

Research Article

Maintenance Optimization of Wind Turbines Using Weather-Dependent Equivalent Age Model

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Abstract

Aging models are important input into wind farm maintenance and financial viability models. Aging of wind turbines depends on many factors, including both ambient and usage conditions. This paper presents a virtual age based maintenance model for wind turbines considering the effect of wind speed and ambient air temperature on turbine aging. Two maintenance thresholds (i.e., corrective threshold and preventive threshold) and three repair actions (i.e., unscheduled corrective, scheduled corrective and preventive actions) are integrated into the maintenance model. The objective is to determine the optimal thresholds values that minimize the expected total maintenance costs. A discreet time simulation model is developed to produce 20 years of weather and usage scenarios for a single onshore wind turbine. The optimization model is formulated as a mixed-integer nonlinear problem and solved using the Nelder–Mead method. A numerical example is presented to highlight the benefits of the proposed approach. Compared with traditional age-based maintenance, the proposed approach can achieve improvement in both availability and costs. The results show



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up to 50% reduction in maintenance cost as well as the significance of the effects of wind speed and ambient air temperature in maintenance planning.

Keywords

Preventive maintenance; condition-based maintenance; wind turbine; equivalent age; imperfect maintenance; weather conditions; renewable energy

1. Introduction

Wind power is rapidly emerging as one of most important renewable energy sources in the world. There is a significant growth in both size and number of wind turbines globally. This rapid growth accounts for 8.4% of the total electricity generation capacity in the United States in 2020 [1]. Modern wind turbine is one of the largest machinery with very sophisticated system of components and a long service life of 20 years. Hundreds of turbines are often installed together in wind farms that are connected to the grid. The significant investment increase in generation capacity comes with a key challenge to manage wind farms to achieve the lowest operation and maintenance cost. According to the International Renewable Energy Agency (IRENA), maintenance costs account for up to 30% of the total levelized cost of energy [2]. A common goal of maintenance is to reduce the overall maintenance cost and improve the availability of the systems. Therefore, more effective maintenance strategies are needed for successful future growth in wind power industry.

Maintenance policies are crucial to ensure power availability, turbines reliability and operation safety. Despite recent technological advances in condition sensing, Time Based Maintenance (TBM) strategy is still widely used in many industries [3]. Condition Based Maintenance (CBM) on the other hand, is quickly gaining interest within the wind power industry as more sophisticated sensors and complex systems are incorporated into wind turbines. It is critical to operational costs and availability to utilize more precise information about remaining turbine useful life to avoid catastrophic failures and reduce cost of maintenance.

The central idea of CBM is to maintain systems or components at exactly the right time, by utilizing information about their actual condition to maintain high reliability while reducing operating costs. In this context, a trade-off is made between the risk of failure during operation (resulting in costly system downtime) and the cost of premature maintenance. Unlike TBM, CBM depends less on the failure history and focuses more on inspections and real time data monitoring of equipment to predict remaining useful life (RUL) and failure rate. The goal for any maintenance policy is to restore the system to a functional state and avoid downtime losses while keeping maintenance cost minimized within technical and financial constraints. Hence, decision support systems are very critical for CBM policies to be successful. Preventive maintenance (PM) planning is a key optimization task in power systems to determine the optimal repair schedules that minimize the total cost of operation.

Traditional PM models are usually formulated as a mixed-integer linear program (MILP) subject to reliability constraints [4]. However, typical PM schedules contain little information on the degradation evolution of individual turbines. Maintenance optimization models have been intensively studied in the literature mostly focusing on two optimality criteria; cost and availability

[5-7]. Several multi-objective and multi-component time-based maintenance models for short term planning horizon have been proposed to mitigate the risk associated with the traditional TBM such as assuming constant operating conditions and depending on historical data [8-10]. Due to the complex nature of aging in complex systems, several studies have developed probabilistic optimization models with imperfect maintenance [11, 12], failure dependencies [13, 14] or economic dependency among components [15, 16]. These maintenance strategies consider the economic dependencies between different wind turbines and/or their turbine components.

The implementation of CBM in wind farms has been studied extensively in the last decade, utilizing the deterioration state information to determine the maintenance plan and reduce O&M cost [17-19]. Recently, Zhang et al. [20] proposed an opportunistic imperfect maintenance policy for wind turbines. The authors proposed a two-threshold policy, where maintenance actions are triggered by the first wind turbine to reach the failure threshold. A lower failure threshold is then applied to the remaining turbines in an effort to group maintenance actions. Besnard and Bertling [21] proposed a CBM strategy using Markov chain to represent the deterioration states of turbine blades. They classified the deterioration state based on the severity of the damage. Shafiee et al. [22] investigated the impact of environmental shocks on blade cracking. They considered crack length threshold to find the optimal CBM policy for a wind farm under harsh marine environments. Mazidi et al. [23] proposed a proportional hazard based maintenance model for wind turbines using SCADA data to determine the stress conditions of wind turbines. However, they did not consider weather conditions or other external factors in their model. Haddad et al. [24] studied the advantages of delaying maintenance actions after a prognostic indication to find the optimal remaining useful life. Their maintenance approach utilizes health condition prediction information to minimize lead time for wind farms. Although these studies propose CBM policies with some weather restrictions, they do not necessarily consider the complex weather conditions as a factor in reliability models.

