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PHM-Based Wind Turbine Maintenance Optimization Using Real Options

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Abstract

A simulation-based real options analysis (ROA) approach is used to determine the optimum predictive maintenance opportunity for a wind turbine with a remaining useful life (RUL) prediction. When an RUL is predicted for a subsystem in a single turbine using PHM, a predictive maintenance option is triggered that the decision-maker has the flexibility to decide if and when to exercise before the subsystem or turbine fails. The predictive maintenance value paths are simulated by considering the uncertainties in the RUL prediction and wind speed (that govern the turbine's revenue earning potential). By valuating a series of European options expiring on all possible predictive maintenance opportunities, a series of option values can be obtained, and the optimum predictive maintenance opportunity can be determined. A case study is presented in which the ROA approach is applied to a single turbine.

1. Introduction

1.1. Background

As a source of renewable energy, wind power is growing throughout the world. The annual growth rate of the global installed wind energy capacity has been more than 10% for 17 years, and the global total wind energy capacity in 2014 was 369,553 MW (Fried, Qiao, Sawyer, and Shukla, 2014).

As a major contributor to the wind turbine levelized cost of energy (LCOE), operations and maintenance (O&M) costs accounts for 0.027 to 0.048 US dollars/kWh (10% to 15% of the LCOE for onshore wind farms and 25% to 30% for offshore wind farms) (Federal Energy Regulation Commission, 2015; IRENA Secretariat, 2012; Verbruggen, 2003).

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Maintenance practices for wind turbines can be generally divided into proactive maintenance and corrective maintenance. Proactive maintenance is carried out at predetermined intervals depending on prescribed criteria to prevent the occurrence of a failure. Typical maintenance activities include: inspection, lubrication, parts replacement, cleaning and adjustments. Proactive maintenance can be divided into preventive and predictive maintenance. Despite the proactive maintenance, unanticipated failures may still occur, resulting in significant downtime, and requiring corrective maintenance.

Preventive maintenance, also known as scheduled maintenance, involves the maintenance activities performed after a predetermined time interval or a specified percentage of system usage, to avoid invalidating the OEM warranty and/or to maintain turbines that have known failure patterns. The current mainstream maintenance practice for wind turbines is preventive maintenance, where the maintenance interval depends on the manufacturer's recommendations, weather conditions, accessibility, availability and the reliability of wind turbines.

PHM technologies have been introduced into wind turbines to avoid premature failures, reduce secondary (collateral) damage to components, reduce maintenance costs, enable remote diagnosis, increase generation and optimize future design (Hameeda, Honga, Choa, Ahnb, and Songc, 2009). A significant body of work on PHM for wind turbine subsystems exists. The key subsystems that the majority of this work focuses on includes: blades and rotor (Hameeda et al., 2009; Hyers, Mcgowan, Sullivan, Manwell, and Syrett, 2006; Nijssen, 2006; Tchakoua, Wamkeue, Ouhrouche, Slaoui-Hasnaoui, Tameghe, and Ekemb, 2014; Tchakoua, Wamkeue, Tameghe, and Ekemb, 2013), gearbox and bearings (Hameeda et al., 2009; Hussain & Gabbar, 2013; Hyers et al., 2006; Niknam, Thomas, Hines, and Sawhney, 2013; Plumley, Wilson, Kenyon, Andrew, Quail, and Athena, 2012; Qu, Bechhoefer, He, and Zhu, 2013; Tamilselvan, Wang, Sheng, and Twomey, 2013; Tchakoua et al., 2014; Tchakoua et al., 2013), generator (Hameeda et al., 2009; Hyers et al., 2006; Tchakoua et al., 2014; Tchakoua et al., 2013; Yang, Sheng, and Court, 2012) and tower (Adams, White, Rumsey, and Farrar, 2011; Chase, Danai, Lackner, and Manwell, 2013; Ciang, Lee, and Bang, 2008; Hameeda et al., 2009; Hyers et al., 2006; Tchakoua et al., 2014; Tchakoua et al., 2013). These works use the data from the supervisory control and data acquisition (SCADA) and other sensors. Vibration analysis, acoustic emission and other methods are applied to monitor the subsystems of wind turbines to identify developing faults. In some cases RULs are predicted using the prognostics approaches such as Mahalanobis distance (Kumar, Chow, and Pecht, 2010) and particle filtering.

Predictive maintenance is enabled by PHM technologies in response to the indicated deteriorated condition/performance or the remaining useful life (RUL) of a component or system. Different from preventive maintenance, predictive maintenance is not performed after a fixed time or usage interval, but when there is an imminent need.

Today's wind turbines emphasize improving the productivity and economics of wind energy. Due to the fact that wind may cause degradation patterns to vary among turbines and with trends toward larger wind farms and the longer distances from the O&M centers, wind farm maintenance decision-makers also want to avoid unnecessary visits to the wind farm by detecting and fixing the problems before failure occurs. For offshore wind farms, even small failures may lead to long downtimes and high O&M costs due to the difficult access and repair at the offshore locations. Therefore the benefits of PHM based predictive maintenance have been recognized, and most modern turbines are equipped with PHM equipment (Byon, Pérez, Ding, and Ntaimo, 2011). Since a failure is a process rather than an event, the earlier the process is detected, the more the flexibility exists for managing the process.

1.2. Review of the Maintenance Modeling Literature

Numerous Discounted Cash Flow (DCF) based maintenance models applicable to wind farms have been developed. These models can be differentiated based on are how maintenance event timing and reliability are modeled.

Most wind farm maintenance models are based on "counting" the number of failures and maintenance events for a wind turbine or farm during a period of time. These approaches usually model reliability with a constant failure rate from which the average failures in an analysis period (e.g., per year) are computed. In these Reliability-Centered Maintenance (RCM) motivated approaches, empirical models are typically used to formulate analytical expressions for the various contributions to the maintenance cost. Relevant works that model the preventive and corrective maintenance strategies for wind turbines and farms include: Joshi, Belgaum, and Jangamshetti (2009); Nordahl (2011); Paida (2012); Rademakers, Braam, Obdam, Frohböse, and Kruse (2008); and Rademakers, Braam, Zaaijer, and Bussel (2003). Predictive maintenance has also been included within these models, aiming to estimate and compare the life-cycle maintenance costs among different maintenance strategies (Andrawus, Watson, Kishk, and Ahaladam, 2006; Gloria, 2013).

An alternative treatment of reliability is to use discrete-event simulation to simulate the failure and maintenance events by sampling from the probability distributions representing the reliability of the system, e.g., CONTOFAX from TU Delft (Koutoulakos, 2008), O2M (Philips, Morgan, and Jacquemin, 2006) and the modeling described by Nielsen and Sørensen (2011).

