Renewable Energy, vol. 116, Part B, pp. 188-198, Feb 2018

Maintenance Scheduling Based on Remaining Useful Life Predictions for Wind Farms Managed Using Power Purchase Agreements

Xin Lei [a,*], Peter A. Sandborn [a]

[a] *Center for Advanced Life Cycle Engineering, Department of Mechanical Engineering, University of Maryland, College Park, MD 20742*

ABSTRACT

Prognostics and Health Management (PHM) technologies have been introduced into wind turbines to forecast the Remaining Useful Life (RUL). PHM with RUL predictions enables predictive maintenance for wind turbines prior to failure, thus avoiding corrective maintenance that may be expensive and cause long downtimes. For a wind farm managed using a power purchase agreement (PPA), a simulation-based European real options analysis model is used to schedule predictive maintenance by maximizing the predictive maintenance option value. For multiple wind turbines indicating RULs concurrently, the predictive maintenance value for each turbine depends on the operational state of all the other turbines, the amount of energy delivered, and the energy delivery target, prices and penalization mechanism for under-delivery defined in the PPA. A case study is presented in which the optimum predictive maintenance opportunity is determined for a wind farm managed using a PPA. To the authors' knowledge, this is the first wind farm maintenance model including a PPA, and the case study demonstrates that the optimum predictive maintenance opportunity for a PPA-managed farm is different from the same farm managed using an "as-delivered" contract, and also differs from the optimum predictive maintenance opportunities for the individual turbines with RULs managed in isolation.

Keywords: remaining useful life (RUL), prognostics and health management (PHM), wind farm, real options analysis (ROA), predictive maintenance, power purchase agreement (PPA)

1. INTRODUCTION

1.1. Background

Maintenance practices for wind turbines generally include corrective maintenance and proactive maintenance: the former is implemented after failures occur, while the latter is carried out at predetermined intervals or time points to prevent failures. Proactive maintenance can be divided into preventive maintenance (also known as scheduled maintenance) and predictive maintenance that results from the inclusion of some type of system health management technology (either condition monitoring or prognostics and health management (PHM)) in the turbine. The major difference between preventive maintenance and predictive maintenance is that the former is performed after a fixed time or usage interval, while the latter is only implemented when there is a need for maintenance.

A failure refers to the event or inoperable state in which the system or part of the system does not perform as previously specified, while a fault is the immediate cause of the failure. After a failure has happened, fault diagnosis can be employed to detect, locate, identify and isolate the fault by applying diagnostic algorithms, e.g., checking the consistency of the feature information of a real-time process that the system is experiencing against a healthy system [1,2]. After fault diagnosis, a corrective maintenance activity can be scheduled.

Condition monitoring is the process of monitoring one or more parameters of condition, in order to detect a significant change that may be indicative of a developing fault [3], in a system prior to failure. Condition monitoring for wind turbines applies vibration analysis, acoustic emission, oil analysis, strain measurement, thermography and other techniques to monitor the current health of the major subsystems such as blades, gearbox, generator, main bearings and the tower, and also identifies the developing faults in real time [4–6]. PHM assesses the current state of health or reliability of a system that has not failed under its actual application conditions, and makes continuously updated predictions of when failure will occur based on its expected future environmental and operational condition [7].[1] Both condition monitoring and the PHM technologies enable predictive maintenance. The primary difference between fault diagnostics and condition monitoring, and PHM, which is relevant to this paper, is that PHM provides an estimate of the remaining useful life (RUL) before failure. The RUL (and its associated uncertainties) is the key driver behind the maintenance optimization model discussed in this paper.

The wind, environmental conditions, and construction and material variations may cause system health degradation patterns to vary among wind turbines in the same farm, and as larger wind farms that are longer distances from operations and maintenance (O&M) centers emerge, wind farm maintenance decision-makers must avoid as many unnecessary visits to the wind farm as possible by implementing predictive maintenance practices. Otherwise, even minor problems may cause long downtimes and high O&M costs, especially for offshore wind farms. The benefits of predictive maintenance (as opposed to proactive and corrective maintenance) are well recognized [8]. Although preventive maintenance is the current mainstream for the wind industry, predictive maintenance is becoming more popular. Since a failure is generally a process rather than a sudden event, the earlier the failure process can be detected, the more flexibility exists for managing the process.

The condition monitoring indications and PHM predictions can be received in real time, for example an on-line wind turbine pitch fault prognosis approach is introduced in [9]. However, much of the value of condition monitoring and PHM is off-line for maintenance planning. When a developing fault is identified by condition monitoring or a remaining useful life (RUL) is predicted by PHM for a wind turbine system, there are multiple choices for the maintenance decision-maker: shutting the system down, reducing loads by changing the operation of the turbine, or implementing predictive maintenance.[2] The major difference between condition monitoring and PHM is that the latter considers the future operational and/or environmental conditions and quantifies the RUL for key subsystems using prognosis approaches [10][11]. The wind farm PHM-based predictive maintenance scheduling using RUL information will be the focus in this paper. Given RUL predictions from the PHM system for wind turbines, the predictive maintenance scheduling is a decision support problem.

1.2. Power Purchase Agreements (PPAs)

A power purchase agreement (PPA) is a performance-based contract, also known as an outcome-based contract, for the purchase and sale of energy between a “buyer” who wants to purchase energy (e.g., a utility) and a “seller” who generates energy (e.g., a wind farm operator). The usage of PPAs is increasing globally for wind farms, as the total number of the wind farms with signed or planned PPAs reached 363, and the total capacity is 32,641 MW at the end of 2014 [12].

Wind farms are typically managed using PPAs for several reasons. First, although the wind energy can be sold into the local energy market, the revenue is uncertain due to the intermittence of wind resources, and the average local market prices that vary daily and hourly tend to be lower than the contract prices defined in PPAs [13]. Second, PPAs guarantee a revenue stream in which the energy generated and delivered will be paid for on the agreed price schedule. Third, the buyers typically don’t build and operate wind farms themselves; instead they prefer to buy energy from the sellers through PPAs [14].

The term of the agreement, the contracting price and the price schedule are generally defined in a PPA [15]. The contract term is typically 20 years [13]. The levelized cost of energy (LCOE) for a wind project represents the estimated cost to generate the wind energy, and is forecasted for the entire contract term. The price of energy in a PPA is negotiated based on the LCOE by accounting for the possible risks that could increase the actual LCOE [16]. The contract price can be either constant or escalated annually throughout the contract term [14].

In a PPA, the buyer may agree to pay for each unit of energy generated and delivered at a set price; in addition, the PPA may also define a maximum energy delivery limit, a minimum energy delivery limit, or both for a year. Once the energy delivered has exceeded the maximum delivery limit, the buyer may choose to buy the excess energy at a lower price, or not to buy at all, e.g., [17–19]. The buyer may also decrease the maximum energy delivery target for the next year by the amount of energy over-delivered in the current year, e.g., [20–23].

[1] Diagnosis is the process of determining what is wrong with a system; prognosis involves predicting the future outcome as a result of the current state of health.

[2] It is also possible that the wind turbine may have autonomous capabilities to avert the potential system failure (e.g., a fault tolerance ability or use of redundancy).

When a minimum delivery limit is defined, the seller may have to compensate the buyer for the output shortfall at an agreed upon price if under-delivery happens, e.g., [21,22,24]. Similarly, the buyer may also increase the minimum energy delivery target for the next year to compensate for the under-delivered amount, e.g., [20].

1.3. Real Options Analysis (ROA)

Discounted cash flow (DCF) analysis is a method used to value a project, company or asset over time. DCF models, whether analytical or simulation-based, capture the time value of money and can capture the uncertainties in the cash flow, but they do not account for the managerial flexibility that the decision-makers have to adapt to future uncertainties. Alternatively, a real option is the right but not the obligation to undertake business initiatives like deferring, abandoning, expanding, staging, or contracting. Real options originate from financial options, and ROA refers to the valuation of the real options. ROA assumes that managerial flexibility allows a value-maximizing decision to be made at each decision point. DCF analysis only accounts for the downside of the future, while ROA captures the value of the upside potential by accounting for the managerial flexibility.

Real options can be categorized as the option to buy (a "call" option) or the option to sell (a "put" option). The most common real options are European and American options: the former has a fixed expiration date, whereas the latter can be exercised at any point in time before the expiration date.

In this paper, the predictive maintenance is scheduled and the optimum predictive maintenance opportunity is determined for a wind farm managed using a PPA with multiple wind turbines indicating RULs. The time-history cumulative revenue loss and the avoided corrective maintenance cost paths are simulated to form the predictive maintenance value paths. By applying a Monte Carlo simulation-based European ROA approach, a series of predictive maintenance options are evaluated, each expiring on the date of a possible maintenance opportunity.

The remainder of the paper is organized as follows: Section 2 formulates the European ROA approach for the wind farm managed using a PPA when multiple wind turbines indicate RULs. Section 3 presents a case study. Finally, Section 4 gives the conclusion and also discusses the future research opportunities.