These maintenance models do not account for the impact of the actual weather conditions on aging. In absence of observable degradation signals, CBM has better performance when it develops a targeted maintenance plan for each wind turbine under variable weather and load conditions. Li et al. [25] presented a multi-component age-based opportunistic maintenance model for wind farms with environmental shocks. The impacts of the shocks are modeled as a random non-homogeneous Poisson process. Specific weather conditions as well as age reduction and imperfect repairs were not considered in this study. Nielsen et al. [26] developed a degradation model for wind turbine blades using a discrete Markov model. The authors proposed a three-threshold configuration for failure, inspection and repair. This study however does not consider the accessibility limitations due to weather conditions. Byon et al. [27] investigated the weather conditions impact on CBM decisions. They proposed a partially observed Markov decision process model to obtain a closed-form solution. However, they only considered the impact of weather conditions on the accessibility of the farm. The primary objectives of condition monitoring systems are to accurately represent the stochastic behaviour of the aging process, assess the system reliability and make a maintenance decision. Operating and environmental conditions in many scenarios, are easy to identify. Since diagnostic covariates cannot reflect precisely the degradation state of the system, decision rules rely on the estimated degradation level reconstructed from these noisy covariates [28]. However, in many cases system degradation is hidden, and system failure is non-self-announcing [29]. This means the system reveals only its degradation state and its failure

through a monitoring procedure. However, some factors that cause the degradation turbine components are uncertain and difficult to predict [30].

Despite many studies on wind turbine maintenance optimization, including studies that involve weather conditions with accessibility constraints, the challenges posed by harsh weather conditions in wind farms have not been adequately addressed in the literature. In particular, there are gaps related to addressing the degradation of wind turbines and taking into account usage and maintenance patterns. To address the above deficiencies, this paper proposes a virtual age model for maintenance optimization of a wind turbine under variable weather conditions. The model considers different age reduction levels under different maintenance actions and weather conditions and investigates the associated economic and technical effects. This paper makes the following contributions:

- Development of comprehensive modeling for wind turbine aging due to ambient air temperature and wind speed and the computation of the associated effects. This is typically neglected in maintenance optimization studies leading to inaccurate cost models.
- Incorporation of two-level threshold maintenance simulation with imperfect repairs in the optimization problem. Wind turbine maintenance models are often have predetermined thresholds values.

The proposed model utilizes real-time weather information to evaluate system health, with a set of maintenance thresholds. The novelty of this model is its ability to (1) simulate operation conditions and estimate the equivalent age of the turbine at any given day, (2) leverage location-specific information in terms of availability and accessibility restrictions, and (3) determine the optimal maintenance threshold values event timeline Using field data, mainly from the literature and real wind measurements, the case study demonstrates that the proposed method addresses practical O&M planning issues and reduces the O&M costs by planning preventive maintenance in low wind conditions to avoid failure during harsh weather seasons.

The rest of the paper is organized as follows: the mathematical formulation of the proposed aging model is presented in Section 2; Section 3 presents the solution approach including both the simulation and optimization algorithms; Section 4 presents numerical results of different scenarios of a wind turbine with the proposed traditional maintenance approach. Three locations for each maintenance method are studied in this section. The total cost of maintenance, turbine availability and daily costs of operation are analyzed; Section 5 concludes the paper and proposes some directions for future work.

2. Proposed Model

Consider a wind turbine with repairable components, each subjected to deterioration. Let $L: \Omega \rightarrow R$ be a random variable that represents the lifetime of a wind turbine in a probability space (Ω, F, P) . During their lifetime, we assume turbines deteriorate contentiously until they experience a fault. Let $F_{\tau}(t)$ be the lifetime distribution function which describes the failure probability before a given time $P(\tau \leq t)$. In this paper, we assume that the turbine lifetime distribution follows a two-parameter Weibull distribution $F(t)$, where t denotes current time, with scale parameter η and shape parameter β :

$$F(t) = 1 - \exp \left[- \left(\frac{t}{\eta} \right)^{\beta} \right] \quad (1)$$

is important to study the effect of weather conditions on wind turbine aging because it has a significant impact on the wind turbine performance and the degradation wind infrastructure [31]. Neshat et al. [32] proposed a deep learning-based prediction model for short term power output forecasting. The authors studied SCADA measurements to analyze the performance of wind turbines. In particular, they investigated the impact of wind speed and wind direction on the power output. It has been reported [33] that wind turbines located at higher elevations with high wind speed conditions, experience higher failure rates. Reder and Melero [34] studied the correlation between air temperature and the reliability of wind turbines and concluded that higher ambient air temperatures cause higher failure rates. Tavner et al [35] has shown that high humidity can reduce the reliability of the drivetrain components. According to Slimacek and Lindqvist [36], external weather factors such as ambient temperature, icing and high winds can increase the failure rate of wind turbines by a factor of 1.7.

The traditional approach to preventive maintenance estimates the Weibull parameters using historical failure data, then schedule maintenance activities based on mean time to failure (MTTF). This approach assumes time independent covariates and linear proportionality with the hazard rate, which is in most cases unrealistic. Data-driven techniques, on the other hand, utilize monitored operational data related to system health. They can be beneficial when the understanding of the system operation is not straightforward or when the system is so complex that developing an accurate model is prohibitively expensive.

Henry and Nachlas [37], developed a virtual age model that overcomes those limitations and represents equipment aging in a more accurate model called Equivalent Age. The model reflects the continuous degradation in equipment life (which usually differs from calendar time) based on operation conditions $X_i(t)$ and usage intensity $Y_i(t)$ which are both time dependent. In this paper, we adopt this concept to model the equivalent age of a wind turbine subjected to variable wind speed and air temperature conditions. While other weather conditions may have impact on wind turbine reliability, in this paper we will only consider wind speed and air temperature because they have higher impact on wind turbine failures [38] than humidity and icing and they are applicable to both onshore and offshore farms as oppose to wave height.

2.1 Equivalent Age Model

Consider a wind turbine system with wind speed measures $V(t)$, and ambient temperature measures $T(t)$, then the equivalent age $\alpha(t)$ at any time t is:

$$\alpha(t) = \int_0^t (\alpha_0)^{q(k)} dk \quad (2)$$

where α_0 is a nominal aging factor and $q(t)$ a linear additive function of two time series: wind speed ($V(t)$) and ambient temperature ($T(t)$):

$$q(t) = \delta(V(t)) + \gamma(T(t)) \quad (3)$$

This model combined with the Weibull distribution can represent a wide range of applications under various assumptions. The equivalent age $\alpha(t)$ (described in equation 2) will replace the calendar time t in (equation 1). If we assume constant wind speed and temperature conditions, this

model is identical to proportional hazards models and age is the same as calendar time. Flexibility of the model is crucial and provides the means for robust decision making within the CBM field.

