Season-Dependent Condition-Based Maintenance for a Wind Turbine Using a Partially Observed Markov Decision Process

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***Abstract*—We develop models and the associated solution tools for devising optimal maintenance strategies, helping reduce the operation costs, and enhancing the marketability of wind power. We consider a multi-state deteriorating wind turbine subject to failures of several modes. We also examine a number of critical factors, affecting the feasibility of maintenance, especially the dynamic weather conditions, which makes the subsequent modeling and the resulting strategy season-dependent. We formulate the problem as a partially observed Markov decision process with heterogeneous parameters. The model is solved using a backward dynamic programming method, producing a dynamic strategy. We highlight the benefits of the resulting strategy through a case study using data from the wind industry. The case study shows that the optimal policy can be adapted to the operating conditions, choosing the most cost-effective action. Compared with fixed, scheduled maintenances and a static strategy, the dynamic strategy can achieve the considerable improvements in both reliability and costs.**

***Index Terms*—Adaptive observers, environmental factors, management decision-making, reliability management, sensory aids, wind energy.**

I. Introduction

PROPELLED by the pressures of mitigating the effects of climate change and high energy costs, wind power becomes one of the fastest growing renewable energy sources around the world. The total capacity of wind energy in the U.S. rose 45% in 2007 and is forecast to nearly triple by 2012 [1]. Despite the vast capacity of wind power reserve, the share of wind energy still remains a small portion of the current energy market.

One of the key factors for enhancing the marketability of wind energy is to cut its operations and maintenance (O&M) costs [2], [3]. According to Walford [3], the contribution of the O&M costs to the total energy production cost is 10%–20% for a wind farm. Vachon [4] shows that the O&M costs can account for 75%–90% of the investment costs, based on a 20-year life cycle for a 100-MW wind farm in North America with 600 turbines of 750 kW each.

Manuscript received July 07, 2009; revised December 17, 2009. First published March 22, 2010; current version published October 20, 2010. This work was supported by the NSF under grants CMMI-0540132 and CMMI-0540278. Paper no. TPWRS-00521-2009.

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Digital Object Identifier 10.1109/TPWRS.2010.2043269

Currently, wind farm operators perform scheduled maintenances on a regular basis. However, wind turbines are subjected to irregular loading [5]. The deterioration progress of turbine components could differ considerably from each other. Some turbine components might deteriorate more slowly than the average aging process, while the others may be faster. For this reason, scheduled maintenances might result in unnecessary visits or could not handle unexpected failures in a timely fashion.

In the efforts to minimize the O&M costs, wind farm operators began to realize that condition-based maintenance (CBM) is essential in an effective maintenance program [6]. Condition-based monitoring, equipped with sensors inside a wind turbine, provides diagnostic information regarding the health condition of the turbine components. Based on the information, one can estimate the deterioration progress that may lead to a major failure or consequential damage. Wind farm operators can plan maintenance tasks in advance before the problem escalates and develops into major failures or critical malfunctions.

Studies have been conducted to examine the effectiveness of CBM strategy for the components in conventional power systems [7]–[10]. For instance, Jirutitijaroen and Singh [10] examine the effect of preventive maintenance and inspection on reliability and costs for a transformer. This study provides practical insights regarding how preventive maintenance and inspection would impact on system performance depending on a transformer's deterioration condition. Our work is similar to previous work like [10] in terms of general methodology but differs in the sense that we focus on modeling the unique aspects encountered in wind farm operations and maintenance.

Recently, a few studies have also been conducted to quantify the benefits of CBM in the wind energy industry. Among them, McMillan and Ault [11] evaluate the cost-effectiveness of CBM by using Monte Carlo simulations. Through simulating various scenarios with different weather profiles and repair costs, they show that wind farm operators can gain remarkable economic benefits for onshore turbines by adopting certain CBM strategy. One would expect more appreciable benefits for offshore wind turbines since the repairs of those turbines are more costly and taking maintenance actions faces more constraints. Similarly, Nilsson and Bertling [12] investigate how much O&M costs can be reduced by utilizing condition monitoring information, affirming a reduction in costs. However, these studies do not discuss what kind of CBM policy could be the most effective one.

Andrawus *et al.* [13] use a statistical analysis to model the failure pattern of wind turbine components. Based on the historical data coming from wind turbine operations, they calculate an optimal replacement cycle for each component that minimizes the total maintenance costs over the component's lifetime. For example, they show that the gearbox and generator should be replaced every six and three years, respectively, in order to attain the minimum repair costs for the 600-kW *horizontal axis* turbines. Their model considers the average aging process of the components, but the degradation behavior of each individual component is not captured.

In this study, we propose a new mathematical model to dynamically schedule maintenance activities based on both the internal condition of each turbine component and the external operating environments. The internal conditions include not only the degree of deterioration status but also the different failure modes associated with individual components. On the other hand, the external operating conditions such as weather climates and lead time to prepare repair resources may not be significantly related to the degradation or failure of a wind turbine component, but they can affect the O&M costs and wind turbine availability considerably [11], [14].

Our model incorporates the information from condition monitoring equipment using a partially observed Markov decision process (POMDP) in order to represent the internal degradation (and failure) status. A POMDP is a sequential decision-making process to control a stochastic system based on the system state [15], [16]. In the POMDP setting, the system condition cannot be observed directly, so that the condition is estimated in a probabilistic sense [17], [18]. In the wind turbine monitoring, cheap but unreliable remote sensors provide abundant yet uncertain information. In this sense, POMDP provides a suitable framework to optimize the wind turbine maintenance activities.

We investigate several unique, but critical, aspects of wind turbine operations. First, we examine the dynamic weather conditions that could have considerable differences season by season. Weather conditions affect the wind farm O&M in several ways. Harsh weather conditions could constrain repairing activities, and these conditions may occur more often in certain periods of a year than in other periods. For example, a wind farm cannot be assessed during storm seasons. In the winter seasons, climbing up an icy turbine tower is not allowed for safety concerns. Also, harsh weather conditions cause the repairing interruption and delay. Many wind turbine-related repairs take several days because of the physical difficulties to repair the components. This relatively long duration of a repairing session increases the chance that a repair is interrupted by adverse weather conditions. With these reasons, it would be better to shift non-urgent maintenance tasks to less windy time in spring or fall [3].

The second factor we consider is different failure modes of each turbine component and the corresponding failure consequences. Each failure mode determines what type of parts/crew is required, which in turn determines the costs, lead time, and repair time. Accordingly, the costs of corrective maintenance (CM) and the downtime due to the occurrence of a turbine failure could vary for different failure modes. For example, a gearbox may fail in various subcomponents including bearing failures, sealing problems, oil system problems, and so on [19], [20]. According to Ribrant [19], it can take several weeks to fix the problems associated with bearing failures, partly because of the long lead time required for skillful labors and cranes to get ready. On the other hand, oil system problem can be fixed within hours [19].

The third factor is the revenue losses during downtime. The inactivity of a wind turbine during lead time and repair time constitutes the unavailability, causing the losses of revenues. Since wind power generations are maximized in high wind speed seasons, downtime during these seasons could lead to huge productivity loss [3].

While modeling the above factors related to wind turbine operations, our model aims to decide the optimal strategy for proper actions to take. There are three types of actions considered in our model: preventive maintenance (PM), on-site observation (OB), and when neither is needed, continue monitoring and takes no action (NA). Regarding PM, we allow multiple repair levels that can bring an operating system to any state between the current state and an "as-good-as-new" state. Also, we examine the effects of each PM on the costs, reliability, and repair durations.