2. Analysis Methodology

2.1. Review of Wind Farm Maintenance Modeling

There exist a significant number of DCF-based wind farm maintenance models, which can be categorized as either: Reliability-Centered Maintenance (RCM) motivated models and simulation-based models. The major differences are how reliability and maintenance timing are modeled.

The RCM motivated models "count" the number of failures, and predictive and corrective maintenance events, and formulate an empirical maintenance cost expression for a wind farm, by assuming a failure rate (e.g., an MTBF) and estimating the average number of failures during a specific period of time, e.g., [25–28]. Some models include predictive maintenance based on condition monitoring technologies indicating health degradations, and compare the life-cycle maintenance costs of various maintenance strategies, e.g., [29,30]. These models determine the number of condition monitoring based predictive maintenance events, but the actual timing of the predictive maintenance events cannot be modeled.

Unlike the RCM motivated models, the simulation-based models can model the uncertainties of the predictive maintenance timing. These models use probability distributions representing the system reliability and a discrete-event simulation to model the failure and maintenance events, e.g., [31–33]. There have been an extensive predictive maintenance optimization studies performed using simulation-based models for wind farms, e.g., [34–37], which are also mainly based on the condition monitoring technologies. In these studies, the health threshold that triggers the predictive maintenance decision can be optimized, the maintenance decisions are made by checking the threshold, and the predictive maintenance will be implemented once the threshold is exceeded. For real wind turbine systems, when a specific threshold has been exceeded, it is not necessarily clear whether it is better to carry out the predictive maintenance as early as possible, to wait for another maintenance opportunity, or to run the system into failure and perform corrective maintenance. For real systems, the predictive maintenance decision depends on how fast future additional damage will accumulate and the type of contract that the wind farm is managed under.

Both RCM motivated and simulation-based models presume fixed future conditions and cash flow scenarios, and do not account for the decision-makers' managerial flexibility to adapt. To capture managerial flexibility during the support of systems, ROA has been applied to the maintenance modeling problems for offshore platforms, production lines, bridges and aircraft, e.g., [38–42]. However, these works only model preventive maintenance using real options, and predictive maintenance is not considered.

In [43] the ROA approach was applied to the wind farm maintenance problem for the first time, and [43] was also the first work to optimize the wind turbine predictive maintenance decision based on the RUL predictions from PHM. However, the approach in [43] cannot be used to schedule the predictive maintenance, because the model determines the best maximum wait-to-maintenance date. In reality when RUL predictions are obtained, the wind farm maintenance decision-makers want to determine the opportunity on which predictive maintenance should be done, given a known maintenance opportunity calendar (with uncertainties). Uncertainties in the RUL predictions and life consumption are not considered in [43], and the cumulative revenue loss during RUL, which reflects the value of the part of the RUL thrown away due to predictive maintenance, is not identified.

In [10], the optimum predictive maintenance opportunity was determined for a single wind turbine indicating an RUL from PHM managed using an "as-delivered" contract. In [10] the cumulative revenue loss and avoided corrective maintenance cost time history paths are simulated considering the uncertainties in the RUL prediction and wind speed, and a simulation-based European ROA approach is applied to valuate a series of European style predictive maintenance options.

In summary, PHM-based predictive maintenance optimization has not been considered by the existing DCF-based wind farm maintenance models, and DCF approaches to maintenance modeling do not include the maintenance decision-makers' managerial flexibility, which is necessary when optimizing the PHM-based predictive maintenance scheduling problem. To manage flexibility, the ROA approach is more suitable than the RCM motivated and simulation-based maintenance models. When deciding the opportunity to schedule the predictive maintenance, a European ROA approach is more applicable than an American ROA approach (such as that used in [43]).

Wind farms are typically managed using PPAs, and no existing maintenance models (DCF or ROA based) account for the terms in the PPAs. The optimum predictive maintenance opportunity for a PPA-managed farm will be impacted by the operational state of all the other turbines, the amount of energy delivered, and the energy delivery target, prices and penalization mechanism for under-delivery defined in the PPA. The optimum predictive maintenance opportunity for a PPA-managed farm can be different from the same farm managed using an "as-delivered" contract, and differ from the optimum predictive maintenance opportunities for the individual turbines with RULs managed in isolation.

2.2. A European ROA Approach for a Single Wind Turbine Managed Using an "As-delivered" Contract

Before we address how to model wind farms managed using PPA contracts, we need to first review the application of the simulation-based European ROA to determine the optimum predictive maintenance opportunity for a single wind turbine managed using an as-delivered contract developed in [10].

For a single wind turbine, predictive maintenance options are created after *in situ* PHM that generates RUL estimations is added to the turbine. When an RUL is predicted for a subsystem, there are multiple choices regarding the predictive maintenance for the maintenance decision-maker: performing the predictive maintenance at the earliest maintenance opportunity, waiting for some time for the predictive maintenance, or doing nothing and letting the turbine run to failure for corrective maintenance. By valuating the predictive maintenance option, the decision if and when to perform the predictive maintenance can be made.

Assume a single wind turbine is managed using an "as-delivered" contract, which simply pays a set price for each unit of the energy delivered. For simplicity, we assume the energy generation capacity will not degrade as damage accumulates in the subsystems, and the predictive maintenance downtime is negligible. At time t_0 an RUL is predicted for a subsystem in calendar time (RUL_C). Assume, for simplicity, that there are no uncertainties in the RUL_C prediction (note, uncertainties in the RUL prediction are included in [5] and in this paper, and will be discussed in detail in Section 2.5). Once the subsystem fails, the turbine will fail too. After time t_0 there are continuous predictive maintenance opportunities, and the maintenance decision-maker aims at determining if and when to implement the predictive maintenance. Since no uncertainty in the RUL has been assumed, the initial predictive maintenance decision will be made at time t_0 and never change.[3] If the predictive maintenance is not implemented, the predictive maintenance option expires, and the turbine will fail at time t_0+RUL_C, leading to a corrective maintenance event with a downtime DT to restore it to operation.

[3] In reality the RUL prediction may be checked periodically, and the maintenance decision can be updated accordingly as well after time t_0. For simplicity RUL_C is assumed to be constant in this section; however the general model described in Section 2.5 does not assume a constant RUL_C. In Section 2.5 the uncertainties in both RUL_C and the wind speed (that sets the consumption rate of the RUL) are considered.

Fig. 1 graphically shows the construction of the predictive maintenance value. Assume the predictive maintenance will be implemented at the maintenance opportunity time t ($t_0 < t < t_0+RUL_C$). The cumulative revenue loss due to predictive maintenance, $R_L(t)$ is maximum (absolute value) at the first maintenance opportunity after time t_0. This is because the most remaining life is disposed of if predictive mainenance is performed at this opportunity. As time advances, less RUL is thown away (and less revenue is lost) until the last predictive maintenance opportunity before time t_0+RUL_C. The avoided corrective maintenance cost, $C_A(t)$, is assumed to be constant. When $R_L(t)$ and $C_A(t)$ are summed, the predictive maintenance value, $V_{PM}(t)$, is obtained, Equation (1), representing the extra value gained by performing the predictive maintenance at time t instead of the corrective maintenance at t_0+RUL_C.

$$V_{PM}(t) = R_L(t) + C_A(t) \tag{1}$$

$R_L(t)$ represents the portion of the RUL thrown away when predictive maintenance is done prior to the end of the RUL. $R_L(t)$ can be calculated as the difference between the cumulative revenue that could be earned by performing the predictive maintenance at time t, $CR_{PM}(t_0,t)$, and waiting until the failure for corrective maintenance, $CR_{CM}(t_0,t_F)$ (where t_F represents the time point when the RUL is used up and failure happens). The subscript "$_{PM}$" represents the predictive maintenance scenario in which predictive maintenance is implemented at time t, while "$_{CM}$" represents the corrective maintenance scenario in which the turbine is run to failure for corrective maintenance. $R_L(t)$ can be calculated as

$$R_L(t) = CR_{PM}(t_0, t) - CR_{CM}(t_0, t_F) \tag{2}$$

where t_F is given by

$$t_F = t_0 + RUL_C \tag{3}$$

$C_A(t)$ represents the corrective maintenance cost that could be avoided by performing the predictive maintenance at time t. $C_A(t)$ is the sum of the avoided corrective maintenance parts, service and labor cost C_{CM} that is assumed to be constant, and the avoided cumulative downtime revenue loss during downtime DT for corrective maintenance L_{DT}.

