An Optimal Number-Dependent Preventive Maintenance Strategy for Offshore Wind Turbine Blades Considering Logistics

Hindawi Publishing Corporation
Advances in Operations Research
Volume 2013, Article ID 205847, 12 pages
http://dx.doi.org/10.1155/2013/205847

Research Article

An Optimal Number-Dependent Preventive Maintenance Strategy for Offshore Wind Turbine Blades Considering Logistics

Mahmood Shafiee, Michael Patriksson, and Ann-Brith Strömberg

Department of Mathematical Sciences, Chalmers University of Technology and University of Gothenburg, SE-412 96 Gothenburg, Sweden

Correspondence should be addressed to Mahmood Shafiee; mahsha@chalmers.se

Received 18 March 2013; Accepted 18 June 2013

Academic Editor: Shey-Huei Sheu

In offshore wind turbines, the blades are among the most critical and expensive components that suffer from different types of damage due to the harsh maritime environment and high load. The blade damages can be categorized into two types: the minor damage, which only causes a loss in wind capture without resulting in any turbine stoppage, and the major (catastrophic) damage, which stops the wind turbine and can only be corrected by replacement. In this paper, we propose an optimal number-dependent preventive maintenance (NDPM) strategy, in which a maintenance team is transported with an ordinary or expedited lead time to the offshore platform at the occurrence of the Nth minor damage or the first major damage, whichever comes first. The long-run expected cost of the maintenance strategy is derived, and the necessary conditions for an optimal solution are obtained. Finally, the proposed model is tested on real data collected from an offshore wind farm database. Also, a sensitivity analysis is conducted in order to evaluate the effect of changes in the model parameters on the optimal solution.

1. Introduction

Wind energy has become an attractive source of renewable energy in the European energy market because it is free, abundant, and perceived as having a low impact on the environment. Over the past five years (2008–2012), the wind energy industry has been the fastest growing renewable energy source with an annual average growth rate of 28% [1]. For instance, in Sweden, 763 MW of wind power (onshore and offshore) was installed in 2011 which increased the wind power capacity to 2906 MW—about 2% of the total electricity consumption [2]. Certain forecasts indicate that the share of wind power in Sweden's electricity generation will reach up to 20% by 2020.

Nowadays more and more wind turbines are being installed offshore due to the high potential of wind energy, less visual disturbance, and larger potential areas for installation. Presently, there are five offshore wind farms in the sea waters of Sweden (Lillgrund, Vanem, Utgrunden, Yttre Stengrund, and Bockstigen) with a total operating capacity of 163.7 MW [3]. However, a wind power system located at sea comes with higher installation costs and more difficult maintenance conditions compared to an onshore system. Furthermore, an offshore wind turbine has undesirable features like a higher failure rate, lower reliability, and higher operation and maintenance (O&M) costs. The O&M costs of onshore wind turbines account for around 20–25% of the wind energy generation cost, whereas in offshore wind farms, they represent a larger portion of the costs—up to 30% [4]. Therefore, there is a critical need to optimize the maintenance management of offshore wind turbines in order to reduce the O&M costs.

The literature on the optimization of maintenance strategies (opportunistic maintenance, reliability centered maintenance, and condition-based maintenance) in the wind energy industry is significant. Byon et al. [5] develop an optimization model to derive an optimal preventive maintenance strategy such that the expected average cost of a wind turbine

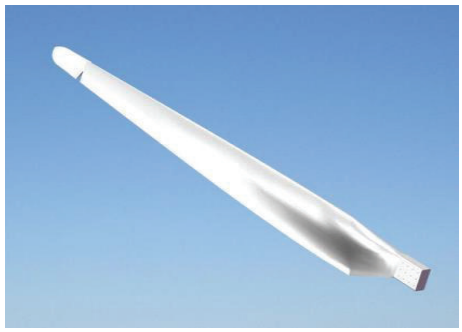

Figure 1: A wind turbine blade made of fibreglass reinforced plastic.

under stochastic weather conditions is minimized. Byon and Ding [6] propose a season-dependent optimal maintenance strategy for a multistate deteriorating wind turbine in order to reduce the operation costs and enhance the marketability of wind power. Tian et al. [7] apply an artificial neural network approach to optimize the condition monitoring strategy for a wind farm assuming the same lead times for all maintenance activities. Nielsen and Sørensen [8] propose an optimal risk-based maintenance strategy for an offshore wind turbine with a single critical component. Ding and Tian [9, 10] develop three opportunistic optimization strategies based on perfect, imperfect, and two-level actions for wind turbines and apply a simulation optimization method to evaluate the maintenance cost of the proposed strategies.

Among the wind turbine components, the blade is one of the most critical and expensive components, whose function is to convert the kinetic energy into mechanical energy. According to the 2003 Netherlands wind energy report, 34% of the total number of failures in offshore wind farms was due to blades failure [11]. Also, a recently conducted study on wind farms in India indicates that the blades system is the most critical cause of turbine failure during the first five years of operation [12].

The blades are usually made from composite materials such as fibreglass reinforced plastic (see Figure 1) with an expected useful lifetime of twenty years. However, in offshore wind farms, the useful lifetime of a blade is significantly shorter than its expected lifetime. The reason is that the blades are "stressed" in a harsh maritime environment and extreme weather conditions and suffer from different types of damages (such as wear, fatigue, deterioration, crack, corrosion, and erosion) [13].

Basically, the damages of wind turbine blades can be categorized into two types. One is a minor damage (such as microscopic cracks arising from fatigue) which is usually detected by *online* condition monitoring techniques (for more details see [14]). This type of damage weakens the system and causes a loss in wind capture without resulting in any turbine stoppage. The other one is a major (catastrophic) damage (such as a metre long fracture) which leads to a turbine system failure and stops the whole wind turbine.

In this paper, we assume that a maintenance team is transported to the offshore platform at the occurrence of the Nth minor damage (to perform preventive maintenance) or the first major damage (to perform corrective replacement), whichever comes first. In practice, N is the damage threshold for performing (PM) action which is considered to be a decision variable under the control of the wind farm manager and should be optimized. This strategy, namely, number-dependent preventive maintenance (NDPM), was first considered by Makabe and Morimura [15–17] and later extended by Morimura [18] and Park [19]. Since then, it has been considered from many different aspects such as when the system is subject to two types of minor and major failures (see Nakagawa [20], Sheu and Griffith [21]); with age-dependent repair costs (see Sheu [22], Sheu et al. [23]); under a repair-cost limit (see Park [24], Chang et al. [25], and Sheu et al. [26]); and with spare parts consideration (see Sheu and Chien [27], Chien [28, 29]).

In addition, most maintenance optimization models in the literature are based on the assumption that the maintenance team is immediately transported to the offshore platform. However, this assumption is unrealistic, as it is often the case that the maintenance team is sent only when the transportation means (ships, helicopters), specialized equipment (lifting cranes), and spare parts become available. Also, in some cases, the maintenance team has to wait for a number of days due to bad weather and sea conditions and then travel to the offshore platform. Since the offshore wind turbines are less accessible and/or are subject to very high costs for transport, an NDPM strategy possesses a huge potential for reducing the maintenance costs and enhancing the reliability of wind turbines, if applied properly.

In this paper, we propose an optimization model to determine the optimal number of minor damages allowed to occur in a blades system before sending a maintenance team to perform preventive maintenance actions. Our objective function is to minimize the long-run expected cost which includes all costs due to corrective replacement, preventive maintenance, logistics, and production loss. To our knowledge, this paper is the first attempt to optimize the NPDM strategy for offshore wind turbine blades subject to damages.