OB is different from the automated remote monitoring system; rather it is the infrequent, non-periodic on-site investigation that wind farm operators can take. OB is fulfilled by either dispatching maintenance crew or, if technologically feasible, invoking more advanced smart sensors; both options are generally very costly, but presumably can help understand the system condition with a high confidence. The co-existence of a cheap but unreliable remote monitoring and an accurate yet costly OB is a unique aspect in the wind industry, not always encountered in other applications.

Taking all of the above aspects into consideration, we derive a season-dependent, dynamic CBM strategy in order to minimize the total O&M costs over a wind turbine's lifetime. This dynamic aspect clearly differentiates this work from our previous work [21], which considers a static, season-independent CBM strategy. In this paper, we formulate the problem as a finite-horizon POMDP model. Parameters in the model are *heterogeneous* (or, non-homogeneous/time-varying) depending on the prevailing weather conditions, which make the resulting strategy *adaptive* to the operating environments. The optimal policy is constructed from the evolution of the deterioration states of individual wind turbine components. We introduce a backward dynamic programming algorithm to solve the problem. To illustrate the application of the model, we perform a case study based on the historical industry data. The results show that significant benefits can be expected by adopting the proposed strategy in the wind industry practices.

The remainder of the paper is organized as follows. We describe the specific aspects of modeling the operations and maintenance of wind turbines in Section II. Then, we present the POMDP model and its solution procedure in Section III. The case study is reported in Section IV. Finally, we conclude the paper in Section V.

II. Modeling the Operations and Maintenance in Wind Farms

In this section, we examine a number of modeling aspects relevant to the O&M in wind farms. We also consider the different choices of maintenance action that the wind farm operators can take, the corresponding effects on the system condition, and the associated costs. It is assumed that the wind farm operators make maintenance decisions in discrete time at $n = 1, 2, \ldots, T$, where T is the terminal period corresponding to the lifetime of a wind turbine.

A. Partial Information About a System

Suppose that the deterioration levels of an *operating* system are classified into a finite number of conditions $1, \ldots, M$ and that the system can experience L types of failures. Then, the system condition can be categorized into a series of states, $1, \ldots, M + L$. State 1 denotes the best condition like "new", and state M denotes the most deteriorated operating condition before a system fails. State $M + l$ reflects the lth failed mode, $l = 1, \ldots, L$. Let us call $S_0 = \{1, \ldots, M + L\}$ the *original state space*.

In reality, the physical condition of a turbine component is not known exactly, but may be estimated from the condition monitoring sensor signals. Estimations rarely reveal perfectly the system conditions and health status due to a wide variety of reasons, such as imperfect models linking measurements to specific faults, as well as noises and contaminations in sensor signals [2]. One way to characterize the information from the sensor signals is to specify a probability vector about the actual underlying condition. A common treatment of the information uncertainty under the POMDP setting is to define a state as a probability distribution, representing one's belief over the corresponding true state. As such, we define the state of the system as the following probability distribution:

$$\pi = [\pi_1, \pi_2, \ldots, \pi_{M+L}] \tag{1}$$

where π_i, $i = 1, \ldots, M + L$ is the probability that the system is in deterioration level i. π is commonly known as an information state in the literature [17]. Then, the state space under the POMDP setting becomes

$$S_1 = \{[\pi_1, \pi_2, \ldots, \pi_{M+L}]; \sum_{i=1}^{M+L} \pi_i = 1, 0 \le \pi_i \le 1, i = 1, \ldots, M + L\}. \tag{2}$$

Let us call S_1 the *partially observed state space*.

When one of the elements in the information state is *one* and other elements are *zero*, the state is called the extreme state, denoted by e_i, $i = 1, \ldots, M + L$, where $e_i = [0, \ldots, 1, \ldots, 0]$ is $(M+L) \times 1$ dimensional row vector with a 1 in the ith position and 0 elsewhere. These extreme states reveal the system's condition perfectly. In other words, e_1 denotes the best condition like an "as-good-as-new" condition, e_M is the most deteriorated condition, and $e_{M+l}, l = 1, \ldots, L$ denotes the lth failure mode.

Note that $\sum_{i=1}^{M} \pi_i = 1$ for an *operating* system since wind turbines no longer operate upon failures. When a system fails with the lth failure mode, the state becomes e_{M+l}.

B. Markovian Deterioration

In this study, we choose a Markov model to represent the aging behavior of a system because of its flexibility and popularity in many applications including modeling the devices used in the power systems [7]–[10], [22], [23]. Markov models have been used to represent the degradation pattern of wind turbine components in several recent studies [5], [11], [24]. When a system undergoes Markovian deterioration, the current state is transited to another state according to a transition probability matrix, $P = [p_{ij}]_{(M+L)\times(M+L)}$. P consists of the four submatrices as follows:

$$P = \begin{bmatrix} P_A & P_B \\ 0_{L\times M} & I_{L\times L} \end{bmatrix} \tag{3}$$

where P_A denotes an $M \times M$ transition matrix from an operating state to another operating state, and P_B is an $M \times L$ transition matrix from an operating state to one of the failure states. $0_{L\times M}$ is an $L \times M$ zero matrix, whereas $I_{L\times L}$ is an identity matrix. Both $0_{L\times M}$ and $I_{L\times L}$ matrices together reflect the fact that once the system fails, it cannot return to any operating state on its own but remains at the same failure state unless a maintenance action is taken. In many practical applications, P is an upper-triangular matrix where the lower off-diagonal elements are zero because a system cannot improve on its own. Fig. 1 illustrates the state transitions with an upper-triangular matrix P in the original state space S_0.

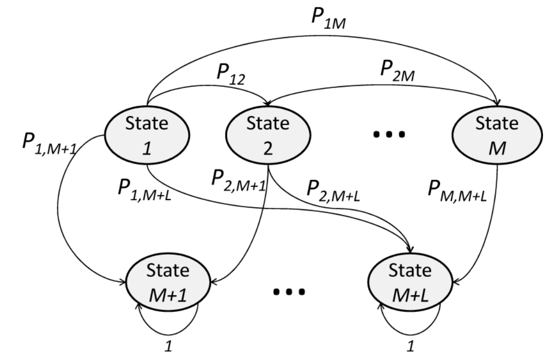


Fig. 1. State transition diagram in the original state space S_0.

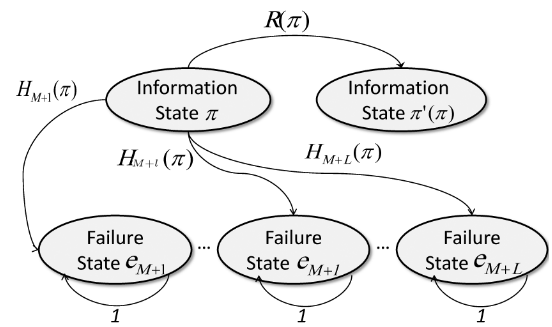


Fig. 2. State transition diagram in the partially observed state space S_1.