2.1.1 Wind Speed Effect Function

One of the most important parameters in determining electric power obtained from wind-based resources is wind speed. The general equation relating wind power P_W to swept area (A), wind speed (v), density of air (ρ), wind turbine power coefficient (C_o) and rated power $P_{W_{rated}}$ is [39]:

$$P_W(v) = \begin{cases} 0, & v < v_{in} \\ \frac{1}{2} \rho C_o A v^3, & v_{in} \leq v < v_{rated} \\ P_{W_{rated}}, & v_{rated} \leq v \leq v_{out} \\ 0, & v > v_{out} \end{cases} \quad (4)$$

Assume the turbine experiences nominal degradation rate at the rated wind speed v_{rated} , and negligible degradation below the cut-in wind speed v_{in} and above the cut-out wind speed v_{out} , then the effect of the intensity wind speed on the equivalent age model can be defined as follow:

$$\delta(V(t)) = \begin{cases} \frac{v(t)^3 - v_{rated}^3}{v_{rated}^3}, & \text{if } v_{in} \leq v(t) \leq v_{out} \\ \delta_0, & \text{otherwise} \end{cases} \quad (5)$$

δ_0 is a negative number to reflect the slow-down of aging when the wind speed is not within operating conditions and the turbine is idle.

2.1.2 Ambient Temperature Effect Function

Fiber Bragg Grating (FBG) sensors have been widely used in the literature to study failure modes and fatigue related issues of wind turbine blades [40-42]. These studies primarily focus on the application of FBG sensors for condition monitoring of thermal strain as a function of temperature. The change in ambient temperature causes thermal expansion and thermo-optic effect. The shift difference of the Bragg wavelength (λ_B) (In case of a pure thermal strain) is defined as follow:

$$\frac{\Delta\lambda_B}{\lambda_B} = (\epsilon_s + \epsilon_e)\Delta T \quad (6)$$

where ϵ_s and ϵ_e and ΔT are the thermal expansion coefficient, the refraction index, and the change in temperature, respectively. Experimental evidence shows this linear dependence between temperature and wavelength shift is valid for fairly large strain and temperature variations [43]. In the equivalent age model, let the following equation represents the effect of ambient air temperature as a linear function of temperature difference:

$$\gamma(T(t)) = \begin{cases} \frac{|\Delta T| - \Delta T_n}{\Delta T_n}, & \text{if } \Delta T \neq 0 \\ \gamma_0, & \text{if } \Delta T = 0 \end{cases} \quad (7)$$

γ_0 is a negative number to reflect the slow-down of aging when the change in ambient temperature is zero. Let the equivalent age of a turbine be denoted by θ . Then the Weibull lifetime distribution is given as follows:

$$F(\theta) = 1 - \exp\left[-\left(\frac{\theta}{\eta}\right)^\beta\right] \tag{8}$$

Equation 8 together with the equivalent age model allows inclusion of wind speed and ambient temperature information from the monitored system.

2.2 Maintenance Model

Modern wind turbines are equipped with automated alarm systems within the condition monitoring equipment so that when a sensor signal exceeds a certain threshold, an alarm is sent to a wind farm operator [44]. Several threshold-type maintenance policies have been presented in the literature by either maximizing the availability or minimizing total costs. In these policies, a component is assigned for maintenance when the conditional probability of failure exceeds a certain level threshold value. The conditional probability of failure in the next day $Pr(1)$, can then be written as:

$$Pr(1) = \frac{F(1 + \theta) - F(\theta)}{1 - F(\theta)} \tag{9}$$

In our proposed maintenance model, two thresholds (preventive threshold p^{pm} and corrective threshold p^{cm}) and three types of maintenance actions are considered:

- Preventive maintenance; a minimal repair with associated cost of C^p , triggered when the probability of failure exceeds the preventive threshold ($Pr(1) \geq p^{pm}$),
- Scheduled corrective maintenance; a major repair with associated cost of C^R , triggered when the probability of failure reaches the corrective threshold ($Pr(1) \geq p^{cm}$),
- Unscheduled corrective maintenance; a major repair after an unexpected failure with associated cost of failure C^F .

For simplicity, we also assume that these activities are instantaneous (as shown in Figure 1), i.e., the time required to maintain the turbine is negligible relative to its age and thus all maintenance activities are assumed to be carried and completed during the same day. However, different costs associated with each maintenance type are imposed.

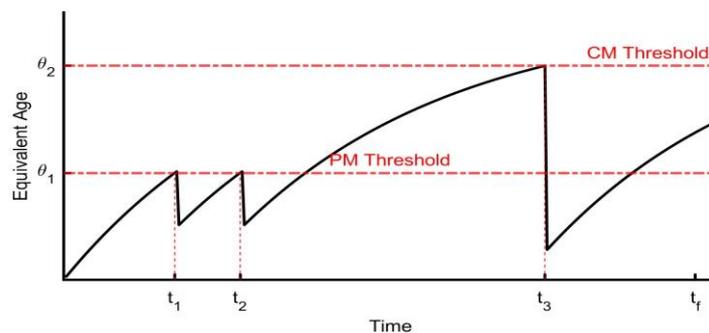


Figure 1 Two-level threshold condition-based maintenance policy.

Maintenance actions reduces the equivalent age of the system at the start of the next period by a certain proportion $M(t)$ of the equivalent age at the time of maintenance or failure. We assume that weather conditions are monitored continuously over the entire period with inspection interval of one day. At the end of each interval, the system is either maintained or no action is taken. We assume that maintenance activities at any time are imperfect and thus reduce the equivalent age of the system but do not bring the system back to the original state (as good as new). The objective of our maintenance model is to find the optimal threshold values such that expected total cost is minimized.