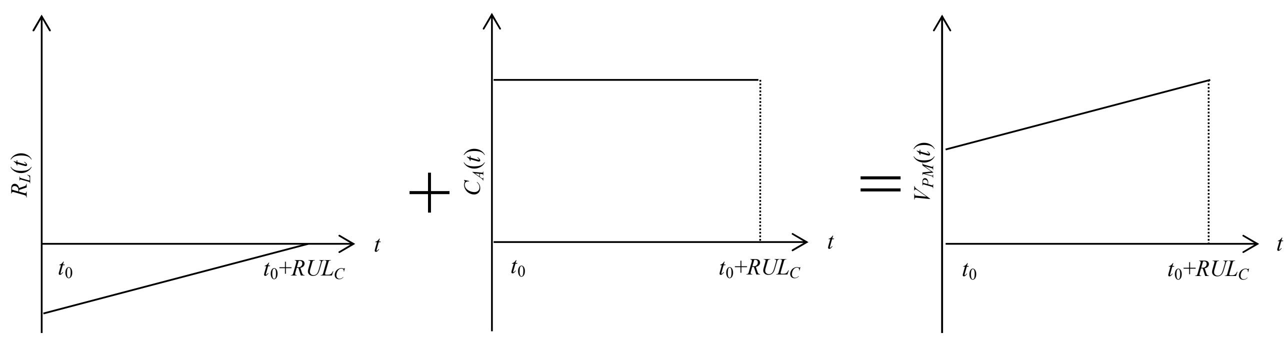

Fig. 1. Simple predictive maintenance value formulation ($R_L(t)$, $C_A(t)$ and $V_{PM}(t)$ have monetary units) [10].

$$C_A(t) = C_{CM} + L_{DT} \tag{4}$$

L_{DT} can be calculated as

$$L_{DT} = CR_{PM}(t_F, t_F + DT) \tag{5}$$

Where $CR_{PM}(t_F,t_F+DT)$ is the cumulative revenue that could be earned in the predictive maintenance scenario during DT.

Detailed calculations of $CR_{PM}(t_0,t)$, $CR_{CM}(t_0,t_F)$ and $CR_{PM}(t_F,t_F+DT)$ are given in [10].

To obtain $V_{PM}(t)$, the predictive maintenance needs to be implemented at time t, which has a cost of C_{PM}. The difference between between $V_{PM}(t)$ and C_{PM} represents the difference between the net revenues that could be earned in the predictive maintenance scenario compared and the corrective maintenance scenario calculated as Equation (6)

$$V_{PM}(t) - C_{PM} = (CR_{PM}(t_0, t) - C_{PM}) - \big(CR_{CM}(t_0, t_F) - C_{CM} - CR_{PM}(t_F, t_F + DT)\big) \tag{6}$$

On the right hand side of Equation (6), in the first pair of parentheses is the net revenue earned in the predictive maintenance scenario, which is a function of time t, and in the second is the net revenue of the corrective maintenance scenario, which is constant.

We assume that the maintenance decision-maker is willing to schedule a predictive maintenance only if the predictive maintenance scenario generates more net revenue than the corrective maintenance scenario, otherwise the turbine will be run to failure for corrective maintenance. All the predictive maintenance opportunities after time t_0 can be treated as real options. On each maintenance opportunity, a European ROA approach can be applied to get the predictive maintenance option value

$$O_{PM}(t) = \begin{cases} max(V_{PM}(t) - C_{PM}, 0), & t_0 < t < t_F \\ 0, & t \geq t_F \end{cases} \tag{7}$$

where $O_{PM}(t)$ is the predictive maintenance option value at time t.[4]

If the difference between $V_{PM}(t)$ and C_{PM} is larger than zero, the predictive maintenance will be implemented and the option value is the difference; otherwise the predictive maintenance will not be implemented and the option will expire leading to zero option value.

We assume the objective of the maintenance decision-maker is to maximize the net revenue that could be earned from time t_0 to either a predictive or corrective maintenance event. So if there are no uncertainties and $V_{PM}(t)$ is larger than C_{PM}, the optimum point in time to perform predictive maintenance would be at the last predictive maintenance opportunity before t_0+RUL_C. Due to uncertainties, there are many possible future paths for the system (only one path is shown in Fig. 1). The analysis described in this section is performed on a representative set of paths generated by accounting for the uncertainties, see Section 2.5.

The model described in [10] is confined to the treatment of a single turbine managed using an as-delivered contract. In the remainder of this section we will discuss uncertainties and extend this model to wind farms (multiple turbines) that are managed using PPA contracts and discuss the solution of the model using ROA.

2.3. Power Purchase Agreement (PPA) Modeling

Now we assume a wind farm managed using a PPA. When there are multiple turbines with RUL predictions, different from the single turbine "as-delivered" case described in Section 2.2, the operational state of all the other turbines in the farm, the amount of energy delivered, and the energy delivery target, prices and penalization mechanism for under-delivery defined in the PPA will also affect the value of the revenue earned, which will affect the $R_L(t)$, $C_A(t)$ and $V_{PM}(t)$. Therefore, it is necessary to develop the PPA-based cumulative revenue and under-delivery penalty calculation method.

Assume the PPA defines an annual energy delivery target ET at the beginning of the year (BOY). During each year, the energy generated before the target is met will be priced by a constant contract price P_C. A lower constant excess price P_E applies for all energy generated thereafter until the end of year (EOY). If the target is not met at EOY, the buyer has to purchase energy from other sources to fulfill the demand with a price P_R (called the replacement price, assumed to be constant and higher than P_C). According to the PPA, the seller must compensate the buyer for the latter's overpaid energy cost, which is calculated as the shortfall energy amount priced by the difference between P_R and P_C. Both the $R_L(t)$ and $C_A(t)$ introduced in Section 2.2 will be influenced by the PPA items, therefore the next step is to develop a PPA framed revenue and penalty model.

At time t_0, there are J turbines operating normally, and K turbines are indicating RULs. Each of the K turbine's RUL (called $RUL_{C,k}$, k = 1 to K) is predicted for some subsystem, and that subsystem will fail before EOY if predictive maintenance is not implemented, causing the turbine to fail. From t_0 to EOY there are multiple predictive maintenance opportunities. Due to the harsh environment and limited maintenance resource availability, especially for the offshore wind farms, we assume that the maintenance decision-maker will carry out predictive maintenance on all the turbines with RUL predictions during a single visit to the farm. The decision-maker wants to decide if and when the predictive maintenance should be scheduled for all K turbines. Otherwise, there will be a corrective maintenance event at EOY to fix and restore all failed turbines to operation.

In the predictive maintenance scenario, if the predictive maintenance implemented on all K turbines at the opportunity time t ($t_0 < t < t_0+RUL_{C,min}$ where $RUL_{C,min}$ is the shortest $RUL_{C,k}$), and all K turbines will be maintained predictively together, the cumulative energy generated from BOY to time t by the whole farm, $CE_{PM}(t)$, can be calculated as

$$CE_{PM}(t) = CE(t_0) + \sum_{\tau=t_0+1}^{t} \sum_{j=1}^{J} E_j(\tau) + \sum_{\tau=t_0+1}^{t} \sum_{k=1}^{K} E_{PM,k}(\tau) \tag{8}$$

[4] Equation (7) does not discount the option value from time t to t_0, i.e., it assumes that the time period is short.

where $CE(t_0)$ is the cumulative energy delivered by the whole wind farm from BOY to time t_0, $E_j(\tau)$ and $E_{PM,k}(\tau)$ are the energy generated by turbine j (the jth turbine operates normally) and k (the kth turbine indicates an RUL) respectively from time τ-1 to τ. And τ is the time index of the year, $t_0 < \tau \leq EOY$. Refer to [10] for the calculation of $E_j(\tau)$ and $E_{PM,k}(\tau)$.

The revenue earned by all K turbines from time τ-1 to τ $R_{PM,K}(\tau)$ can be calculated as

$$R_{PM,K}(\tau) = P_{PM}(\tau) \sum_{k=1}^{K} E_{PM,k}(\tau) \tag{9}$$

where $P_{PM}(\tau)$ is the energy price at time τ if predictive maintenance is implemented at time t, defined as

$$P_{PM}(\tau) = \begin{cases} P_C, & CE_{PM}(\tau) \leq ET \\ P_E, & CE_{PM}(\tau) > ET \end{cases} \tag{10}$$

The cumulative revenue earned from time τ_1 to τ_2 by all K turbines $CR_{PM,K}(\tau_1, \tau_2)$ can be calculated as ($t_0 < \tau_1 < \tau_2 \leq EOY$)

$$CR_{PM,K}(\tau_1, \tau_2) = \sum_{\tau=\tau_1+1}^{\tau_2} R_{PM,K}(\tau) \tag{11}$$

If under-delivery penalty UP_{PM} happens at EOY, it can be calculated as

$$UP_{PM} = \begin{cases} \big(ET - CE_{PM}(EOY)\big)(P_R - P_C), & CE_{PM}(EOY) < ET \\ 0, & CE_{PM}(EOY) \geq ET \end{cases} \tag{12}$$

Similarly, in the corrective maintenance scenario, the cumulative energy generated from BOY to time t by the whole farm, $CE_{CM}(t)$ can be calculated as

$$CE_{CM}(t) = CE(t_0) + \sum_{\tau=t_0+1}^{t} \sum_{j=1}^{J} E_j(\tau) + \sum_{\tau=t_0+1}^{t} \sum_{k=1}^{K} E_{CM,k}(\tau) \tag{13}$$

where $E_{CM,k}(\tau)$ is the energy generated by turbine k from time τ-1 to τ

$$E_{CM,k}(\tau) = \begin{cases} E_{PM,k}(\tau), & t_0 < \tau < t_0 + RUL_{C,k} \\ 0, & t_0 + RUL_{C,k} \leq \tau \leq EOY \end{cases} \tag{14}$$