The rest of this paper is organized as follows. In Section 2, we present the problem definition. In Section 3, we describe the model components and use these in Section 4 to formulate our optimization model. In Section 5, the proposed model is tested using real data from an offshore wind farm database. Finally, in Section 6, we conclude this study with a brief discussion on topics for future research.

2. Problem Definition

Suppose that the lifetime T of a wind turbine blade has the density function $f : R_+ \mapsto [0, 1]$, cumulative distribution function $F : R_+ \mapsto [0, 1]$, defined by $F(t) = \int_0^t f(x)dx$, and survival function $\overline{F} : R_+ \mapsto [0, 1]$, defined by $\overline{F}(t) = 1 - F(t)$ with $\overline{F}(0) = 1$.

We consider a preventive maintenance model of a blades system, in which the system consists of n_b i.i.d. blade lifetimes in series and is subject to damages. Suppose that the number of damages arriving in the interval $[0, t)$ in each blade is a nonhomogenous Poisson process (NHPP) with an intensity

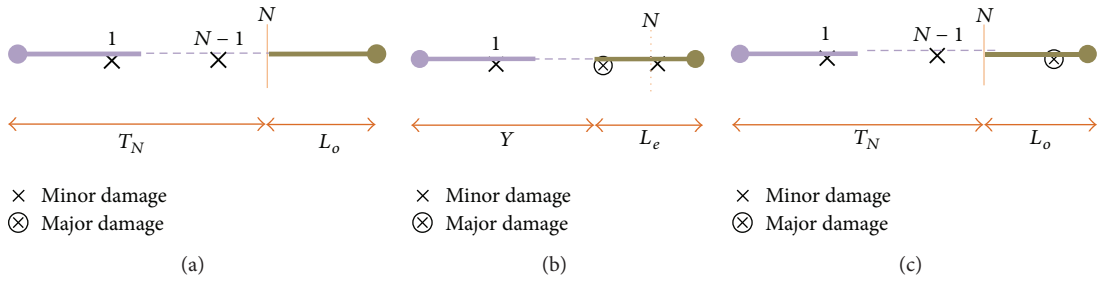

Figure 2: Three cases of an NDPM cycle.

function $h(t)$, defined by $h(t) = f(t)/\overline{F}(t)$, and a mean value function $H(t)$, defined by $H(t) = \int_0^t h(x)dx$ with $H(0) = 0$. The assumption of NHPP has been considered extensively in shock and damage modelling in various domains (see, e.g., [30]) as well as wind energy industry (see [31]).

Further, it is assumed that the probability that a certain damage is a minor (major) damage is q $[p = 1-q]$, where $0 \leq p, q \leq 1$. The case $p = 0$ $(p = 1)$ indicates that the damages are always minor (major). In this paper, the probability p is considered as a constant value. However, this is unrealistic in some situations, especially in offshore environments. Then, a possibly more flexible model could be suggested by assuming p as a weather-dependent function, which will be considered in our future work.

In the model to be developed in this article, the maintenance team is transported with an ordinary or expedited lead time to the offshore platform at the occurrence of the Nth minor damage or the first major damage, whichever comes first. More precisely, the decision to repair or replace the blades system is made according to the following scheme (see Figure 2).

(a) No Major Damage Occurs before the Nth Minor Damage or during the Ordinary Logistics Lead Time following the Nth Minor Damage (Figure 2(a)). In this case, the maintenance expeditions are initiated immediately after the Nth minor damage, and the maintenance team is transported as soon as weather and sea conditions permit. Let $L_o > 0$ $[c_o > 0]$ denote the ordinary logistics lead time (cost), where L_o is the length of the interval between the time at which the maintenance decision is made and the time when the maintenance is performed and c_o is the total cost of *hiring the service vessels, ordering* spare parts, and transporting the maintenance team. Here, the maintenance strategy is to perform a perfect or complete preventive maintenance action on each blade at a cost c_p, which returns the blades system to an "as-good-as-new" state.

(b) A Major Damage Occurs before the Nth Minor Damage (Figure 2(b)). In this case, the blades system will be nonoperational and the wind turbine is shut down. Since such an event is costly, an *expedited* logistics plan is initiated at a shorter-than-ordinary lead time, but higher-than-ordinary cost [32]. We define the expedited logistics lead time, L_e, as follows:

$$L_e = L_o - \xi_L, \tag{1}$$

where ξ_L (≥ 0) is the "expedited lead time term", and the expedited logistics cost, c_e is

$$c_e = c_o + \xi_c, \tag{2}$$

where ξ_c (≥ 0) is the "expedited cost term". Here, the maintenance strategy is to perform a corrective replacement on the failed blade at a cost c_r $(> c_p)$ and a perfect PM action on each un-failed blade.

(c) No Major Damage Occurs before the Nth Minor Damage, but a Major Damage Occurs during the Ordinary Logistics Lead Time following the Nth Minor Damage (Figure 2(c)). In this case, the wind turbine is shut down until the ordinary lead time has elapsed during which the maintenance team performs maintenance activities. Here, the maintenance strategy is the same as for case (b).

Let the random variable T_i, $i = 1, 2, \ldots$, represent the waiting time until the ith minor damage occurs in the blades system. Since the minor damages in the blades system occur according to an NHPP with a mean value function $qn_bH(t)$, the survival function of T_i is given by

$$\begin{aligned}\overline{F}_{T_i}(t) &= \Pr\left(T_i > t\right) = \sum_{k=0}^{i-1} P_k(t) \\ &= \left[\overline{F}(t)\right]^{qn_b} \times \sum_{k=0}^{i-1} \frac{\left[qn_bH(t)\right]^k}{k!}, \quad t \geq 0,\end{aligned} \tag{3}$$

where $\overline{F}(\cdot)$ and $H(\cdot)$ denote, respectively, the survival and the cumulative distribution function of each blade. $P_k(t)$ is the conditional probability of k minor damages occurring during the time interval $[0, t)$ on knowing that no major damage has occurred within $[0, t)$ and can be expressed as

$$\begin{aligned}P_k(t) &= \overline{F}_{T_{k+1}}(t) - \overline{F}_{T_k}(t), \\ k &= 0, 1, 2, \ldots, \quad \text{with } \overline{F}_{T_0}(t) = 0.\end{aligned} \tag{4}$$

Further, let Y denote the time to the first major damage in the blades system. Since the minor damages in the blades system occur at an NHPP with a mean value function

$pn_bH(t)$, the survival and the distribution function of Y, respectively, are given by

$$\overline{F}_Y(y) = \Pr(Y > y) = e^{-pn_bH(y)} = \left[\overline{F}(y)\right]^{pn_b}, \quad y \geq 0, \tag{5}$$

$$f_Y(y) = -\frac{d}{dy}\,\overline{F}_Y(y) = pn_b h(y)\,\overline{F}_Y(y), \quad y \geq 0. \tag{6}$$

The following fact will be utilized in the forthcoming section, for the random variables T_N and Y, we have

$$\begin{aligned}
&\int_0^\infty F_Y(t)\,dF_{T_N}(t) \\
&\quad = -\int_0^\infty F_Y(t)\,d\overline{F}_{T_N}(t) \\
&\quad = -\left[F_Y(t)\,\overline{F}_{T_N}(t)\Big|_0^\infty - \int_0^\infty \overline{F}_{T_N}(t)\,d\overline{F}_Y(t)\right],
\end{aligned} \tag{7}$$

and then by using (6) we have

$$\int_0^\infty F_Y(t)\,dF_{T_N}(t) = pn_b\int_0^\infty h(t)\,\overline{F}_{T_N}(t)\,\overline{F}_Y(t)\,dt. \tag{8}$$