First, we define x_i and y_i , as binary variables, to represent the preventive and corrective maintenance actions in day i as:

$$x_i = \begin{cases} 1, & \text{if the system is in PM} \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

$$y_i = \begin{cases} 1, & \text{if the system is in CM} \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

The following objective function computes the total cost $C(t)$ as a summation of the costs in each day i based on the cost of; preventive maintenance C^P , corrective maintenance C^R , system failure C^F and loss of production $C(i)^L$:

$$C(t) = \sum_{i=1}^N \{ (C^P + C(i)^L)(x_i) + (C^R + C(i)^L)(y_i) + (1 - x_i)(1 - y_i)[F(\theta(i))(C^F + C(i)^L) - (1 - F(\theta(i)))C(i)^L] \} \tag{12}$$

Any downtime due to delay of corrective maintenance causes loss of production $C(i)^L$. This delay cost is defined as follows:

$$C(i)^L = Pw(v(i)) \times W^{price} \tag{13}$$

where W^{price} is the energy price per kWh . To account for the imperfect maintenance and its impact on the equivalent age, let $M(i)$ be a maintenance function that acts as an age reduction after a maintenance activity in day i . This definition affects aging behaviour directly after maintenance and restores equipment age to a younger state but not to a perfect condition. While the turbine might experience some performance degradation after maintenance actions, in this paper we assume that the turbine will operate in full power after each maintenance. However, the equivalent age of the turbine must be updated to reflect any age reduction due to maintenance. Let $M^P(i)$ and $M^R(i)$ be the age reduction for PM and CM actions respectively:

$$M(i) = \begin{cases} 0, & \text{if the system is functioning} \\ M^P = e^{-\frac{2i}{L}}, & \text{if the system is in PM} \\ M^R = R, & \text{the system is in CM} \end{cases} \tag{14}$$

where L is the planned lifetime of the turbine and R is a constant proportion of the equivalent age at the time of the corrective maintenance. Then the equivalent age $\theta(i)$ at any given day i is:

$$\theta(i) = \sum_{k=1}^i (\alpha_0^{q(k)} - M(k)) \tag{15}$$

After each maintenance action, the nominal aging rate α_0 increases by a small increment λ to describe the aging evolution of the system with a faster deterioration rate after each imperfect maintenance. Assuming constant weather conditions, this problem can be solved as a simple age-based maintenance policy. The probabilistic behaviour of aging under different weather conditions is often neglected in the condition-based maintenance literature. Another major weather-related consideration in wind farm maintenance is the accessibility of a turbine. To ensure safe access to a wind farm, weather conditions must be suitable to perform required maintenance.

To perform maintenance, we assume weather conditions should be within allowed limits during the day of maintenance. In this paper, we assume a turbine is only accessible if wind speed is below a safe threshold v_s and the ambient temperature is within the range of $(T_l$ to $T_u)$. Therefore, we can rewrite the binary maintenance variables x_i and y_i as:

$$x_i = \begin{cases} 1, & \text{if } \begin{cases} (p^{pm} \leq Pr(1) < p^{cm}), \\ (v(i) < v_s), \\ (T_l < T(i) < T_u) \end{cases} \\ 0, & \text{otherwise} \end{cases} \tag{16}$$

$$y_i = \begin{cases} 1, & \text{if } \begin{cases} (Pr(1) \geq p^{cm}), \\ (v(i) < v_s), \\ (T_l < T(i) < T_u) \end{cases} \\ 0, & \text{otherwise} \end{cases} \tag{17}$$

Assuming current and near future weather conditions are known, any triggered maintenance action is delayed until weather conditions become favorable. When weather conditions are unfavorable upon reaching the first maintenance threshold, *PM* work is delayed and the turbine continues to operate until the weather becomes favorable. If the turbine fails or the *CM* threshold is reached, any delay due to harsh weather incurs $C(i)^L$ production losses per day because the turbine cannot operate until *CM* is completed.

Determining the next maintenance decision, daily, can only indicate whether maintenance actions should be taken in that particular day and may result in lower or higher cost per maintenance action. Due to the probabilistic nature of this maintenance model with varying wind speed and temperature, it is very difficult to be modeled using analytical models only, as the parameters involved are time variant and their values cannot be captured analytically. However, simulation models are very helpful to address dynamic conditions in the study of condition-based maintenance.

3. Solution Approach

To evaluate the performance of the proposed maintenance model over the 20 years' service life of a wind turbine, weather conditions are required for the entire period. Due to the complexity of weather forecasting, we use historical weather data to generate hourly wind speed and temperature measurements. To illustrate the stochastic nature of weather conditions, we first fit the historical data to a statistical distribution, then use Markov Chain Monte Carlo (MCMC) method

to generate N samples of wind speed and temperature profiles. MCMC has been widely used in literature to generate synthetic wind speed and wind power time series due to its ability to accurately replicate the statistical properties of hourly wind speeds compared to other approaches like autoregression and wavelet-based models [45-47].

Suppose failure distribution of a wind turbine is known, and the equivalent age values at each instant can be computed. The simulation model of the proposed maintenance model can then calculate the average cost for each weather profile. Algorithm 1 summarizes the simulation procedure. The detailed simulation steps are:

Step 1: Define model inputs for a specific wind turbine and a specific location. Specify Weibull parameters, maintenance costs, age reduction values of each maintenance action, nominal wind and temperature effect values, power curve parameters and wind turbine specifications.