Suppose that the current information state of an operating system is π and NA is taken. The probability that the system will still operate until the next decision point is $R(\pi) = \sum_{i=1}^{M} \sum_{j=1}^{M} \pi_i p_{ij}$. People call this probability as the *reliability* of the system [18]. Based on the law of conditional

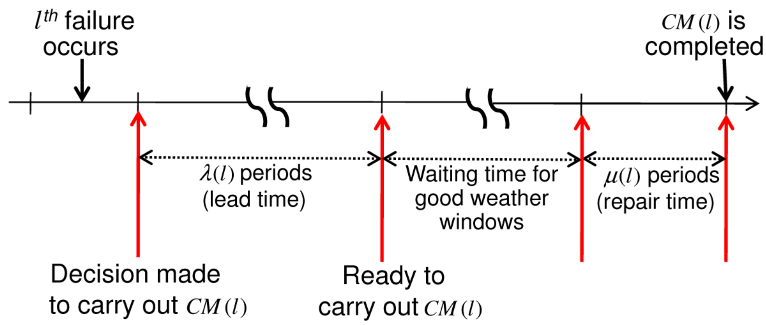


Fig. 3. Corrective maintenance after a failure with the lth failure mode. The figure illustrates the repairing process after a major failure where $\mu(l) = 1$. For a minor failure, the process would be similar except $\mu(l) = 0$.

probability [18], the information state after the next transition, given that the system is not yet failed, is

$$\pi'_j(\pi) = \begin{cases} \frac{\sum_{i=1}^{M} \pi_i p_{ij}}{R(\pi)}, & j = 1, 2, \ldots, M \\ 0, & j = M+1, \ldots, M+L. \end{cases} \quad (4)$$

As such, the system is transited to the next state $\pi'(\pi) = [\pi'_1(\pi), \ldots, \pi'_M(\pi), 0, \ldots, 0]$ with probability $R(\pi)$. If the system fails and results in the lth failure mode with probability $H_l(\pi) = \sum_{i=1}^{M} \pi_i p_{i,M+l}$, the state becomes e_{M+l} in the next period. Also, the total probability that the system fails until the next period is $H(\pi) = 1 - R(\pi) = \sum_{j=M+1}^{M+L} H_l(\pi)$, which is called the *hazard rate* of the system. Fig. 2 illustrates the state transition diagram in the partially observed state space S_1 without any maintenance interruption.

C. Corrective Maintenance (CM)

According to Walford [3], the portion of the corrective maintenance costs is between 30% and 60% of the total O&M costs. Not only do the direct costs (to fix the failed components), but the indirect costs such as revenue losses also contribute considerably to the corrective maintenance costs. This is mainly the result of a typically long downtime, due to usually restricted accessibility to a wind farm and limited availability of parts and crew [14].

Components of a wind turbine may experience different types of failure, and the consequences of different failures are not the same, much as expected [25]. Suppose that a system can experience L types of failures. Upon a failure with the lth failure mode, parts are ordered and crews are arranged, which supposedly takes $\lambda(l)$ lead time. When all of the parts and crew are available, and if the weather conditions are good enough to allow the repair work to go ahead, the crew carry out a CM for the lth failure mode [namely, $\mathrm{CM}(l)$] for $\mu(l)$ repair periods at cost $C_{\mathrm{CM}(l)}$ (note: $\lambda(l)$ and $\mu(l)$ take non-negative integer values, meaning 0 period, 1 period, 2 periods, and so on). If the prevailing weather conditions are not good enough, however, the crew must wait until the weather conditions permit a repair. Let $W_{\mathrm{CM}(l),n}$ represent the probability that the prevailing weather conditions during the nth period are harsh, and CM for the lth failure mode is thus prohibited, $l = 1, \ldots, L$.

Without loss of generality, we order the failure states such that a lower index implies a more serious failure mode. We assume that major repairs that fix serious problems take one full period [that is, $\mu(l) = 1$], whereas the repair time for minor problems is negligible compared to the duration of a period [that is, $\mu(l) = 0$]. Understandably, major repairs require that the weather conditions stay permitting for the whole repair period, costlier resources, and longer lead time than minor repairs. Therefore, we have $W_{\mathrm{CM}(l),n} \geq W_{\mathrm{CM}(l'),n}$, $C_{\mathrm{CM}(l)} \geq C_{\mathrm{CM}(l')}$, and $\lambda(l) \geq \lambda(l')$ for $l \leq l'$.

Unless the repair is completed, wind turbines can no longer be operated after a failure, causing τ_n revenue losses at period n. Note that τ_n is a time-dependent parameter, varying season by season. After the repair, the system is renewed to an as-good-as-new state. Fig. 3 illustrates the repair process after a failure occurs.

D. Preventive Maintenances (PMs)

PMs are the actions to repair the system that has deteriorated but not yet failed [26]. The PMs are divided based on how system condition can be improved with maintenance efforts. Recall that the condition of an *operating* system in this study is modeled by M discrete levels, which suggests that there can be at most $M-1$ choices for the PM actions, namely, $\mathrm{PM}(1), \ldots, \mathrm{PM}(M-1)$, where $\mathrm{PM}(m)$ denotes the PM action which repairs the system to the state e_m at cost $C_{\mathrm{PM}(m)}$. For example, choosing $\mathrm{PM}(1)$ corresponds to performing a major repair such as overhaul or replacement, which returns the system to an as-good-as-new state, e_1. On the other hand, $\mathrm{PM}(M-1)$ spends the least efforts and time to bring the system state to e_{M-1}. Accordingly, $C_{\mathrm{PM}(m)} \geq C_{\mathrm{PM}(m')}$, $\forall m \leq m'$.

Depending on which PM level is chosen, the repair time and the requirements for weather conditions may differ, and consequently, the production loss during a repair can be different. Similar to the CM cases, we assume that major PMs require one full period under good weather windows. If the weather becomes harsh during a repair, the crew have to hold the repair work until the weather returns to good conditions. On the other hand, minor PMs could be done almost instantaneously under tolerable operating conditions. Let $W_{\mathrm{PM}(m),n}$ represent the probability that the weather conditions at period n do not allow $\mathrm{PM}(m)$ to be performed, $m = 1, \ldots, M-1$. Then, we have $W_{\mathrm{PM}(m),n} \geq W_{\mathrm{PM}(m'),n}$ for $m \leq m'$.

E. Observation (OB)

Through the remote monitoring system, the wind farm operators can attain the partial (and imperfect) information about the turbine system condition, while OB is the action to evaluate the system's exact deterioration level at cost $C_{\rm OB}$. So the information state after an OB takes place reverts to one of the extreme states e_i, $i=1,\ldots,M$, where e_i is defined earlier in Section II-A. After an OB, the decision maker will choose an adequate maintenance action in that same decision period, based on the updated information state.

III. POMDP Model With Heterogeneous Parameters

In this section, we present a wind turbine O&M model under a POMDP framework with heterogeneous parameters. Our model extends the model introduced in our previous work [21] by incorporating more practical aspects of wind turbine operations. We formulate the problem as a finite-horizon discounted cost model, and devise a backward dynamic programming to solve for the optimal policy numerically.

A. Model Formulation

Let $V_n(\pi)$ denote the minimum expected total cost-to-go at the nth period (the total costs incurred from the current period n to the terminal period T) when the current state is π. Also, let us denote the discount factor by β. At each decision epoch, there are $m+1$ possible action alternatives: NA, $\mathrm{PM}(1),\ldots,\mathrm{PM}(m-1)$, and OB.

