IIE Transactions

Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/uiie20

Wind turbine operations and maintenance: a tractable approximation of dynamic decision making

Eunshin Byon [a]

[a] Industrial and Operations Engineering Department , University of Michigan , Ann Arbor , MI , 48109-2117 , USA

Accepted author version posted online: 18 Sep 2012.Published online: 11 Jul 2013.

To cite this article: Eunshin Byon (2013) Wind turbine operations and maintenance: a tractable approximation of dynamic decision making, IIE Transactions, 45:11, 1188-1201, DOI: 10.1080/0740817X.2012.726819

To link to this article: http://dx.doi.org/10.1080/0740817X.2012.726819

IIE Transactions (2013) **45**, 1188–1201
Copyright © "IIE"
ISSN: 0740-817X print / 1545-8830 online
DOI: 10.1080/0740817X.2012.726819

Wind turbine operations and maintenance: a tractable approximation of dynamic decision making

EUNSHIN BYON

Industrial and Operations Engineering Department, University of Michigan, Ann Arbor, MI 48109-2117, USA
E-mail: ebyon@umich.edu

Received October 2011 and accepted August 2012

Timely decision making for least-cost maintenance of wind turbines is a critical factor in reducing the total cost of wind energy. The current models for the wind industry as well as other industries often involve solving computationally expensive algorithms such as dynamic programming. This article presents a tractable approximation of the dynamic decision-making process to alleviate the computational burden. Based upon an examination of decision rules in stationary weather conditions, a new set of decision rules is developed to incorporate dynamic weather changes. Since the decisions are made with a set of If–Then rules, the proposed approach is computationally efficient and easily integrated into the simulation framework. It can also benefit actual wind farm operations by providing implementable control. Numerical studies using field data mainly from the literature demonstrate that the proposed method provides practical guidelines for reducing operational costs as well as enhancing the marketability of wind energy.

[Supplementary materials are available for this article. Go to the publisher's online edition of *IIE Transactions* for detailed proofs.]

Keywords: Condition-based maintenance, dynamic programming, management decision-making, Markov decision processes, reliability, wind energy

1. Introduction

Globally, the wind power industry is seeking more cost-effective Operations and Maintenance (O&M; Walford, 2006; Wiser and Bolinger, 2008; Asmus, 2010). The U.S. Department of Energy (Wiser and Bolinger, 2008) reported that actual O&M costs are between \$0.008/kWh and \$0.018/kWh, depending on a facility's size and location. Asmus (2010), who compiled extensive field data, found an even higher O&M cost at the level of \$0.027/kWh (or €0.019/kWh). These high O&M costs account for a significant portion of total generation costs (Lu *et al.*, 2009).

Recent studies have proposed various O&M strategies for wind turbines (Andrawus *et al.*, 2007; Byon *et al.*, 2010; Byon and Ding, 2010; Tian *et al.*, 2011). Among them, the dynamic Condition-Based Maintenance (CBM) model discussed in Byon and Ding (2010) considered a system's intrinsic aging characteristics as well as external, non-stationary environmental conditions. Thus, the dynamic CBM model gives more satisfactory results than other CBM models when there are strong seasonal variations. In the meanwhile, work has been undertaken to simulate the dynamic operations of wind turbines for evaluating the effectiveness of various O&M strategies (Rademakers *et al.*, 2003; Foley and Gutowski, 2008; McMillan and Ault, 2008; Byon *et al.*, 2011). In order to reflect the recent trend of constructing large-scale wind farms with hundreds of turbines, it is necessary to perform a farm-level simulation rather than the individual turbine-level ones.

Integrating a sophisticated maintenance model—for example, the dynamic CBM model in Byon and Ding (2010)—into a farm-level simulation introduces two significant issues. First, even though the backward Dynamic Programming (DP) algorithm can be used to solve the dynamic CBM model, the DP algorithm is computationally demanding for solving large-scale problems. This DP procedure is invoked by the simulation command module at every decision epoch when decisions need to be made. Understandably, including such a DP procedure makes the farm-level simulation extremely sluggish. For example, the DP procedure uses several hours to determine the maintenance actions for 100 turbines considering a 20-year lifetime. Second, the DP procedure requires knowledge about weather conditions over the entire decision horizon to determine an optimal O&M policy. One of the most common approaches in DP is to estimate the parameters from historical data, but if the actual weather condition deviates considerably from historical patterns, the O&M policy cannot adapt to reality. Due to these problems, to the best of our knowledge the current simulation models incorporate only a simplified form of maintenance policies rather than a sophisticated one such as the dynamic CBM.

The research question we address is *how to devise a tractable approximation of dynamic decision making*? The new solution procedure for O&M decision making described in this article adds two features to the dynamic CBM model: a simple control to implement and a mechanism dynamically adapted to current weather conditions. The first feature is desirable to manage large-scale operations, and the second feature utilizes the most refined, real-time weather information with a much reduced degree of uncertainty. Although motivated by integrating a dynamic CBM policy into wind farm simulations, the resulting features of the new policy can be beneficial in actual operations.

We develop a set of linear decision rules by analytically deriving the control limits for each action in closed-form expressions. The rules contain sufficiently detailed descriptions of non-stationary weather profiles and are simple enough to reduce computational run times. The numerical results from a variety of implementation settings indicate that the proposed method generates computationally feasible solutions and achieves a performance level similar to the DP approach. Using field data mainly from the literature and real wind measurements, the case study demonstrates that the proposed method addresses practical O&M planning issues and reduces the O&M costs by planning preventive maintenance in low wind conditions to avoid failures during harsh weather seasons.

The remainder of this article is organized as follows. Section 2 reviews the literature on analytical and simulation studies. Section 3 presents the dynamic CBM formulation. Section 4 proposes rule-based decision-making procedures for the dynamic CBM model. The results from numerical analyses and a case study are reported in Section 5 and Section 6, respectively. The conclusions and suggestions for future research appear in Section 7.

2. Literature review

In analytical studies to develop cost-effective decision strategies for wind farm operations, there are two major approaches: statistical models and Markov process–based models. The statistical approach uses measured failure data to evaluate the reliability level of several critical components in a wind turbine. In this approach, a Weibull distribution is commonly used to analyze the lifetime of a system (Andrawus *et al.*, 2007; Tavner *et al.*, 2007; Guo *et al.*, 2009). Andrawus *et al.* (2007) used the time-to-failure information to assess the reliability level of a turbine's critical components including the main bearing, gearbox, generator, and control system. They identified the optimal repair or replacement time for each component to minimize O&M costs. Tavner *et al.* (2007) and Guo *et al.* (2009) utilized summary statistics such as number of failures occurring monthly or quarterly and combined a Weibull process with a Poisson process to model the failure patterns of wind turbines over time.

The second approach uses Markov models to represent aging behaviors of a system. Because of their flexibility and popularity, Markov models are widely used in conventional power systems (Jirutitijaroen and Singh, 2004; Yang *et al.*, 2008) and recently in the wind power industry (Sayas and Allan, 1996; McMillan and Ault, 2008). However, these studies do not embed decision-making capabilities to control a stochastic aging system.

A Markov Decision Process (MDP) provides a framework to make a decision for an optimal control (or, policy; Puterman, 1994). In an MDP an optimal control is sequentially determined based on the knowledge of a system's current state and future evolution. After each control action, the system follows a Markov process, but the transition probability from a state to another state depends on the decision made. MDP is widely used in the literature on optimal preventive maintenance for general systems (Lovejoy, 1987; Maillart, 2006; Maillart and Zheltova, 2007). Byon and Ding (2010) and Byon *et al.* (2010) presented two MDP models that reflected unique aspects of turbine maintenance including stochastic weather environments, lengthy lead times, and revenue losses during downtimes. For more discussions regarding the uniqueness of wind turbine O&M, see Byon and Ding (2010) and Byon *et al.* (2010).

Another category develops simulation models that approximate the dynamic operations of a wind farm (Rademakers *et al.*, 2003; Andrawus *et al.*, 2007; Foley and Gutowski, 2008; McMillan and Ault, 2008; Byon *et al.*, 2011). Foley and Gutowski (2008) and McMillan and Ault (2008) analyzed the performance of wind power systems under different environmental settings, geographical terrains, and locales. McMillan and Ault (2008) and Byon *et al.* (2011) investigated the effect of different maintenance strategies on the reliability of wind farms using performance indices such as the number of failures, O&M costs, and availability.

This article presents computationally efficient approximations that allow the most cost-effective maintenance actions to be selected from an optimization model during the simulation runs. The set of new solution tools and efficient algorithms enables a sophisticated dynamic maintenance decision model to be included in the feedback loop of a farm-level simulation, thereby attaining an effective integration.

3. Problem setting and dynamic CBM model

In this study, we propose a dynamic policy that approximates the solution of the dynamic CBM model presented in Byon and Ding (2010). For the sake of readability, we summarize the problem setting and dynamic CBM model in Byon and Ding (2010). We believe that the dynamic CBM model represents what should be considered in the wind turbine O&M.