The revenue earned by all K turbines from time τ-1 to τ, $R_{CM,K}(\tau)$ can be calculated as

$$R_{CM,K}(\tau) = P_{CM}(\tau) \sum_{k=1}^{K} E_{CM,k}(\tau) \tag{15}$$

where $P_{CM}(\tau)$ is the energy price at time τ if all K turbines are run to failure

$$P_{CM}(\tau) = \begin{cases} P_C, & CE_{CM}(\tau) \leq ET \\ P_E, & CE_{CM}(\tau) > ET \end{cases} \tag{16}$$

The cumulative revenue earned from time τ_1 to τ_2 by all K turbines $CR_{CM,K}(\tau_1, \tau_2)$ can be calculated as

$$CR_{CM,K}(\tau_1, \tau_2) = \sum_{\tau=\tau_1+1}^{\tau_2} R_{CM,K}(\tau) \tag{17}$$

The under-delivery penalty UP_{CM} can be calculated as

$$UP_{CM} = \begin{cases} \big(ET - CE_{CM}(EOY)\big)(P_R - P_C), & CE_{CM}(EOY) < ET \\ 0, & CE_{CM}(EOY) \geq ET \end{cases} \tag{18}$$

In this section, PPA-based wind farm cumulative revenue and under-delivery penalty modeling have been introduced. The next step is to simulate the PPA-based $R_L(t)$, $C_A(t)$ and $V_{PM}(t)$, and also apply the European ROA approach to a wind farm managed under a PPA.

2.4. European ROA Approach for Multiple Wind Turbines Managed Using a PPA

Section 2.3 formulated the cumulative revenue and under-delivery penalty. In this section we calculate the cumulative revenue loss and avoided corrective maintenance cost and determine the predictive maintenance value using ROA. This is done by modeling the PPA-based $R_L(t)$, $C_A(t)$ and $V_{PM}(t)$ for the K turbines with RUL predictions, then applying the European ROA approach to obtain the $O_{PM}(t)$, based on which, the optimum predictive maintenance opportunity can be determined for the K turbines.

The cumulative revenue loss by implementing predictive maintenance, $R_L(t)$, can be calculated as

$$R_L(t) = CR_{PM,K}(t_0, t) - CR_{CM,K}(t_0, EOY) \tag{19}$$

The avoided corrective maintenance cost by replacing corrective maintenance with predictive maintenance at t, can be calculated as

$$C_A(t) = C_{CM,K} + (UP_{CM} - UP_{PM}) + L_{DT} \tag{20}$$

where $C_{CM,K}$ is the corrective maintenance parts, service and labor cost for all K turbines at EOY defined as

$$C_{CM,K} = \sum_{k=1}^{K} C_{CM,k} \tag{21}$$

The second item in parentheses in Equation (20) is the under-delivery penalty due to corrective maintenance. L_{DT} can be calculated as

$$L_{DT} = CR_{PM,K}(t, EOY) - CR_{CM,K}(t, EOY) \tag{22}$$

The predictive maintenance value $V_{PM}(t)$ is

$$V_{PM}(t) = R_L(t) + C_A(t) \tag{23}$$

The predictive maintenance opportunities that follow time t_0 can be treated as real options, and on each opportunity t, the European ROA approach can be applied as

$$O_{PM}(t) = \begin{cases} max\left(V_{PM}(t) - C_{PM,K}, 0\right), & t_0 < t < t_0 + RUL_{C,min} \\ 0, & t_0 + RUL_{C,min} \le t \le EOY \end{cases} \tag{24}$$

where $C_{PM,K}$ is the corrective maintenance parts, service and labor cost for all K turbines at time t defined as

$$C_{PM,K} = \sum_{k=1}^{K} C_{PM,k} \tag{25}$$

The European ROA approach has the flexibility to choose not to carry out the predictive maintenance if corrective maintenance is more beneficial. On each predictive maintenance opportunity before $RUL_{C,min}$, if $V_{PM}(t)$ is higher than $C_{PM,K}$, predictive maintenance will be implemented on all K turbines; otherwise, all K turbines will be run to failure, and the $O_{PM}(t)$ is 0. After $RUL_{C,min}$, the predictive maintenance option expires and the $O_{PM}(t)$ is 0. By valuating the option values of all possible maintenance opportunities between t_0 and $RUL_{C,min}$ as a series of European options, the optimum predictive maintenance opportunity can be determined as the opportunity with highest $O_{PM}(t)$.

The maintenance decision-maker may also want to schedule predictive maintenance for each of the K turbines individually, in which case the $V_{PM}(t)$ paths can be generated for each of the K turbines first. Then the European ROA can be applied to each of the K turbines to determine its own optimum predictive maintenance opportunity.

2.5. Uncertainties and Path Simulation

So far we have not addressed uncertainties in the RUL predictions. Without RUL uncertainties,the optimum predictive maintenance opportunity is always at the peak point of the $V_{PM}(t)$ curve (Fig. 1), which is the last opprtunity before $RUL_{C,min}$. Wind turbines are always in presence of random factors, both the RUL predictions and the rate at which the predicted remaining life is consumed, are uncertain [44]. For example, the RUL for a particular subsystem may be articulated in rotational cycles and there would generally be uncertainty in the number of cycles remaining. Additionally, the mapping of the cycles to time requires assumptions about the wind and other environmental conditions (which are also uncertain) – this is the rate of the RUL consumption.

Uncertainty quantification refers to the quantitative characterization and reduction of uncertainties, to quantify the uncertainties in system output (e.g., the optimum predictive maintenance opportunity) given the uncertain inputs (e.g., the RUL prediction and the RUL consumption rate). Research has been performed on uncertainty quantification techniques for system fault diagnosis and for PHM, e.g., a real-time fault diagnosis technique was developed for stochastic nonlinear systems subject to unknown input disturbances and Brownian motion [45]. Uncertainty quantification approaches include probabilistic approaches and non-probabilistic approaches. Simulation-based methods, such as Monte Carlo simulation, are one type of the probabilistic approach [46]. Monte Carlo simulation can avoid an analytical calculation that can be cumbersome and less general, therefore it has been widely used in the wind farm maintenance modelling area [32–37,43], and will be used here.

We first assume the turbine RUL is consumed by rotor rotations in cycles. Therefore a probability distribution can be used to represent the uncertain RUL estimation in cycles caused by fatigue for each of the K turbines at time t_0; this includes uncertainties from the sensors, data reduction methods, damage accumulation models and the material parameters [10]. The mean of the distribution is $RUL_{F,k}$ with known standard deviation.[5] For example, the RUL distribution assumed in the case study in Section 3 is shown in the right plot of Fig. 2. By using Monte Carlo simulation, M $ARUL_{F,k}$ samples (the actual RUL sample in cycles) can be simulated for turbine k.

We assume that wind is the major environmental load that causes damage to the wind turbine's key subsystems (e.g., blade, main shaft and gearbox) after time t_0. A probability distribution can be used to describe the historical wind speed data, and using Monte Carlo simulation and the Power Law, M wind speed paths can be simulated, each of which represents a possible future wind profile that the whole wind farm is going to experience after time t_0. The wind speed distribution assumed for the case study is shown in the left plot of Fig. 2 in Section 3. So for turbine k, by calculating the RUL consumption caused by the rotor rotational cycles under wind, M $ARUL_{C,k}$ (the actual RUL sample in calendar time) can be obtained from the M $ARUL_{F,k}$ samples and wind speed paths. This process is repeated for all the K turbines with RUL predictions [10].

A Monte Carlo simulation method can be used to generate M paths for $R_L(t)$, $C_A(t)$ and $V_{PM}(t)$, each of which represents one possible future that could happen. At each possible predictive maintenance opportunity, the M $O_{PM}(t)$ paths can be averaged to get the expected predictive maintenance option value $EO_{PM}(t)$. So by checking all possible opportunities, the optimum predictive maintenance opportunity can be selected as the one with highest $EO_{PM}(t)$.

3. CASE STUDY

In this section, the European ROA approach is applied to a wind farm managed using a PPA with multiple turbines indicating RULs concurrently.