Step 2: Obtain weather data from land weather stations near the selected site. Extract hourly wind speed and temperature measurements into monthly time series to capture the seasonal variations and trends in weather conditions. Wind speed measurements are typically taken from land stations at low height h_1 . Therefore, all wind speed v_1 values at height h_1 are extrapolated using the power law to estimating wind speed v_2 values at the hub height h_2 :

$$v_2 = v_1 \left(\frac{h_2}{h_1} \right)^\kappa \tag{18}$$

where κ is the power exponent for different types of terrain and atmospheric stability conditions. Fit data to their corresponding statistical distributions. Hourly air temperature measurements are fit to normal distribution with mean μ and standard deviation σ [48]. Weibull distribution is widely used to model wind speed v [49-51]. The probability density function is given by:

$$f(v; c, k) = \frac{k}{c} \left(\frac{v}{c} \right)^{k-1} \exp\left(-\left(\frac{v}{c}\right)^k\right), v \geq 0 \tag{19}$$

where k and c are the shape and scale parameters respectively. This procedure is applied month by month to preserve seasonality in wind speed and air temperature. Statistical parameters can be different from month to month, meaning each month has an associated Normal and Weibull parameters defining hourly air temperature and wind speed distributions from that month.

Algorithm 1 Proposed simulation procedure

Input: Global parameters ($t^{max}, \eta, \beta, \alpha_0, \delta_0, \gamma_0, C^F, C^P, C^R, M^P, M^R, p^{pm}, p^{cm}$)	
<hr/>	
1:	$t \leftarrow$ zero
2:	$\theta \leftarrow$ zero
3:	$t_f \leftarrow$ generate a random failure time. {using Weibull distribution (η, β)}
4:	for $j = 1$ to $iter$ do :
5:	for $i = 1$ to t^{max} do :
6:	$q(i) \leftarrow \delta(v(i)) + \gamma(T(i))$ {compute the weather effects}
7:	$\theta(i) \leftarrow \alpha_0^{q(i)} + \theta(i - 1)$ {compute the equivalent age}
8:	$Pw(v(i)) \leftarrow$ using equation (4) {compute the wind power}

9:	$Pr(1) \leftarrow$ using equation (9)	{compute the conditional failure probability}
10:	if $\theta(i) \geq t_f$ then	
11:	if $((v(i) < v_s) \& (T_l < T(i) < T_u))$ then	{check weather conditions}
12:	$C(i) \leftarrow C^R + C^F$	{maintenance cost due to failure}
13:	$M(i) \leftarrow M^R$	{age reduction due to corrective maintenance}
14:	$\theta(i) \leftarrow \theta(i) - M(i)$	{update the equivalent age}
15:	$t_f \leftarrow \theta(i) + \text{random.weibull}(\eta, \beta)$	{generate a new failure time}
16:	$\alpha_0 \leftarrow \alpha_0 + \lambda$	{update the nominal aging rate}
17:	else	
18:	$C(i) \leftarrow C(i)^L$	{compute delay cost using equation (13)}
19:	$\theta(i) \leftarrow \theta(i - 1)$	{failure age}
20:	end if	
21:	else if $Pr(1) \geq p^{cm}$ then	{check corrective maintenance threshold}
22:	if $((v(i) < v_s) \& (T_l < T(i) < T_u))$ then	{check weather conditions}
23:	$C(i) \leftarrow C^R$	{corrective maintenance cost}
24:	$M(i) \leftarrow M^R$	{age reduction due to corrective maintenance}
25:	$\theta(i) \leftarrow \theta(i) - M(i)$	{update the equivalent age}
26:	$t_f \leftarrow \theta(i) + \text{random.weibull}(\eta, \beta)$	{generate a new random failure time}
27:	$\alpha_0 \leftarrow \alpha_0 + \lambda$	{update the nominal aging rate}
28:	else	
29:	$C(i) \leftarrow C(i)^L$	{compute delay cost using equation (13)}
30:	$\theta(i) \leftarrow \theta(i - 1)$	{turbine is down}
31:	end if	
32:	else if $Pr(1) \geq p^{pm}$ then	{check preventive maintenance threshold}
33:	if $((v(i) < v_s) \& (T_l < T(i) < T_u))$ then	{check weather conditions}
34:	$C(i) \leftarrow C^P$	{preventive maintenance cost}
35:	$M(i) \leftarrow M^P$	{age reduction due to preventive maintenance}
36:	$\theta(i) \leftarrow \theta(i) - M(i)$	{update the equivalent age}
37:	$t_f \leftarrow \theta(i) + \text{random.weibull}(\eta, \beta)$	{generate a new failure time}
38:	$\alpha_0 \leftarrow \alpha_0 + \lambda$	{update the nominal aging rate}
39:	end if	
40:	end if	
41:	end for	
42:	$TC(j) \leftarrow \sum_{i=1}^{t^{max}} C(i)$	{compute total cost for each iteration}
43:	end for	
44:	return $\leftarrow E(TC)$	{compute the expected total cost}

Step 3: Using MCMC, generate Z time series of size $(m \times n)$ of hourly wind speeds $((v_1(\cdot), v_2(\cdot), v_3(\cdot) \dots, v_z(\cdot)))$ and ambient air temperatures $((T_1(\cdot), T_2(\cdot), T_3(\cdot) \dots, T_z(\cdot)))$ using their corresponding distributions previously obtained in Step 2. $T_z(i, j)$ and $v_z(i, j)$ represent the

values in the weather profile z of the ambient temperature and wind speed during hour i and month j . Where n the number of months and m is represents the number of hours in a month.

Step 4: Set initial age and time to zero, total simulation time to t^{max} (hours), the maximum number of iterations to $iter$. Define initial aging rate α_0 and initial maintenance thresholds p^{pm} and p^{cm} . Generate the first random failure time t_f from the Weibull distribution defined in step 1.

Step 5: Start the simulation model for weather profile z with discrete time steps in 1-hour intervals i . Calculate hourly weather effects $q(i)$, cumulative equivalent age $\theta(i)$ and output power $Pw(v_i)$ using the IEC 61400-12-1 standard [52].