The model considered is a discrete-time, Partially Observed Markov Decision Process (POMDP). In a POMDP, an optimal control is determined in each decision epoch, based on a system's current state and future evolution (Puterman, 1994; Byon and Ding, 2010). Assume that the status of a system can be classified into a set of M degradation conditions, $e_1, e_2, \cdots, e_M$, and L different types of failures, $e_{M+1}, e_{M+2}, \cdots, e_{M+L}$. Without loss of generality, a lower index implies a healthier condition. If the system status is fully observable, the state space for the system status is $\mathbf{\Psi} = \{e_1, \cdots, e_M, e_{M+1}, \cdots, e_{M+L}\}$. We assume that when the system fails, the failure status is observable. The physical condition for the *operating* system is not completely observable but can be estimated using a discrete random variable, $\tilde{e}_0$. Let π_i denote the probability that the operating system is in status e_i; i.e., $\pi_i = P\{\tilde{e}_0 = e_i\}$, $i = 1, \cdots, M$. Then, we redefine the state for the operating system as follows:

$$\boldsymbol{\pi} = [\pi_1, \cdots, \pi_M], \tag{1}$$

where $\sum_{i=1}^{M} \pi_i = 1$. Note that the state e_i, $i = 1 \cdots, M$, is the same as $\boldsymbol{\pi}$ in Equation (1) whose ith element is *one* and other elements are *zero*.

If No Action (NA) is taken, it is assumed that the system degrades according to a Markovian deterioration process with a transition probability matrix $\mathbf{P} = [p_{ij}]_{(M+L)\times(M+L)}$. The probability that the system will still operate until the next period is $R(\boldsymbol{\pi}) = \sum_{i=1}^{M} \sum_{j=1}^{M} \pi_i p_{ij}$, which is called the *reliability* of the system (Maillart, 2006). Given that the system has not yet failed, the state after the next transition is

$$\pi'_j(\boldsymbol{\pi}) = \begin{cases} \dfrac{\sum_{i=1}^{M} \pi_i p_{ij}}{R(\boldsymbol{\pi})}, & j = 1, 2, \cdots, M, \\ 0, & j = M+1, \cdots, M+L. \end{cases} \tag{2}$$

With probability $H_l(\boldsymbol{\pi}) = \sum_{i=1}^{M} \pi_i p_{i,M+l}$, the system can fail with the lth mode and the state results in e_{M+l}. The failed state is observable and, thus, for each failure mode l, only one Corrective Maintenance (CM), namely, $CM(l)$, is carried out at cost $C_{CM(l)}$. In this case, operators arrange for repairs, which takes $\lambda(l)$ lead time (note: $\lambda(l)$ takes nonnegative integer values). We consider perfect corrective repair, so the system condition returns to e_1 after $CM(l)$. Let $\mu_{CM(l)}$ denote the repair period for $CM(l)$, which is determined according to the failure mode. Assume that to fix significant failure types, substantial repairs are performed during one period—i.e., $\mu_{CM(l)} = 1$—and that for insignificant failure mode, repairs can be done immediately; i.e., $\mu_{CM(l)} = 0$. Maintenance activities can be constrained by adverse weather conditions. Let $W_{CM(l),n}$ represent the probability that the prevailing weather conditions are adverse (subscript n denotes the number of periods remaining until the terminal period) and, thus, $CM(l)$ is not allowed.

Preventive Maintenance (PM) is modeled with multiple levels of repair efforts, depending on how much the system condition can be improved. Let $PM(m)$ return the condition to the state e_m at cost $C_{PM(m)}$ for $m = 1, \cdots, M-1$. $PM(m)$ with a low value of m is a major preventive repair that significantly improves the system condition. Assume that such major maintenance takes one period; i.e., $\mu_{PM(m)} = 1$. $PM(m)$ with the high value of m, which slightly improves the system condition, is a minor maintenance that can be done immediately; i.e., $\mu_{PM(m)} = 0$. $W_{PM(m),n}$ denotes the probability that $PM(m)$ cannot be performed due to the adverse weather conditions. Assume that the system cannot operate until the scheduled PM is finished. As such, revenue losses are incurred during either the preventive repair or repair delay. When the scheduled PM is interrupted and delayed due to harsh weather condition, the turbine does not operate until the weather returns to good conditions.

OBservation (OB) assesses the system's exact deterioration level at cost C_{OB}. After observation, the least costly action in the same period is selected among NA or $PM(m)$'s, $m = 1, \cdots, M-1$, based on the updated state information.

In summary, for the operating system whose condition is not completely observable, we consider $M+1$ action choices, NA, $PM(1), \cdots, PM(M-1)$, and OB. When the system fails, the failed status is observable, and one CM action that corresponds to each failure mode is carried out. Let $V_n(\boldsymbol{\pi})$ denote the minimum expected total cost-to-go as follows:

$$\begin{aligned} V_n(\boldsymbol{\pi}) = \min\{&NA_n(\boldsymbol{\pi}), PM_n(1), \cdots, \\ &PM_n(M-1), OB_n(\boldsymbol{\pi})\}, \end{aligned} \tag{3}$$

where

$$\begin{aligned} NA_n(\boldsymbol{\pi}) = &\sum_{l=1}^{L} (\tilde{\tau}_n(l) + CM_{n-\lambda(l)-1}(e_{M+l})) H_l(\boldsymbol{\pi}) \\ &+ V_{n-1}(\boldsymbol{\pi}'(\boldsymbol{\pi})) R(\boldsymbol{\pi}), \end{aligned} \tag{4}$$

$$PM_n(m) = \begin{cases} W_{PM(m),n}(\tau_n + PM_{n-1}(m)) \\ \quad + (1 - W_{PM(m),n})(\tau_n + C_{PM(m)} + V_{n-1}(e_m)) \\ \qquad \text{for } \mu_{PM(m)} = 1, \\ W_{PM(m),n}(\tau_n + PM_{n-1}(m)) \\ \quad + (1 - W_{PM(m),n})(C_{PM(m)} + V_n(e_m)) \\ \qquad \text{for } \mu_{PM(m)} = 0, \end{cases} \tag{5}$$

$$OB_n(\boldsymbol{\pi}) = C_{OB} + \sum_{i=1}^{M} V_n(e_i)\pi_i, \tag{6}$$

and

$$\tilde{\tau}_n(l) = \begin{cases} \sum_{t=1}^{\lambda(l)} \tau_{n-t} & \text{for } \lambda(l) > 0, \\ 0 & \text{for } \lambda(l) = 0, \end{cases} \tag{7}$$

$$CM_n(e_{M+l}) = \begin{cases} W_{CM(l),n}(\tau_n + CM_{n-1}(e_{M+l})) \\ \quad + (1 - W_{CM(l),n})(\tau_n + C_{CM(l)} + V_{n-1}(e_1)) \\ \qquad \text{for } \mu_{CM(l)} = 1, \\ W_{CM(l),n}(\tau_n + CM_{n-1}(e_{M+l})) \\ \quad + (1 - W_{CM(l),n})(C_{CM(l)} + V_n(e_1)) \\ \qquad \text{for } \mu_{CM(l)} = 0. \end{cases} \tag{8}$$

The first term in Equation (4) is the cost-to-go when the system fails. $\tilde{\tau}_n(l)$ in Equations (4) and (7) are the revenue losses during the lead time upon a failure with the lth mode, and τ_n is the revenue losses at period n. The second term in Equation (4) implies that when the system does not fail with probability $R(\boldsymbol{\pi})$, the system will transit to the next state $\boldsymbol{\pi}'(\boldsymbol{\pi})$ at the next period. The first term in Equation (5) is the revenue losses from repair delays that are caused by adverse weather conditions occurring with probability $W_{PM(m),n}$. The second term in Equation (5) implies the preventive repair costs under favorable weather conditions. In Equation (6), $OB_n(\boldsymbol{\pi})$ consists of two factors: direct cost to inspect the system C_{OB} as well as the post-maintenance cost after the system condition is evaluated precisely. $CM_n(e_{M+l})$ in Equation (8) reflects the CM cost for the lth failure mode.

Remark 1. A couple of possible extensions of the model in Equations (3) to (8) will be the subjects of future research. First, while this article assumes that the technology of the new and older parts used in CM are similar and that system deterioration after CM will follow the same transition matrix, $\mathbf{P} = [p_{ij}]_{(M+L)\times(M+L)}$, our future research will consider using improved technology that has slow deterioration rates and high reliability. Second, while this article assumes that the revenue losses do not depend on the system condition, our future research will consider such dependency in order to analyze the effects on O&M decision making.

In setting the discount factor to one, note that the model in Equations (3) to (8) slightly differs from the original model in Byon and Ding (2010). The reason is that since our proposed method to be discussed in the following sections allows the maintenance decision to be made quickly, the decision period usually will be days or weeks, where the discount rate is practically one.

Table 1 summarizes the parameters and how to estimate them for the dynamic CBM model. The output from the dynamic CBM model is the maintenance action among the $M+1$ choices (NA, OB, and $PM(m)$, $m = 1, \cdots, M-1$) to be determined in each period by the decision maker.