We assume there is an offshore wind farm with 5 turbines, the buoy height 10-year 10-minute average wind speed data are obtained from the buoy station [47]. A Weibull wind speed distribution (left plot of Fig. 2) is assumed with parameters η =

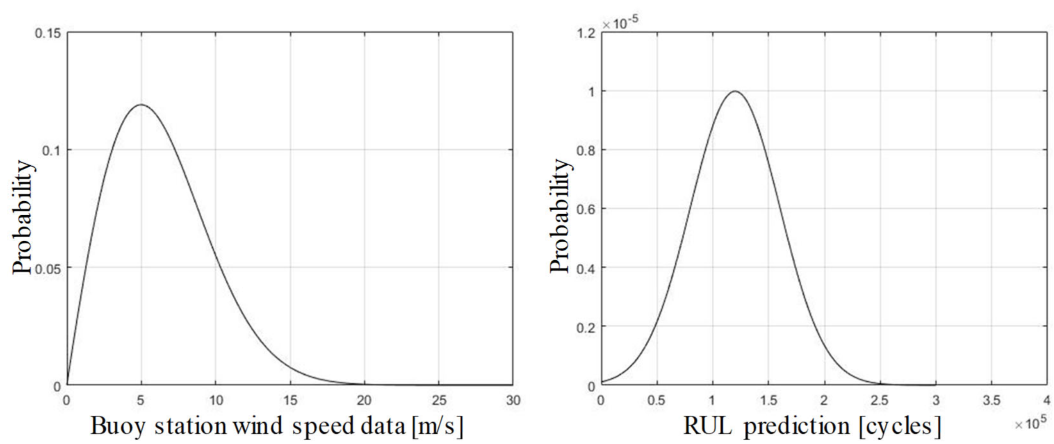

Fig. 2. Left – Weibull distribution for the buoy station wind speed data, and right – normal distribution for the turbine 1 RUL prediction.

[5] It should be noted that the RUL can be represented as a time or any applicable lifetime usage measure depending on the particular failure mechanism, and the model developed in this paper is applicable to any RUL distribution type.

7.1470 m/s and β = 1.9733 [10]. All 5 turbines are assumed to be Vestas V-112 3.0 MW, with rated output power of 3 MW [48].

We assume in the PPA managing the farm the ET is 40,000 MWh, P_C, P_E and P_R are assumed to be \$20/MWh, \$10/MWh and \$40/MWh respectively. At t_0 = 8000 hrs when $EC(t_0)$ is 36,000 MWh, RULs are predicted for turbine 1 to be 120,000 cycles (with 40,000 cycles standard deviation) and for turbine 2 to be 150,000 cycles (with 50,000 cycles standard deviation). For each turbine, a normal distribution (shown in the right plot of Fig. 2) is used to represent the RUL estimations [49–51]. We assume all the other turbines are operating normally. The $R_L(t)$, $C_A(t)$ and $V_{PM}(t)$ paths can be generated for turbines 1 and 2 according to Equations (8) through (23) as shown in Fig. 3.

As shown in the left plot in Fig. 3, all the $R_L(t)$ paths start at different points on the vertical axis, because the longer the $ARUL_{C,k}$ is, the more cumulative revenue will be lost if predictive maintenance is implemented, and the lower the path's initial value is. All the $R_L(t)$ paths are ascending over time, because the later the predictive maintenance is carried out, the less cumulative revenue will be lost. All the $R_L(t)$ paths terminate at different time points of $ARUL_{C,min}$, due to the uncertainties in the RUL prediction and the wind speed. In the middle plot in Fig. 3, each $C_A(t)$ path is constant over time. L_{DT} has different levels, because the lengths of turbines 1 and 2's total corrective maintenance downtime differ among the paths (caused by the uncertainties in the RUL prediction), and the wind speed is uncertain too, therefore all $C_A(t)$ paths have different values (UP_{PM} and UP_{CM} are both \$0 in this example). By combining $R_L(t)$ and $C_A(t)$ paths according to Equation (23), the $V_{PM}(t)$ paths shown in the right plot in in Fig. 3 are obtained.

Based on 10,000 simulated $V_{PM}(t)$ paths, using Equation (24) and (25), $O_{PM}(t)$ values are obtained. Then at each predictive maintenance opportunity, all $O_{PM}(t)$ values are averaged to get the $EO_{PM}(t)$ values as shown in Fig. 4. The optimum predictive maintenance opportunity (indicated by the dash line) is 321 hours, with $EO_{PM}(t)$ of \$8,821. In Fig. 5, at the selected optimum predictive maintenance opportunity, 93.5% of the paths choose to implement the predictive maintenance, indicating that the European ROA approach is not targeting the total avoidance of failure and corrective maintenance, but rather maximizing the $EO_{PM}(t)$ value. The ultimate tradeoff of the European ROA approach is to minimize the corrective maintenance risk while minimizing the value of the part of the RUL thrown away by predictive maintenance.

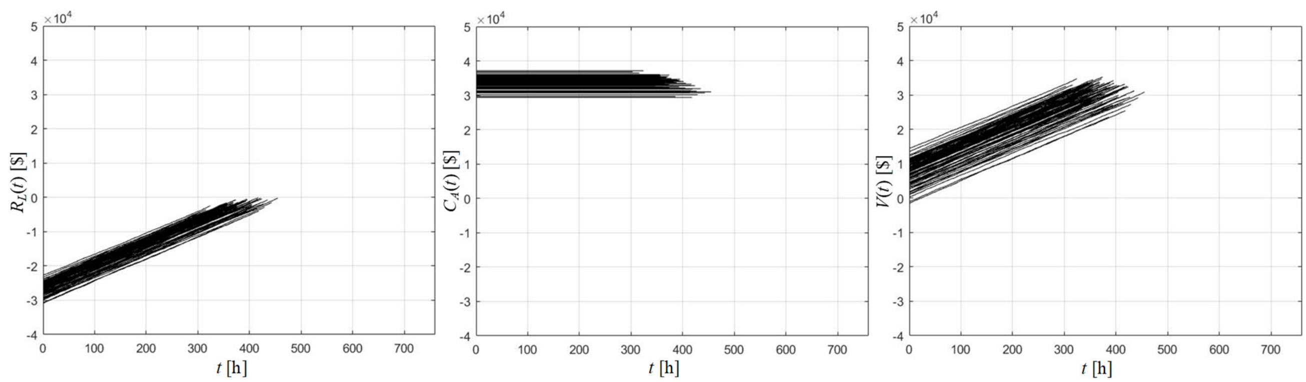

Fig. 3. Left – $R_L(t)$ paths, middle – $C_A(t)$ paths, and right –$V_{PM}(t)$ paths for turbines 1 and 2 (100 paths are shown).

If the predictive maintenance is only available every 48 hours, the $EO_{PM}(t)$ is shown in the left plot of Fig. 6. The optimum predictive maintenance opportunity changes to 14 days (336 hours) after time t_0, with the $EO_{PM}(t)$ value of \$8,314. If compare with the case in Fig. 4, due to the constraint on the predictive maintenance opportunities, the optimum predictive maintenance opportunity is 15 hours later (+4.7%), while the $EO_{PM}(t)$ value is \$507 fewer (-5.7%).

If the same wind farm is managed using an "as-delivered" contract with the same P_C, the optimum predictive maintenance opportunity will change to 12 days (288 hours) after t_0 with the $EO_{PM}(t)$ value of \$15,671 as shown in the right plot of Fig. 6. The change happens because in the PPA case over-delivery happens on some paths before EOY, which makes the RL_{DT} and $C_A(t)$ lower than the "as-delivered" contract case. For the PPA case, if there are turbines not operating at time t_0, the optimum predictive maintenance opportunity will shift to 12 days (288 hours) after t_0 as shown in Fig. 7. When one or two turbines are down, L_{DT} of some paths will become higher because with less operational turbines, ET will be reached later, which means the higher P_C will apply for a longer period of time. For some other paths under-delivery will happen. Therefore, $C_A(t)$ will increase and the optimum predictive maintenance opportunity selection tends to be more conservative.

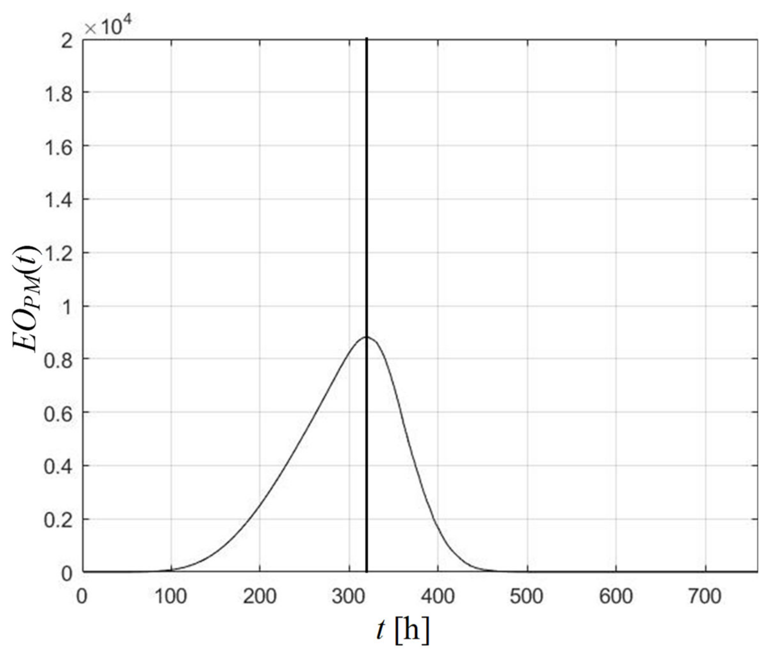

Fig. 4. $EO_{PM}(t)$ curve for turbine 1 and 2 (predictive maintenance opportunity is once every hour).