3. Components of the Model

3.1. Expected Length of an NDPM Cycle. As shown in Figure 2, the length of an NDPM cycle with N allowable minor damages in a blades system, $\mathrm{CL}(N)$, can be expressed as

$$\mathrm{CL}(N) = \begin{cases} Y + L_e & \text{if } Y < T_N \\ T_N + L_o & \text{if } Y \geq T_N. \end{cases} \tag{9}$$

Then the expected length of the cycle, $E[\mathrm{CL}(N)]$, is given by

$$\begin{aligned}
E[\mathrm{CL}(N)] = &\int_0^\infty\int_0^t (y + L_e)\,dF_Y(y)\,dF_{T_N}(t) \\
&+ \int_0^\infty\int_t^\infty (t + L_o)\,dF_Y(y)\,dF_{T_N}(t).
\end{aligned} \tag{10}$$

By using (1) and (8), we have that

$$\begin{aligned}
&E[\mathrm{CL}(N)] \\
&\quad = \left[L_e\int_0^\infty F_Y(t)\,dF_{T_N}(t) + L_o\int_0^\infty \overline{F}_Y(t)\,dF_{T_N}(t)\right] \\
&\qquad + \left[\int_0^\infty\int_0^t y\,dF_Y(y)\,dF_{T_N}(t) + \int_0^\infty t\overline{F}_Y(t)\,dF_{T_N}(t)\right] \\
&\quad = L_o - \xi_L\int_0^\infty F_Y(t)\,dF_{T_N}(t) + \int_0^\infty\int_0^t \overline{F}_Y(y)\,dy\,dF_{T_N}(t) \\
&\quad = L_o - pn_b\xi_L\int_0^\infty h(t)\,\overline{F}_{T_N}(t)\,\overline{F}_Y(t)\,dt \\
&\qquad + \int_0^\infty \overline{F}_{T_N}(t)\,\overline{F}_Y(t)\,dt.
\end{aligned} \tag{11}$$

3.2. Expected Logistics Costs. Because the expedited logistics cost only occurs in case (b), the expected logistics cost per cycle, $E[c_L(N)]$, is given by

$$\begin{aligned}
E[c_L(N)] = &\, c_e\int_0^\infty\int_0^t dF_Y(y)\,dF_{T_N}(t) \\
&+ c_o\int_0^\infty\int_t^\infty dF_Y(y)\,dF_{T_N}(t).
\end{aligned} \tag{12}$$

By using (2) and (8), we have that

$$\begin{aligned}
&E[c_L(N)] \\
&\quad = c_e\int_0^\infty F_Y(t)\,dF_{T_N}(t) + c_o\int_0^\infty \overline{F}_Y(t)\,dF_{T_N}(t) \\
&\quad = c_o + \xi_c\int_0^\infty F_Y(t)\,dF_{T_N}(t) \\
&\quad = c_o + pn_b\xi_c\int_0^\infty h(t)\,\overline{F}_{T_N}(t)\,\overline{F}_Y(t)\,dt.
\end{aligned} \tag{13}$$

3.3. Expected Cost of Production Loss. Let $E[c_P(N)]$ be the expected cost of production loss per cycle with N allowable minor damages in a blades system. We assume the following cost structure (see Figure 3):

$$E[c_P(N)] = c_m E[N_m(N)] + c_M E[\mathrm{DL}(N)], \tag{14}$$

where c_m is the fixed cost of production loss due to a minor damage, c_M is the fixed cost of production loss per unit downtime, $E[N_m(N)]$ is the expected number of minor damages per cycle, and $E[\mathrm{DL}(N)]$ is the expected downtime within the cycle. In practice, c_m can be considered as a fixed penalty cost resulting from a small reduction in efficiency of wind capture and c_M is obtained as follows [33]:

$$c_M = Wc_E f, \tag{15}$$

where W is the wind power rating, c_E is the cost of energy, and f is the capacity factor of the wind turbine.

As illustrated in Figure 2, the expected number of minor damages per cycle, $E[N_m(N)]$, can be expressed as

$$\begin{aligned}
&E[N_m(N)] \\
&\quad = \overbrace{\int_0^\infty \overline{F}_Y(t + L_o)\times\left(N + \int_t^{t+L_o} qn_b h(u)\,du\right)dF_{T_N}(t)}^{\text{case (a)}} \\
&\qquad + \overbrace{\int_0^\infty\int_0^t\int_0^y qn_b h(u)\,du\,dF_Y(y)\,dF_{T_N}(t)}^{\text{case (b)}} \\
&\qquad + \overbrace{\int_0^\infty\int_t^{t+L_o}\left(N + \int_t^y qn_b h(u)du\right)dF_Y(y)dF_{T_N}(t)}^{\text{case (c)}}.
\end{aligned} \tag{16}$$

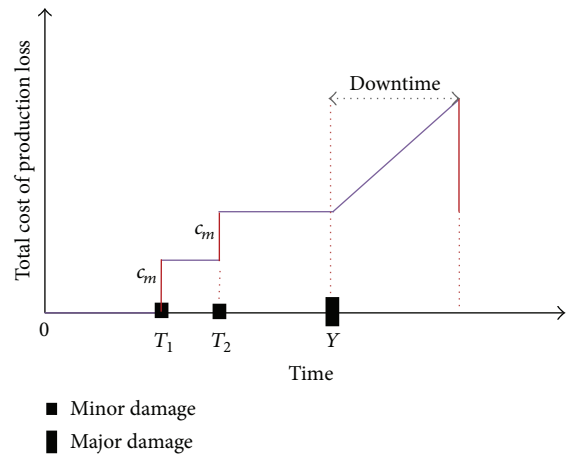

Figure 3: The cost structure for production loss.

By using (6) and (8), we have

$$\begin{aligned}
&E\left[N_m(N)\right] \\
&= N\int_0^\infty \overline{F}_Y(t)\,dF_{T_N}(t) \\
&\quad + qn_b\left(\int_0^\infty\int_0^{t+L_o} H(y)\,dF_Y(y)\,dF_{T_N}(t)\right. \\
&\qquad + \int_0^\infty \overline{F}_Y(t+L_o)\,H(t+L_o)\,dF_{T_N}(t) \\
&\qquad \left. - \int_0^\infty \overline{F}_Y(t)\,H(t)\,dF_{T_N}(t)\right) \\
&= N - Npn_b\int_0^\infty h(t)\,\overline{F}_{T_N}(t)\,\overline{F}_Y(t)\,dt \\
&\quad + qn_b\left(\frac{\int_0^\infty F_Y(t+L_o)\,dF_{T_N}(t)}{pn_b}\right. \\
&\qquad - \int_0^\infty h(t)\,\overline{F}_{T_N}(t)\,\overline{F}_Y(t)\,dt \\
&\qquad \left. + pn_b\int_0^\infty h(t)\,H(t)\,\overline{F}_{T_N}(t)\,\overline{F}_Y(t)\,dt\right) \\
&= N + \frac{q}{p}F_Y(L_o) - n_b(Np+q)\int_0^\infty h(t)\,\overline{F}_{T_N}(t)\,\overline{F}_Y(t)\,dt \\
&\quad + qn_b\left(\int_0^\infty h(t+L_o)\,\overline{F}_{T_N}(t)\,\overline{F}_Y(t+L_o)\,dt\right. \\
&\qquad \left. + pn_b\int_0^\infty h(t)\,H(t)\,\overline{F}_{T_N}(t)\,\overline{F}_Y(t)\,dt\right).
\end{aligned} \tag{17}$$