When NA is selected at the current state π, the total cost-to-go is as follows:

$$\mathrm{NA}_n(\pi)=\sum_{l=1}^{L}\left(\tilde{\tau}_n(l)+\beta^{\lambda(l)+1}\mathrm{CM}_{n+\lambda(l)+1}(e_{M+l})\right)\times H_l(\pi)+V_{n+1}(\pi'(\pi))R(\pi) \quad (5)$$

where

$$\tilde{\tau}_n(l)=\left(\sum_{t=1}^{\lambda(l)}\beta^t\tau_{n+t}\right)\cdot I(\lambda(l)>0)+0\cdot I(\lambda(l)=0) \quad (6)$$

and

$$\begin{aligned}\mathrm{CM}_n(e_{M+l})=&\,W_{\mathrm{CM}(l),n}(\tau_n+\beta\mathrm{CM}_{n+1}(e_{M+l}))\\&+(1-W_{\mathrm{CM}(l),n})(\tau_n\cdot I(\mu(l)=1)\\&+C_{\mathrm{CM}(l)}+V_{n+\mu(l)}(e_1)).\end{aligned} \quad (7)$$

Under NA, the system could either end up with the lth failure mode with probability $H_l(\pi)$ $l=1,\ldots,L$, or transit to the next state $\pi'(\pi)$ with probability $R(\pi)$. In (5), the first term $\tilde{\tau}_n(l)$ is the total revenue losses during the lead time, upon a system failure. If the system fails and the lead time is nonzero [that is, $\lambda(l)>0$], the wind farm would lose the revenue of $\sum_{t=1}^{\lambda(l)}\beta^t\tau_{n+t}$, as shown in the first component of (6). Note that these revenue losses depend on weather conditions, which indicates that if the system fails during the windy seasons and the failure requires long lead time, one should expect significant production losses. On the contrary, the second term in (6) implies the cases of minor failures with *zero* lead time.

$\mathrm{CM}_n(e_{m+l})$ in (7) reflects the CM costs for the lth failure mode. The first component is the expected costs caused by delays due to harsh weather conditions, which would occur with probability $W_{\mathrm{CM}(l),n}$. The second component indicates the repair costs under good weather conditions. Note that $\tau_n\cdot I(\mu(l)=1)$ in (7) specifies the revenue losses during a major repair that takes one full period. After the repair, the system condition is restored to the best condition, e_1.

Next, let us consider the actions of PM. $\mathrm{PM}(m)$ action, $m=1,\ldots,M-1$, which improves the system condition to the state e_m, can be categorized into minor repairs and major repairs in a broad sense. We assume that the repair time for minor repairs is negligible. Therefore, minor repairs can be carried out almost instantaneously as long as the weather conditions are good. But, if the weather conditions are not good during the whole period, NA is taken. On the other hand, major repairs take one full period and if the weather conditions become harsh during the repair, the job has to be halted and will be resumed in the next period. The following formulation in (8) is the total-cost-to-go for $\mathrm{PM}(m)$ for $m=1,\ldots,M-1$:

$$\mathrm{PM}_n(m)=\begin{cases}W_{\mathrm{PM}(m),n}\mathrm{NA}_n(\pi)\\+(1-W_{\mathrm{PM}(m),n})(C_{\mathrm{PM}(m)}+V_n(e_m))\\\qquad\text{for minor repairs}\\W_{\mathrm{PM}(m),n}(\tau_n+\mathrm{PM}_{n+1}(m))\\+(1-W_{\mathrm{PM}(m),n})(\tau_n+C_{\mathrm{PM}(m)}+V_{n+1}(e_m))\\\qquad\text{for major repairs.}\end{cases} \quad (8)$$

Finally, we model the action of OB. The observation costs are divided into the direct costs to inspect the system and the post maintenance costs after the system condition is evaluated precisely. The following $\mathrm{OB}_n(\pi)$ and $\mathrm{Post}_n(\pi)$ together represent that after each observation at cost $C_{\rm OB}$, the state is updated to e_i with probability π_i and then we choose the least costly action in the same decision period, among NA or $\mathrm{PM}(m)$, $m=1,\ldots,M-1$:

$$\mathrm{OB}_n(\pi)=C_{\rm OB}+\sum_{i=1}^{M}\mathrm{Post}_n(e_i)\pi_i \quad (9)$$

where

$$\mathrm{Post}_n(e_i)=\min\{\mathrm{NA}_n(e_i),\mathrm{PM}_n(1),\ldots,\mathrm{PM}_n(M-1)\}. \quad (10)$$

Note that OB cannot be optimal at the extreme points, e_i, $i=1,\ldots,M$ because $\mathrm{OB}_n(e_i)$ is always greater than $\min\{\mathrm{NA}_n(e_i),\mathrm{PM}_n(1),\ldots,\mathrm{PM}_n(M-1)\}$ for $C_{OB}>0$.

Now, the optimal value function can be written as follows:

$$V_n(\pi)=\min\{\mathrm{NA}_n(\pi),\mathrm{PM}_n(1),\ldots,\mathrm{PM}_n(M-1),\mathrm{OB}_n(\pi)\}. \quad (11)$$

Solving the optimization in (11) gives the optimal decision rule $\delta_n(\pi)$ at the current state π. Here, $\delta_n(\pi)$ will take one of the possible maintenance actions, NA, $\mathrm{PM}(1),\ldots,\mathrm{PM}(m-1)$, OB, specifying the best action selection when the system occupies the state π at a specified decision epoch n [27]. The optimal policy at the state π, denoted by $\Delta(\pi)$, is the vector of the optimal decision rules to be used through decision epochs, that is, $\Delta(\pi)=(\delta_1(\pi),\ldots,\delta_T(\pi))$, where T denotes the terminal period.

B. Solutions: Backward Dynamic Programming

In order to attain the optimal policy and optimal value, we use a backward dynamic programming [27]. First, we set the set of states *a priori*. To do so, let us consider a sample path starting from a state π. A sample path is the series of information states evolving over time under NA [17], [18]. We denote a sample path starting from π by $\{\pi, \pi^2, \ldots, \Pi(\pi)\}$ where $\pi^2 = \pi'(\pi)$, $\pi^3 = \pi'(\pi^2)$ and so on. The last state $\Pi(\pi)$ in the sample path implies a stationary state or an absorbing state [18], which is defined by $\Pi(\pi) \equiv \pi^{k^*}$ where $k^* = \min\{k : \|\pi^{k+1} - \pi^k\| < \epsilon\}$ with a small ϵ. As long as the Markov chain is acyclic, $\Pi(\pi)$ exists for any $\epsilon > 0$ [18].

Observing from (5)–(10), one can find that the total cost-to-go associated with each possible action as well as the optimal value $V_n(\pi^k)$ at π^k and period n are only dependent on the values at the next state π^{k+1} and the extreme states $e_i, i = 1, \ldots, M+L$. Utilizing this understanding, we can step backwards along the path, recursively solving for the corresponding optimal action. The following algorithm summarizes the solution procedure that finds the optimal polices along a sample path. We also provide an overview of the algorithm in Fig. 4.

Backward Dynamic Programming Algorithm

For a given π and the parameter values [that is, $\beta, P, C_{\mathrm{CM}(l)}, C_{\mathrm{PM}(m)}, C_{\mathrm{OB}}, \lambda(l), \mu(l), \tau_n, W_{\mathrm{CM}(l),n}$, $W_{\mathrm{PM}(m),n}, \forall l, m, n$], use the following procedure along the sample path emanating from π.