4. Rule-based, dynamic CBM policy

This section discusses the approach for attaining a tractable approximation of the dynamic CBM model's solution. The proposed approach takes hints from the approach used in Byon *et al.* (2010), which considers time-invariant weather parameters. Note that Byon *et al.* (2010) provided closed-form expressions of decision boundaries but only for a restricted case with one failure mode and one repair level. Section 4.1 extends their results to provide optimal control limits for a multi-failure mode and multi-level maintenance model and characterizes the solution structure of the extended model. In Sections 4.2 and 4.3, the decision boundaries are adjusted by coupling non-stationary weather conditions to the decision rules.

4.1. *Static decision boundary for multi-mode, multi-level maintenance*

Assume that the weather parameters in Equations (4) to (8) are time-invariant or homogeneous. We call the model with the time-invariant parameters a *static* CBM model. In the static CBM model, weather conditions are stationary, and $W_{CM(l),n}$, $W_{PM(m),n}$, and τ_n for all l, m in Equations (4) to (8) can be replaced with $W_{CM(l)}$, $W_{PM(m)}$, and τ. Additionally, the revenue losses during the lead time upon a system failure with the lth mode, $\tilde{\tau}_n(l)$ in Equation (7), are replaced by $\tau \times \lambda(l)$.

Similar to the model in Byon *et al.* (2010), the extended model with multi-failure mode and multi-level maintenance has a limiting property as n becomes large, namely, that for $0 \le W_{CM(l)} < 1$ and $0 \le W_{PM(m)} < 1$ for all l, m, $V_n(\boldsymbol{\pi})$ approaches a line with slope g and intercept $b(\boldsymbol{\pi})$ as follows:

$$\lim_{n\to\infty} V_n(\boldsymbol{\pi}) = n \times g + b(\boldsymbol{\pi}), \tag{9}$$

where g denotes the *average cost* per period under the optimal policy and $b(\boldsymbol{\pi})$ is the *bias*, or the *relative cost*, when the state starts from $\boldsymbol{\pi}$. After substituting Equation (9) into

Table 1. Parameters of the dynamic CBM model

Notation	*Explanation*	*Unit*	*Source for estimation*
$W_{CM(l),n}$, $W_{PM(m),n}$	Weather prohibiting probability for CM(l) and PM(m)	Real value ([0, 1])	Historical weather data or forecast information
$\lambda(l)$	Lead time for lth failure mode	Non-negative integer	Wind farm operational data
$\mu_{CM(l)}$, $\mu_{PM(m)}$	Repair time for CM(l) or PM(m)	Non-negative integer	
$C_{CM(l)}$,	CM cost for lth failure mode	Monetary	
$C_{PM(m)}$	PM cost for mth repair level	Monetary	
C_{OB}	OB cost	Monetary	
p_{ij}	Degradation transition probability	Real value ([0, 1])	
π_i	Probability that current condition is e_i	Real value ([0, 1])	Condition monitoring sensors

Equations (4) to (8), $b(\boldsymbol{\pi})$ becomes

$$b(\boldsymbol{\pi}) = \min \begin{cases} b_{NA}(\boldsymbol{\pi}) = \sum_{l=1}^{L} C'_{CM(l)} H_l(\boldsymbol{\pi}) \\ \quad + b(\pi'(\boldsymbol{\pi}))R(\boldsymbol{\pi}) - g, \\ b_{PM(m)}(\boldsymbol{\pi}) = C'_{PM(m)}, \\ b_{OB}(\boldsymbol{\pi}) = C'_{OB} \\ \qquad \text{for } m = 1, \cdots, M-1, \end{cases} \tag{10}$$

where

$$C'_{CM(l)} = C_{CM(l)} + \lambda(l) \times (\tau - g) + \begin{cases} \dfrac{W_{CM(l)}(\tau - g)}{1 - W_{CM(l)}} & \text{for } \mu_{CM(l)} = 0 \\ \dfrac{\tau - g}{1 - W_{CM(l)}} & \text{for } \mu_{CM(l)} = 1 \\ \qquad \text{for } l = 1, \cdots, L, \end{cases} \tag{11}$$

$$C'_{PM(m)} = C_{PM(m)} + b(e_m) + \begin{cases} \dfrac{W_{PM(m)}(\tau - g)}{1 - W_{PM(m)}} & \text{for } \mu_{PM(m)} = 0 \\ \dfrac{\tau - g}{1 - W_{PM(m)}} & \text{for } \mu_{PM(m)} = 1 \\ \qquad \text{for } m = 1, \cdots, M-1, \end{cases} \tag{12}$$

$$C'_{OB} = C_{OB} + \sum_{i=1}^{M} b(e_i)\pi_i. \tag{13}$$

In Equation (10), the first term of $b_{NA}(\boldsymbol{\pi})$ is associated with the L failure modes. Because L different failure modes are considered, there are multiple $C'_{CM(l)}$ variables in $b_{NA}(\boldsymbol{\pi})$. In Equation (13), the second term $b(e_m)$ exists because the system returns to the state e_m after PM(m). Equations (10) to (13), as well as the decision boundaries shown in Table 2, can be derived following steps similar to those in Maillart (2006) and Byon *et al.* (2010). See the supplement for a detailed explanation at the publisher's online edition.

Next, we derive a set of closed-form expressions for the optimal policy. By comparing $PM(m)$, $m = 1, \cdots, M-1$, to one another, the best level of PM is identified as m^*, which gives the minimum bias; that is,

$$m^* \equiv \operatorname{argmin}_{m=1,\cdots,M-1}\{b_{PM(m)}(\boldsymbol{\pi})\}. \tag{14}$$

Now, the preference conditions are established by comparing pairwise $b_{NA}(\boldsymbol{\pi})$, $b_{PM(m^*)}(\boldsymbol{\pi})$, and $b_{OB}(\boldsymbol{\pi})$. Table 2 summarizes the preference conditions between any two actions. In the preference conditions in Table 2, the values of g and $b(e_i)$, $i = 1, \cdots, M$, can be obtained by applying the standard *policy* (or *value*) *iteration* along the sample paths emanating from the states, e_i, $i = 1, \cdots, M$ (for the details of finding g and $b(e_i)$, see Byon *et al.* (2010)). By a sample path of $\boldsymbol{\pi}$, we mean the sequence of states over time when no action is taken, which is denoted by $\{\boldsymbol{\pi}, \boldsymbol{\pi}^2, \cdots, \Pi(\boldsymbol{\pi})\}$, where $\boldsymbol{\pi}^2 = \pi'(\boldsymbol{\pi})$, $\boldsymbol{\pi}^3 = \pi'(\boldsymbol{\pi}^2)$ and so on (Maillart, 2006; Byon *et al.*, 2010). $\Pi(\boldsymbol{\pi})$, defined by $\Pi(\boldsymbol{\pi}) \equiv \boldsymbol{\pi}^{k^*(\pi)}$ where $k^*(\boldsymbol{\pi}) = \min\{k : ||\boldsymbol{\pi}^{k+1} - \boldsymbol{\pi}^k|| < \epsilon\}$ with small $\epsilon > 0$, is a stationary state or an absorbing state (Maillart, 2006). Once the values of g and $b(e_i)$ are obtained, the preference conditions in Table 2 can be directly computed.

4.2. *Approximated decision boundary for dynamic decision making*

As mentioned, our objective is to determine a maintenance policy of the dynamic CBM model via decision rules. We take cues from the static decision boundaries in Table 2 and modify them to incorporate non-stationary weather changes.

First, we use the conditions in the second and third rows of Table 2 to decide the action preference between PM versus NA and PM versus OB. The condition under which $PM(m^*)$ is preferred to NA holds for the state whose sample path is in $\prec_{st}$-increasing order. Since the $\prec_{st}$-increasing order in a sample path is satisfied in most commonly encountered aging systems, we relax these restrictions and apply the preference rule of $PM(m^*)$ to NA to all states. Furthermore, although the last row of Table 2 that compares NA with OB explains the preference conditions of NA to OB, we assume that OB is preferred to NA when the inequality in the last row is not satisfied.

Table 2. Preference conditions for the optimal policy of the static CBM model

Actions	*Preference conditions*
PM(m^*) versus NA	NA is preferred to $PM(m^*)$ if $\sum_{l=1}^{L}(C'_{CM(l)} - C'_{PM(m^*)})H_l(\pi) - g \le 0$
	PM(m^*) is preferred to NA if $\sum_{l=1}^{L}(C'_{CM(l)} - C'_{PM(m^*)})H_l(\pi) - g > 0$ for $\boldsymbol{\pi}$ whose sample path is in $\prec_{st}$–increasing order[a]
PM(m^*) versus OB	$PM(m^*)$ is preferred to OB if $C'_{PM(m^*)} < C'_{OB}$, and *vice versa*
NA versus OB	NA is preferred to OB if $\sum_{l=1}^{L}(C'_{CM(l)} - C'_{OB})H_l(\pi) + R(\boldsymbol{\pi})(\sum b(e_i)(\pi'_i(\boldsymbol{\pi}) - \pi_i)) - g < 0$

[a]The condition under which $PM(m^*)$ is preferred to NA holds when **P** has Increasing Failure Rate (IFR) and the sample path of $\boldsymbol{\pi}$ is in $\prec_{st}$-increasing order; i.e., $\pi \prec_{st} \pi^2 \prec_{st} \cdots \prec_{st} \Pi(\pi)$. Here, IFR implies that the more deteriorated system is more likely to deteriorate further and/or to fail (Maillart, 2006), and the sample path in $\prec_{st}$-increasing order implies that the next state is more deteriorated than the previous state in a stochastic sense. See the supplement for the mathematical definitions.