Because a wind turbine shutdown occurs only in cases (b) and (c), the expected turbine downtime within the cycle, $E[\mathrm{DL}(N)]$, can be expressed as

$$\begin{aligned}
E\left[\mathrm{DL}(N)\right] = {} & \overbrace{L_e\int_0^\infty\int_0^t dF_Y(y)\,dF_{T_N}(t)}^{\text{case (b)}} \\
& + \overbrace{\int_0^\infty\int_t^{t+L_o}(t+L_o-y)dF_Y(y)dF_{T_N}(t)}^{\text{case (c)}},
\end{aligned} \tag{18}$$

and then by using (1), we have

$$\begin{aligned}
&E\left[\mathrm{DL}(N)\right] \\
&= L_e\int_0^\infty F_Y(t)\,dF_{T_N}(t) - L_o\int_0^\infty F_Y(t)\,dF_{T_N}(t) \\
&\quad - \int_0^\infty\int_t^{t+L_o} F_Y(y)\,dy\,d\overline{F}_{T_N}(t) \\
&= -pn_b\xi_L\int_0^\infty h(t)\,\overline{F}_{T_N}(t)\,\overline{F}_Y(t)\,dt \\
&\quad + \int_0^{L_o} F_Y(y)\,dy + \int_0^\infty \overline{F}_{T_N}(t)\left[\overline{F}_Y(t) - \overline{F}_Y(t+L_o)\right]dt.
\end{aligned} \tag{19}$$

By substituting (17) and (19) into (14), we have

$$\begin{aligned}
&E\left[c_P(N)\right] \\
&= c_m\left[N + \frac{q}{p}F_Y(L_o) - n_b(Np+q)\int_0^\infty h(t)\,\overline{F}_{T_N}\overline{F}_Y(t)\,dt\right. \\
&\qquad + qn_b\left(\int_0^\infty h(t+L_o)\,\overline{F}_{T_N}(t)\,\overline{F}_Y(t+L_o)\,dt\right. \\
&\qquad \left.\left. + pn_b\int_0^\infty h(t)\,H(t)\,\overline{F}_{T_N}(t)\,\overline{F}_Y(t)\,dt\right)\right] \\
&\quad + c_M\left\{-pn_b\xi_L\int_0^\infty h(t)\,\overline{F}_{T_N}(t)\,\overline{F}_Y(t)\,dt\right. \\
&\qquad + \int_0^{L_o} F_Y(y)\,dy \\
&\qquad \left. + \int_0^\infty \overline{F}_{T_N}(t)\left[\overline{F}_Y(t) - \overline{F}_Y(t+L_o)\right]dt\right\}.
\end{aligned} \tag{20}$$

3.4. Expected Maintenance Costs. Since a corrective replacement strategy is applied only in cases (b) and (c) and the perfect preventive maintenance strategy is utilized for unfailed

blade(s) in all three cases, the total expected maintenance cost per cycle, $E[c_M(N)]$, is

$$\begin{aligned} E\left[c_M(N)\right] &= \overbrace{n_b c_p \int_0^{\infty} \overline{F}_Y(t+L_o)\, dF_{T_N}(t)}^{\text{case (a)}} \\ &\quad + \overbrace{\left[c_r + (n_b-1)c_p\right] \int_0^{\infty} F_Y(t)\, dF_{T_N}(t)}^{\text{case (b)}} \\ &\quad + \overbrace{\left[c_r + (n_b-1)c_p\right] \int_0^{\infty} \left[F_Y(t+L_o) - F_Y(t)\right] dF_{T_N}(t)}^{\text{case (c)}}. \end{aligned} \tag{21}$$

By using (8), we have

$$\begin{aligned} E\left[c_M(N)\right] &= n_b c_p \int_0^{\infty} \overline{F}_Y(t+L_o)\, dF_{T_N}(t) \\ &\quad + \left[c_r + (n_b-1)c_p\right] \int_0^{\infty} F_Y(t+L_o)\, dF_{T_N}(t) \\ &= n_b c_p + \left(c_r - c_p\right) \int_0^{\infty} F_Y(t+L_o)\, dF_{T_N}(t) \\ &= n_b c_p + \left(c_r - c_p\right) \\ &\quad \times \left[F_Y(L_o) + p n_b \int_0^{\infty} \overline{F}_{T_N}(t)\, h(t+L_o)\, \overline{F}_Y(t+L_o)\, dt\right]. \end{aligned} \tag{22}$$

4. The Model Formulation and Analysis

From the *renewal reward theorem* (see [34, page 52]), the expected cost rate for an infinite time span is the expected operational cost incurred in a cycle divided by the expected cycle length, that is,

$$\frac{\text{Expected operational cost incurred in a cycle}}{\text{Expected length of a cycle}}. \tag{23}$$

The expected operational cost over a cycle is the sum of the expected logistics costs, the expected cost of production loss, and the expected maintenance costs. Thus, the expected cost rate for an NDPM cycle with N allowable minor damages in a blades system, $\mathrm{CR}(N)$, can be expressed as

$$\mathrm{CR}(N) = \frac{E\left[c_L(N)\right] + E\left[c_P(N)\right] + E\left[c_M(N)\right]}{E\left[\mathrm{CL}(N)\right]}, \tag{24}$$

where $E[\mathrm{CL}(N)]$ is given by (11), $E[c_L(N)]$ is given by (13), $E[c_P(N)]$ is given by (20), and $E[c_M(N)]$ is given by (21). For an infinite-horizon case, under the criterion of the expected long-term cost per unit time, the optimal policy is to determine the value of $N = N^*$ which minimizes $\mathrm{CR}(N)$. Therefore, the optimization model can be formulated as follows:

$$\begin{aligned} \text{minimize} &\left(\delta_{11}(N) + \int_0^{\infty} \delta_{12}(t,N)\, \overline{F}_{T_N}(t)\, \overline{F}_Y(t)\, dt \right. \\ &\left. + \int_0^{\infty} \delta_{13}(t)\, \overline{F}_{T_N}(t)\, \overline{F}_Y(t+L_o)\, dt\right) \\ &\times \left(L_o + \int_0^{\infty} \delta_{21}(t)\, \overline{F}_{T_N}(t)\, \overline{F}_Y(t)\, dt\right)^{-1}, \end{aligned} \tag{25}$$

where

$$\begin{aligned} \delta_{11}(N) &= c_o + c_m N + \left(c_m \frac{1-p}{p} + c_r - c_p\right) F_Y(L_o) \\ &\quad + c_M \int_0^{L_o} F_Y(y)\, dy + n_b c_p, \\ \delta_{12}(t,N) &= n_b \left[(1-c_M)\, p\xi_c \right. \\ &\quad \left. + c_m \left\{\left(p\left[(1-p)\, n_b H(t) + 1 - N\right] - 1\right)\right\}\right] \\ &\quad \times h(t) + c_M, \\ \delta_{13}(t) &= n_b \left[c_m + p\ \left(c_r - c_p - c_m\right)\right] h(t+L_o) - c_M, \\ \delta_{21}(t) &= 1 - p n_b \xi_L h(t), \\ p &\in [0,1],\ N \in \{1,2,\ldots\}. \end{aligned} \tag{26}$$