Step 6: Every 24 hours, check $\theta(i)$ against t_f . If $\theta(i) < t_f$, then check the conditional probability of failure within a day $Pr(1)$ against CM threshold p^{cm} . If $(\theta(i) < t_f$ and $Pr(1) < p^{cm})$, then check $Pr(1)$ against PM threshold p^{pm} . Otherwise, if $(\theta(i) < t_f$ and $Pr(1) < p^{pm})$ then no action is required. Skip steps 7-8.

Step 7: If $\theta(i) \geq t_f$ or $Pr(1) \geq p^{cm}$ and weather conditions are favorable then perform corrective maintenance. Set y_i to one, x_i to zero and $M(i)$ to M^R . Update current equivalent age $\theta(i)$, aging rate α_0 , failure time t_f and maintenance cost C . If weather conditions are not favorable, wind turbine is assumed down for the next 24 hours and production loss cost $C(i)^L$ is accumulated for each 24 hours until weather conditions become favorable.

Step 8: If $(\theta(i) < t_f)$ and $(p^{pm} \leq Pr(1) < p^{cm})$ and weather conditions are favorable then perform preventive maintenance. Set x_i to one, y_i to zero and (i) to M^P . Update current equivalent age $\theta(i)$, aging rate α_0 , failure time t_f and maintenance cost $C(i)$. If weather conditions are not favorable, PM is delayed until weather conditions become favorable and wind turbine is assumed operating until the next inspection.

Step 9: If $i < t^{max}$, return to step 5. If $i \geq t^{max}$ and $j < N$, calculate total cost $TC(j)$ and return to step 4. If $i \geq t^{max}$ and $j \geq N$, terminate simulation and calculate the expected total cost $E(TC)$:

$$E(TC) = \sum_{j=1}^N \frac{TC(j)}{N} \quad (20)$$

Step 10: Finally, a minimum search algorithm (Nelder-Mead) is applied to update the initial threshold values in step 4 and determine the optimal threshold values p^{pm} and p^{cm} that minimize the expected total maintenance cost $E(TC)$.

We follow the procedure of the Nelder-Mead method described in [53] for constrained optimization problems. Nelder-Mead method (Algorithm 2) is a gradient free heuristic that uses geometric patterns to minimize the objective function in n dimensions space. The procedure involves ordering the vertices of the simplex and replacing the worst point with a point reflected through the centroid of the remaining vertices. The simplex then can expand away from the worst point, contract away from the worst point in one direction, or shrink towards the best point. The algorithm terminates when the maximum number of iterations is reached or the difference between the best and worst objective function values of the current simplex is smaller than a positive scalar ϵ .

Nelder-Mead is suitable to solve our mixed-integer nonlinear problem. It is easy to implement and needs on average two function evaluations per iteration. However, it is very sensitive to the

initial starting point witch is not desirable to find global minimum. To avoid this issue, we repeat the algorithm with randomly generated starting points between the upper bound x_i^U and the lower bound x_i^L . The algorithm is implemented in MATLAB using the suggested control parameters in the literature [54] as shown in Table 1.

Table 1 Optimization control parameters.

Parameter	Description	Value
<i>iter</i>	Iterations number	1000
x_0	starting point vector	1
<i>r</i>	reflection coefficient	1
<i>e</i>	expansion coefficient	2
<i>c</i>	contraction coefficient	0.5
<i>s</i>	shrinkage coefficient	0.5
ϵ	solution change tolerance	10^{-6}

Algorithm 2 Nelder-Mead Method.

Input:

call the simulation algorithm (algorithm 1).
 randomly generate an initial solution $x_0(p^{pm}, p^{cm})$.

- 1: **repeat**
- 2: order the vertices of the simplex such that: $E(TC(x_0)) \geq E(TC(x_1)) \geq E(TC(x_2)) \dots \dots \geq E(TC(x_n))$
- 3: compute the centroid x_g of all the points: $x_g = \frac{1}{n} \sum_{i=1}^n x_i$
- 4: compute the reflection of x_n in respect to the centroid: $x_r = x_g + r(x_g - x_n)$
- 5: **if** $E(TC(x_r)) > E(TC(x_{n-1}))$ **then**
- 6: compute the expansion point: $x_e = x_g + e(x_g - x_n)$
- 7: **if** $E(TC(x_e)) > E(TC(x_r))$ **then**
- 8: replace x_n with x_e
- 9: **E else**
- 10: replace x_n with x_r
- 11: **E end if**
- 12: **else**
- 13: compute the contraction point: $x_c = x_g + c(x_g - x_n)$
- 14: **if** $E(TC(x_c)) \geq E(TC(x_n))$ **then**
- 15: replace x_n with x_c
- 16: **else**
- 17: shrink the simplex
- 18: **for all** x_i **do**
- 19: replace x_i with: $x_i = x_g + s(x_i - x_g)$
- 20: **end for**

21: **end if**
 22: **end if**
 23: **until** convergence

4. Numerical Results

In this section, we present a numerical example illustrating the proposed maintenance policy. We assume that the wind farm maintenance decisions are made on daily basis. Appropriate parameter values are selected based on the published data or discussions with our industry partners. We present four simulation scenarios to highlight the performance of the proposed model at different geographical locations and compare it to traditional age-based models. First, we select a specific wind turbine (Enercon E-126 [55] with wind curve parameters as shown in Table 2. We also identify three different regions and obtain their historical weather data from the National Oceanic and Atmospheric Administration (NOAA) [56]. Hourly data measurements were collected from 15 land-based weather stations in three states (Texas, California, and Illinois) for the period from 2015 to 2018. The raw data are then extrapolated from the land station height ($h_1 = 3m$) to hub height ($h_2 = 135$) using Equation 18. After fitting the historical wind speed and temperature data with their corresponding distributions, MCMC was used to generate 5 stochastic hourly weather condition time series for each state for the entire service life of 20 years. Table 3 shows summary statistics for the raw historical data. To compare each scenario, we conduct simulations using the same parameter values explained in Table 4. We simulate the turbine equivalent age and weather conditions for each instance with 100 replications, performed over 7300 days (20 years). Then, we obtain the average maintenance cost per day and the failure and maintenance frequencies per year.