- Step 1) Construct using (4) a sample path $\Omega_\pi = \{\pi, \pi^2, \ldots, \Pi(\pi)\}$, emanating from π. Similarly, generate the extreme sample paths, $\Omega_{e_1}, \ldots, \Omega_{e_M}$, originating from the extreme states $e_m, m = 1, \ldots, M$.
- Step 2) Set the terminal values $V_T(\pi)$ according to the business situations. (Alternatively, the terminal values can be set *arbitrarily* for large T.)
- Step 3) Repeat for $n = T-1, T-2, \ldots, 1$:
  - — a) Set the time-varying parameter values such as $W_{\mathrm{CM}(l),n}$, $W_{\mathrm{PM}(m),n}$, and τ_n, $l = 1, \ldots, L$, $m = 1, \ldots, M-1$.
  - — b) Find the optimal decision rule and optimal value at each extreme point e_i, $i = 1, \ldots, M$. That is, compute $\mathrm{NA}_n(e_i), \mathrm{PM}_n(1), \ldots, \mathrm{PM}_n(M-1)$, for $i = 1, \ldots, M$. Then, find $V_n(e_i) = \min\{\mathrm{NA}_n(e_i), \mathrm{PM}_n(1), \ldots, \mathrm{PM}_n(M-1)\}$ and the corresponding $\delta_n(e_i)$, $i = 1, \ldots, M$.
  - — c) Compute the total-cost-to-go $\mathrm{CM}_n(l)$ for each CM with the lth failure mode, $l = 1, \ldots, L$.
  - — d) For $\forall \pi^k \in \Omega_\pi$, compute the total cost-to-go associated with each action, $\mathrm{NA}_n(\pi^k)$, $\mathrm{PM}_n(1), \ldots, \mathrm{PM}_n(M-1)$, $\mathrm{OB}_n(\pi^k)$.
  - — e) Get the optimal value function $V_n(\pi^k)$, $\forall \pi^k \in \Omega_\pi$ and the corresponding optimal decision rule.
  - — f) Set $n = n-1$, and go back to Step 3a).

At Step 2 of the algorithm, one option to assign the terminal value is to use the salvage value of the component. Alternatively, we can set the terminal values *arbitrarily* since the terminal value would not affect the optimal decision rules at the initial periods when T is large enough. This is due to having a discount factor $\beta < 1$. Without loss of generality, $V_T(\pi) = 0$ can be used, $\forall \pi$.

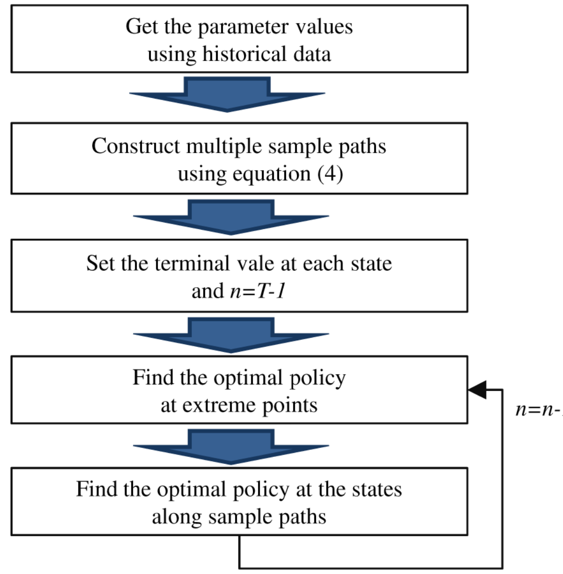


Fig. 4. Overview of the proposed backward dynamic programming algorithm.

We evaluate the optimal values at the extreme states at Step 3b), before evaluating the optimal values at other non-extreme states at Steps 3d) and e). Note that for calculating the optimal values for the extreme states, OB is not considered as one of the potential optimal actions for selection because we already knew that OB cannot be optimal at the extreme points [see (9) and (10)]. But, in order to compute $\mathrm{OB}_n(\pi^k)$ at the non-extreme states, we need to know $V(e_i)$'s, $i = 1, \ldots, M$, which explains why Step 3b) comes first before Steps 3d) and e).

Since the weather related parameters [that is, $W_{\mathrm{CM}(l),n}$, $W_{\mathrm{PM}(m),n}$, τ_n] are season-dependent, the above procedure generates a *non-stationary* optimal policy, making the policy dynamically adjusted to seasonal effects.

IV. Case Study

In this section, we present a case study illustrating the utility of the proposed dynamic maintenance policy. Most critical failures of a wind turbine are associated with its gearbox, generator, or blades because of their large size, long lead time for repairs, high capital cost, difficulty in replacement, and lengthy downtime compounded by adverse weather conditions [11], [19], [20]. In our case study, we examine the failures at a gearbox because gearbox problems have been identified a long while ago as one of the most serious problems in wind turbines, and the recent large-scale wind turbines with new designs still suffer badly from gearbox failures [12], [28]. We do want to note, however, that similar analysis can be performed for other wind turbine components as well.

A. Problem Description

We assume that the wind farm operators make maintenance decisions on a weekly basis. Appropriate parameter values are

TABLE I
FAILURE TYPES OF A GEARBOX

Subcomponent[a]	failure frequency[a]	Average (min-max) downtime (hours)[a]	lead time (weeks)[b]	repair time (weeks)[b]	Corresponding repair action
Bearings	37.6%	562 (15-2 067)	2	1	$CM(1)$
Gearwheels	2.8%	272 (57-383)	1	1	$CM(2)$
Not specified	40.4%	230 (9-1 248)	1	1	$CM(3)$
Sealing	7.3%	52 (2-218)	0	0	$CM(4)$
Oil systems	11.9%	26 (1-63)	0	0	$CM(5)$

[a] The data are obtained from Ribrant's studies [19], [20]
[b] The lead time and repair time associated with each failure mode are set on a weekly basis for the modeling purpose

selected based on the published data or discussions with our industry partners.

Ribrant [19], [20] examines the failure frequencies of different failure modes and the corresponding downtime in gearboxes of wind turbines with a rated power of 490 kW or more. Table I summarizes the statistics related to the gearbox failures. The failures of bearings and gearwheels often demand a total change of the gearbox, resulting in a long downtime. The unspecified failure types in the fourth row of Table I sometimes correspond to other serious failures which require a replacement of the whole gearbox [19]. The other two failure modes require minor repairs in general. The first three columns are obtained from Ribrant's studies [19], [20]. Based on these numbers, we set the lead time and repair time for each failure type, as shown in the fourth and fifth columns.

Generally, a transition matrix P can be obtained from operational data by taking a long-run history about the degradation states and counting transitions. For critical equipment such as circuit breakers and transformers in the conventional power systems, aging-related data have been accumulated for a long time, and several repair strategies have been presented using a Markov process [7]–[10], [22], [23]. For the wind industry, there is a lack of data in the public domain for calculating the precise transition matrix for wind turbine components. For the time being, the common remedy researchers adopt is to use the limited amount of data, combined with expert judgments or simulations, to estimate the transition probabilities, for instance, the approach used in the study of McMillan and Ault [11].

In this study we follow a similar approach to handle the transition probabilities as in the above-mentioned literature. We analytically derive the *first passage time* [29] to the failure as a function of the elements of a transition matrix, which is called a *mean time to the first failure* (MTTF or MTTFF) in the reliability study [10]. The inverse of *MTTF* gives the average failure frequency. Then, we apply a similar transition matrix used in [18] and modify the matrix to be consistent with the overall failure frequency of a gearbox and the frequency of each failure mode shown in Table I. According to Ribrant [19], the failure frequency of a gearbox ranges from 0.05–2.29 times per year, depending on the turbine manufacturers and models. Since most wind farm operators currently perform scheduled maintenances regularly, we believe that this failure frequency is the result under the scheduled maintenance practice. Based on these understandings, we construct the transition matrix P with the following submatrices:

$$P_A = \begin{bmatrix} 0.93 & 0.04 & 0.029 \\ 0.00 & 0.95 & 0.03 \\ 0.00 & 0.00 & 0.96 \end{bmatrix},$$
$$P_B = \begin{bmatrix} 0 & 0 & 0 & 0 & 0.001 \\ 0.008 & 0.001 & 0.008 & 0.001 & 0.002 \\ 0.015 & 0.002 & 0.016 & 0.003 & 0.004 \end{bmatrix}. \quad (12)$$

Since we consider one week as a transition period, P represents a weekly-based deterioration process. The state can be represented as an eight-dimensional row vector, $\pi = \{\pi_1, \pi_2, \pi_3, \pi_4, \ldots, \pi_8\}$. π_1, π_2, and π_3 are the probabilities of being in a *normal*, *alert*, and *alarm* condition, respectively, and π_4 to π_8 represent the five different failure modes, as shown in Table I.