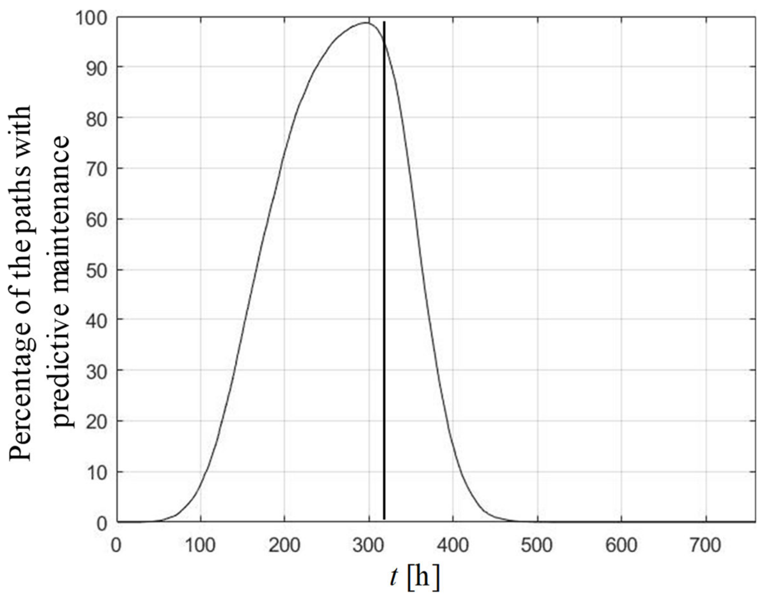

Fig. 5. Percentage of the paths implementing predictive maintenance (predictive maintenance opportunity is once per hour).

If either turbine 1 or 2 are managed in isolation using a PPA, when the RUL is predicted, the optimum predictive maintenance opportunity may be different from when they are managed within a wind farm. Assume the P_C, P_E and P_R are the same as the previous wind farm case. At t_0 = 8000 hrs of the year, ET = 8,000 MWh, $EC(t_0)$ = 7,200 MWh (both are 1/5 of the wind farm case), an RUL is predicted for turbine 1. As shown in Fig. 8, by applying the European approach, the optimum predictive maintenance opportunity is 12 days (288 hours) after t_0. While accoding to the left plot of Fig. 6, the optimum predictive maintenance opportunity for turbines 1 and 2 in the 5-turbine farm with all turbines operating normally is 14 days (336 hours) after t_0. The difference happens because over-delivery will happen in the wind farm case while not in the turbine 1 in isolation case.

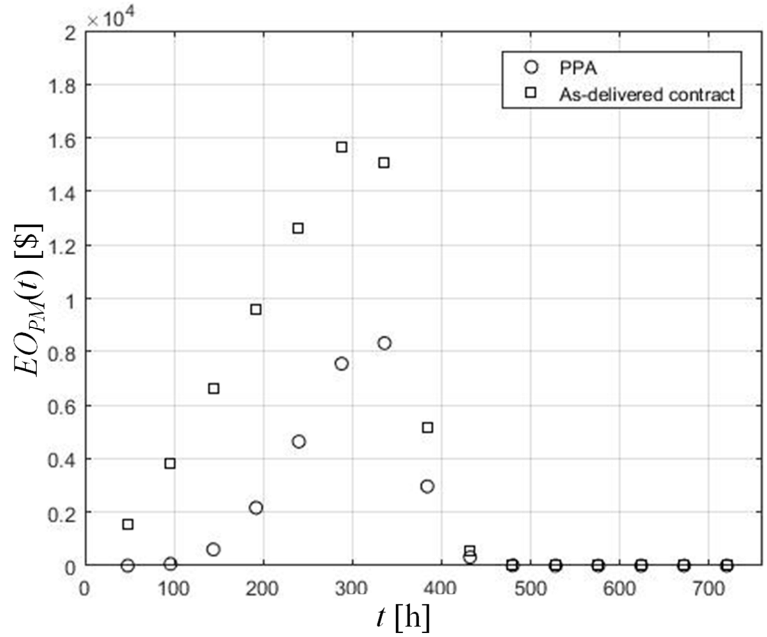

Fig. 6. $EO_{PM}(t)$ curves for turbines 1 and 2 when managed using a PPA or an "as-delivered" contract (predictive maintenance opportunity is once every 48 hours).

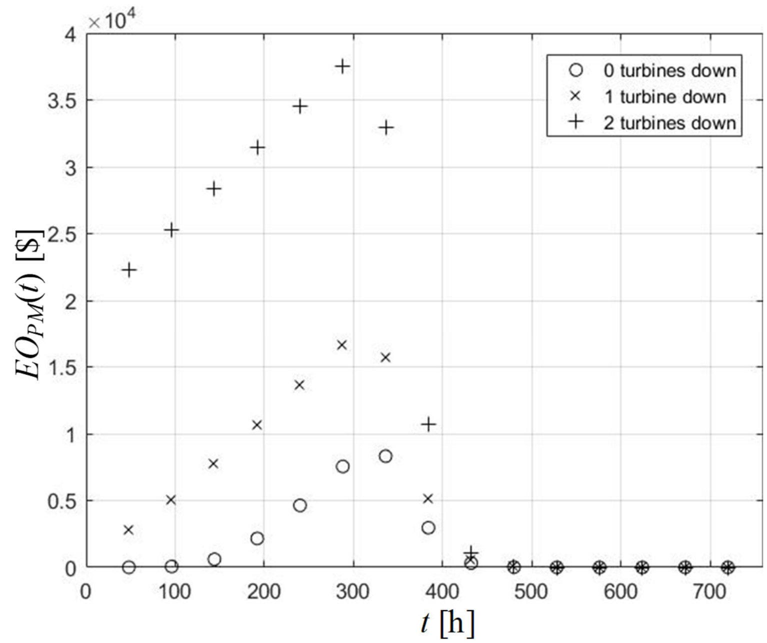

Fig. 7. $EO_{PM}(t)$ curve for turbines 1 and 2 when the number of turbines down is varying (predictive maintenance opportunity is once every 48 hours).

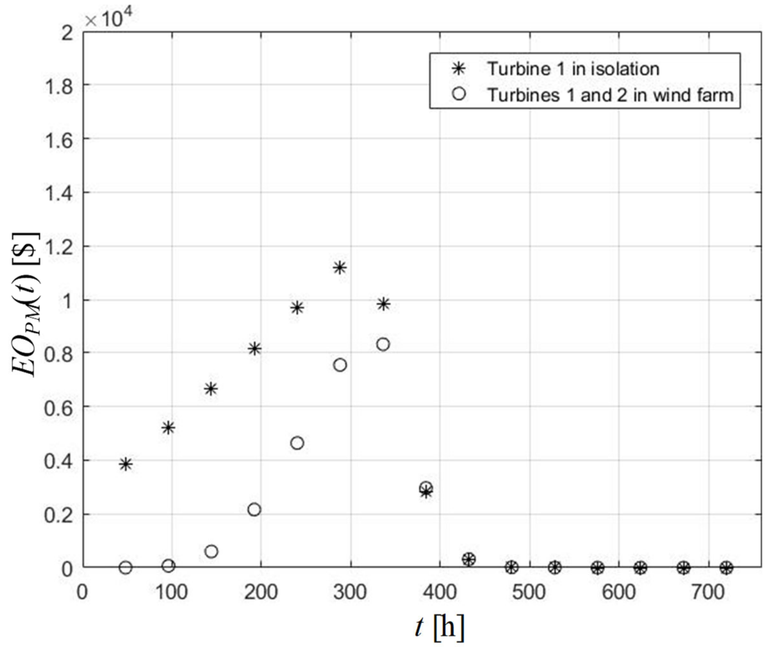

Fig. 8. $EO_{PM}(t)$ curves for when turbine 1 is managed in isolation, and when turbines 1 and 2 are managed in a wind farm (predictive maintenance opportunity is once every 48 hours).

4. Conclusion

The objective of the work presented in this paper is to schedule the optimum predictive maintenance opportunity for wind farms managed using PPAs with multiple turbines indicating RULs concurrently. The model presented in this paper extends a model described in [10] that only applies to a single turbine and an "as-delivered" contract to a wind farm managed using a PPA. Uncertainties in the wind speed and the RUL predictions are considered, and a Monte Carlo simulation based European ROA approach is applied. The predictive maintenance value for each turbine with an RUL prediction depends on the operational state of all the other turbines in the same farm, the amount of energy delivered, and the energy delivery target, prices and penalization mechanism for under-delivery defined in the PPA. According to the case study, when there are turbines that are not operating in the farm, the revenue loss and under-delivery penalties due to corrective maintenance on some paths will be significant; therefore, the optimum predictive maintenance opportunity selection will tend to be conservative. More importantly, the optimum predictive maintenance opportunity for a wind farm that is managed using a PPA, may differ from when the same farm is managed using an "as-delivered" contract, and also differ from when the individual turbines with RULs are managed in isolation. The reason is that the cumulative energy delivered, contract and excess prices, energy delivery target and the under-delivery penalization mechanism defined in the PPA influence the values of both the cumulative revenue loss and the avoided corrective maintenance cost. This influence was demonstrated in a case study where an over-delivery occurs by the *EOY* and therefore the avoided corrective maintenance cost is lower than in the "as-delivered" contract case.