There has been significant research on simulation-based predictive maintenance optimization for wind turbines and farms. Pazouki, Bahrami, and Choi (2014) propose a PHM-based predictive maintenance optimization model by choosing the failure probability threshold that triggers the predictive maintenance and the periodic inspection interval as the two decision variables. Byon and Ding (2010) develop a season-dependent dynamic model to schedule maintenance activities based on the deterioration status, failure modes, weather, and maintenance lead time, assuming the wind farm operators make maintenance decisions on a weekly basis. Tian, Jin, Wu, and Ding (2011) develop an optimal predictive maintenance policy for a wind farm consisting of multiple wind turbines using PHM information. Besnard and Bertling (2010) present a simulation-based predictive maintenance optimization approach applied to blades, by assuming that an inspection is carried out if blade deterioration is observed by online PHM, and a maintenance decision is made at the inspection.

DCF models (whether RCM motivated or simulation based) do not account for the managerial flexibility that the decision-makers have to adapt to future uncertainties; rather they presume the future conditions and cash flow scenarios are fixed. A real option is the right but not the obligation to undertake certain business initiatives, such as deferring, abandoning, expanding, staging, or contracting a capital investment project (Kodukula & Papudesu, 2006). Real options originate from financial options, and real options analysis (ROA) refers to the valuation of the real options. ROA assumes that a value-maximizing decision will always be made at each decision point.

ROA has been previously applied to the maintenance modeling problems. An ROA model for offshore platform life-cycle cost-benefit (LCCB) analysis is developed by treating maintenance and decommissioning as real options (Heredia-Zavoni & Santa-Cruz, 2004; Santa-Cruz & Heredia-Zavoni, 2011). Jin, Li, and Ni (2009) present an analytical ROA cost model to schedule joint production and preventive maintenance under uncertain demands. In the study by Koide, Kaito, and Abe (2001), the maintenance and management costs of an existing bridge for thirty years is analyzed and minimized using ROA. Goossens, Blokland,

and Curran (2011) develop a model to assess the differences in performance between different aircraft maintenance operations.

For the wind farm maintenance optimization problem, Haddad, Sandborn, and Pecht (2014) were the first to apply the ROA to estimate the values of maintenance options created by the implementation of PHM in wind turbines. When an RUL is predicted for a subsystem or turbine, there are multiple choices for the decision-maker including: performing predictive maintenance at the first maintenance opportunity, waiting until closer to the end of the RUL to perform maintenance, or doing nothing, i.e., letting the turbine run to failure. In order to accommodate these choices, predictive maintenance triggered by a PHM prediction can be treated as a real option. When the value of the predictive maintenance option is determined, a decision-maker has a basis upon which to make a decision to perform the predictive maintenance or not and if the maintenance is to be done, when. Haddad et al. (2014) demonstrate that the fundamental tradeoff in predictive maintenance problems with PHM is finding the point in time to perform predictive maintenance that minimizes the risk of expensive corrective maintenance (which increases as the RUL is used up), while maximizing the revenue earned during the RUL (which increases as the RUL is used up).

1.3. Shortcomings of the State-of-the-Art Models

Predictive maintenance has not been considered in most existing wind farm maintenance models, and for the models that do include a predictive maintenance strategy, the predictive maintenance is assumed to happen on a fixed schedule. The exact time and sequences of failures and maintenance events are not accommodated in simple RCM inspired models. Uncertainties from many sources such as the RUL predictions and maintenance opportunities have not been integrated into the analytical expressions.

Existing simulation-based wind farm maintenance models can capture the uncertainties mentioned above and also the nonlinear effects, such as the combined occurrences of failures and the accessibility of maintenance crew and equipment. However these optimization models are mainly based on the PHM technologies indicating deteriorated condition/performance rather than giving RUL predictions. Therefore they assume the predictive maintenance decisions are made on a periodic basis (e.g., weekly or monthly) after an online or on-site inspection, and that the predictive maintenance will be implemented immediately once a decision is made. The decision variables to be optimized are the threshold (e.g., the failure probability) to trigger the predictive maintenance and the inspection interval applicable for the whole life cycle. Whereas given a specific time point at which the threshold is exceeded (e.g., an RUL is predicted), it is unknown if carrying out the predictive maintenance immediately is a better choice than waiting for a longer time or even letting the system fail and performing corrective maintenance. This type of decision basis for maintenance is particularly problematic when the wind farm is operated under an outcome-based contract defining performance requirements and penalties.

ROA-based models have been developed for the maintenance modeling problem (Heredia-Zavoni et al., 2004; Santa-Cruz & Heredia-Zavoni, 2011; Jin et al., 2009; Koide et al., 2001; Goossens et al., 2011). However none of these works consider PHM technologies and the predictive maintenance, rather they model preventive maintenance as real options.

Haddad et al. (2014) were the first to apply ROA to the wind turbine PHM-based predictive maintenance optimization problem. However their approach does not answer the question "on which day the predictive maintenance should be scheduled after the RUL indication". The wait-to-maintain-option defined by Haddad et al. (2014) is treated as an American option, therefore their model determines the best maximum wait-to-maintenance date, and at each maintenance opportunity before that date, the decision-maker is implicitly expected to compare the predictive maintenance option value at that opportunity and the option value of waiting. If the former is higher than the latter, the predictive maintenance will be implemented at that opportunity; otherwise the decision-maker will wait until the next opportunity. The Haddad et al. (2014) solution is correct for the assumption that an optimal decision will be made on or before some maximum waiting duration and the solution delivered is the optimum maximum wait to date. Unfortunately, in reality maintenance decision-makers for wind turbines (especially offshore turbines) face a somewhat different problem: given that the maintenance opportunity calendar is known (with associated uncertainties) when the RUL indication is obtained, on what date should the predictive maintenance be done to get the maximum option value – this is not the problem solved by Haddad et al. (2014). This constraint makes the problem a series of European-style options, i.e., options that can only be exercised on a specific date rather than American options that can be exercised any time before a specific date.

Haddad et al. (2014) also make the assumption that there are no uncertainties in the remaining lifetime consumption and the forecasting ability of PHM. However, since the environmental conditions, primarily the wind speed, are uncertain, the lifetime consumption (the rate at which the RUL is actually used up) is subject to significant uncertainties. The RUL itself is also uncertain since the forecasting ability of PHM is also subject to uncertainties created by the sensor data collected, the data reduction methods, the damage accumulation models applied and the material parameters assumed in the models. In addition, the cumulative revenue rather than the revenue loss during RUL is simulated by Haddad et al. (2014), while it is the latter that actually reflects value of the part of the RUL thrown away due to predictive maintenance (see Section 2.1).