Next, we want to bind the dynamic weather conditions to the decision rules. Note that in the static CBM model, $C'_{CM(l)}$ and $C'_{PM(m)}$ in Equations (12) and (13), respectively, reflect the weather effects as well as direct repair costs. In Equation (12), the second term $\lambda(l) \times (\tau - g)$ represents the revenue losses during the lead time. In the dynamic CBM model, since the revenue losses depend on a period, we replace the second term with $\tilde{\tau}_n(l) - \lambda(l) \times g$ where $\tilde{\tau}_n(l)$ is the total revenue losses during the lead time, as defined in Equation (7). The third term in Equation (12) is the expected revenue losses due to repair delay after the maintenance resources are ready. Thus, $\tau_{n-\lambda(l)-1}$ and $W_{CM(l),n-\lambda(l)-1}$ substitute for τ and g in the third term, respectively (note that n implies the number of remaining periods until the terminal period; as such, $n - \lambda(l) - 1$ is the $(\lambda(l) + 1)$th period after the period n). Regarding PM, since $PM(m)$ can be carried out during the current period as long as the weather is favorable, τ_n and $W_{PM(m),n}$ can still be used in the PM formulation. In summary, we redefine the repair costs as follows:

$$C^{\mathrm{D}}_{CM(l)} = C_{CM(l)} + \tilde{\tau}_n(l) - \lambda(l) \times g^{\mathrm{D}} + \begin{cases} \dfrac{W_{CM(l),n-\lambda(l)-1}(\tau_{n-\lambda(l)-1} - g^{\mathrm{D}})}{1 - W_{CM(l),n-\lambda(l)-1}} & \text{for } \mu_{CM(l)} = 0, \\ \dfrac{\tau_{n-\lambda(l)-1} - g^{\mathrm{D}}}{1 - W_{CM(l),n-\lambda(l)-1}} & \text{for } \mu_{CM(l)} = 1, \end{cases} \tag{15}$$

$$C^{\mathrm{D}}_{PM(m)} = C_{PM(m)} + b^{\mathrm{D}}(e_m) + \begin{cases} \dfrac{W_{PM(m),n}(\tau_n - g^{\mathrm{D}})}{1 - W_{PM(m),n}} & \text{for } \mu_{PM(m)} = 0, \\ \dfrac{\tau_n - g^{\mathrm{D}}}{1 - W_{PM(m),n}} & \text{for } \mu_{PM(m)} = 1, \end{cases} \tag{16}$$

$$C^{\mathrm{D}}_{OB} = C_{OB} + \sum_{i=1}^{M} b^{\mathrm{D}}(e_i), \tag{17}$$

where the superscript D indicates the dynamic strategy. Computing $C^{\mathrm{D}}_{CM(l)}$ requires weather forecast information only up to the lead time. Thanks to today's sophisticated weather forecast technology, the near-future weather information is usually deemed reliable (The Weather Research and Forecasting Model, 2011).

Next, to find the maintenance policy, we replace $C'_{CM(l)}$, $C'_{PM(m^*)}$, $C'_{OB(m^*)}$, $b(e_i)$, and g in Table 2 with $C^{\mathrm{D}}_{CM(l)}$, $C^{\mathrm{D}}_{PM(m^*)}$, C^{D}_{OB}, $b^{\mathrm{D}}(e_i)$, and g^{D}, respectively. Here, g^{D} and $b^{\mathrm{D}}(e_i)$, $i = 1, \cdots, M$, can be obtained by applying the standard policy (or value) iteration along the sample paths of the e_i variables with the redefined repair costs. Since the policy iteration is applied *only* to the sample paths of e_i variables, this leads to substantial reductions in computation time compared with the DP algorithm (Section 5 explains how carrying out the policy (or value) iteration along the sample paths of e_i variables is less demanding than a backward DP).

Let $\delta^{\mathrm{D}}(\boldsymbol{\pi})$ denote the policy derived from the rule-based, dynamic algorithm at a state $\boldsymbol{\pi}$. The algorithm to find $\delta^{D}(\boldsymbol{\pi})$ is as follows.

Algorithm 1 (Basic approximation)
Input: $\lambda(l)$, $\mu(l)$, $C_{CM(l)}$, $C_{PM(m)}$, C_{OB}, for all l, m.
Output: maintenance action among the $M+1$ choices (NA, OB, and $PM(m)$, $m = 1, \cdots, M-1$)
For each period n, apply the following steps:

Step 1. Based on the weather forecast information, estimate the parameters $\tau_n, \cdots, \tau_{n-\lambda(l)-1}$, $W_{CM(l),n-\lambda(l)-1}$, and $W_{PM(m),n}$ for all l, m.
Step 2. Compute g^{D} and $b^{\mathrm{D}}(e_i)$, $i = 1, \cdots, M$, by applying the policy (or value) iteration to the states along the sample paths of e_i variables.
Step 3. Compute $C^{\mathrm{D}}_{CM(l)}$, $C^{\mathrm{D}}_{PM(m)}$, and C^{D}_{OB} using Equations (15) to (17).
Step 4. Apply the following decision rules:

4.1. Find the most preferable PM action $PM(m^*)$ which gives the minimum $C^{\mathrm{D}}_{PM(m)}$ in Equation (16).
4.2. Suppose that $\sum_{l=1}^{L}(C^{D}_{CM(l)} - C^{D}_{PM(m^*)})H_l(\boldsymbol{\pi}) - g^{D} > 0$. $\delta^{D}(\boldsymbol{\pi}) = PM(m^*)$ if $C^{D}_{PM(m^*)} < C^{D}_{OB}$. Otherwise, $\delta^{D}(\boldsymbol{\pi}) = OB$.
4.3. Suppose that $\sum_{l=1}^{L}(C^{D}_{CM(l)} - C^{D}_{PM(m^*)})H_l(\boldsymbol{\pi}) - g^{D} \le 0$. $\delta^{D}(\boldsymbol{\pi}) = NA$ if $\sum_{l=1}^{L}(C^{D}_{CM(l)} - C^{D}_{OB})H_l(\boldsymbol{\pi}) + R(\boldsymbol{\pi})(\sum b^{D}(e_i)(\pi'_i(\boldsymbol{\pi}) - \pi_i) - g^{D}) < 0$. Otherwise, $\delta^{D}(\boldsymbol{\pi}) = OB$.

Since we have derived the proposed dynamic decision rules by modifying the static rules, we want to learn how the algorithm performs in non-stationary weather conditions. To do so, we compare the policy obtained through the DP procedure with the new policy generated from Algorithm 1. We utilize the real weather data collected by West Texas Mesonet (2007) and use the parameters in Table 3 with the short lead time and P_2 in Equation (22) in Section 5.

Figure 1 gives an example of the maintenance policies during a transitional period from harsh to mild seasons for an operating system. In this example, the operating system conditions are classified into normal, alert, and alarm conditions, and π_1, π_2 and π_3 denote the probability for each condition. In the figure, the X-axis is the alert probability π_2, and the Y-axis is the alarm probability π_3. Therefore, the state space in this example is defined as the triangle surrounded by the X-axis, Y-axis, and $\pi_2 + \pi_3 = 1$ (Byon and Ding, 2010). We evaluate the optimal policy at a set of finite number of states as shown in Fig. 1 (note: each grid point in Fig. 1 corresponds to a state). A square, a circle and an "x" at each grid point represent that the DP procedure suggests PM, OB, and NA at the corresponding state, respectively. Since Fig. 1 shows the maintenance decisions for an operating system, CM is not considered. Assuming

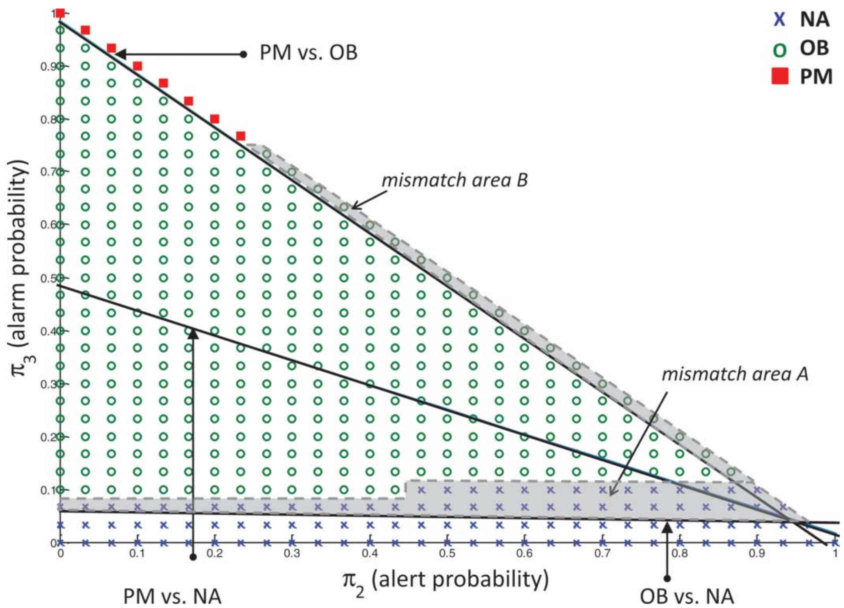

Fig. 1. Decision rules superimposed on optimal policy with Mesonet weather profile (color figure provided online).

that the DP procedure has complete firsthand knowledge on the sequence of weather conditions throughout the turbine's service life, the solution from the DP procedure is indeed the optimal policy. As discussed in Byon and Ding (2010), the states in the upper-left corner correspond to seriously deteriorating conditions. For those states, the optimal policy suggests performing preventive repairs to avoid a catastrophic failure in the near future. On the other hand, the states in the lower part imply healthy conditions and, thus, NA is suggested. For other states, OB action becomes the optimal policy.