Remark: Using Monte Carlo simulations, we validate that the failure frequencies with P_A and P_B in (12) are consistent with the industry statistics under scheduled maintenance. The parameter values presented in (12), however, may not be a definitive set of values; rather they could be a starting point for deriving condition-based maintenance policy and evaluating the benefits of the proposed model framework. As McMillan and Ault point out [11], future work is needed to better quantify the parameter values. Rademakers *et al.* [14] also suggest that industry parties should collaborate with one another to collect and share data for the improvement of wind farm O&M. It also should be emphasized that a much refined definition of system conditions allowing more levels of possible PM actions may be necessary in real situations while we only consider these three levels of system conditions in this case study. Doing so will need to use an information state π of a higher dimension, but the proposed methodology can be similarly applied.

Fig. 5 illustrates the partially observed state space for an operating system. In the figure, the X-axis denotes the *alert* probability π_2, whereas the Y-axis is the *alarm* probability π_3. Since $\pi_1 + \pi_2 + \pi_3 = 1$, the origin (0,0) implies the best condition, e_1. The state space is defined as the triangle surrounded by the X-axis, Y-axis, and $\pi_2 + \pi_3 = 1$. Note that $\pi_2 \geq 0$, $\pi_3 \geq 0$, and $\pi_2 + \pi_3 \leq 1$. Therefore, all states can only fall inside the triangular area, as shown in Fig. 5. The *area A* in the upper-left corner of the triangle depicts the states corresponding to seriously deteriorating conditions. The states belonging to this area might need some kinds of remedies to avoid a catastrophic failure in the near future. On the other hand, the *area B* in the lower-left

TABLE II
MAINTENANCE COSTS AND HARSH WEATHER PROBABILITIES FOR EACH MAINTENANCE ACTION

Repair types[a]		Repair costs[b]	Weather parameters			
			Spring	Summer	Fall	Winter
Major CM	$CM(1)$	78 368	0.1	0.4	0.1	0.6
	$CM(2)$	78 368	0.1	0.4	0.1	0.6
	$CM(3)$	39 234	0.1	0.3	0.1	0.4
Minor CM	$CM(4)$	7 837	0.05	0.2	0.05	0.2
	$CM(5)$	7 837	0.05	0.2	0.05	0.2
Major PM	$PM(1)$	8 182	0.1	0.3	0.1	0.4
Minor PM	$PM(2)$	2 727	0.05	0.2	0.05	0.2

[a] Major repairs take one week, whereas the duration for minor repairs is negligible.
[b] The monetary unit is *pounds*(£)

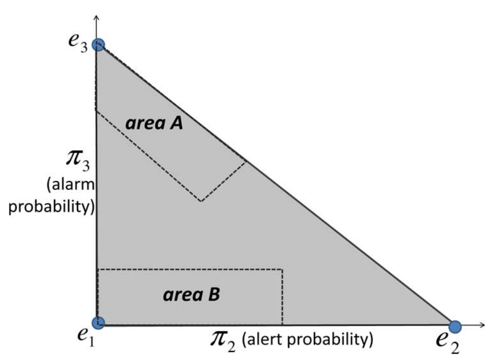


Fig. 5. Partially observed state space for an operating system.

corner implies the healthy conditions. The states outside these two areas are those whose aging conditions are in between.

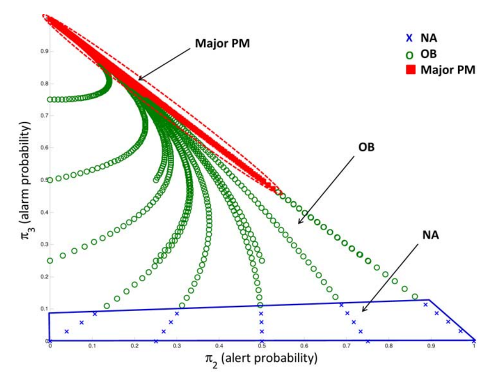
There are five types of corrective maintenances, $\mathrm{CM}(1),\ldots,\mathrm{CM}(5)$ and two types of preventive maintenances, $\mathrm{PM}(1)$ and $\mathrm{PM}(2)$. To get the maintenance costs, we refer to Andrawus *et al.*'s study [13]. Rademakers *et al.* also discuss different cost factors in their study in [14]. According to Andrawus *et al.* [13], a major CM, as a result of unanticipated failures, costs £78 368, and a major preventive repair costs £8182. Therefore, we set $C_{\mathrm{CM}(1)}$ and $C_{\mathrm{CM}(2)}$ to be £78 368 and $C_{\mathrm{PM}(1)}$ to be £8182 because $\mathrm{CM}(1)$, $\mathrm{CM}(2)$, and $\mathrm{PM}(1)$ correspond to major repairs. There are no cost figures for $C_{\mathrm{PM}(2)}$ in the literature, and not for $C_{\mathrm{CM}(3)}$ through $C_{\mathrm{CM}(5)}$, either. So based on the suggestions of our industry partners, we set $C_{\mathrm{CM}(3)}$ to be the half of the major CM cost, and $C_{\mathrm{CM}(4)}$ and $C_{\mathrm{CM}(5)}$ to be one tenth of the major CM cost, respectively. Similarly, $\mathrm{PM}(2)$ corresponds to the minor repair and its cost $C_{\mathrm{PM}(2)}$ is assumed to be one third of the major PM cost. The OB cost of a gearbox is set to be £200 [13]. These costs are summarized in the second column of Table II.

Furthermore, these maintenance activities are constrained by the weather conditions. The weather conditions would depend on the locations, terrains of the wind farm site. We set the probabilities that the harsh weather conditions would occur each season in the third column of Table II.

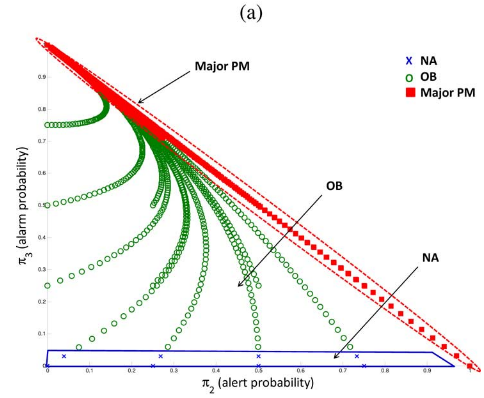
Revenue losses per period depend on the weather conditions. We set the average revenue losses to be £4433 [13]. Then, we adjust the revenue losses across the four seasons from spring to winter to be 80%, 120%, 80%, and 130% of the average revenue losses, respectively. Table III summarizes the potential revenue losses per week for each season.