In this paper, the optimum predictive maintenance opportunity is determined for a wind turbine indicating an RUL. The time-history cumulative revenue loss and the avoided corrective maintenance cost paths are simulated and combined to form the predictive maintenance value paths. By applying a simulation-based European ROA approach, a series of predictive maintenance options are evaluated by considering all possible maintenance opportunities.

The remainder of the paper is structured as following: Section 2 explains the European ROA approach. Section 3 presents a case study applied to a single turbine indicating an RUL. Finally, Section 4 concludes the work and discusses future research opportunities.

2. ANALYSIS METHODOLOGY

2.1. Predictive Maintenance Options

Predictive maintenance options are created when *in situ* PHM is added to systems. In this case the PHM approach generates an RUL estimate that can be used to take predictive action(s) prior to the failure of a system. The real option is defined by Haddad et al. (2014) as,

- Buying the option = paying to add PHM to the system
- Exercising the option = performing predictive maintenance prior to system failure after an RUL indication
- Exercise price = predictive maintenance cost
- Letting the option expire = doing nothing and running the system to failure then perform corrective maintenance

The value from exercising the option is the sum of the cumulative revenue loss and the avoided corrective maintenance cost.

The cumulative revenue loss is the difference between the cumulative revenue that could be earned by waiting until the end of the RUL to do corrective maintenance versus performing the predictive maintenance earlier than the end of the RUL. Restated, this is the portion of the system's RUL thrown away when predictive maintenance is done prior to the end of the RUL. The Appendix provides a more detailed discussion and construction of the revenue loss portion of the predictive maintenance value.

Avoided corrective maintenance cost includes avoided corrective maintenance parts, service and labor cost, avoided cumulative downtime revenue loss, and avoided collateral damage to the system (if any).

When the cumulative revenue loss (R_L) and the avoided corrective maintenance cost (C_A) are summed, the predictive maintenance value (V_{PM}) is obtained as

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

Figure 1 graphically shows the construction of V_{PM}. Assume at some time point (called time 0) a RUL in calendar time is predicted for a subsystem (e.g., for the blade, main shaft or gearbox), called the RUL_C. Assume there are no uncertainties in the prediction of the RUL_C, and once the subsystem fails the turbine will fail, therefore the RUL_C is also the calendar time when the turbine system fails. The absolute value of the R_L is largest at time 0, because all of the RUL in the system is disposed of if maintenance is performed at time 0. As time advances, less remaining useful life is thrown away (and less revenue that could be earned is lost) until RUL_C is reached at which point R_L is zero. C_A is assumed to be constant until the RUL_C at which point it drops to zero.

The predictive maintenance opportunity that follows the remaining useful life prediction can be treated as a real option,

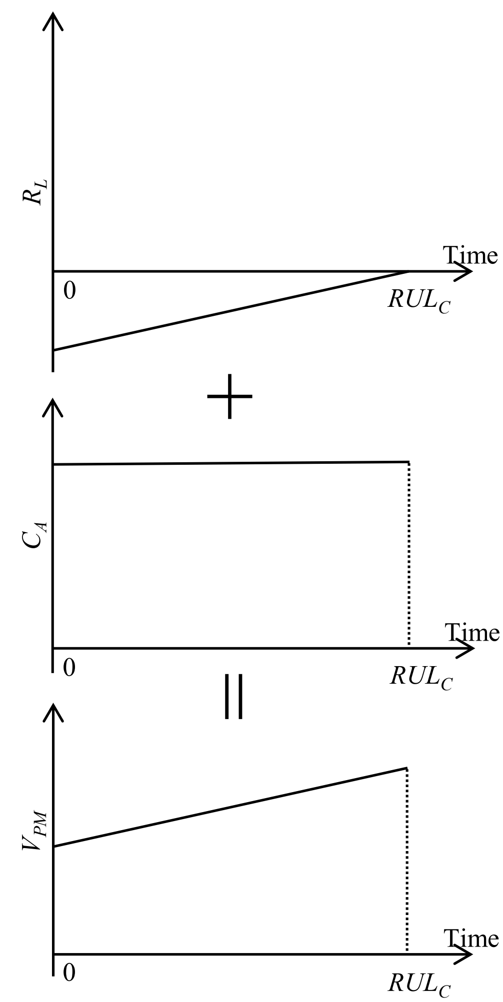

Figure 1. Simple predictive maintenance value formulation (R_L, C_A and V_{PM} have monetary units, e.g., dollars)

and an ROA can be applied to valuate the predictive maintenance option as a "European" style option as

$$O_{PM} = max(V_{PM} - C_{PM}, 0) \quad (2)$$

Where O_{PM} is the predictive maintenance option value, and C_{PM} is the predictive maintenance cost. If the difference between V_{PM} and C_{PM} is larger than 0, the option is said to be "in the money" and the predictive maintenance will be implemented (the option value is the difference); otherwise the predictive maintenance will not be implemented and the option will be expired leading to 0 option value.

2.2. Modeling

Initially we assume a wind turbine is managed in isolation under an "as-delivered" energy purchase contract between the wind energy seller and buyer, which simply pays a set price for all the energy delivered. After time 0 there are multiple predictive maintenance opportunities, and the decision-maker must decide whether and when the predictive maintenance should be scheduled. If the predictive maintenance is not implemented, the turbine will fail at the RUL_C, and after a downtime DT (including the wait-to-maintenance time and the maintenance time, assumed to be constant) a corrective maintenance event will be completed to fix and restore it to operation.

2.2.1. Cumulative Revenue Loss

We assume that the turbine energy generation capacity will not degrade as damage accumulates in the subsystems, and the downtime for predictive maintenance is negligible. If the predictive maintenance is going to be implemented before the end of the RUL_C, the revenue earned in a unit time period τ-1 to τ, $R_{PM}(\tau)$ is

$$R_{PM}(\tau) = E_{PM}(\tau) P_C \quad (3)$$

where $0 < \tau \leq RUL_C + DT$, P_C is the energy price, which is assumed to be constant, and $E_{PM}(\tau)$ is the energy generated from τ-1 to τ.

So the cumulative revenue earned from time τ_1 to τ_2, $CR_{PM}(\tau_1, \tau_2)$, can be calculated as

$$CR_{PM}(\tau_1, \tau_2) = \sum_{\tau=\tau_1+1}^{\tau_2} R_{PM}(\tau) \quad (4)$$

where $0 < \tau_1 < \tau_2 \leq RUL_C + DT$.