With this optimal policy as a benchmark, we superimpose the decision boundaries from Algorithm 1 on the optimal policy in Fig. 1. The PM region from Algorithm 1 is defined as the area above both the PM versus OB and PM versus NA lines. Likewise, the NA region is the area below the PM versus NA and OB versus NA lines. The OB region is between the PM versus OB and OB versus NA lines. Overall, the results from the two methods are consistent, but there is some discrepancy in the two shaded areas; i.e., mismatch area A and B. As a criterion to measure the effectiveness of the proposed approximation method, we define the "match rate" as the ratio of the states for which the approximation scheme generates the optimal policy. In this example, the proposed method generates the optimal policy in 87% of the states among the total grid points shown in Fig. 1.

Since weather conditions evolve with seasonal variations, the performance of the approximation scheme could differ over the decision horizon. Considering weekly decision making, we compute the match rates for each period in a 20-year service time. The upper, solid curve in Fig. 2 shows the match rates in each week's decision in the first year, and the lower curve shows the probability, $W_{PM(1),n}$, that

Table 3. Parameters

Repair types	*Wind speed constraints (m|s)*	*Repair costs (\$)*	*Lead time (weeks)* Short	Medium	Long
CM					
Oil systems	18	12 279	0	1	2
Sealing	18	12 279	0	2	5
Not specified	12	61 394	1	6	10
Gearwheels	10	122 787	1	6	10
Bearings	10	122 787	2	6	10
Major PM	12	12 820			
Minor PM	18	4273			
OB		313			

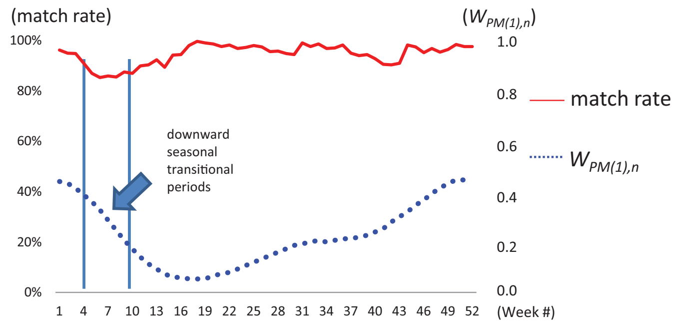

Fig. 2. Match rates in Mesonet weather profile (rapid downward transition) (color figure provided online).

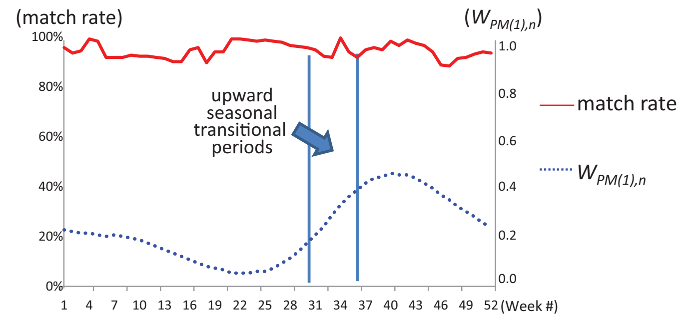

Fig. 3. Match rates with reverse Mesonet weather profile (rapid upward transition) (color figure provided online).

$PM(1)$, which improves the system condition to e_1, cannot be carried out. From the lower curve, we observe the rapid seasonal changes from adverse to mild, which we call a *downward* seasonal transition as the values of the weather parameters decrease during these periods. Although the match rates are very high in most periods, they decline in seasonal transitional periods. During these periods, the optimal policies, which are obtained with the assumptions that future weather conditions are completely known, suggest delaying repair actions until the weather becomes favorable. However, Algorithm 1 only considers the weather conditions in the near future up to lead time (see Step 1 of Algorithm 1). Thus, when the lead time is shorter than the length of the seasonal transitional periods, Algorithm 1 may not fully capture the weather changes in the transitional periods.

Looking again at Fig. 1, which shows the O&M decisions at one of the downward transitional periods in Fig. 2, note the gap appearing between the approximation policy and the optimal policy when comparing NA and OB (mismatch area A) and PM and OB (mismatch area B). The gap occurs because the optimal policy presumably “knows” that the weather condition will become mild in the near future and thus tends to take less intensive O&M actions at the current period and delay intensive maintenance actions until the upcoming mild periods. In mismatch area A, the optimal policy advises taking NA, whereas the approximation scheme suggests OB. In this case, the additional cost incurred by employing the approximation scheme is at most the OB cost. Note that the OB cost is the least expensive of the action costs. In mismatch area B, the optimal policy prefers OB to PM and defers PM to future mild periods, whereas the approximation scheme suggests PM at the current period. Since the probability of repair interruption is higher at the current period than the upcoming mild period, the additional costs incurred by the approximation scheme (which suggests PM now), compared to the DP (which delays PM in the near future), are the revenue losses when adverse weather conditions interrupt PM advised by the approximation scheme. Section 5.3 shows the simulation results to compare the O&M costs under the approximation algorithm and the optimal policy.

We can also determine whether the match rates decrease in the seasonal transitional periods where the weather moves rapidly from mild to adverse, by reversing the order of weather parameters in the Mesonet weather profile. Figure 3, which displays the match rates in this reverse Mesonet weather profile each week, shows that the match rates do not decrease during the rapid upward transition periods. In fact, the match rates are over 88% in every period over a year, demonstrating that Algorithm 1 provides good estimates of the optimal policy in this case. During the upward transition periods, in preparation for the upcoming harsh weather season, the optimal decision is to take PM for moderately deteriorated states as well as seriously ill-conditioned states (Byon and Ding, 2010). The approximation rules generate similar patterns during these periods. Figures 2 and 3 also demonstrate that the match rates do not decline when the seasonal transition is slow (note: the lower curves in both figures show slow upward and downward transitions, respectively).

These results indicate the need for additional calibration when the downward transition is very rapid and the lead time is short.

4.3. *Adjustment of parameters for rapid seasonal changes*

Recall that during fast downward transitional periods, unlike the approximation scheme, the optimal policy suggests PM in fewer number of states but NA in more states as shown in mismatch areas A and B in Fig. 1. Considering this aspect, we can calibrate Algorithm 1 by lowering the CM cost in Equation (15) and increasing the PM cost in Equation (16). To do so, we apply the lowest possible revenue losses $\tau^{\min}$ and weather prohibiting probability $W_{CM(l)}^{\min}$ to Equation (15). On the contrary, the highest revenue losses $\tau^{\max}$ and weather prohibiting probability $W_{PM(m)}^{\max}$ are used in Equation (16). The values of these parameters can be obtained from the past data and weather forecast information.

Then, the adjusted cost factors are

$$C^{\mathrm{aD}}_{CM(l)} = C_{CM(l)} + (\tau^{\min} - g^{\mathrm{aD}}) \times \lambda(l) + \begin{cases} \dfrac{W^{\min}_{CM(l)}(\tau^{\min} - g^{\mathrm{aD}})}{1 - W^{\min}_{CM(l)}} & \text{for } \mu_{CM(l)} = 0, \\ \dfrac{\tau^{\min} - g^{\mathrm{aD}}}{1 - W^{\min}_{CM(l)}} & \text{for } \mu_{CM(l)} = 1, \end{cases} \tag{18}$$

$$C^{\mathrm{aD}}_{PM(m)} = C_{PM(m)} + b^{\mathrm{aD}}(e_m) + \begin{cases} \dfrac{W^{\max}_{PM(m)}(\tau^{\max} - g^{\mathrm{aD}})}{1 - W^{\max}_{PM(m)}} & \text{for } \mu_{PM(m)} = 0, \\ \dfrac{\tau^{\max} - g^{\mathrm{aD}}}{1 - W^{\max}_{PM(m)}} & \text{for } \mu_{PM(m)} = 1, \end{cases} \tag{19}$$

$$C^{\mathrm{aD}}_{OB} = C_{OB} + \sum_{i=1}^{M} b^{\mathrm{aD}}(e_i), \tag{20}$$

where the superscript aD denotes the adjusted dynamic approximation. Note that different τ values—i.e., $\tau^{\min}$ and $\tau^{\max}$—are employed in Equations (18) and (19), respectively. Depending on τ, we get different g^{aD} and $b^{\mathrm{aD}}(e_i)$ variables from the policy (or value) iteration. Since $b^{\mathrm{aD}}(e_i)$ is the relative *cost* when the state starts at e_i (Puterman, 1994), $b^{\mathrm{aD}}(e_i)$ increases with the cost parameter values. If we use $\tau^{\max}$ instead of $\tau^{\min}$, we will get higher $b^{\mathrm{aD}}(e_i)$ values, which, in turn, increase the OB cost in Equation (20). In Fig. 1, more mismatches are observed in comparing OB with NA. We want to use a higher OB cost so that the approximation rule, just like the optimal policy, prefers NA to OB during the rapid seasonal changes. Accordingly, we use $\tau^{\max}$ (and $W^{\min}_{CM(l)}$, $W^{\max}_{PM(m)}$ for all l, m) when we employ the policy (or value) iteration.