Table 2 Enercon E-126 wind turbine information.

Parameter	Description	Value
$P_{w_{rated}}$	Rated power (kW)	7580
v_{rated}	Rated wind speed (m/s)	17
v_{in}	Cut-in wind speed (m/s)	2.5
v_{out}	Cut-out wind speed m/s	25
L	Service life(years)	20
C_0	Maximum power coefficient	0.48
d_r	Rotor diameter (m)	127
h_2	Hub height (m)	135

Table 3 Summary statistics of raw hourly weather data.

	Wind Speed (m/s)			Air Temperature (°C)			
	max	μ	σ	max	min	μ	σ
Texas	50	6.5	4	41	-11	20	8.2
California	43	4.2	3.5	42	-6	15.5	6.9

Illinois	36	3.2	2	38	-30	10	11
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Table 4 Reliability and maintenance parameters.

Parameter	Description	Value
β	Weibull Shape	3
η	Weibull Scale (days)	2400
C^P	PM Cost (1000 \$)	38
C^R	CM Cost (1000 \$)	63
C^F	Failure Cost (1000 \$)	150
w^{price}	Wind Price (\$/kWh)	0.05
M^P	PM age reduction factor	0.3
M^R	CM age reduction factor	0.6
α_0	Nominal aging rate	1.3
δ_0	Effect of ambient temperature	-5
γ_0	Effect of idle wind turbine	-10

Table 5 and Table 6 summarize the simulation results of each maintenance scenario under both traditional and proposed age models, respectively. The optimal maintenance policy obtained by our proposed approach shows remarkable reductions in both failure frequency and maintenance costs compared with the traditional age-based approach. The daily maintenance costs are decreased by 50%, 39.3% and 23.7% for California, Illinois and Texas respectively, demonstrating the cost reduction that can be achieved by adopting the proposed strategy.

Table 5 Optimal maintenance thresholds and costs using the traditional model.

	Texas	California	Illinois
PM Threshold (%)	0.069	0.054	0.109
CM Threshold (%)	0.105	0.059	0.118
PM Rate (per year)	0.45	0.6	0.35
CM Rate (per year)	0.025	0.055	0.007
Failure Rate (per year)	0.032	0.01	0.035
Downtime (days/year)	24.8	7.75	10.25
Maintenance Cost (\$/day)	83.0	62.9	69.5

Table 6 Optimal maintenance thresholds and costs using the proposed model.

	Texas	California	Illinois
PM Threshold (%)	0.081	0.038	0.093

CM Threshold (%)	0.127	0.046	0.108
PM Rate (per year)	0.405	0.29	0.31
CM Rate (per year)	0.045	0.005	0.007
Failure Rate (per year)	0.025	0.0165	0.005
Downtime (days/year)	15.85	3.8	4.35
Maintenance Cost (\$/day)	63.3	31.42	42.2

We can compare our policy that uses weather information gained from historical data, with traditional age-based policies that do not include weather conditions. We compare these policies under the same weather accessibility constraints recommended in the literature [57, 58]. We assume maintenance can only be carried out if wind speed is below 10 m/s and ambient temperature is within the range of -15° to 25° . We use a Weibull-based reliability model, widely used in the literature [20, 59] with Weibull parameters and maintenance costs as given in Table 4.

We repeat this simulation procedure 100 times for each weather profile with different initial random failure time and calculate the optimal threshold values that minimize the average daily cost of maintenance over the entire period for each scenario. We also track average daily operational revenue, average number of unexpected failures and preventive and corrective maintenance, for better comparison. To verify that our results from the proposed simulation model and the Nelder-Mead algorithm are indeed optimal or near optimal, we run our model several times with different randomly generated initial feasible solutions. The algorithm is implemented in MATLAB 2018b and all experiments are run with an Intel Core i7-4790K 4.0 GHz CPU on Windows 10 machine with 24 GB RAM. Each simulation run takes 20 seconds on average while the average time till convergence is 8.1 minutes. The stopping criteria used to terminate the optimization procedure is an error of 10^{-6} of the function values. Figure 2 shows an example of the number of iterations until convergence required by the Nelder-Mead algorithm for each weather scenario.

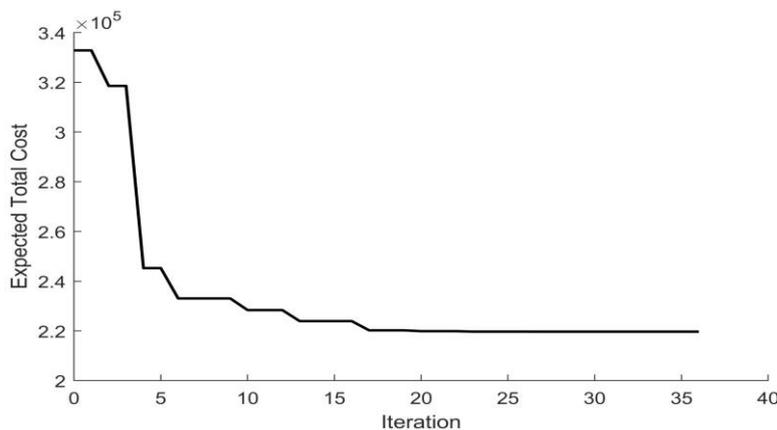
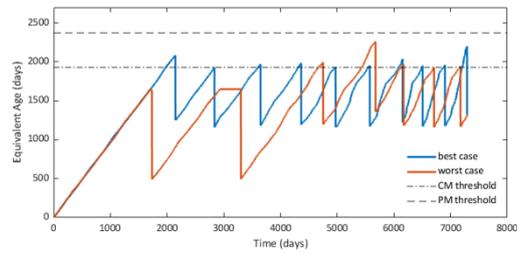


Figure 2 Number of iterations for convergence of the proposed model to the optimal solution.