Similarly, if the predictive maintenance is not going to be implemented, when the turbine fails after the RUL_C, it will be down for a time period DT until the corrective maintenance is finished. The energy generated from τ-1 to τ, $E_{CM}(\tau)$ can be calculated as

$$E_{CM}(\tau) = \begin{cases} E_{PM}(\tau), & 0 < \tau \leq RUL_C \\ 0, & RUL_C < \tau \leq RUL_C + DT \end{cases} \quad (5)$$

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

$$R_{CM}(\tau) = E_{CM}(\tau) P_C \quad (6)$$

The cumulative revenue earn from time τ_1 to τ_2, $CR_{CM}(\tau_1, \tau_2)$, can be calculated as

$$CR_{CM}(\tau_1, \tau_2) = \sum_{\tau=\tau_1+1}^{\tau_2} R_{CM}(\tau) \quad (7)$$

Assume that the predictive maintenance opportunity is at time t, where $0 < t < RUL_C$. The cumulative revenue loss by implementing predictive maintenance at time t, $R_L(t)$, can be calculated as

$$R_L(t) = CR_{PM}(0, t) - CR_{CM}(0, RUL_C) \quad (8)$$

2.2.2. Avoided Corrective Maintenance Cost and Predictive Maintenance Value

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

$$C_A(t) = C_{CM} + L_{DT} \quad (9)$$

where C_{CM} is the corrective maintenance parts, service and labor cost, which is assumed to be constant. The second item is the cumulative revenue loss during downtime DT for corrective maintenance, which can be calculated as

$$L_{DT} = CR_{PM}(RUL_C, RUL_C + DT) \quad (10)$$

The predictive maintenance value $V_{PM}(t)$ at time t, representing the extra value obtained by carrying out the predictive maintenance at time t rather than waiting for the corrective maintenance, is

$$\begin{aligned} V_{PM}(t) &= R_L(t) + C_A(t) \\ &= -CR_{CM}(t, RUL_C) + C_{CM} \\ &\quad + CR_{PM}(RUL_C, RUL_C + DT) \end{aligned} \quad (11)$$

2.2.3. Uncertainties and Paths Simulation

All of the modeling discussed so far assumes that there are no uncertainties in the predicted RUL_C. If there were no uncertainties, the optimum point in time to perform maintenance would be at the peak value point (at the RUL_C). Unfortunately everything is uncertain, which makes the problem more challenging. To model the uncertainties, a simulation method is used to generate "paths", where each path represents one possible future scenario that could happen. The future wind speed paths are simulated first and then used to generate the R_L, C_A and V_{PM} paths.

Future Wind Speed Paths Simulation

We assume that wind is the major environmental load causing damage to the key subsystems in the turbines (e.g., blade, main shaft and gearbox). A probability density function (PDF) is used to describe the historical wind speed data. Assume the historical wind speed S is recorded at height B, the probability function f(·) assuming a Weibull distribution is

$$\mathrm{f}(S) = \frac{\beta}{\eta}\left(\frac{S}{\eta}\right)^{\beta-1} \exp\left(-\left(\frac{S}{\eta}\right)^{\beta}\right) \tag{12}$$

where β is the shape parameter, $1 \leq \beta < 10$, and η is the scale parameter, which can be estimated as (Manwell, McGowan, and Rogers, 2009)

$$\beta = \left(\frac{\sigma}{\mu}\right)^{-1.086} \tag{13}$$

$$\eta = \frac{\mu}{\Gamma(1 + 1/\beta)} \tag{14}$$

where μ is the mean and σ is the standard deviation of recorded wind speed data, and $\Gamma(\cdot)$ is a Gamma function.

After Weibull distribution parameters are estimated, Monte Carlo simulation can be used to simulate a time series of the wind speed $S_B(\tau)$ at height B. The Power Law (Manwell et al., 2009) is then used to convert to wind speed $S_H(\tau)$ at the wind turbine hub height H

$$\frac{S_H(\tau)}{S_B(\tau)} = \left(\frac{H}{B}\right)^{\alpha} \tag{15}$$

where α is the Power Law exponent.

Using Monte Carlo simulation and the Power Law, M buoy height wind speed profiles (called wind speed paths) can be simulated, with each path representing a possible future wind profile after time 0.

Time to Failure Simulation

Assume a RUL is predicted in cycles caused by fatigue (RUL_F) at time 0,[1] a probability distribution can be assumed to represent the uncertainties due to PHM sensor data, data reduction methods, failure models, damage accumulation models and material parameters. For example a normal distribution has been used to represent the RUL estimations (Rodrigues & Yoneyama, 2013; Sankararaman & Goebel, 2013; Tian, Zhang, and Cheng, 2011). However, it should be noted that the model developed in this paper is generally applicable to any type of RUL distribution. RUL_F is assumed to be the mean of the distribution. For each of the M simulated wind speed paths, the distribution (assumed to be normal for illustration purposes) in Figure 2 is sampled to obtain an actual RUL sample ($ARUL_F$, measured in cycles) from the

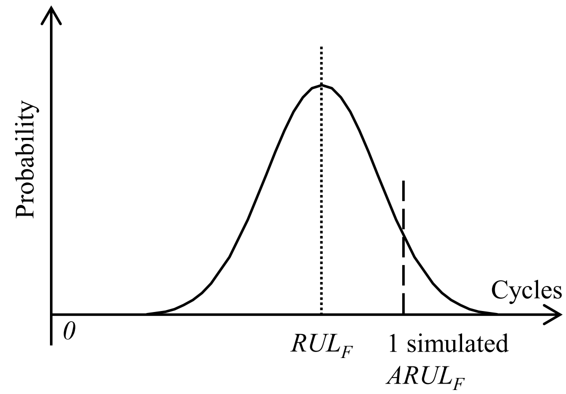

Figure 2. An $ARUL_F$ obtained from the RUL distribution

distribution. Each combination of the $ARUL_F$ and the corresponding wind speed path represents a possible initial RUL and its future wind speeds.

The next step is to simulate the $ARUL_C$ (the actual RUL sample in calendar time) using the simulated wind speed paths. It is assumed that the RUL is consumed by rotor rotational cycles caused by the wind. When the wind speed is higher than the cut-in speed and lower than the rated speed, rotor rotational speed increases linearly with the wind speed until the rotor's nominal rotational speed. In this case the rotor rotational speed is constant at the nominal rotational speed; if the wind speed is higher than the cut-out speed, rotor stops rotating. Figure 3 shows this relationship, in which ω is the rotor's nominal rotational speed, S_{CI}, S_{RW} and S_{CO} are the cut-in, rational and cut-out wind speed for the wind turbine respectively.