Now, these adjusted parameters are used in the preference conditions to find the maintenance policy during the fast downward transitional periods. The definition of the downward transitional periods can depend on local weather profiles. In this work, we define the downward transitional periods when $W_{CM(1),n}$ is in two thirds of its range (i.e., when $W_{CM(1),n}$ is between $W^{\min}_{CM(1)} + (1/6)(W^{\max}_{CM(1)} - W^{\min}_{CM(1)})$ and $W^{\min}_{CM(1)} + (5/6)(W^{\max}_{CM(1)} - W^{\min}_{CM(1)})$). Algorithm 2 summarizes this adjusted approximation scheme.

Figure 4 shows the results when we apply Algorithm 2 to the example in Fig. 2. We observe that the adjusted scheme improves the performance of Algorithm 1 during fast downward transitional periods.

5. Numerical analysis

This section evaluates the performance and application of the proposed approach. We specifically analyze the O&M of a gearbox; as one of the most vulnerable components it is of special interest to the global wind industry (Ribrant, 2006; McMillan and Ault, 2008; Knight, 2011).

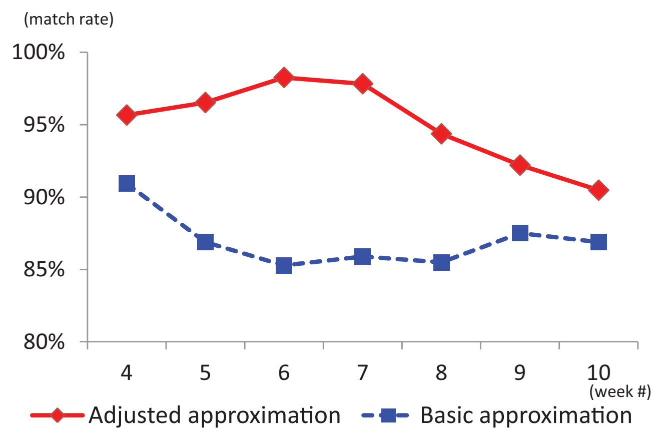

Fig. 4. Improvement in match rates by adjusting cost parameters during fast downward transitional periods in the Mesonet weather profile (color figure provided online).

Algorithm 2 (Adjusted approximation)
Input and output: Same as **Algorithm 1**.
During fast downward transitional periods, apply the following steps (for all other periods, apply **Algorithm 1**).

Step 1. Based on the past data and recent weather information, estimate the weather-related parameters, $\tau^{\max}$, $\tau^{\min}$, $W^{\min}_{CM(l)}$, and $W^{\max}_{PM(m)}$ for all l, m.

Step 2. Compute g^{aD} and $b^{\mathrm{aD}}(e_i)$, $i = 1, \cdots, M$, by applying the policy (or value) iteration to the states along the sample paths of e_i variables with the parameters $\tau^{\max}$, $W^{\min}_{CM(l)}$, and $W^{\max}_{PM(m)}$ for all l, m.

Step 3. Compute adjusted cost factors $C^{\mathrm{aD}}_{CM(l)}$, $C^{\mathrm{aD}}_{PM(m)}$, and C^{aD}_{OB} using Equations (18) to (20).

Step 4. Apply the same decision rules in Step 4 of Algorithm 1 after replacing $C^{\mathrm{D}}_{CM(l)}$, $C^{\mathrm{D}}_{PM(m)}$, C^{D}_{OB}, g^{D}, and $b^{\mathrm{D}}(e_i)$ with $C^{\mathrm{aD}}_{CM(l)}$, $C^{\mathrm{aD}}_{PM(m)}$, C^{D}_{OB}, g^{aD}, and $b^{\mathrm{aD}}(e_i)$.

5.1. *Parameters and specific problem settings*

We consider an operational, 100-unit wind facility in West Texas. In order to generate wind speeds at the target wind farm, we rely on several years of real wind data from West Texas Mesonet, a network of meteorological instruments dispersed across West Texas that has collected weather measurements in a 3-second interval (West Texas Mesonet, 2007).

Table 3 explains the parameters used in this study. The second column of Table 3 shows the wind speeds beyond which a specific repair action will be disallowed (McMillan and Ault, 2008). From these weather restrictions, we compile $W_{CM(l),n}$ and $W_{PM(m),n}$ values for all l, m for each week n. We also compute the revenue losses using the Mesonet data by setting the revenue losses during downtime at \$50 per MWh (American Wind Energy Association, 2008; Wiser and Bolinger, 2008). We use the same cost parameters in Byon and Ding (2010), most of which are obtained from Ribrant (2006) and Andrawus *et al.* (2007). The monetary unit of each cost factor was originally in pounds (£; Andrawus *et al.*, 2007), but we convert it to the U.S. dollar with an exchange rate of 1 pound = 1.5668 dollars. Table 3, column 3 summarizes the repair costs. To examine the effect of lead time, we consider three sets of lead times, as shown in the fourth to sixth columns.

We consider the transition matrix used in Byon and Ding (2010), P_1 in Equation (21). Additionally, we employ a slightly modified matrix, P_2 in Equation (22), representing a slowly deteriorating system since P_1 reflects more frequent failures than the recent failure rates encountered in industry (only the first three rows in each matrix are shown):

$$P_1 = \begin{array}{c} \\ e_1 \\ e_2 \\ e_3 \end{array} \begin{array}{c} \begin{array}{cccccccc} e_1 & e_2 & e_3 & e_4 & e_5 & e_6 & e_7 & e_8 \end{array} \\ \begin{bmatrix} 0.93 & 0.04 & 0.029 & 0.001 & 0 & 0 & 0 & 0 \\ 0 & 0.95 & 0.03 & 0.002 & 0.001 & 0.008 & 0.001 & 0.008 \\ 0 & 0 & 0.96 & 0.004 & 0.003 & 0.016 & 0.002 & 0.015 \end{bmatrix} \end{array}, \quad (21)$$

$$P_2 = \begin{array}{c} \\ e_1 \\ e_2 \\ e_3 \end{array} \begin{array}{c} \begin{array}{cccccccc} e_1 & e_2 & e_3 & e_4 & e_5 & e_6 & e_7 & e_8 \end{array} \\ \begin{bmatrix} 0.95 & 0.04 & 0.005 & 0.004 & 0.001 & 0 & 0 & 0 \\ 0.00 & 0.95 & 0.03 & 0.006 & 0.001 & 0.007 & 0.002 & 0.004 \\ 0.00 & 0.00 & 0.96 & 0.01 & 0.002 & 0.015 & 0.003 & 0.01 \end{bmatrix} \end{array}. \quad (22)$$

In Equations (21) and (22), each row corresponds to the operating states e_1, e_2, e_3. The first three columns and the next five columns correspond to the operating states e_1, e_2, e_3 and five failure modes, $e_4, \cdots, e_8$, respectively. The number in the first three columns, p_{ij}, $i, j = 1, 2, 3$, is a transition probability from the ith operating state to the jth operating state, to represent weekly deterioration. Each number in the last five columns, p_{ij}, $i = 1, 2, 3$, $j = 4, \cdots, 8$, denotes a probability from an operating state, e_i, to one of the failure states. The last five rows of P are omitted: the first three columns of the last five rows make an 5×3 zero matrix and the next five columns make an 5×5 identity matrix.

5.2. *Performance evaluation*

We use two dimensions to assess the performance of the proposed approximation schemes: (i) computational efficiency and (ii) approximation accuracy. First, we compare the computational efforts of the approximated schemes with the DP procedure. Suppose that we want to find the optimal O&M policy for G states, π_j, $j = 1, \cdots, G$, when N periods are left. The DP procedure discussed in Byon and Ding (2010) requires $O((\sum_{j=1}^{G} k^*(\pi_j) + \sum_{i=1}^{M} k^*(e_i))K'(M+1)N)$ arithmetic operations. Here, $k^*(\pi_j)$ is the number of states in the sample path of π_j and K' corresponds to the number of arithmetic operations to compute each action cost at each state. In general problems, K' and $K = (\sum_{j=1}^{G} k^*(\pi_j) + \sum_{i=1}^{M} k^*(e_i))$ are the same. In our problem, K' is much less than K according to the algorithm in Byon and Ding (2010). $M + 1$ is the number of O&M actions considered at each decision period.