TABLE III
REVENUE LOSSES

Spring	Summer	Fall	Winter
3 546	5 320	3 546	5 763



(a)

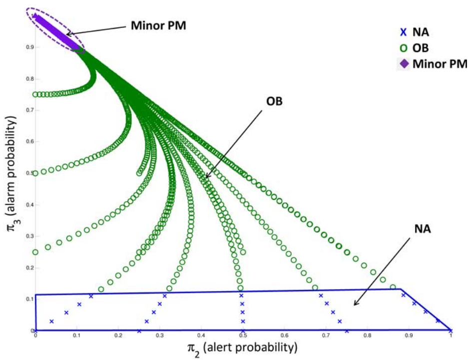


(b)

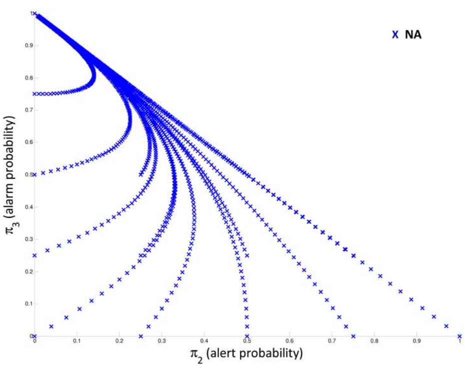
Fig. 6. Optimal decision rule during spring season. (a) In the beginning of spring. (b) At the end of spring.

B. Results

With these parameter values, we compute the optimal policy during a 20-year decision horizon. Since we consider the decision makings on a weekly basis, we set the discount factor β as 0.99, which is close to *one*. Figs. 6–8 show, respectively, the optimal actions for spring, summer, and fall seasons in the first

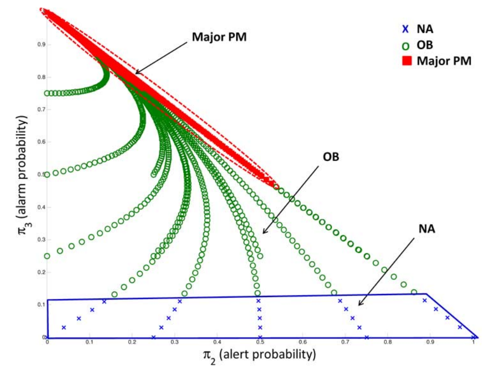


(a)

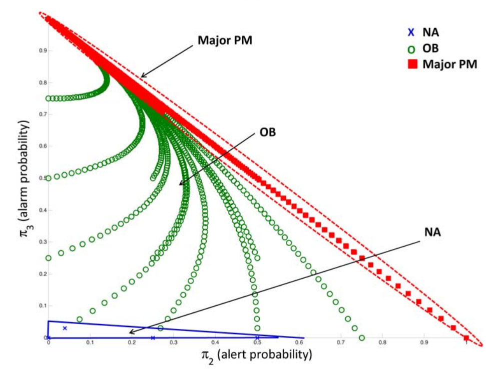


(b)

Fig. 7. Optimal decision rule during summer season. (a) In the beginning of summer. (b) At the end of summer.

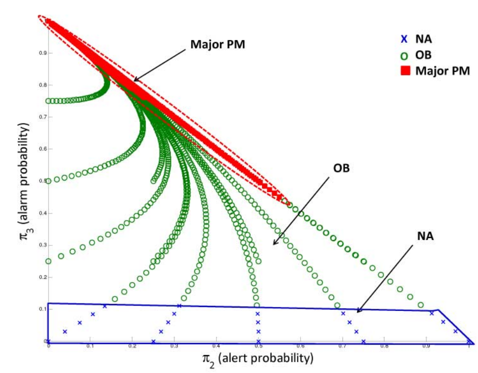


(a)

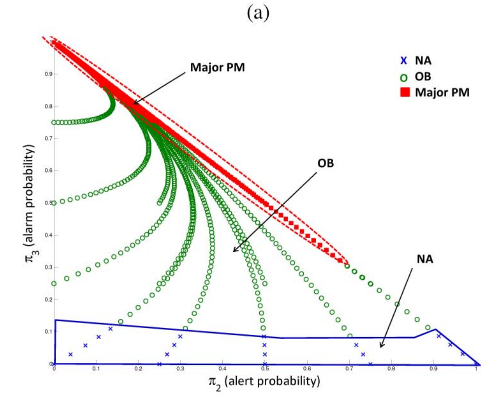


(b)

Fig. 8. Optimal decision rule during fall season. (a) In the beginning of fall. (b) At the end of fall.



(a)



(b)

Fig. 9. Optimal decision rule in the middle of spring and fall. (a) In the middle of spring. (b) In the middle of fall.

year of operations along a number of series of the sample paths. The optimal actions for winter season are almost similar to the results for summer season.

It is interesting to see that the optimal policy is non-stationary. That is, the optimal action is not the same throughout the decision periods. It is worth noting a few features of the optimal decision rules.

- In the beginning of mild weather seasons such as spring and fall, we take the major PMs when the system is estimated to be ill-conditioned. Toward the end of mild seasons, the optimal decision is to take the major PMs even for the moderately deteriorated condition like e_2 in order to minimize the risk of failures during the upcoming harsh weather seasons.
- The optimal decisions of spring and fall seasons are slightly different. The NA area at the end of fall season in Fig. 8(b) is smaller than the one in Fig. 6(b). Fig. 9 compares the two optimal policies in the middle of spring and fall seasons. The area where the major PM is optimal in Fig. 9(b) is larger than the area in Fig. 9(a). All these are because of the more restricted maintainability of the wind turbines during the (almost entire) winter season.
- In the beginning of harsh weather seasons such as summer storm season and winter season, it is recommended to take the minor PMs for the seriously ill-conditioned system to avoid failures during the remaining harsh weather periods, occurring of which may cause tremendous repair costs. However, at the end of harsh weather seasons, NA is dominated in all the states because it would be better to wait for the next mild periods rather than performing risky repair activities right away.

TABLE IV
AVERAGE OF SIMULATION RESULTS FOR DIFFERENT MAINTENANCE STRATEGIES (STANDARD DEVIATION IN PARENTHESIS)

	Scheduled maintenance	Static CBM strategy	Dynamic CBM strategy[a]
# failures per year	1.29 (0.31)	0.74 (0.30)	0.55 (0.16)
O&M costs per year [b]	68 320 (13 510)	65 690 (9 020)	57 990 (8 900)

[a] Proposed maintenance strategy in this paper
[b] The monetary unit is *pounds*(£)

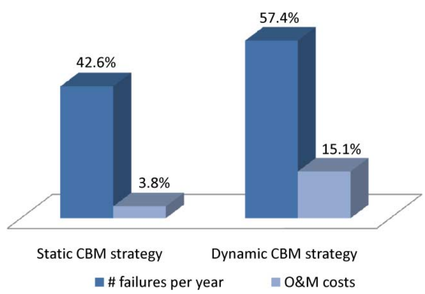


Fig. 10. Reduction (%) of failure frequency and maintenance costs of the two CBM strategies compared with the current industry practices.

- OB is taken when the system conditions are not clear. However, OB is taken more often in the beginning or middle of harsh weather seasons to decide the most suitable maintenance tasks than in the mild seasons. Understandably, doing so will help reap more economical benefits.

C. Practical Use of the Model

In the interest of making the resulting method easier to use for practitioners, we hereby summarize the major steps below regarding how to obtain the non-stationary optimal policy and how to interpret it for maintenance decisions in practice.

Step 1) Obtain parameter values needed for modeling using historical data. These parameters include weather-dependent parameters [$W_{\mathrm{CM}(l),n}$, $W_{\mathrm{PM}(m),n}$, τ_n for $\forall l, m, n$], costs [$C_{\mathrm{CM}(l)}$, $C_{\mathrm{PM}(m)}$, C_{OB} for $\forall l, m$], and failure/degradation related parameters [P, $\lambda(l)$, $\mu(l)$ for $\forall l$].

Step 2) Calculate the optimal maintenance policy of each week for a whole year using the backward dynamic programming, explained in Section III-B.