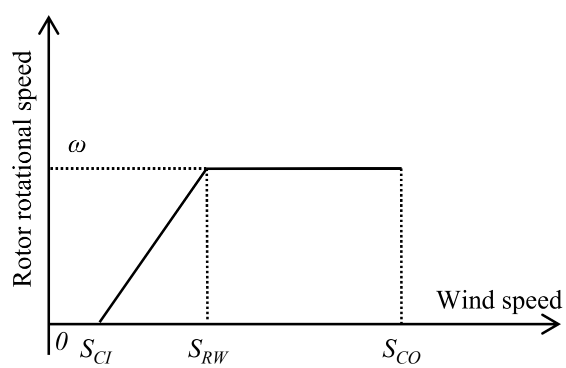

Figure 3. The relationship between the wind speed and the wind turbine rotor rotational speed

[1] The RUL can be represented as a time or any applicable lifetime usage measure depending on the particular failure mechanism(s) that are relevant and their primary life driver(s).

The RUL consumption (measured in cycles) caused to the turbine from τ-1 to τ, $D(\tau)$ can be calculated as,

$$D(\tau) = \begin{cases} \dfrac{l \cdot \omega \cdot S_H(\tau)}{S_{RW}}, & S_{CI} \leq S_H(\tau) \leq S_{RW} \\ l \cdot \omega, & S_{RW} < S_H(\tau) \leq S_{CO} \\ 0, & others \end{cases} \quad (16)$$

where l is the unit time period for simulation (e.g., l = 1 hour).

For each $ARUL_F$ and the corresponding wind speed path, by solving the following equation, an $ARUL_C$ is obtained as below, which represents the actual calendar time to failure

$$ARUL_F = \sum_{\tau=1}^{ARUL_C} D(\tau) \quad (17)$$

***R_L*, *C_A* and *V_{PM}* Paths Simulation**

We can now generate the R_L and C_A paths, based on which the V_{PM} paths can be calculated from Eq. (11). To calculate $R_L(t)$ we need to determine the energy generated if predictive maintenance is implemented, $E_{PM}(\tau)$. This can be calculated as

$$E_{PM}(\tau) = \begin{cases} 0, & S_H(\tau) < S_{CI} \; or \; S_H(\tau) > S_{CO} \\ g(S_H(\tau)), & S_{CI} \leq S_H(t) \leq S_{RW} \\ E_R, & S_{RW} < S_H(t) \leq S_{CO} \end{cases} \quad (18)$$

where g(·) is the power curve function, $g(S_H(\tau))$ is the energy generated from τ-1 to τ. E_R is the energy generated from τ-1 to τ with the rated power.

Based on the M future wind speed paths, M R_L, C_A and V_{PM} paths can be simulated by using Eqs. (8), (9), and (11), where each of which starts at time 0 and ends at its corresponding $ARUL_C$.

2.2.4. European ROA Approach

We assume that the decision-maker is willing to schedule a predictive maintenance only if the predictive maintenance is more beneficial than the corrective maintenance, otherwise it is better to have the turbine run to failure. Therefore the predictive maintenance opportunities that follow an RUL prediction can be treated as real options, and on each maintenance opportunity, a European ROA can be applied to valuate the predictive maintenance option as a "European" style option,

$$O_{PM}(t) = \begin{cases} max(V_{PM}(t) - C_{PM}, 0), & 0 < t < ARUL_C \\ 0, & t \geq ARUL_C \end{cases} \quad (19)$$

where $O_{PM}(t)$ is the predictive maintenance option value at time t. Equation (19) does not discount the option value from t to 0, implicitly assuming that the time period t and the discount rate are small.

An ROA is used to valuate the option values of all possible maintenance opportunities after time 0 as a series of European options as shown in Figure 4. In Figure 4 an example V_{PM} path and three predictive maintenance opportunities t_1, t_2 and t_3 are shown. On the predictive maintenance opportunity before the $ARUL_C$ (t_1 or t_2), if the predictive maintenance value is higher than the predictive maintenance cost, maintenance will be implemented (this is the case for t_2); otherwise, the turbine will be run to failure, and the option value is 0 (this is the case for t_1). After the $ARUL_C$, the option expires and the option value is 0 (the case for t_3).

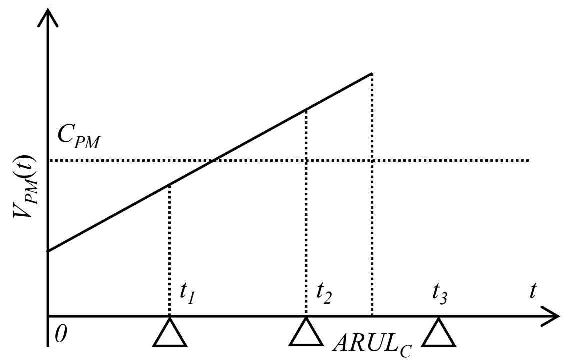

Figure 4. An example of the ROA valuation

At each predictive maintenance opportunity, the M option values (corresponding to the M value paths) are averaged to get the expected predictive maintenance option value ($EO_{PM}(t)$). By considering all the maintenance opportunities, the optimum predictive maintenance opportunity can be selected that generates the maximum expected option present value.

3. CASE STUDY

In this section, the European ROA approach is applied to a single offshore wind turbine.

Buoy height (5 m above sea level) 10-year (2003 to 2012) 10-minute average wind speed data are obtained from station 44009 of the National Data Buoy Center, which is the closest buoy to the Maryland Wind Energy Area (National Data Buoy Center, 2013). An offshore wind farm in this area with Vestas V-112 3.0 MW offshore wind turbines is assumed for the study (Vestas, 2013). The rated output power is 3 MW, cut-in, rational and cut-out speeds are 3 m/s, 12 m/s and 25 m/s respectively, nominal rotational speed is 14 RPM, and hub height is assumed to be 100 m above sea level. The parameter α is determined empirically as 0.11 for the area (Manwell et al., 2009). The Weibull distribution parameters for buoy height wind speed are η = 7.1470 m/s and β = 1.9733.

