lump sum estimates for performance measures. By contrast, the discrete event model considers dynamic state changes of a wind turbine as a result of stochastic events. The model allows operators to gain a detailed knowledge of the lifetime evolution of wind power systems, in addition to gathering the performance statistics. For simulating the wind condition, the authors in [45] use the actual wind speed data measured by the west Texas Mesonet [115]. Because the simulation model considers the spatial correlation of wind speeds at wind turbine sites, power generations at different turbines naturally become correlated. This correlation phenomenon, however simple and intuitive, is often ignored in the wind energy literature, which usually assumes independent, identical turbines in a wind farm. The simulation model in [45] provides a tool for wind farm operators to select the most cost-effective O&M strategy.

5 Generation Adequacy Assessment Models

Generation adequacy assessment deals with assessing the existence of sufficient facilities within the power system to satisfy consumer demands (or, loads) or system operational constraints [44, 47]. A complete power system can be categorized into three segments: generation, transmission and distribution. And there are three hierarchical levels that provide a basic framework for the power system adequacy evaluation, as illustrated in Fig. 2 [44, 47, 116]. Most of the reliability work is focused on the hierarchical levels 1 and 2. There is very limited work on hierarchical level 3 assessment, which considers all three functional zones. One reason for this is that considering all the three zones simultaneously, the problem becomes too complex to be computationally tractable. But perhaps the more important reason is that consideration of the three zones altogether is not deemed critical or even desirable. Instead, the level 2 analysis is used to provide reliability indices (such as failure and repair rates) for major nodes to the third zone (i.e., to which distribution facilities are connected). The analysis of the third zone is then conducted independently using the reliability parameters of these nodes as the starting point. We focus on the hierarchical levels 1 and 2 in this section. We also briefly discuss the power quality issues in Sect. 5.3.

Recall that the criteria investigated in Sects. 3 and 4 focus on evaluating performance of an individual turbine, or a farm. The criteria include MTTF, MTTR,

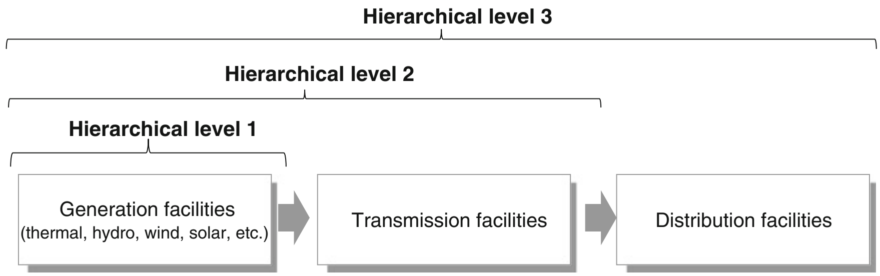

Fig. 2 Hierarchical levels for generation adequacy assessment

number of failures, O&M costs, etc. At the power system level, however, power utilities use different criteria to determine adequate generation and transmission capacity in various scenarios. We summarize the criteria commonly used in this line of literature [116]:

- Loss of load expectation (LOLE): Expected number of hours per year when demand exceeds available generating capacity.
- Loss of load probability (LOLP): Probability that loads exceed available generating capacity.
- Loss of energy expectation (LOEE), Expected unserved energy (EUE), Expected energy not supplied (EENS): Expected amount of energy not supplied by the generating system in a given time period.
- Energy index of unreliability (EIU): Ratio of the LOEE to the total energy demand.
- Capacity factor (CF): Ratio of actual energy output to energy output if generators operated at rated power outputs in a given time period.