In the proposed method, we employ policy or value iterations to get g and $b(e_i)$ values and then apply the linear rules to find the approximate policy at each state. The policy iteration needs $(1/3)(\sum_{i=1}^{M} k^*(e_i))^3 + (\sum_{i=1}^{M} k^*(e_i))(2M + L)(M+1)$ arithmetic operations per iteration, whereas the value iteration requires $(\sum_{i=1}^{M} k^*(e_i))(2M + L)(M+1)$ computational efforts per iteration (Puterman (1994), Sections 8.5 and 8.6). The policy iteration requires more computational efforts per iteration than the value iteration, but the policy iteration typically takes a small number of iterations to converge on solution (Tsitsiklis, 2007). In our problem, the policy iteration terminates within 10 iterations. The term $(1/3)(\sum_{i=1}^{M} k^*(e_i))^3$ in the policy iteration's complexity involves finding a solution of a linear system with $\sum_{i=1}^{M} k^*(e_i)$ equations. Here, each equation in the linear system corresponds to each state in the sample paths of e_i, and the unknowns in each equation correspond to the next states that the system might possibly visit after a transition. In our problem, the number of next states is less than $2M + L$, so solving the linear model does not require large computational efforts.

Compared with the DP procedure that needs the value function evaluations for the states in the G sample paths of π_j and M sample paths of e_i for N periods, the proposed approach only needs to run the policy or value iteration for the states in the M sample paths of e_i. As a result, the proposed method significantly reduces computation time for large-size problems. Considering 20 years of service time and weekly decision making and evaluating the the maintenance policy of 100 turbines, the approximation schemes achieve a 98% reduction of computation time compared with the DP.

Second, we measure the approximation accuracy. Through extensive numerical trials, we find that the match rates are sensitive to the OB cost and lead time, relative to other parameters. Table 4 and Table 5 summarize the match rates with a wide range of OB costs and three sets of lead times for $\mathbf{P}_1$ and $\mathbf{P}_2$, respectively. The short, medium, and long lead time correspond to the fourth to sixth columns in Table 3 and represent the cases where the lead time for major repairs is shorter than, close to, or longer than the length of transitional periods, respectively.

In all scenarios, both approximation schemes achieve more than an 85% match rate on average. Notably, with a lead time long enough to cover the transitional periods (i.e., in the case of medium and long lead time in Table 3), the basic approximation provides very accurate estimates

Table 4. Match rates (%) with $\mathbf{P}_1$

	Basic approximation (Algorithm 1) Lead time			*Adjusted approximation (Algorithm 2)* Lead time		
C_{OB}	*Short*	*Medium*	*Long*	*Short*	*Medium*	*Long*
313[a]	95 (86–100)	96 (81–100)	98 (88–100)	95 (82–100)	96 (83–100)	98 (88–100)
1923[b]	92 (79–98)	94 (84–100)	96 (87–100)	93 (82–98)	93 (79–100)	95 (79–100)
3846[c]	88 (70–97)	92 (85–98)	93 (86–99)	90 (77–97)	92 (83–98)	92 (78–99)

Note: The number in each cell is the average of weekly match rates over a year. The numbers in parentheses indicate the range of weekly match rates.
[a,b,c]These OB costs are equivalent to 2.4, 15, and 30% of the major PM cost, respectively.

of the optimal policy. When the lead time is close to the transitional periods, the adjusted CM cost of the basic approximation scheme in Equation (15) can fully consider the changing weather conditions during the transitional periods through the parameters $\tilde{\tau}_n$ and $W_{CM(l),n-\lambda-1}$. Additionally, when the lead time gets longer, there are significant revenue losses during the downtime upon a failure. Therefore, the optimal policy shows less tendency to delay repair actions and the match rate increases accordingly. In these cases, the adjusted approximation scheme does not provide a benefit in improving the match rates.

When the lead time is short, the adjusted approximation scheme improves the match rates in most cases. Table 5 indicates that in some special circumstances, namely, when the lead time is short and the OB cost is high (for example, 30% of the major PM cost), the basic approximation scheme generates relatively low match rates in a few weeks (note that the minimum match rate is 50% in the second column and last row of Table 5). As expected, these low rates occur in the downward seasonal transitional periods. In this case, the adjusted approach improves the match rates by 15%, but no sufficient improvement is made.

5.3. *Impact on O&M costs*

To understand the impact of the relatively low match rates that occurred during the transitional periods on the system performance, we evaluate the O&M costs under the approximation schemes and compare them with the costs under the optimal policy. We perform multiple Monte Carlo simulations during a 20-year lifetime.

Using the results obtained from the DP procedure as a benchmark, Table 6 shows the difference in the O&M costs for each approximation scheme. Since the simulation results using $\mathbf{P}_1$ and $\mathbf{P}_2$ are consistent with one another and the match rates with $\mathbf{P}_2$ are slightly lower than those with $\mathbf{P}_1$ in most cases, we only present the results with $\mathbf{P}_2$ in the following discussions. The simulation results demonstrate that the proposed approach leads to a performance similar to that of the optimal policy, implying that the influence of the mismatch that may occur during the transitional periods is not substantial in terms of overall O&M costs. As discussed in Section 4.2, the largest mismatch is observed in the comparison of NA and OB (see Fig. 1). Since the optimal policy tends to prefer the NA option, the additional costs of the approximation schemes are at most the OB

Table 5. Match rates (%) with $\mathbf{P}_2$

	Basic approximation (Algorithm 1) Lead time			*Adjusted approximation (Algorithm 2)* Lead time		
C_{OB}	*Short*	*Medium*	*Long*	*Short*	*Medium*	*Long*
313[a]	94 (85–100)	95 (81–100)	98 (84–100)	95 (90–100)	96 (82–100)	98 (84–100)
1923[b]	88 (70–98)	94 (84–100)	95 (87–100)	90 (78–98)	94 (86–100)	96 (87–100)
3846[c]	85 (50–97)	90 (80–98)	93 (81–99)	87 (65–97)	91 (80–98)	93 (81–99)

Note: The number in each cell is the average of weekly match rates over a year. The numbers in parentheses indicate the range of weekly match rates.
[a,b,c]These OB costs are equivalent to 2.4, 15, and 30% of the major PM cost, respectively.

Table 6. Simulation results: difference of O&M costs (in %) for the two approximation methods and the DP procedure (with $\mathbf{P}_2$ in Equation (22))

	Basic approximation (Algorithm 1) Lead time			*Adjusted approximation (Algorithm 2)* Lead time		
C_{OB}	*Short*	*Medium*	*Long*	*Short*	*Medium*	*Long*
313	0.1	0.1	−0.3	0.1	−0.2	0.3
1923	−0.4	0.2	0.3	0.3	0.1	0.3
3846	0.3	−0.2	0.1	−0.1	−0.2	−0.4

Note: The number in each cell is the difference between the O&M costs under the approximation policy and the O&M costs under the optimal policy divided by the O&M costs under the optimal policy.

cost when this mismatch occurs. Furthermore, when the transition is fast, the length of the transitional periods is short. Therefore, the additional costs incurred during this short period of time have little impact on the annual O&M costs.

Overall, the basic approximation scheme (Algorithm 1) gives high-precision solutions. Especially when the lead time is close to, or longer than, the transitional periods, the decision rules generate high match rates. The wind power industry reports that lead times are lengthy due to the sheer size of components, limited warehouse space, and the long distances from operational/repair centers to actual sites (Pacot *et al.*, 2003; Knight, 2011; Byon *et al.*, in press). For example, when a gearbox fails with major problems, it is removed from the turbine, delivered to a repair center, and inspected before return delivery. This sequence of actions can take 8 to 9 weeks (Knight, 2011). Considering this long lead time in practice, the basic approximation scheme is a highly suitable procedure.

We acknowledge that in certain limited circumstances, namely, when weather conditions change rapidly from harsh to mild seasons, the OB cost is high and the lead time is short, the proposed approximations provide less ideal estimates of the optimal policy. Fortunately, the good news is that these less than ideal estimates will have little impact on overall O&M costs.

6. Comparison of different O&M policies

The maintenance strategy presented in this study can be easily incorporated into a large-scale wind farm simulation framework because the decision rules consist of simple *If–Then* rules. Using a discrete-event simulation platform (Byon *et al.*, 2011), we performed a case study for the operations of the wind farm with 100 turbines in West Texas described in Section 5.1. Based on wind measurements collected from West Texas Mesonet, we simulated the wind speeds at each wind turbine of the wind farm (for details of wind speed simulation, see Byon *et al.* (2011)). The simulation model also generated internal (i.e., degradation and failure) conditions of turbine systems, and an O&M action was determined at each decision point as the simulation runs.

We implemented four different O&M strategies to compare their performance.

1. Scheduled maintenance: Performed preventive repairs on a regular basis during mild weather seasons; represents current industry practice (Walford, 2006; McMillan and Ault, 2008).
2. Dynamic CBM #1 (basic approximation): Used Algorithm 1 to decide the maintenance actions.
3. Dynamic CBM #2 (adjusted approximation): Used Algorithm 2.
4. Static CBM: Considered a system's degradation but ignored weather constraints; sets $W_{CM(l)} = W_{PM(m)} = 0$ for all l, m in Algorithm 1.