If a finite integer value of N^* satisfies the inequalities $\mathrm{CR}(N^*+1) \geq \mathrm{CR}(N^*)$ and $\mathrm{CR}(N^*) < \mathrm{CR}(N^*-1)$, then $N = N^*$ is the optimal solution. From (25), we can show that $\mathrm{CR}(N+1) \geq \mathrm{CR}(N)$ whenever $Q(N) \geq 0$, where

$$\begin{aligned} Q(N) &= A(N) \\ &\quad \times \left(\left(L_o + \int_0^{\infty} \delta_{21}(t)\, \overline{F}_{T_{N+1}}(t)\, \overline{F}_Y(t)\, dt\right)\right. \\ &\quad \left. \times \left(L_o + \int_0^{\infty} \delta_{21}(t)\, \overline{F}_{T_N}(t)\, \overline{F}_Y(t)\, dt\right)\right)^{-1}, \end{aligned} \tag{27}$$

Input: $n_b, f(\cdot), p, L_o, L_e, c_o, c_e, c_r, c_p, c_m, W, E, f$.
Step 1. Set $N := 1$, CR $(0) := \infty$.
Step 2. Compute $\overline{F}_Y(\cdot)$, $\delta_{11}(1)$, $\delta_{12}(\cdot, 1)$, $\delta_{13}(\cdot)$ and $\delta_{21}(\cdot)$.
Step 3. Compute $\overline{F}_{T_N}(\cdot)$, $\delta_{11}(N+1)$ and $\delta_{12}(\cdot, N+1)$.
Step 4. Compute $Q(N)$.
Step 5. If the condition $Q(N) \geq 0$ in (27) is satisfied, then $N^* := N$, $\mathrm{CR}(N^*) := \mathrm{CR}(N)$ and go to the output, otherwise, let $N = N + 1$, and go to Step 3.
Output: $N^*, \mathrm{CR}(N^*)$
Stop. End.

Algorithm 1: Find the optimal allowable number of minor damages in a blades system.

and

$$\begin{aligned}
A(N) &= L_o c_m \\
&\quad + \left(\int_0^\infty \left[\delta_{11}(N+1)\, \delta_{21}(t) - L_o \delta_{12}(t, N) \right] \right. \\
&\qquad \times \overline{F}_{T_N}(t)\, \overline{F}_Y(t)\, dt \\
&\quad - \int_0^\infty \left[\delta_{11}(N)\, \delta_{21}(t) - L_o \delta_{12}(t, N+1) \right] \\
&\qquad \times \overline{F}_{T_{N+1}}(t)\, \overline{F}_Y(t)\, dt \\
&\quad + \left[\int_0^\infty \overline{F}_{T_{N+1}}(t) \left[\left\{ \delta_{12}(t, N+1)\, \overline{F}_Y(t) \right. \right. \right. \\
&\qquad \left. \left. \left. + \delta_{13}(t)\, \overline{F}_Y(t + L_o) \right\} \right] dt \right] \\
&\quad \times \int_0^\infty \delta_{21}(t)\, \overline{F}_{T_N}(t)\, \overline{F}_Y(t)\, dt \\
&\quad - \left[\int_0^\infty \overline{F}_{T_N}(t) \left\{ \delta_{12}(t, N)\, \overline{F}_Y(t) \right. \right. \\
&\qquad \left. \left. + \delta_{13}(t)\, \overline{F}_Y(t + L_o) \right\} dt \right] \\
&\quad \times \left. \int_0^\infty \delta_{21}(t)\, \overline{F}_{T_{N+1}}(t)\, \overline{F}_Y(t)\, dt \right).
\end{aligned} \tag{28}$$

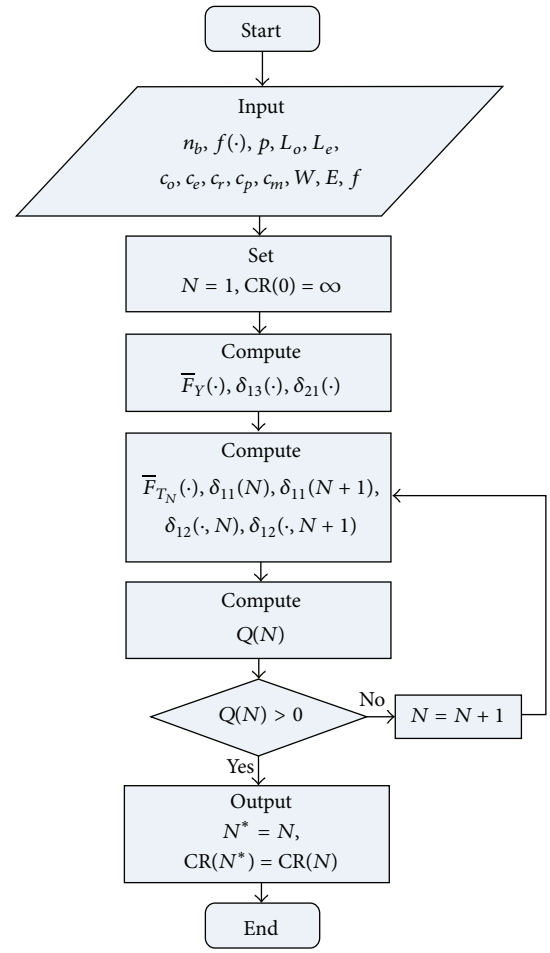

Figure 4: The flow sheet for computation of the optimal solution.

It should be noted that if $\delta_{21}(t) \geq 0$ or $h(t) \leq (pn\xi_L)^{-1}$ for all $t \geq 0$, then the condition $Q(N) \geq 0$ will become $A(N) \geq 0$.

As the proposed optimization model is fairly complicated (the variable of interest is included in the integrands), obtaining a general analytical solution is probably impossible. We have chosen to use Algorithm 1 to find the optimal solution through a numerical procedure.

In addition, a flow sheet representing the computing procedure is presented in Figure 4.

5. An Illustrative Case

In order to illustrate the proposed model, we present a case study composed by real data gathered from an offshore wind database. The field failure parameters have been used as in [35], and some real logistic parameters have been gathered from the Opti-Owecs offshore wind farm project, which has also been studied in [36]. Consider a *deteriorating* wind turbine blades system with $n_b \in \{1, 2, 3\}$ blades (Figure 5), in

Table 1: Summary of the parameter values.

Wind turbine parameters	$W = 1.2$ MW, $f = 0.4$
Blades system	$\lambda = 0.03$/day, $\beta = 2$ (meantime to damage is 29.54 days)
Cost parameters	$c_r = 600000$ (€), $c_p = 200000$ (€), $c_m = 5000$ (€), $c_o = 25000$ (€), $c_e = 30000$ (€), $c_E = 36$ €/MW
Lead time	$L_o = 2$ days, $L_e = 1$ day

(a) (b) (c)

Figure 5: A blades system with (a) one blade, (b) two blades, and (c) three blades.

Table 2: N^* and $\mathrm{CR}(N^*)$ for $p \in \{0.1, 0.2, \ldots, 0.9\}$ and $n_b \in \{1, 2, 3\}$.

p	$n_b = 1$		$n_b = 2$		$n_b = 3$	
	N^*	$\mathrm{CR}(N^*)$	N^*	$\mathrm{CR}(N^*)$	N^*	$\mathrm{CR}(N^*)$
0.1	6	6377.2	11	12674.4	19	19426.3
0.2	3	8857.0	6	17463.1	10	26720.4
0.3	2	10843.2	4	21188.0	7	32327.9
0.4	2	12566.4	3	24342.9	6	37036.3
0.5	2	14188.3	3	27111.1	5	41160.9
0.6	1	15559.6	2	29639.0	4	44865.0
0.7	1	16858.0	2	31918.7	4	48253.1
0.8	1	18135.4	2	34060.1	3	51381.3
0.9	1	19392.2	2	36061.4	3	54302.4

which the time to damage follows a two-parameter Weibull distribution function; that is,

$$F(t) = 1 - \exp\left\{-(\lambda t)^{\beta}\right\},$$
$$h(t) = \lambda\beta(\lambda t)^{\beta-1} \quad \text{with } \lambda > 0,\ \beta > 1, \tag{29}$$

where λ is the scale parameter and β is the shape parameter. Table 1 summarizes the values of the model parameters.