In the future, the collateral damage that causes higher corrective maintenance costs, the power generation capacity degradation and the escalating predictive maintenance cost due to damage accumulation will be studied. The uncertainties in the predictive maintenance opportunities will also be introduced.

The current model only determines the optimum opportunity for a single predictive maintenance event; the model could be extended throughout the wind farm's whole life cycle by assuming that the predictive maintenance after RUL predictions will always be scheduled using the developed approach. Therefore, multiple predictive maintenance, corrective maintenance and preventive maintenance events can be considered using an ROA-based discrete-event simulator, and a life-cycle maintenance model to estimate the life-cycle O&M costs and net revenue for a wind farm using a PPA could be developed.

The uncertainties in the RUL prediction represent an important input to the model developed in this paper. Understanding the causes and correlation of these uncertainties represents a critical topic for future research to support all types of maintenance modeling.

ACKNOWLEDGEMENT

Funding for the work was provided by Exelon for the advancement of Maryland's offshore wind energy and jointly administered by MEA and MHEC, as part of "Maryland Offshore Wind Farm Integrated Research (MOWFIR): Wind Resources, Turbine Aeromechanics, Prognostics and Sustainability".

NOMENCLATURE

$ARUL_{C,k}$	RUL sample in calendar time for turbine k
$ARUL_{C,min}$	shortest $ARUL_{C,k}$
BOY	beginning of the year
C_{CM}	corrective maintenance parts, service and labor cost for a single turbine
$C_{CM,k}$	corrective maintenance parts, service and labor cost of turbine k
$C_{CM,K}$	corrective maintenance parts, service and labor cost of all K turbines
C_{PM}	predictive maintenance parts, service and labor cost for a single turbine
$C_{PM,k}$	predictive maintenance parts, service and labor cost of turbine k
$C_{PM,K}$	predictive maintenance parts, service and labor cost of all K turbines
$C_A(t)$	avoided corrective maintenance cost at time t
$CE(t_0)$	cumulative energy delivered by the whole wind farm from BOY to t_0
$CE_{CM}(t)$	cumulative energy delivered by the whole wind farm from BOY to t in the corrective maintenance scenario
$CE_{PM}(t)$	cumulative energy delivered by the whole wind farm from BOY to t in the predictive maintenance scenario
$CR_{CM,K}(\tau_1, \tau_2)$	cumulative revenue earned from time τ_1 to τ_2 by all K turbines in the corrective maintenance scenario
$CR_{PM,K}(\tau_1, \tau_2)$	cumulative revenue earned from time τ_1 to τ_2 by all K turbines in the predictive maintenance scenario
DT	downtime of corrective maintenance for a single turbine
$E_j(\tau)$	energy generated by turbine j from τ-1 to τ
$E_{CM,k}(\tau)$	energy generated by turbine k from τ-1 to τ in the corrective maintenance scenario
$E_{PM,k}(\tau)$	energy generated by turbine k from τ-1 to τ in the predictive maintenance scenario
$EO_{PM}(t)$	expected predictive maintenance option value at time t
EOY	end of the year
ET	annual energy delivery target of the wind farm in PPA
J	number of turbines operating normally in the wind farm at time t_0
K	number of turbines indicating $RULs$ in the wind farm at time t_0
L_{DT}	revenue loss during downtime for corrective maintenance
M	number of wind speed paths
$O_{PM}(t)$	predictive maintenance option value at time t
P_C	contract price in PPA
$P_{CM}(\tau)$	energy price at time τ in the corrective maintenance scenario
P_E	excess price in PPA
$P_{PM}(\tau)$	energy price at time τ in the predictive maintenance scenario
P_R	replacement price in PPA
$R_{CM,K}(\tau)$	revenue earned by all K turbines from τ-1 to τ in the corrective maintenance scenario
$R_{PM,K}(\tau)$	revenue earned by all K turbines from τ-1 to τ in the predictive maintenance scenario
$R_L(t)$	cumulative revenue loss at time t
RUL_C	predicted remaining useful life for a subsystem in a single turbine in calendar time
$RUL_{C,k}$	predicted remaining useful life for turbine k in calendar time
$RUL_{C,min}$	shortest $RUL_{C,k}$
$RUL_{F,k}$	predicted remaining useful life for turbine k in cycles
t	time of the predictive maintenance opportunity, $t_0 < t < t_0+RUL_{C,min}$
t_F	time when the RUL for a single turbine is used up and failure happens

t_0	time of the year when RULs are predicted for K turbines and predictive maintenance decision needs to be made
UP_{CM}	under-delivery penalty in the corrective maintenance scenario
UP_{PM}	under-delivery penalty in the predictive maintenance scenario
$V_{PM}(t)$	predictive maintenance value at time t
β	Weibull distribution shape parameter
η	Weibull distribution scale parameter
τ	time of the year, $t_0 < \tau \leq EOY$

REFERENCES

[1] Z. Gao, C. Cecati, S.X. Ding, A Survey of Fault Diagnosis and Fault-Tolerant Techniques Part I: Fault Diagnosis, IEEE Trans. Ind. Electron. 62 (2015) 3768–3774. doi:10.1109/TIE.2015.2417501.

[2] Z. Gao, C. Cecati, S.X. Ding, A Survey of Fault Diagnosis and Fault-Tolerant Techniques—Part II: Fault Diagnosis With Knowledge-Based and Hybrid/Active Approaches, IEEE Trans. Ind. Electron. 62 (2015) 3768–3774. doi:10.1109/TIE.2015.2419013.

[3] E. Wiggelinkhuizen, T. Verbruggen, H. Braam, L. Rademakers, M.C. Tipluica, A. Maclean, A.J. Christensen, J. a S. Dk, E. Becker, P.C.M.G. D, D. Scheffler, N.E.G. D, CONMOW : Condition Monitoring for Offshore Wind Farms, in: 2002: pp. 1–10. https://pdfs.semanticscholar.org/d502/a71b5898a61b42bea1ff19b41ddf1414aa88.pdf (accessed March 8, 2017).

[4] B. Lu, Y. Li, X. Wu, Z. Yang, A review of recent advances in wind turbine condition monitoring and fault diagnosis, Electron. Mach. Wind. (2009) 1–7. doi:10.1109/PEMWA.2009.5208325.

[5] Z. Hameed, Y.S. Hong, Y.M. Cho, S.H. Ahn, C.K. Song, Condition monitoring and fault detection of wind turbines and related algorithms: A review, Renew. Sustain. Energy Rev. 13 (2009) 1–39. doi:10.1016/j.rser.2007.05.008.

[6] F.P. García Márquez, A.M. Tobias, J.M. Pinar Pérez, M. Papaelias, Condition monitoring of wind turbines: Techniques and methods, Renew. Energy. 46 (2012) 169–178. doi:10.1016/j.renene.2012.03.003.

[7] M. Pecht, Prognostics and Health Management of Electronics, Wiley, 2009. doi:10.1002/9780470061626.shm118.

[8] E. Byon, E. Perez, Y. Ding, L. Ntaimo, Simulation of Wind Farm Operations and Maintenance Using Discrete Event System Specification, Trans. Soc. Model. Simul. Int. 87 (2010) 1093–1117. doi:10.1177/0037549711376841.

[9] P.C. Matthews, B. Chen, P.J. Tavner, Automated on-line fault prognosis for wind turbine pitch systems using supervisory control and data acquisition, IET Renew. Power Gener. 9 (2015) 503–513. doi:10.1049/iet-rpg.2014.0181.

[10] X. Lei, P.A. Sandborn, PHM-Based Wind Turbine Maintenance Optimization Using Real Options, Int. J. Progn. Heal. Manag. 7 (2016) 1–14.

[11] Z. Hameed, S.H. Ahn, Y.M. Cho, Practical Sspects of a Condition Monitoring System for a Wind Turbine with Emphasis on Its Design, System Architecture, Testing and Installation, Renew. Energy. 35 (2009) 879–894. doi:10.1016/j.renene.2009.10.031.

[12] R. Wiser, M. Bolinger, 2014 Wind Technologies Market Report, 2015. doi:10.2172/1220532.

[13] E. Einowski, J. Martin, The Law of Wind: A Guide to Business and Legal Issues, 2014. http://www.stoel.com/webfiles/LawOfWind.pdf.

[14] M.J. Barradale, Impact of Policy Uncertainty on Renewable Energy Investment: Wind Power and PTC, 2008. http://papers.ssrn.com/sol3/Papers.cfm?abstract_id=1085063.