Please note that the load in the above criteria implies customer demand, whereas the load in Sect. 3.3 denotes the stress on the facility structure. There are also newly introduced indices associated with wind energy as follows [21, 62, 117]:

- Expected wind energy supplied (EWES): Expected amount of energy offset of conventional fuel energy by wind energy application.
- Expected surplus wind energy (ESWE): Expected amount of wind energy that was available but not utilized.
- Expected available wind energy (EAWE): Expected amount of wind energy that would be generated in a year, if there were no wind turbine failures (or, outages).
- Expected generated wind energy (EGWE): Expected maximum amount of energy that would be generated in a year by wind turbines considering their failure rates.

5.1 Hierarchical Level 1 Assessment

Hierarchical level 1 (HL 1) assessment concerns evaluating the reliability of generation capacity. The goal is to determine whether the installed generating capacity satisfies the forecast system loads at an acceptable risk level, considering the uncertainty introduced by the corrective/preventive maintenance and load forecast errors [44]. In these calculations, it is assumed that the transmission system is capable of transporting all the power from generation points to the load points. We consider two main approaches: the analytical methods and Monte Carlo simulations.

5.1.1 Analytical Methods

One of the popular analytical approaches is to use a multi-state model which discretizes the power outputs into a finite number of states and assign a probability to each state based on historical data of generating units [47–49]. The number of states can be decided depending on the characteristics of wind data and accuracy requirement [47].

The initial multi-state analytical model with unconventional energy sources can be found in the study by Singh and Gonzales [50]. It is shown in [50] that under the significant penetration of variable energy sources, incorrect consideration of correlations between loads and unconventional units can give optimistic results for risk assessment. To address this issue, Singh and Kim [53] define the discretized state as a vector which contains hourly loads and output from each unconventional unit (note that the number of states here is equal to the number of hourly observations). Then, they apply a clustering algorithm to group the states into a smaller number of clusters. The clustering algorithm produces the mean value (cluster centroid) of each cluster as well as the frequency of each cluster. These pieces of information are used to calculate indices of interest such as LOLP, LOLE and EUE. Later a straightforward method [54] is introduced for computing the EUE in a fast manner when renewable sources are included.

In a multi-state model, finding the most probable states, contributing significantly to system adequacy indices, is through some optimal search algorithm. For example, Wang and Singh [57] use a population-based stochastic search algorithm to find out the set of the most probable failure states in a modified IEEE Reliability Test System (IEEE-RTS). The system adequacy indices used in [57] include LOLE, LOLF and EES. A later paper [58] compares the results obtained by various population based methods, when wind energy is included as one of the generation sources.

Dobakhshari and Fotuhi-Firuzabad [55] present an alternative procedure based on a Markov process. The Markov model is used to represent the output power of a wind farm housing multiple wind turbines. Analogously, Leite et al. [56] use a Markov model to model wind speeds. They use actual time series data of wind speeds at several Brazilian regions, and accommodate time-varying patterns of wind speeds. They cluster wind speeds into a finite number of states, and examine the consequence of having different number of states. The ideal number of clustered states depends on the characteristics of winds at a given site. The choice also depends on the computational precision desired and computational capacity. The annual power generation is estimated for the studied sites, demonstrating favorable characteristics of having wind power generation in Brazil. The resulting capacity factor for wind power generation is between 28 and 37 %, a value considered higher than the global average. The results from this study also confirm that seasonality significantly affects the reliability of wind turbines.

5.1.2 Monte Carlo Simulation

There are two approaches in generation adequacy assessment using Monte Carlo simulation [118]. The first one is a sequential Monte Carlo simulation which chronologically simulates a realization of stochastic process for a give time period. In contrast, non-sequential Monte Carlo simulation use the state sampling approach in which each state is randomly sampled without reference to the chronological system operation [118].

Sequential Monte Carlo simulations are performed in [59–62]. Billinton and Bai [59] quantify the contribution of wind energy to the reliability performance of a power system. Wind speeds are simulated using an autoregressive moving average (ARMA) time series approach. Using the two reliability indices, LOLE and LOEE, they investigate the effects of wind turbine capacity and mean wind speeds on the generation adequacy. They also compare the contribution of wind power with that of conventional generators. In doing so, they replace conventional power units with wind turbines, and investigate the capacity of wind turbines (together with mean wind speed) required to maintain the same reliability level. Based on a case study in Canada, they point out that wind power contribution is highly dependent on the wind site conditions, and that wind energy independence among multiple sites has a significant positive impact on the reliability contribution.