3.1. Simulation of *R_L*, *C_A* and *V_{PM}* Paths

We assume there is a single wind turbine operated under an "as-delivered" contract with P_C of \$20/MWh. A PHM

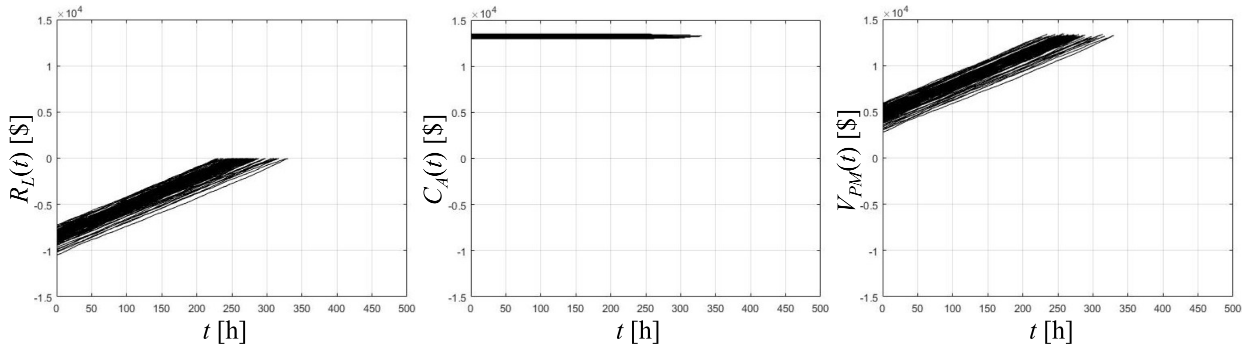

Figure 5. Left – cumulative revenue loss, middle – avoided corrective maintenance cost, and right – predictive maintenance value paths for a single turbine (100 paths are shown)

indication is triggered and a RUL_F of 100,000 cycles is predicted for a key subsystem (e.g., the main shaft). A normal distribution is assumed to represent the RUL uncertainties with the mean of 100,000 cycles and the standard deviation of 25,000 cycles. Predictive and corrective maintenance costs are assumed to be \$9,000 and \$10,000, respectively. Corrective maintenance downtime is assumed to be 100 hours. Using Monte Carlo simulation, 10,000 $ARUL_F$ samples are obtained.

By applying Eqs. (3) through (11), 10,000 R_L, C_A and V_{PM} paths are simulated as Figure 5.

As shown in the left plot in Figure 5, all the R_L paths start at different points on the vertical axis: the longer the $ARUL_C$ of a path is, the more cumulative revenue will be missed if one chooses to do predictive maintenance at the earliest opportunity, and therefore the lower the path's initial value. All paths are ascending over time, since the later the predictive maintenance is done, the smaller the cumulative revenue will be lost. Finally all the paths terminate at different time points when the RUL is used up, which represents the uncertainties in the predicted RUL and the wind speed. As can be seen in the middle plot in Figure 5, each C_A path is constant over time, while due to the variance in the cumulative revenue loss during downtime (see Eq. (10)), all paths have different but similar values. The combinations of the R_L and C_A paths according to Eq. (11), result in V_{PM} paths that are ascending (see the right plot in Figure 5).

3.2. Results from European ROA Approach

With the simulated 10,000 V_{PM} paths, using Eq. (19), predictive maintenance option values are obtained. At each predictive maintenance opportunity, all option values are averaged to get the expected predictive maintenance option values as shown in Figure 6, together with the histogram of $ARUL_C$. The optimum predictive maintenance opportunity (indicated by the dash line) is 237 hours for the example case, with an expected predictive maintenance option value of \$2,976.4. As can be seen from the $ARUL_C$ histogram, the ROA approach is not aiming to totally avoid corrective maintenance, but rather to maximize the expected predictive maintenance option value. According to Figure 7, at the optimum predictive maintenance opportunity, 93.9% of the paths choose to implement the predictive maintenance. The results suggest that waiting for some time to implement the predictive maintenance, rather than implementing the predictive maintenance immediately after the PHM indication or waiting until closer to the end of the RUL, which represents the tradeoff to minimize the risk of corrective maintenance while minimize the value of the part of the RUL thrown away.[2]

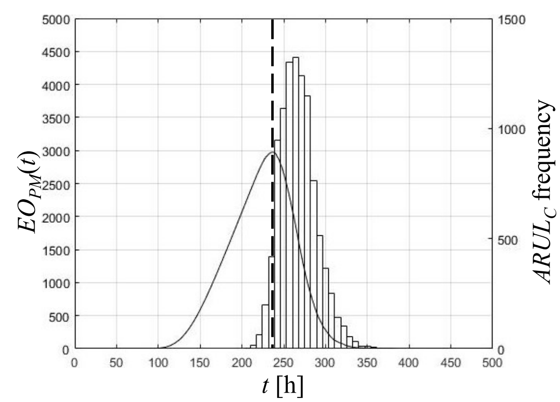

Figure 6. Expected predictive maintenance option value curve (predictive maintenance opportunity is once per hour) together with the histogram of $ARUL_C$

[2] A stochastic DCF approach was applied to a similar example (Lei, Sandborn, Goudarzi, and Bruck, 2015) that assumes that the predictive maintenance will always be implemented at some selected opportunity rather than treated as an option. Alternatively, the European ROA approach is an asymmetric approach that captures the upside value (when predictive maintenance is more beneficial) while limiting the downside risk (when corrective maintenance is more beneficial). The European ROA approach will suggest a more conservative opportunity for predictive maintenance with a higher expected option value than the expected net present value (NPV) from the stochastic DCF approach.

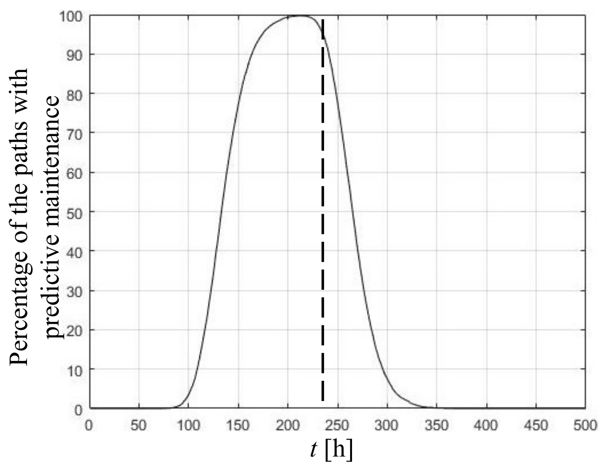

Figure 7. Percentage of the paths implementing predictive maintenance (predictive maintenance opportunity is once per hour)

If the predictive maintenance is available every 48 hours (instead of every hour), the expected predictive maintenance option value curve is shown in Figure 8. The optimum predictive maintenance opportunity (indicated by the dash line) is 240 hours after time 0, with the expected predictive maintenance option value of $2,959.8. Comparing with the case in Figure 6 where the predictive maintenance opportunity is once per hour, the optimum predictive maintenance opportunity is 3 hours later (+1.3%), while the expected predictive maintenance option value is $16.6 fewer (-%0.6), both are caused by the constraint on the predictive maintenance opportunities. Figure 9 is the box plot showing the variance of the predictive maintenance option values on the maintenance opportunities with non-zero expected predictive maintenance option values.