A MATLAB program for the minimization of the long-run average cost per unit time in (25) has been written. Algorithm 1 is iterated until the optimal value, N^*, is found. However, when p tends to zero (i.e., when the damages tend to target only minor failures), the value of N^* tends to infinity, which decreases the performance of Algorithm 1.

Table 2 presents the optimal number N^* of allowable minor damages in a blades system and the corresponding long-run expected cost, $\mathrm{CR}(N^*)$, for a range of values of $p \in \{0.1, 0.2, \ldots, 0.9\}$ and $n_b \in \{1, 2, 3\}$. Table 2 shows that as the probability, p, of a major damage increases, the optimal value of N^* decreases; however, the optimal long-run expected cost, $\mathrm{CR}(N^*)$, increases. Moreover, as shown in Figure 6, the long-run expected costs per blade in two- and three-bladed systems are very close to each other, but they have a noticeable difference compared with the long-run expected cost in a single-blade system.

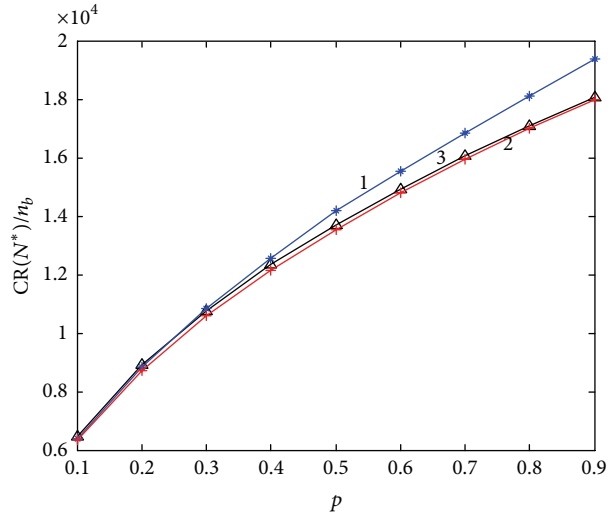

Figure 6: $\mathrm{CR}(N^*)/n_b$ for $p \in \{0.1, 0.2, \ldots, 0.9\}$ and $n_b \in \{1, 2, 3\}$.

The long-run expected cost, $\mathrm{CR}(N)$ for a range of values of $N \in \{1, 2, \ldots, 10\}$, $p = 0.5$, and $n_b \in \{1, 2, 3\}$ is shown in Figure 7.

Since most wind turbines have three blades, we conduct a sensitivity analysis to evaluate the effect of changes in the

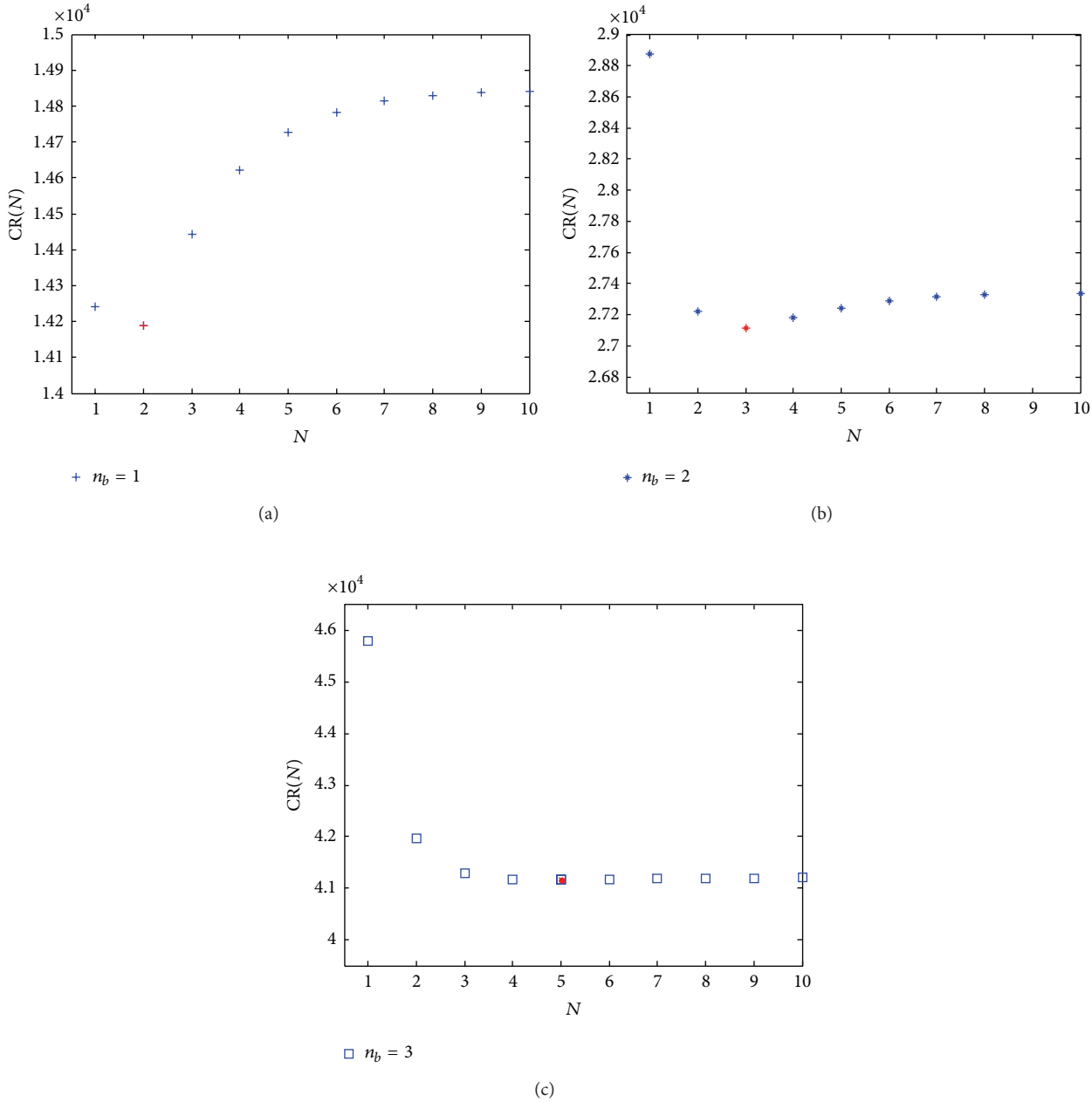

FIGURE 7: CR(N) for $N \in \{1, 2, \ldots, 10\}$, $p = 0.5$ and $n_b \in \{1, 2, 3\}$.

values of the model parameters on the optimal solution for three-bladed wind turbine systems.

(i) Sensitivity Analysis for λ. The optimal number of allowable minor damages in a three-bladed system and the corresponding long-run expected cost for $p \in \{0.1, 0.3, \ldots, 0.9\}$ and $\lambda \in \{0.01, 0.03, 0.05\}$ are given in Table 3.