Step 3) Plot the figures as shown in Figs. 6–9 or create some look-up tables, which represent the options of optimal policy of each week.

Step 4) In the beginning of each period, estimate the system state (π_1, π_2, π_3) using sensor data.

Step 5) Get the optimal policy by looking up the figures or using the look-up table built in (Step 3) and select the optimal action.

Note that Steps 1)–3) are associated with the derivation of the optimal policy. Once we obtain the optimal policy for each period for a whole year, wind farm operators, in the execution mode, just need to estimate the system states and to check in which policy region the state estimate falls, and then take actions according to the corresponding policy type of that region, as explained in Steps 4) and 5).

Based on the above discussion, the resulting policy (figures) can be understood as follows: the viable operating region (the triangle in Fig. 5) can be partitioned into subregions corresponding to different actions (that is, NA, OB, major PM, and minor PM). Note that each curve in Figs. 6–8 [except Fig. 7(b)] has a couple of different colors (and shapes) in order to specify different optimal policies along a sample path. By obtaining the optimal policies along multiple sample paths, we can easily identify each region where a specific action is optimal. Then, at the beginning of each decision period, wind farm operators just need to estimate the system states (π_2 and π_3, the horizontal and vertical axes in the figure) and to check which subregion the state estimate falls in, and then take actions according to the corresponding type of that subregion. For example, in the beginning of spring [see Fig. 6(a)], if a state falls in a major PM area in the upper-left corner surrounded by the red dashed boundary, wind farm operators should take major preventive repairs.

D. Monte Carlo Simulation

To quantify the benefits of the proposed dynamic CBM strategy, we compare the optimal policy with two other maintenance strategies. The first strategy is the fixed scheduled maintenance, reflecting the current industry practices. The other strategy is a similar CBM strategy, but without considering the seasonal weather effects.

To compare each strategy, we conduct Monte Carlo simulations using the same parameter values explained in Section IV-A. We simulate the system states following the transition matrix with P_A and P_B in (12). We also simulate the weather scenarios with the given probabilities in Table II. For each strategy, 30 trajectories (or, runs) of simulations are performed over 1040 periods (= 52 weeks $\times$ 20 years). Then, we obtain the average failure frequency and O&M costs per year. Table IV and Fig. 10 summarize the simulation results of each maintenance strategy, and we will explain the implications of the results.

1) Results From Current Industry Practices: Current industry practices are mainly based on scheduled maintenances, which conducts PMs on a regular basis in low wind speed seasons [3], [12]. The frequency of the scheduled maintenance usually depends on the manufacturer's recommended maintenance program [30]. However, according to Nilsson and Bertling [12], wind farm operators usually carry out minor maintenances twice a year and major maintenances once every two to four years, respectively. Following the industry practices, we set the scheduled minor maintenances to be carried out in spring and fall, and major preventive maintenances to be performed once every three years in spring. The simulation results indicate that generators would fail 1.29 times per year

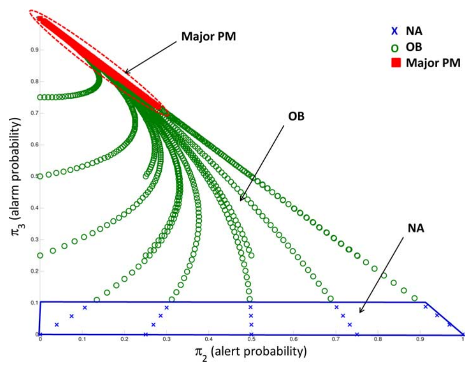


Fig. 11. Optimal decision rule under stationary weather conditions.

on average, resulting in £68 320 O&M costs per year under this scheduled maintenance strategy.

2) Results From the Static CBM Strategy: Suppose that in order to produce a condition-based maintenance policy, wind farm operators consider a gearbox's degradation status but ignore the weather constraints. That is, the maintenance policy is obtained with the assumption that maintenance tasks can be performed anytime although repair tasks are constrained by seasonal weather effects. To implement this strategy, we set $W_{\mathrm{CM}(l),n}$'s and $W_{\mathrm{PM}(m),n}$'s to be *zero*, and use constant τ_n for $\forall l, m, n$ in the proposed procedure in this study. Then, the resulting decision rules under the assumption of these static weather conditions are applied at each period in the simulation. This strategy is similar to the one presented in our previous study [21] in the sense that homogeneous weather-related parameters are used, and thus, the resulting strategies are static over the decision horizon [but the difference is that [21] used non-zero constants for $W_{\mathrm{CM}(l),n}$'s and $W_{\mathrm{PM}(m),n}$'s].

Fig. 11 illustrates the optimal decision rules under this static CBM strategy. With this strategy, wind farm operators take the action based on the degradation state of a gearbox, but the same maintenance action will be applied to the same state over the different seasons. The third column of Table IV summarizes the results from this strategy. Since this strategy considers the deterioration status, one can make timely decisions regarding when to take maintenance actions to avoid failures. As a result, the failure frequency is reduced by $42.6\%(= (1.29 - 0.74)/1.29)$, compared with the result of the scheduled maintenance. However, the reduction of maintenance costs comes at an unimpressive $3.8\%(= (68\,320 - 65\,690)/68\,320)$ since this strategy does not consider the weather impacts (see the graph in the left side of Fig. 10).

3) Results From the Dynamic CBM Strategy: In this strategy, the optimal maintenance action suggested by this study, which considers the costs, degradation status, and weather conditions, is taken at each decision period. The final column of Table IV summarizes the results from the optimal policy. The reductions in both failure frequency and O&M costs are remarkable, compared with the scheduled maintenance. The failure frequency and O&M costs are decreased by $57.4\%(= (1.29-0.55)/1.29)$ and $15.1\%(= (68\,320 - 57\,990)/68\,320)$, respectively, demonstrating that substantial benefits can be anticipated by adopting the proposed dynamic CBM strategy in the practices of wind power industry (see the graph in the right side of Fig. 10).

V. Conclusion

In this study we construct a new stochastic model for choosing the cost-effective maintenance actions and scheduling adaptive yet costly on-site observations for wind turbine operations and maintenance. We develop a season-dependent, dynamic optimal policy to respond to the time-varying weather conditions. We also examine other unique aspects in wind turbine maintenance such as different failure modes, partial as well as perfect repairs, and stochastic revenue losses. All these factors render critical implications in the actual wind farm O&M.

The case study of a gearbox, a critical component in a wind turbine prone to major failures, demonstrates the benefits of adopting the proposed CBM strategy. The failure frequency and the overall costs can be considerably reduced when the proposed policy is applied to a wind farm, instead of simply following the scheduled maintenance practices. Also, we show that using a static CBM strategy without considering the seasonal weather effects could potentially improve the reliability of a turbine component, as compared to the current practices, but the cost reduction is not as appreciable as the dynamic CBM strategy can provide. This difference in cost savings is because the repairing activities during harsh weather seasons would often result in repairing interruptions and delays, which lead to the potential production loss.

As future work, we could extend the model to incorporate multiple components of a wind turbine. In this study we assume the independence of each component operation. However, when a component fails, it may cause other components to malfunction; this is known as "cascading effects". It would be interesting to see how robust the recommended maintenance policy can perform for a wind turbine when multiple components are considered. In parallel to this study, we are developing a large-scale simulation model for wind farm operations with hundreds of turbines, using a discrete event specification (DEVS) formalism [31]. The model and maintenance strategy presented in this paper will be integrated into the DEVS simulation model to validate the optimal policy, and to see if further modifications are necessary.

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