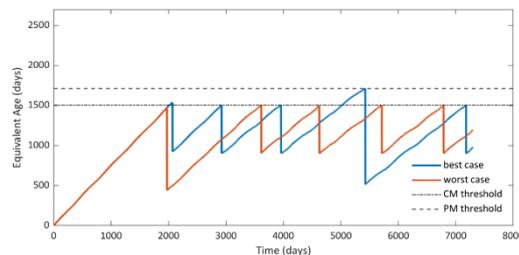
First, we run the simulation model under traditional age-based preventive maintenance using only the Weibull distribution function described in Table 4. In the case of California, the optimal preventive maintenance threshold is 0.054 with an average maintenance cost of (\$62.9 per day), which is twice the average maintenance cost obtained by the proposed model as shown in Table 5.

The expected number of failures, PM, CM and downtime days per year are all higher as well. In this example, California represent the least harsh environment and thus, under our model the turbine will have slower aging and lower failure rate. However, the traditional approach does not take that into account, resulting in over maintaining the system over the entire service life.

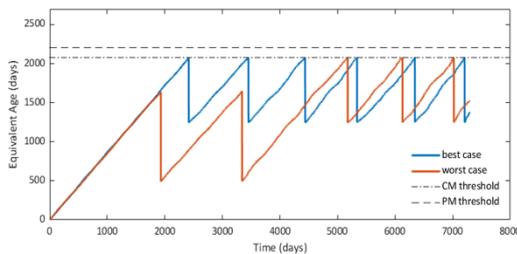
Figure 3 shows the best and worst case results for each state from the simulation study with 100 iterations, where each iteration consists of 5 weather profiles. Moreover, Figure 3 illustrates the effect of imperfect maintenance, weather constraints and weather profiles on overall aging of the system.



(a) Texas



(b) California



(c) Illinois

Figure 3 Best and worst case simulation results for each state.

The lifetime distribution function in traditional models is independent of weather conditions and thus the optimal solution may underestimate or overestimate the component lifetimes under different usage and weather conditions. In the case of Texas and Illinois, the proposed model shows significant improvement in availability over the traditional approach, reducing the average downtime from 24.8 days/year to 15.85 days/year in Texas. Texas has harsh weather with a wide range of temperatures and high wind speeds, causing higher downtime and revenue losses. The failure rate in the Illinois case is also significantly lower under our model (0.005 failure per year) compared to (0.035 failure per year) using the traditional approach.

All scenarios presented in this section are used to illustrate the effect of weather conditions at different locations over the same type of wind turbine. The equivalent age is obtained by simulating

the proposed model using the optimal threshold values and various weather profiles for all three states. The optimal threshold values with the lowest average daily maintenance cost were obtained using the Nelder-Mead method. Texas has the highest expected maintenance cost of (\$63.3 per day) with thresholds values of $p^{cm} = 0.081\%$ and $p^{pm} = 0.127\%$. Texas weather profiles have higher wind speeds and temperatures on average as presented in Table 2 which results in faster aging process and more inaccessible days due to weather constraints. California on the other hand, has the lowest expected maintenance cost of (\$31.42 per day) with thresholds values of $p^{cm} = 0.038\%$ and $p^{pm} = 0.046\%$.

As shown in the results, the threshold values are higher under harsh environment reflecting the faster aging of the turbine and thus, reaching the thresholds faster. The width of the preventive maintenance window (the difference between the two thresholds) is also higher under harsh weather as we can see in the case of Texas and Illinois compared to California. This is to allow operators more time because of the limited accessibility to the farm due to unfavorable weather conditions. The results presented in Table 6 demonstrates the advantage of the proposed model over the traditional age-based policy in Table 5 in providing more scenario specific results.

5. Conclusions

In this paper we construct a weather-based equivalent age model for choosing the most cost-effective maintenance actions under specific weather scenarios. We develop a two-threshold maintenance simulation model for wind turbines to respond to the time-varying weather conditions. We examine the impact of wind speeds and air temperatures on wind turbine maintenance with imperfect repairs, accessibility constraints and revenue losses. The proposed simulation model uses historical weather data to generate 20-year-long weather measurements for given locations, and use equivalent age model with Weibull distribution to estimate wind turbine aging under different weather profiles. We show the advantage of our approach to generate scenario-based results that are less dependent on generic lifetime distributions. The economic impact of multiple wind and temperature profiles with two maintenance levels are evaluated with and without the proposed age model. The results show that in all cases, the implementation of age model both reduces the average daily cost of maintenance by more than 23% and the average downtime by more than 49% when compared to the traditional age-based approach. The proposed model has successfully maintained lower number of failures per year and therefore minimized revenue losses. At the highest level of wind speed and temperature variations, the results show that our model is capable of significantly reducing the total cost by 50% compared to traditional models. Age reduction due to imperfect maintenance can be observed in all cases which results in reduction of time between maintenance actions. Maintenance frequencies can be significantly reduced when the proposed model is applied instead traditional age models.

There are several aspects in our modeling that warrant further investigation. In this paper, we assume that aging can be calculated precisely via monitoring. However, in many cases, aging is a stochastic process with more than two conditions involved, requiring to more data intensive models. Extending the model to account for other operating and environment conditions would allow for more accurate condition-based maintenance policy using the adaptive strength of this model. We also assume the entire turbine is one component with known Weibull parameters. We used this simplified model to allow for an intuitive and clear demonstration of our proposed approach. In

practice, wind turbines should be modeled as a system of components with their own parameters. Future work could extend the model to incorporate multiple wind turbines. In this study we assume maintenance is instantaneous. However, when a turbine fails, maintenance activities may not start immediately and repairing activities may take up to several days.

Author Contributions

Ali Aldubaisi: Research, data validation, algorithm codes, paper draft, and results. Jorge Valenzuela: Conceptualization, methodology, supervision, revision.

Competing Interests

The authors have declared that no competing interests exist.

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