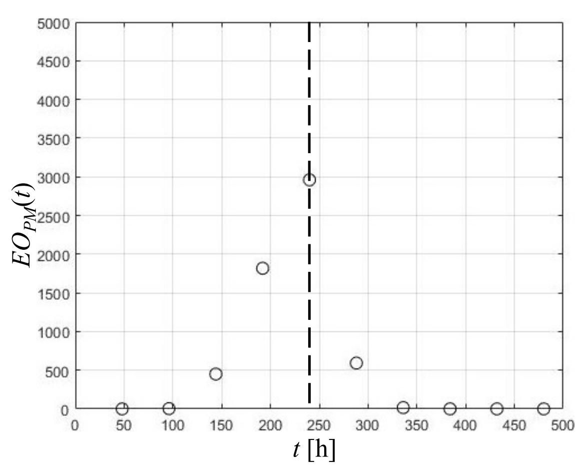

Figure 8. Expected predictive maintenance option value curve (predictive maintenance opportunity is once every 48 hours)

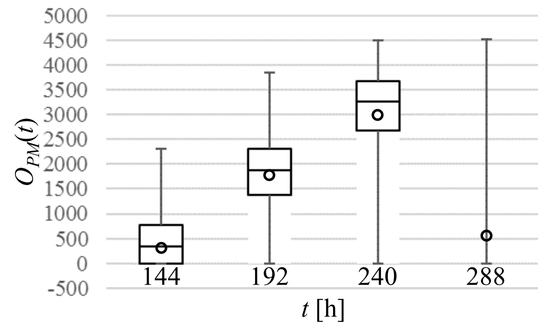

Figure 9. Box plot for the predictive maintenance option values on the predictive maintenance opportunities with non-zero expected predictive maintenance option values (3rd, 4th, 5th and 6th opportunities in Figure 8)

If the predictive maintenance opportunities are limited to once every 72 hours and 96 hours, the optimum predictive maintenance opportunities suggested by the European approach are plotted in Figure 10 (indicated by the arrows). The optimum opportunities shift as expected due to the changes in the predictive maintenance schedule.

4. CONCLUSION

The objective of the work presented in this paper is to determine the optimum predictive maintenance opportunity for a single wind turbine indicating an RUL. Uncertainties in the wind speed and the RUL prediction are considered, and a European ROA approach is applied. This work demonstrates the predictive maintenance option's flexibility to expire if the predictive maintenance value is not enough to cover the predictive maintenance cost. Unlike previous real options analyse (Haddad et al., 2014), which found the longest possible time to wait to perform maintenance and did not

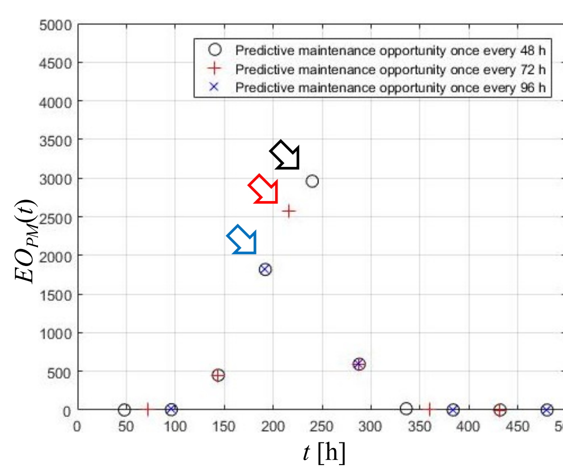

Figure 10. Expected predictive maintenance option value curve when the predictive maintenance opportunity is once every 48 hours, 72 hours, or 96 hours

include RUL uncertainties, the model presented in this paper finds the best maintenance opportunity and includes RUL uncertainties due to uncertain wind speed and PHM prediction inaccuracies.

In the future, the current model for a single turbine will be extended to a wind farm managed via a power purchase agreement (PPA) with multiple turbines indicating RULs concurrently. The predictive maintenance value for each turbine with an RUL is expected to depend on the operational state of the other turbines, the amount of energy delivered and to be delivered by the whole wind farm.

The current model, which only considers a single maintenance event, could be extended through the wind farm's life, by assuming that the optimum predictive maintenance opportunity will be determined after each RUL prediction. On each optimum date, if the wind turbines with RULs have not failed yet, and the predictive maintenance value is higher than the predictive maintenance cost, the predictive maintenance will be implemented; otherwise all turbines will be run to failure for corrective maintenance. Multiple predictive maintenance, corrective maintenance and preventive maintenance events can be simulated by using an ROA based discrete-event simulator to develop a life-cycle maintenance model to estimate the wind farm life-cycle O&M costs and net revenue. The O&M costs from multiple maintenance strategies (e.g., the preventive maintenance strategy, the corrective maintenance strategy and the predictive maintenance strategy implementing the predictive maintenance at the earliest opportunity) will be compared to quantitatively determine the O&M cost savings of the suggested ROA-based predictive maintenance scheduling method.

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APPENDIX – CUMULATIVE REVENUE LOSS CONSTRUCTION

This section provides a detailed discussion and construction of the cumulative revenue loss portion of the predictive maintenance value based on the following simplified scenario with no uncertainties.

Assume a wind turbine is expected to operate for a total time period of T (e.g., 20 years). Only one subsystem may fail, and PHM has been introduced to predict that subsystem's RUL. After an RUL indication is given by PHM, there is only one predictive maintenance opportunity before the turbine system fails (predictive maintenance downtime is ignored). If predictive maintenance does not occur, there will be a corrective maintenance event when the turbine system fails (corrective maintenance downtime is ignored in this simplified construction). We assume the wind speed during T is always constant, and therefore the rate at which the RUL is consumed is constant. Let d_{RUL} be the time from the maintenance event to the next RUL indication, d_{PM} be the time from the RUL indication to the predictive maintenance opportunity, and d_{CM} be the time from the RUL indication to the turbine system failure, d_{RUL}, d_{PM} and d_{CM} are all constant, and $d_{PM} < d_{CM}$.

If the predictive maintenance strategy is always implemented during T, the total number of maintenance events, N_{PM} (assume for simplicity that T is a multiple of $d_{RUL} + d_{PM}$, so there is no remainder) is,

$$N_{PM} = \frac{T}{d_{RUL} + d_{PM}} \tag{20}$$

If the corrective maintenance strategy is always implemented during T, the total number of maintenance events, N_{CM} (assume for simplicity that T is a multiple of $d_{RUL} + d_{CM}$) is,

$$N_{CM} = \frac{T}{d_{RUL} + d_{CM}} \tag{21}$$

So we can get the relationship between N_{PM} and N_{CM} ($N_{PM} > N_{CM}$),

$$N_{CM} = \frac{N_{PM}(d_{RUL} + d_{PM})}{d_{RUL} + d_{CM}} \tag{22}$$

An example of the relationships among d_{RUL}, d_{PM} and d_{CM} is shown in Figure 11 (assume that both the last predictive and the last corrective maintenance event will still be implemented) where each arrow signifies an RUL indication, each triangular represents a predictive maintenance event and each diamond represents a corrective maintenance event.