Wangdee and Billinton [60] further examine the impact on the system reliability indices of wind speed correlation between two wind farms, and obtain a similar conclusion. Moharil and Kulkarni [61] conduct an analogous analysis, which studies a case of three different wind-generating stations in India.

Karki and Billinton [62] use a sequential Monte Carlo simulation to help determine appropriate wind power penetration in an existing power system from both reliability and economic aspects. The generating system consists of both wind turbines and conventional generators. The time-to-failure for both types of power generators is assumed to be exponentially distributed, and then, the MTTF of each generator can be estimated from historical data. To evaluate the energy costs and utilization efficiency of wind turbines, they create a couple of new probabilistic performance indices by combining EWES, ESWE and CF as follows:

$$\text{Wind utilization factor (WUF)} = \frac{EWES}{EWES + ESWE} \times 100 \tag{10}$$

$$\text{Wind utilization efficiency (WUE)} = CF \times WUF \tag{11}$$

Note that WUF is the ratio of the wind energy supplied to the total wind energy generated. WUE implies the ratio of the actual energy utilized to the total energy generated based on the rated wind turbine capacity. Based on a case study of a small power generating system, they show that as more wind turbines are added in the power system, the reliability level increases. On the other hand, the utilization of wind power, measured by WUF and WUE, decreases with increasing wind energy capacity. Considering the fact that investment cost linearly increases with the number of wind turbines in general, they present the procedure to decide the appropriate wind penetration level in a power system.

The sequential Monte Carlo approach can provide detailed information about the system behavior over time, but it requires higher computational efforts especially when the number of generators is large. To overcome this issue, Vallée et al. [63] present a non-sequential Monte Carlo simulation to estimate the wind power capacity of a given country, and perform a case study for Belgium. They use the Weibull distribution to characterize the wind speeds at ten wind farms spreading over the country. They categorize the wind speeds into a finite number of states and assign a probability to each state. Wind power production at each site is simulated using the state probabilities, and then the country-wide wind power production in a country is computed by summing up the powers from individual wind farms. They divide the entire country into four regions (north, south, center, and off-shore) and investigate how the geographical repartition of wind turbine installations affects the country's wind production capacity. Their case study shows that spreading wind turbines over a broad geographical area help ensure a positive wind power output at any given time and avoid the situation of no wind power production for the whole country. The study also reveals that contribution of wind power production is more reliable when the offshore wind energy penetration is higher than the onshore penetration.

5.2 Hierarchical Level 2 Assessment

Hierarchical Level 2 (HL 2) assessment considers the evaluation of both generation and transmission facilities for their ability to supply adequate, dependable, and suitable electrical energy at bulk power load points [44]. This analysis is also called "composite system reliability (or, adequacy) evaluation" or "bulk power system reliability".

Generation adequacy studies accounting for wind generation have been developed for the HL 1 level (load covering with transmission system assumed always available) [64]. Relatively fewer papers and reports are found on the HL 2 assessment due to the complexity associated with modeling the generation and transmission facilities, as well as capturing the intermittent wind characteristics [65]. In the meanwhile, assessment of adequate transmission facilities to deliver wind power to the power grid becomes extremely important as many geographical sites with good wind resources are not necessarily located close to the existing power grid or load centers [66].