[15] K. Hernandez, C. Richard, J. Nathwani, Estimating Project LCOE – an Analysis of Geothermal PPA Data, in: Proc. 41st Work. Geotherm. Reserv. Eng., Stanford, CA, 2016: pp. 1–8. https://pangea.stanford.edu/ERE/db/GeoConf/papers/SGW/2016/Hernandez1.pdf (accessed August 29, 2016).

[16] M. Bruck, N. Goudarzi, P. Sandborn, A Levelized Cost of Energy (LCOE) Model for Wind Farms that Includes Power Purchase Agreement (PPA) Energy Delivery Limits, in: Proc. ASME 2016 Power Conf., Charlotte, NC, 2016: pp. 1–9.

[17] Bonneville Power Administration, Klondike III Wind Project Power Purchase: Administrator's Record of Decision, 2007. https://www.bpa.gov/power/pgc/wind/KlondikeROD.pdf.

[18] City of Gloucester, Power Purchase Agreement, 2011. http://gloucester-ma.gov/DocumentCenter/Home/View/1125.

[19] Sonoma Clean Power, Feed-in Tariff Power Purchase Agreement, 2014. https://sonomacleanpower.org/wp-content/uploads/2014/09/SCP-FIT-PPA-Approved-2014-07.pdf.

[20] City of Anaheim, Long Term Power Purchase Agreement (Wind Power), 2003. http://local.anaheim.net/docs_agend/questys_pub/MG35236/AS35275/AS35278/AI35947/DO35950/1.pdf.

[21] Delmarva Power & Light Company, Renewable Wind Energy Power Purchase Agreement, 2008. http://www.delmarva.com/uploadedFiles/wwwdelmarvacom/AESPPA.pdf.

[22] CORE International Inc., Namibia IPP and Investment Market Framework Technical Assistance: Annex X Model PPA for Medium Scale IPPs, 2006. https://library.pppknowledgelab.org/PPPIRC/documents/1601/download.
[23] Xcel Energy, Wind Energy Purchase Agreement, 2013. https://www.xcelenergy.com/staticfiles/xe/Regulatory/Regulatory PDFs/NM-2013-Wind-Purchased-Power-Agreemtents/NM-2013-Wind-PPA-Mammoth-Plains.pdf.
[24] PacifiCorp, Power Purchase Agreement, 2014. http://www.pacificorp.com/content/dam/pacificorp/doc/Energy_Sources/Customer_Generation/Company_Qualified_Facility_Program.pdf.
[25] L.W.M.M. Rademakers, H. Braam, M.B. Zaaijer, G.J.W. van Bussel, Assessment and Optimisation of Operation and Maintenance of Offshore Wind Turbines, 2003. https://www.ecn.nl/fileadmin/ecn/units/wind/docs/dowec/2003-EWEC-O_M.pdf.
[26] L.W.M.M. Rademakers, H. Braam, T.S. Obdam, P. Frohböse, N. Kruse, Tools for Estimating Operation and Maintenance Costs of Offshore Wind Farms: State of the Art, in: Proc. EWEC 2008, Brussels, 2008.
[27] M.K. Paida, Life-Cycle Cost Analysis of a Wind Park, National Technical University of Athens, 2012.
[28] M. Nordahl, The Development of a Life Cycle Cost Model for an Offshore Wind Farm, Chalmers University of Technoloty, 2011. http://studentarbeten.chalmers.se/publication/152402-the-development-of-a-life-cycle-cost-model-for-an-offshore-wind-farm%5Cnhttp://publications.lib.chalmers.se/records/fulltext/152402.pdf.
[29] G. Puglia, Life Cycle Cost Analysis on Wind Turbines, Chalmers University of Technology, 2013.
[30] J.A. Andrawus, J. Watson, M. Kishk, A. Adam, The Selection of a Suitable Maintenance Strategy for Wind Turbines, Wind Eng. 30 (2006) 1–18. doi:10.1260/030952406779994141.
[31] J.J. Nielsen, J.D. Sørensen, On risk-based operation and maintenance of offshore wind turbine components, Reliab. Eng. Syst. Saf. 96 (2010) 218–229. doi:10.1016/j.ress.2010.07.007.
[32] J.L. Phillips, C.A. Morgan, J. Jacquemin, Evaluating O&M strategies for offshore wind farms through simulation - the impact of wave climatology, in: Proc. OWEMES, 2006.
[33] E. Koutoulakos, Wind Turbine Reliability Characteristics and Offshore Availability Assessment, Delft University of Technology, 2008.
[34] F. Besnard, L. Bertling, An Approach for Condition-Based Maintenance Optimization Applied to Wind Turbine Blades, IEEE Trans. Sustain. Energy. 1 (2010) 77–83. doi:10.1109/TSTE.2010.2049452.
[35] Z. Tian, T. Jin, B. Wu, F. Ding, Condition Based Maintenance Optimization for Wind Power Generation Systems Under Continuous Monitoring, Renew. Energy. 36 (2011) 1502–1509. doi:10.1016/j.renene.2010.10.028.
[36] E. Byon, Y. Ding, Season-Dependent Condition-Based Maintenance for a Wind Turbine Using a Partially Observed Markov Decision Process, IEEE Trans. Power Syst. 25 (2010) 1823–1834. doi:10.1109/TPWRS.2010.2043269.
[37] E. Pazouki, H. Bahrami, S. Choi, Condition Based Maintenance Optimization of Wind Turbine System Using Degradation Prediction, in: Proc. 2014 IEEE PES Gen. Meet. | Conf. Expo., 2014: pp. 1–5. doi:10.1109/PESGM.2014.6939918.
[38] H.G. Goossens, W.W.A.B. van Blokland, R. Curran, The Development and Application of a Value-Driven Aircraft Maintenance Operations Performance Assessment Model combined with Real Options Analysis, in: Proc. 11th AIAA Aviat. Technol. Integr. Oper. Conf., 2011: pp. 1–22.
[39] Y. Koide, K. Kaito, M. Abe, Life-Cycle Cost Analysis of Bridges Where the Real Options Are Considered, Proc. Curr. Futur. Trends Bridg. Des. Constr. Maint. (2001) 387–395.
[40] X. Jin, L. Li, J. Ni, Option Model for Joint Production and Preventive Maintenance System, Int. J. Prod. Econ. 119 (2009) 347–353. doi:10.1016/j.ijpe.2009.03.005.
[41] S. Santa-Cruz, E. Heredia-Zavoni, Maintenance and Decommissioning Real Options Models for Life-Cycle Cost-Benefit Analysis of Offshore Platforms, Struct. Infrastruct. Eng. 7 (2014) 733–745. doi:10.1080/15732470902842903.
[42] E. Heredia-Zavoni, S. Santa-Cruz, Maintenance Decisions for Offshore Structures Using Real Options Theory, in: Proc. 23rd Int. Conf. Offshore Mech. Arct. Eng., 2004: pp. 417–425. doi:10.1115/OMAE2004-51467.
[43] G. Haddad, P.A. Sandborn, M.G. Pecht, Using Maintenance Options to Maximize the Benefits of Prognostics for Wind Farms, Wind Energy. 17 (2014) 775–791. doi:10.1002/we.1610.
[44] P.A. Sandborn, C. Wilkinson, A Maintenance Planning and Business Case Development Model for the Application of Prognostics and Health Management (PHM) to Electronic Systems, Microelectron. Reliab. 47 (2007) 1889–1901. doi:10.1016/j.microrel.2007.02.016 ER.
[45] X. Liu, Z. Gao, Robust finite-time fault estimation for stochastic nonlinear systems with Brownian motions, J. Franklin Inst. (2016). doi:10.1016/j.jfranklin.2016.08.018.
[46] S.H. Lee, W. Chen, A comparative study of uncertainty propagation methods for black-box-type problems, Struct. Multidiscip. Optim. 37 (2009) 239–253. doi:10.1007/s00158-008-0234-7.
[47] National Data Buoy Center, Station 44009 (LLNR 168) - DELAWARE BAY 26 NM Southeast of Cape May, NJ,

(2013). http://www.ndbc.noaa.gov/station_history.php?station=44009 (accessed August 24, 2016).
[48] Vestas, 3 MW Platform, (2014). http://pdf.directindustry.com/pdf/vestas/3-mw-platform-2014/20680-574616.html.
[49] L.R. Rodrigues, T. Yoneyama, Maintenance Planning Optimization Based on PHM Information and Spare Parts Availability, in: Proc. Annu. Conf. PHM Soc. 2013, 2013: pp. 1–7.
[50] S. Sankararaman, K. Goebel, Why is the Remaining Useful Life Prediction Uncertain?, in: Proc. Annu. Conf. PHM Soc. 2013, 2012: pp. 1–13.
[51] Z. Tian, Y. Zhang, J. Cheng, Condition Based Maintenance Optimization for Multi-component Systems, in: Proc. Annu. Conf. PHM Soc. 2011, 2011: pp. 1–6. http://www.phmsociety.org/sites/phmsociety.org/files/phm_submission/2011/phmc_11_003.pdf.