In implementing the dynamic CBM strategies, we made more approximations by using constant values for g^{D} and $b^{\mathrm{D}}(e_i)$. That is, g^{D} and $b^{\mathrm{D}}(e_i)$ were computed *a priori* using the average of historical values for τ_n, $W_{CM(l),n}$, and $W_{PM(m),n}$ values. Therefore, as an alternative to getting g^{D} and $b^{\mathrm{D}}(e_i)$ values at each decision point during simulations (or field operations), we used constant values so that no numerical evaluation was required during the simulation runs.

Table 7 compares the performance of the four O&M strategies over a 20-year service time. The O&M cost under the scheduled maintenance is in the ballpark of the cost reported in Wiser and Bolinger (2008), but it lies closer to the low bound, because we only consider the gearbox rather than all of the components in a turbine.

Using the scheduled maintenance as a benchmark, we find that the O&M costs drop by 23–24% when applying the dynamic CBM policies. Table 7 also shows that the dynamic CBM policies lead to a lower frequency of turbine failures with fewer preventive repairs.

When the static CBM strategy is employed, the average number of failures is close to the result of the dynamic CBM strategies because these three CBM strategies schedule preventive repairs based on the degradation status of a system to avoid failures. This result shows the advantages of CBM, which plans maintenance based on the deterioration

Table 7. Simulation results for gearbox maintenance

	Scheduled maintenance	*Dynamic CBM #1*	*Dynamic CBM #2*	*Static CBM*
Number of failures per year	0.77	0.42 (45%)	0.42 (45%)	0.43 (44%)
Number of preventive repairs per year	2.0	1.1	1.1	1.3
O&M costs per year ($/kWh)	0.0083	0.0064 (23%)	0.0063 (24%)	0.0073 (12%)

Note: The number in parentheses is indicates the improvement (percentage) compared with the scheduled maintenance.

condition. Nevertheless, the static policy does not reduce the O&M costs as substantially as the dynamic policies because the static CBM policy does not adapt to changing weather patterns. Since the static policy does not plan the O&M activities in low wind seasons, the repairs advised under the static CBM model are more prone to repair interruptions and incur revenue losses during the maintenance delay. In contrast, the dynamic decision rules in the proposed approach guides the weather-dependent O&M activities and limits the preventive repair activities during harsh weather seasons. As a result, the dynamic CBM strategies cost $0.9 to $1.0 per MWh less than the static CBM strategy.

In summary, the dynamic CBM strategies are superior to the other two O&M strategies. The static CBM model is a valid alternative for wind farms with relatively stable weather conditions, but they do not work as well for weather patterns with drastic season-by-season changes.

7. Conclusion

The dynamic CBM model is attractive because of its flexibility, yet its solution approach using the DP procedure requires significant computational resources for large-scale wind farm simulations and/or field operations. This article presented a tractable approximation scheme for use in dynamic decision making that links external (weather) and internal (system health) conditions to linear decision rules. The advantages of the decision rules of the static CBM model were used to derive a new set of dynamic decision rules. Improvements were then proposed to make the decision rules more adaptive to rapid changes in weather conditions.

The numerical results conducted in various implementation settings demonstrated that the proposed method produces sensible CBM actions, justifying the insights gained from using the decision rule–based approach. The results suggest that the new approach will also provide practical guidelines for actual wind farm O&M.

Based upon our results, we plan to extend the current optimization and simulation models to incorporate the interactions among multiple units of wind turbines. In the literature on wind energy system maintenance, most current research considers each component independently, neglecting any economic or structural interdependencies. We believe that the neglect is due to the difficulties of finding structural results analytically and obtaining numerical results in a timely fashion. Therefore, some type of approximation approach may be inevitable for handling multi-component cases. We hope this study is one good step toward that direction.

References

American Wind Energy Association. (2008) Wind Energy Costs. http://awea.org/, accessed November 11, 2008.

Andrawus, J.A. Watson, J. and Kishk, M. (2007) Modelling system failures to optimise wind farms. *Wind Engineering*, **31**, 503–522.

Asmus, P. (2010) *The Wind Energy Operations & Maintenance*, London, UK.

Byon, E. and Ding, Y. (2010) Season-dependent condition-based maintenance for a wind turbine using a partially observed Markov decision process. *IEEE Transactions on Power Systems*, **25**(4), 1823–1834.

Byon, E., Ntaimo, L. and Ding, Y. (2010) Optimal maintenance strategies for wind power systems under stochastic weather conditions. *IEEE Transactions on Reliability*, **59**(2), 393–404.

Byon, E., Ntaimo, L., Singh, C. and Ding, Y. Wind energy facility reliability and maintenance, in *Handbook of Wind Power Systems: Optimization, Modeling, Simulation and Economic Aspects* (in press).

Byon, E., Pérez, E., Ding, Y. and Ntaimo, L. (2011) Simulation of wind farm maintenance operations and maintenance using discrete event system specification. *Simulation*, **87**(12), 1093–1117.

Foley, J.T. and Gutowski, T.G. (2008) TurbSim: reliability-based wind turbine simulator, in *Proceedings of the 2008 IEEE International Symposium on Electronics and the Environment*, IEE Press, Piscataway, NJ, pp. 1–5.

Guo, H., Watson, S., Tavner, P. and Xiang, J. (2009) Reliability analysis for wind turbines with incomplete failure data collected from after the date of initial installation. *Reliability Engineering & System Safety*, **94**(6), 1057–1063.

Jirutitijaroen, P. and Singh, C. (2004) The effect of transformer maintenance parameters on reliability and cost: a probabilistic model. *Electric Power System Research*, **72**(3), 213–234.

Knight, S. (2011) From turbine removal to testing—the gearbox repair process (insert of "Sizing up growing gearbox repair market"). *Wind Power Monthly*, **27**(9), 76.

Lovejoy, W. (1987) Some monotonicity results for partially observed Markov decision processes. *Operations Research*, **35**(5), 736–742.

Lu, B., Li, Y., Wu, X. and Yang, Z. (2009) A review of recent advances in wind turbine condition monitoring and fault diagnosis, in *Proceedings of the 2009 IEEE conference on Power Electronics and Machines in Wind Applications*, IEEE Press, Piscataway, NJ, pp. 1–7.

Maillart, L.M. (2006) Maintenance policies for systems with condition monitoring and obvious failures. *IIE Transactions*, **38**(6), 463–475.

Maillart, L.M. and Zheltova, L. (2007) Structured maintenance policies in interior sample paths. *Naval Research Logistics*, **54**(6), 645–655.

McMillan, D. and Ault, G.W. (2008) Condition monitoring benefit for onshore wind turbines: sensitivity to operational parameters. *IET Renewable Power Generation*, **2**(1), 60–72.

Pacot, C., Hasting, D. and Baker, N. (2003) Wind farm operation and maintenance management, in *Proceedings of the PowerGen Conference Asia*, pp. 25–27.

Puterman, M. (1994) *Markov Decision Process*, Wiley, New York, NY.

Rademakers, L., Braam, H., Zaaijer, M. and van Bussel, G. (2003) Assessment and optimisation of operation and maintenance of offshore wind turbines. Technical report, ECN Wind Energy, Petten, The Netherlands.

Ribrant, J. (2006) Reliability performance and maintenance—a survey of failures in wind power systems. Master's thesis, KTH School of Electrical Engineering, Stockholm, Sweden.

Sayas, F.C. and Allan, R.N. (1996) Generation availability assessment of wind farms. *IEE Proceedings - Generation, Transmission and Distribution*, **144**(5), 1253–1261.

Tavner, P.J., Xiang, J. and Spinato, F. (2007) Reliability analysis for wind turbines. *Wind Energy*, **10**(1), 1–8.

Tian, Z., Jin, T., Wu, B. and Ding, F. (2011) Condition based maintenance optimization for wind power generation systems under continuous monitoring. *Renewable Energy*, **36**(5), 1502–1509.

Tsitsiklis, J.N. (2007) Computational Complexity in Markov Decision Theory. *International Journal of Computer Mathematics and Its Applications*, **9**(1), 45–54.

Walford, C. (2006) Wind turbine reliability: understanding and minimizing wind turbine operation and maintenance costs. Technical report, Sandia National Laboratories, Albuquerque, NM.

The Weather Research and Forecasting Model. (2011) http://www.wrf-model.org/, accessed May 5, 2011.

West Texas Mesonet (2007) http://www.mesonet.ttu.edu/, accessed October 18, 2007.

Wiser, R. and Bolinger, M. (2008) Annual report on U.S. wind power installation, cost, performance trend: 2007. Technical report, U.S. Department of Energy, Washington, DC.

Yang, F., Kwan, C. and Chang, C. (2008) Multiobjective evolutionary optimization of substation maintenance using decision-varying Markov model. *IEEE Transactions on Power Systems*, **23**(3), 1328–1335.

Biography

Eunshin Byon received her B.S. and M.S. in Industrial and Systems Engineering from the Korea Advanced Institute of Science and Technology and Ph.D. in Industrial and Systems Engineering from Texas A&M University. She is currently an Assistant Professor in the Department of Industrial and Operations Engineering at the University of Michigan. Her research interests include operations and management of wind power systems, quality and reliability engineering, and discrete-event simulation. She is a member of IIE, INFORMS, and IEEE.