When a large-scale wind farm is connected to a weak transmission facility, transmission reinforcement may be necessary in order to increase the system capability to absorb more wind power at specified locations [65]. Billinton and Wangdee [65] study three different cases, and examine possible transmission reinforcement alternatives for the purpose of absorbing a significant amount of wind capacity without violating the transmission constraints. Similarly, Vallée et al. [64]

propose a tool that uses Monte Carlo simulations to assist system planners and transmission operators for the purpose of qualitatively assessing the impact of wind energy production as wind penetration increases. Karki and Patel [66] discuss the issues of determining the appropriate transmission line size and evaluating the reliability of combined wind generation and transmission systems.

A multi-state model for composite system adequacy assessment can be found in [51, 52]. Billinton and Gao [52] present a procedure that can be used in either HL 1 or HL 2 reliability evaluation. This procedure quantifies the effects of connecting multiple wind farms at different locations into a bulk power system. The benefits in doing so depend significantly on the actual transmission network. The expected energy not supplied decreases as the number of wind farms increases if the wind farms are connected at relatively strong points in the transmission system. Otherwise, the benefits are not substantial.

Another approach for the HL 2 assessment is to use a hybrid approach combining the Monte Carlo and population-based methods. One drawback of using the Monte Carlo simulation is the long computation time to achieve the satisfactory statistical convergence of adequacy index values [119]. To address this challenging problem, Wang and Singh [119] apply a classification method called an artificial immune recognition system (AIRS). They consider LOLP as the reliability criterion. Using Monte Carlo simulation, they first sample a system state consisting of a load level, generation status, and transmission line status, and then perform a power flow calculation. If the sampled state does not satisfy the sampled loads, the state is classified as a "loss-of-load" class; otherwise, it becomes a "no-loss-of-load" class. After using samples to train the AIRS algorithm, the binary classifier can predict the LOLP of a given power system. Their case studies show remarkable reductions in computation time over a pure Monte Carlo simulation. The case studies are performed with conventional generators. But the authors of this chapter believe that a similar approach can be applied to wind power systems with minimal modifications.

5.3 Power Quality

Due to the stochastic nature of wind power production, connection of wind turbine generators to the power network can lead to grid instability, wind-energy rejection (thus, the financial losses of wind farm owners), harmonics, or even failures, if these systems are not properly controlled [120–122]. Power electronic converters are used to match the characteristics of wind turbines with the requirements of grid connections, terms of including frequency, voltage, control of active and reactive power, and harmonics [123].

This chapter mainly addresses the reliability issues of wind power systems in "facility" aspects and generation adequacy of the power system. The power quality issues and those of the transients like stability are typically not included in the adequacy analysis and thus are out of the scope of this chapter. Chen et al. [123] provides a comprehensive review of the state of the art of power electronics for wind turbines. Interested readers can refer to [123] for further detailed information.

6 Summary

This chapter reviews the studies relevant to the reliability and maintenance issues of wind energy facilities, with the ultimate objective of achieving sustainable and competitive energy supply. Unlike conventional power plants largely operated under steady states, wind turbines operate in highly stochastic environments under non-stationary loading. Although more power can be harvested during the seasons with strong winds, wind turbines are prone to failures during such weather conditions and repairs are difficult to carry out and more costly. Moreover, the variable, intermittent nature of wind power generation has a significant effect on overall power system reliability.

With these unique operating characteristics for wind energy generation, traditional approaches applied in other industries may not necessarily be effective for maintaining wind energy facilities and enhancing their reliability. The wind power industry faces new challenges pertaining to developing and deploying innovative, practical operational strategies to lower maintenance cost. The exciting news is that, as evident in this chapter, there has already been a rich body of work dedicated to studies directly relevant to wind energy applications. We observe that accurate reliability predictions and cost-effective O&M strategies are pressingly needed to address the approaching challenges faced by the global wind power industry. We also believe that considering today's trend of the ever increasing scale of wind farms, a well-planned maintenance strategy will have to be coordinated with a supply chain management program that can organize repair resources in a just-in-time manner. Addressing these challenges in a comprehensive program is not trivial. However, a successful development and implementation of such a program can result in significant benefits to the wind power industry.

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