Table 3 shows that as the scale parameter of Weibull distribution λ grows (i.e., the mean time to arrive a damage decreases), the optimal value of N^* and the optimal long-run expected cost, CR(N^*), increase.

(ii) Sensitivity Analysis for c_m. The optimal number of allowable minor damages in a three-bladed system and the corresponding long-run expected cost for $p \in \{0.1, 0.3, \ldots, 0.9\}$ and $c_m \in \{2000, 5000, 8000\}$ are given in Table 4.

Table 4 shows that as the fixed cost of production loss due to a minor damage c_m becomes larger, the optimal value of N^* decreases; however, the optimal long-run expected cost, CR(N^*), increases.

(iii) Sensitivity Analysis for c_e. The optimal number of allowable minor damages in a blades system and the corresponding

Table 3: Sensitivity analysis for λ.

p	$\lambda = 0.01$ (meantime to damage: 88.62 days)		$\lambda = 0.03$ (meantime to damage: 29.54 days)		$\lambda = 0.05$ (meantime to damage: 17.72 days)	
	N^*	CR(N^*)	N^*	CR(N^*)	N^*	CR(N^*)
0.1	19	6547.9	19	19426.3	19	32021.0
0.3	7	10999.3	7	32327.9	8	52826.0
0.5	5	14087.0	5	41160.9	5	66855.0
0.7	3	16597.0	4	48253.1	4	78000.0
0.9	3	18759.0	3	54302.4	4	87434.0

Table 4: Sensitivity analysis for c_m.

p	$c_m = 2000$ €		$c_m = 5000$ €		$c_m = 8000$ €	
	N^*	CR(N^*)	N^*	CR(N^*)	N^*	CR(N^*)
0.1	20	18960.0	19	19426.3	18	19888.0
0.3	7	32104.0	7	32327.9	7	32552.0
0.5	5	41034.0	5	41160.9	5	41288.0
0.7	4	48190.0	4	48253.1	4	48316.0
0.9	3	54284.0	3	54302.4	3	54320.0

Table 5: Sensitivity analysis for c_e.

p	$c_e = 25000$		$c_e = 30000$		$c_e = 35000$	
	N^*	CR(N^*)	N^*	CR(N^*)	N^*	CR(N^*)
0.1	19	19344.0	19	19426.3	18	19508.0
0.3	7	32182.0	7	32327.9	7	32474.0
0.5	5	40966.0	5	41160.9	5	41355.0
0.7	4	48021.0	4	48253.1	3	38486.0
0.9	3	54039.0	3	54302.4	3	54566.0

Table 6: Sensitivity analysis for L_e.

p	$L_e = 0.5$		$L_e = 1.0$		$L_e = 1.5$	
	N^*	CR(N^*)	N^*	CR(N^*)	N^*	CR(N^*)
0.1	18	19586.0	19	19426.3	20	19268.0
0.3	7	32808.0	7	32327.9	8	31856.0
0.5	4	41968.0	5	41160.9	5	40376.0
0.7	3	49388.0	4	48253.1	4	47158.0
0.9	3	55770.0	3	54302.4	4	52910.0

long-run expected cost for $p \in \{0.1, 0.3, \ldots, 0.9\}$ and $c_m \in \{25000, 30000, 35000\}$ are given in Table 5.

Table 5 shows that the expedited logistics cost does not have any significant effect on the optimal value of N^*; however, as the expedited logistics cost reduces to the ordinary logistics cost (i.e., the expedited cost term ξ_c becomes zero), the optimal long-run expected cost, CR(N^*), also decreases.

(iv) Sensitivity Analysis for L_e. The optimal number of allowable minor damages in a three-bladed system and the corresponding long-run expected cost for $p \in \{0.1, 0.3, \ldots, 0.9\}$ and $L_e \in \{0.5, 1.0, 1.5\}$ are given in Table 6.

Table 6 shows that as the expedited logistics lead time gets closer to the ordinary logistics lead time (or, the expedited lead time term, ξ_L, becomes smaller), the optimal value N^* and the optimal long-run expected cost, CR(N^*) increase.

6. Conclusions and Topics for Future Research

In this paper, a cost-rate optimization model is developed in order to determine the optimal number of minor damages allowed to occur in a blades system before sending a maintenance team to the offshore platform in order to perform preventive maintenance actions. There is a wide scope for future research in the area of maintenance optimization for offshore wind turbine blades. Some of the possible extensions are (a) investigating the optimal solution for a case that the probability p is a random variable that depends on the weather conditions; (b) formulating and analyzing the model when the blade damages form a non-Poisson arrival stream; (c) developing an age-based preventive maintenance strategy for offshore blades systems with $n \geq 2$ blades, in which in the event of a blade failure a PM action will be performed on the un-failed blade if its operational age exceeds a certain threshold$a > 0$; and finally (d) providing a cost comparison of our proposed maintenance strategy with other common strategies (such as age-based PM and opportunistic maintenance).

We have worked on some of these extensions and our findings will be reported in the near future.

Notations

n_b: The number of blades in a wind turbine system; $n_b \in \{1, 2, \ldots\}$

T: The lifetime of a blade (day)

$f(\cdot)[F(\cdot)]$: The probability density [cumulative distribution] function of T

$h(\cdot)[H(\cdot)]$: The failure rate [cumulative failure rate] function of T

p: Pr{a certain damage is a major damage}; $p \in [0, 1]$

q: Pr{ a certain damage is a minor damage}; $q = 1 - p$

i: The index number of minor damages in the blades system; $i \in \{1, 2, \ldots\}$

N: The allowable number of minor damages before transporting a maintenance team to offshore platform [decision variable]
T_i: The waiting time until the ith minor damage occurs (day)
Y : The time to the first major damage (day)
$F_{T_i}(\cdot)[\overline{F}_{T_i}(\cdot)]$: The cumulative distribution [survival] function of T_i
$F_Y(\cdot)[\overline{F}_Y(\cdot)]$: The cumulative distribution [survival] function of Y
L_o $[L_e]$: The ordinary [expedited] logistics lead time (day)
c_o $[c_e]$: The ordinary [expedited] logistics cost (€)
ξ_L $[\xi_c]$: The expedited lead time (day) [cost (€)] term
c_r: The expected replacement cost of a blade (€)
c_p: The cost of performing a perfect PM on an un-failed blade (€)
c_m: The fixed cost of production loss due to a minor damage (€)
c_M : The fixed cost of production loss per unit downtime (€/day)
W: The wind turbine power rating (MW)
c_E: The cost of energy (€/MW)
f: The capacity factor of each wind turbine
$E[CL(N)]$: The expected length of an NDPM cycle (day)
$E[DL(N)]$: The expected downtime within the cycle (day)
$E[c_L(N)]$: The expected logistics cost per cycle (€)
$E[c_P(N)]$: The expected cost of production loss per cycle (€)
$E[N_m(N)]$: The total expected number of minor damages within the cycle (€)
$E[c_M(N)]$: The total expected maintenance cost per cycle (€)
$CR(N)$: The long-run expected cost per unit time (€/day).

Acknowledgments

The authors would like to thank the Editor and two anonymous reviewers for several comments that made it possible to substantially improve the presentation of the paper. This research was supported by the Swedish Energy Agency through Chalmers Energy Area of Advance and Grant no. 2010-004592.

References

[1] European Wind Energy Association, *Wind in power*, 2012 European statistics, 2013, http://www.ewea.org/fileadmin/files/library/publications/statistics/Wind_in_power_annual_statistics_2012.pdf.