Assume the revenue per unit time is r (the revenue rate), according to the definition of cumulative revenue loss, for the predictive maintenance strategy we can get the R_L for each predictive maintenance event as

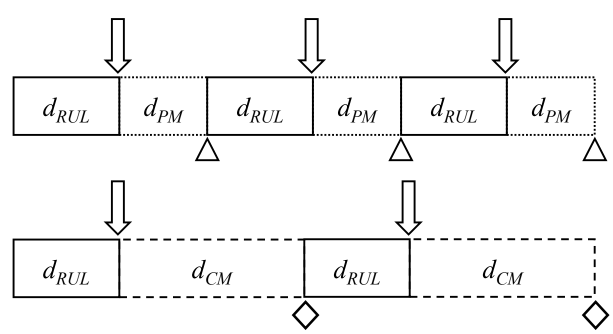

Figure 11. Same time period (T): top: with a predictive maintenance strategy, and bottom: with a corrective maintenance strategy (assume $N_{PM} = 3$ and $N_{CM} = 2$)

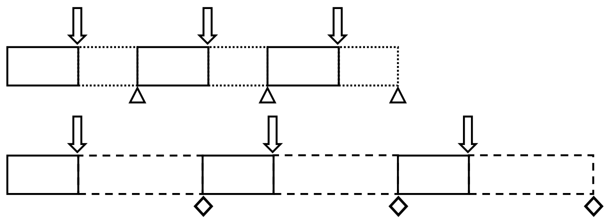

Figure 12. Same number of spare parts ($N_{PM} = N_{CM} = 3$): top: period T with the predictive maintenance strategy, and bottom: $T + ET$ with the corrective maintenance strategy

$$R_L = r(d_{PM} - d_{CM}) \tag{23}$$

So the total R_L during T is

$$N_{PM}R_L = rN_{PM}(d_{PM} - d_{CM}) \tag{24}$$

Now we can address the question of where the R_L happens and how. In the corrective maintenance strategy, if there will be $N_{PM} – N_{CM}$ more corrective maintenance events after T, the turbine system can last longer for a time period of ET calculated as

$$ET = (N_{PM} - N_{CM})(d_{RUL} + d_{CM}) \tag{25}$$

The total revenue earned during ET is,

$$rET = r(N_{PM} - N_{CM})(d_{RUL} + d_{CM}) \tag{26}$$

So by substituting Eq. (22) into (26)

$$rET = -rN_{PM}(d_{PM} - d_{CM}) = -N_{PM}R_L \tag{27}$$

Given a fixed number of spare parts, the magnitude of the total R_L during T ($-N_{PM}R_L$) represents the extra revenue could be earned (rET) during extra operating time (ET) by replacing the predictive maintenance strategy with the corrective maintenance strategy. Figure 12 shows that based on the case in Figure 11, there will be one more corrective maintenance event during ET.

In this simple example with no uncertainties, within T both the predictive and corrective maintenance strategy will generate the same cumulative revenue, while the former will require more spare parts. If the wind turbine is supported under either a predictive or corrective maintenance assumption with an identical number of spare parts, the corrective maintenance strategy allows it to operate for an extra period of time (because corrective maintenance does not throw away any part life). The cumulative revenue loss associated with the predictive maintenance strategy corresponds to the revenue that would be earned in this extra period of time.

NOMENCLATURE

$ARUL_C$	RUL sample in calendar time
$ARUL_F$	RUL sample in cycles
B	height of the recorded wind speed data
C_{CM}	corrective maintenance cost
C_{PM}	predictive maintenance cost
C_A	avoided corrective maintenance cost
$C_A(t)$	avoided corrective maintenance cost with predictive maintenance at time t
$CR_{CM}(\tau_1, \tau_2)$	cumulative revenue earned from time τ_1 to τ_2 with the turbine running to failure
$CR_{PM}(\tau_1, \tau_2)$	cumulative revenue earned from τ_1 to τ_2 with predictive maintenance
$D(\tau)$	RUL consumption in cycles from τ-1 to τ
d_{CM}	time from the RUL indication to the turbine system failure
d_{PM}	time from the RUL indication to the predictive maintenance event
d_{RUL}	time from the maintenance event to the next RUL indication
DT	downtime for corrective maintenance
$E_{CM}(\tau)$	energy generated from τ-1 to τ with the turbine running to failure
$E_{PM}(\tau)$	energy generated from τ-1 to τ with predictive maintenance
E_R	energy generated by wind turbine from time τ-1 to τ with rated power
$EO_{PM}(t)$	expected predictive maintenance option value at time t
ET	extra time period the wind turbine system can operate by $N_{PM} – N_{CM}$ spares after T
$f(\cdot)$	probability distribution function of historical wind speed data
$g(\cdot)$	power curve function
H	wind turbine hub height
l	time step
L_{DT}	revenue loss during downtime for corrective maintenance
M	number of wind speed paths
N_{PM}	total number of predictive maintenance events during T
N_{CM}	total number of corrective maintenance events during T
$O_{PM}(t)$	predictive maintenance option value at time t
P_C	energy price
r	revenue during a unit time (revenue rate)
$R_{CM}(\tau)$	revenue earned from τ-1 to τ with the turbine running to failure
$R_{PM}(\tau)$	revenue earned from τ-1 to τ with predictive maintenance
R_L	cumulative revenue loss
$R_L(t)$	cumulative revenue loss with predictive maintenance at time t
RUL_C	predicted remaining useful life in calendar time
RUL_F	predicted remaining useful life in cycles
S	Historical wind speed
$S_B(\tau)$	simulated wind speed on height B from τ-1 to τ
S_{CI}	cut-in speed of the wind turbine

S_{CO}	cut-out speed of the wind turbine
$S_H(\tau)$	simulated wind speed on height H from τ-1 to τ
S_{RW}	rational wind speed of the wind turbine
t	time of the predictive maintenance opportunity
T	total operating time
V_{PM}	predictive maintenance value
$V_{PM}(t)$	predictive maintenance value with predictive maintenance at time t
α	Power Law exponent
β	Weibull distribution shape parameter
$\Gamma(\cdot)$	Gamma function
η	Weibull distribution scale parameter
μ	mean of the recorded wind speed data
σ	standard deviation of the recorded wind speed data
τ	time after time 0 with l per step
ω	nominal rotational speed of the wind turbine rotor

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