[2] Swedish Energy Agency, *Energy in Sweden* 2011, 2012, http://www.energimyndigheten.se/en/About-us/Press-/News/New-publication-Energy-in-Sweden-2011/.

[3] M. Bilgili, A. Yasar, and E. Simsek, "Offshore wind power development in Europe and its comparison with onshore counterpart," *Renewable and Sustainable Energy Reviews*, vol. 15, no. 2, pp. 905–915, 2011.

[4] M. Nordahl, *The development of a life cycle cost model for an offshore wind farm [M.S. thesis]*, Department of Applied Mechanics, Chalmers University of Technology, 2011, http://publications.lib.chalmers.se/records/fulltext/152402.pdf.

[5] E. Byon, L. Ntaimo, and Y. Ding, "Optimal maintenance strategies for wind turbine systems under stochastic weather conditions," *IEEE Transactions on Reliability*, vol. 59, no. 2, pp. 393–404, 2010.

[6] E. Byon and Y. Ding, "Season-dependent condition-based maintenance for a wind turbine using a partially observed markov decision process," *IEEE Transactions on Power Systems*, vol. 25, no. 4, pp. 1823–1834, 2010.

[7] Z. Tian, T. Jin, B. Wu, and F. Ding, "Condition based maintenance optimization for wind power generation systems under continuous monitoring," *Renewable Energy*, vol. 36, no. 5, pp. 1502–1509, 2011.

[8] J. J. Nielsen and J. D. Sørensen, "On risk-based operation and maintenance of offshore wind turbine components," *Reliability Engineering and System Safety*, vol. 96, no. 1, pp. 218–229, 2011.

[9] F. Ding and Z. Tian, "Opportunistic maintenance optimization for wind turbine systems considering imperfect maintenance actions," *International Journal of Reliability, Quality and Safety Engineering*, vol. 18, no. 5, pp. 463–482, 2011.

[10] F. Ding and Z. Tian, "Opportunistic maintenance for wind farms considering multi-level imperfect maintenance thresholds," *Renewable Energy*, vol. 45, pp. 175–182, 2012.

[11] L. W. M. M. Radmakers, H. Braam, M. B. Zaaijer, and G. J. W. van Bussel, *Assessment and optimization of operation and maintenance of offshore wind turbines*, 2003, http://www.ecn.nl/fileadmin/ecn/units/wind/docs/dowec/2003-EWEC-O_M.pdf.

[12] G. M. J. Herbert, S. Iniyan, and R. Goic, "Performance, reliability and failure analysis of wind farm in a developing Country," *Renewable Energy*, vol. 35, no. 12, pp. 2739–2751, 2010.

[13] D. J. Lekou and P. Vionis, "Report on repair techniques for composite parts of wind turbine blades," Tech. Rep., 2002, http://www.wmc.eu/public_docs/10059_000.pdf.

[14] A. Saeed, *Online condition monitoring system for wind turbine: case study [M.S. thesis]*, Department of Electrical Engineering, Blekinge Institute of Technology, 2008, http://www.bth.se/fou/cuppsats.nsf/all/3a7cde7b4a7d576ec12578160076cf54/$file/Wind_Turbine-Master_thesis-BTH.pdf.

[15] H. Makabe and H. Morimura, "A new policy for preventive maintenance," *Journal of Operations Research Society of Japan*, vol. 5, pp. 110–124, 1963.

[16] H. Makabe and H. Morimura, "On some preventive maintenance policies," *Journal of Operations Research Society of Japan*, vol. 6, pp. 17–47, 1963.

[17] H. Makabe and H. Morimura, "Some considerations on preventive maintenance policies with numerical analysis," *Journal of the Operations Research Society of Japan*, vol. 7, pp. 154–171, 1965.

[18] H. Morimura, "On some preventive maintenance policies for IFR," *Journal of the Operations Research Society of Japan*, vol. 12, pp. 94–124, 1970.

[19] K. S. Park, "Optimal number of minimal repairs before replacement," *IEEE Transactions on Reliability*, vol. 28, no. 2, pp. 137–140, 1979.

[20] T. Nakagawa, "Generalized models for determining optimal number of minimal repairs before replacement," *Journal of the Operations Research Society of Japan*, vol. 24, no. 4, pp. 325–337, 1981.

[21] S. H. Sheu and W. S. Griffith, "Optimal number of minimal repairs before replacement of a system subject to shocks," *Naval Research Logistics*, vol. 43, no. 3, pp. 319–333, 1996.

[22] S. H. Sheu, "A generalized model for determining optimal number of minimal repairs before replacement," *European Journal of Operational Research*, vol. 69, no. 1, pp. 38–49, 1993.

[23] S. H. Sheu, W. S. Griffith, and T. Nakagawa, "Extended optimal replacement model with random minimal repair costs," *European Journal of Operational Research*, vol. 85, no. 3, pp. 636–649, 1995.

[24] K. S. Park, "Optimal number of minor failures before replacement," *International Journal of Systems Science*, vol. 18, no. 2, pp. 333–337, 1987.

[25] C. C. Chang, S. H. Sheu, and Y. L. Chen, "Optimal number of minimal repairs before replacement based on a cumulative repair-cost limit policy," *Computers & Industrial Engineering*, vol. 59, no. 4, pp. 603–610, 2010.

[26] S. H. Sheu, C. C. Chang, and Y. H. Chien, "Optimal age-replacement time with minimal repair based on cumulative repair-cost limit for a system subject to shocks," *Annals of Operations Research*, vol. 186, pp. 317–329, 2011.

[27] S. H. Sheu and Y. H. Chien, "Optimal age-replacement policy of a system subject to shocks with random lead-time," *European Journal of Operational Research*, vol. 159, no. 1, pp. 132–144, 2004.

[28] Y. H. Chien, "A number-dependent replacement policy for a system with continuous preventive maintenance and random lead times," *Applied Mathematical Modelling*, vol. 33, no. 3, pp. 1708–1718, 2009.

[29] Y. H. Chien, "Optimal number of minimal repairs before ordering spare for preventive replacement," *Applied Mathematical Modelling*, vol. 34, no. 11, pp. 3439–3450, 2010.

[30] T. Nakagawa, *Shock and Damage Models in Reliability Theory*, Springer, London, UK, 2007.

[31] E. Byon, L. Ntaimo, C. Singh, and Y. Ding, "Wind energy facility reliability and maintenance," in *Handbook of Wind Power Systems: Optimization, Modeling, Simulation and Economic Aspects*, P. Pardalos, M. V. Pereira, S. Rebennack et al., Eds., Springer, London, UK, 2013.

[32] J. H. Bookbinder and M. Çakanyildirim, "Random lead times and expedited orders in (*Q, r*) inventory systems," *European Journal of Operational Research*, vol. 115, no. 2, pp. 300–313, 1999.

[33] J. A. Andrawus, *Maintenance optimization for wind turbines [Ph.D. thesis]*, Robert Gordon University, 2008, https://openair.rgu.ac.uk/handle/10059/268.

[34] S. M. Ross, *Applied Probability Models with Optimization Applications*, Holden-Day, San Francisco, Calif, USA, 1970.

[35] F. Besnard and L. Bertling, "An approach for condition-based maintenance optimization applied to wind turbine blades," *IEEE Transactions on Sustainable Energy*, vol. 1, no. 2, pp. 77–83, 2010.

[36] A. Karyotakis, *On the optimization of operation and maintenance strategies for offshore wind farms [Ph.D. thesis]*, Department of Mechanical Engineering, University College London, 2011, http://www.ecn.nl/docs/library/report/2011/m11103.pdf.