PHM Based Predictive Maintenance Option Model for Offshore Wind Farm O&M Optimization

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ABSTRACT

A simulation-based real options analysis (ROA) approach is used to determine the optimum predictive maintenance opportunity for multiple wind turbines with remaining useful life (RUL) predictions in offshore wind farms managed under outcome-based contracts, i.e., power purchase agreements (PPAs). 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 predictions and wind speeds (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 selected. The optimum predictive maintenance opportunity can also be determined using a stochastic discounted cash flow (DCF) approach that assumes the predictive maintenance will always be implemented on the selected opportunity. For a wind farm managed via a PPA with multiple turbines indicating RULs concurrently, the predictive maintenance value for each turbine depends on the operational state of the other turbines, the amount of energy delivered and to be delivered by the whole wind farm. A case study is presented in which the stochastic DCF and European ROA approaches are applied to a single turbine and to a wind farm managed via a PPA. The optimum predictive maintenance opportunities obtained from the two approaches are compared and it is demonstrated that 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.

1. INTRODUCTION

The global cumulative wind power capacity at the end of 2013 was 318,105 megawatts (MW), representing an average annual growth of approximately 25% over the last 10 years (Fried, Sawyer, Shukla, and Qiao, 2014a). For offshore wind, at the end of 2013 the global cumulative capacity was roughly 6.8 gigawatts (GW), of which 6.6 GW was in the Europe Union (EU), providing 0.7% of the EU's total energy consumption (Fried, Shukla, Sawyer, and Teske, 2014b).

Operation and maintenance (O&M) cost, as a major contributor to the wind levelized cost of energy (LCOE), accounts for 0.027 to 0.048 US dollars/kilowatt-hour (USD/kWh), (IRENA Secretariat, 2012). Maintenance for wind turbines has been categorized as scheduled preventive maintenance, corrective maintenance and predictive maintenance (Karyotakis, 2011; Kovacs, Erdos, Viharos, and Monostori, 2011; Nilsson & Bertling, 2007). The cost of corrective maintenance (after failure happens) is expensive for offshore wind farms, since it requires expensive resources such as vessels, and maintenance windows are limited due to the harsh marine environment (Kovacs et al., 2011).

Prognostics and Health Management (PHM) technologies have been introduced into wind turbines to assess the reliability and forecast remaining useful life (RUL) of key subsystems (Haddad, Sandborn, and Pecht, 2014). PHM based predictive maintenance is expected to reduce the wind farm O&M cost (Tchakoua, Wamkeue, Ouhrouche, Slaoui-Hasnaoui, Tameghe, and Ekemb, 2014). Once a PHM indication and a RUL prediction is triggered for a subsystem in a turbine, the maintenance decision-maker needs to decide if and when to perform the predictive maintenance. To address this challenge, Haddad et al. (2014) treated the predictive maintenance opportunities as American style real options. An American real option can be exercised on or prior to a predetermined expiration time (Kodukula & Papudesu, 2006). Haddad et al. (2014) determined the latest predictive maintenance opportunity (the optimum American real option expiration time) by minimizing the risk of expensive corrective maintenance after failures, while reducing the RUL thrown away by predictive maintenance.

Lei, Sandborn, Bakhshi, and Kashani-Pour (2015) developed a European style Real Options Analysis (ROA) approach based on Haddad et al. (2014). Different from the American real option, a European real option can only be exercised on the predetermined expiration time (Kodukula and Papudesu, 2006). Lei et al. (2015) determined the optimum predictive maintenance opportunity (the optimum European real option expiration time), and extended the European ROA approach to multiple turbines with remaining useful life (RUL) predictions in offshore wind farms managed under outcome-based power purchase agreements (PPAs). Lei et al. (2015) considered the operational status of the other turbines, the lower price for over-delivered energy, and the penalties for under-delivered energy defined by PPAs.

During the predictive maintenance value formulation, both Haddad et al. (2014) and Lei et al. (2015) only considered the cumulative revenue earned between the RUL indication and the predictive maintenance opportunities. However, if the predictive maintenance is not implemented and the turbine is run to failure (where corrective maintenance occurs), more revenue can be earned. Therefore, to reflect the true value of predictive maintenance, the difference between the cumulative revenue earned up to either predictive or corrective maintenance should be considered, and the revenue lost due to predictive maintenance should be included in the analysis.

According to Lei et al. (2015), the European ROA approach assumes that the predictive maintenance is an option but not an obligation, and will only be implemented if the predictive maintenance value is higher than the predictive maintenance cost. Alternatively, the optimum predictive maintenance opportunity can also be determined by a stochastic discounted cash flow (DCF) approach that assumes the predictive maintenance will always be implemented at the selected opportunity no matter how much the predictive maintenance value is.

In this paper, for multiple turbines indicating RULs in an offshore wind farm managed via a PPA, the optimum predictive maintenance opportunity is determined. The time-history cost avoidance and cumulative revenue lost paths are simulated and combined to form the predictive maintenance value paths. By applying the simulation-based European ROA approach (Lei et al., 2015), a series of predictive maintenance options are evaluated by considering all possible maintenance opportunities. Assuming that all turbines with RULs are maintained concurrently, the optimum predictive maintenance opportunity can be determined as the one with the maximum option value. The stochastic DCF approach is also applied to the simulated predictive maintenance value paths, and the results from the two approaches are compared.

The remainder of the paper is structured as following: Section 2 explains the European ROA and stochastic DCF approaches. Section 3 presents a case study for the two approaches applied to both a single turbine and multiple turbines indicating RULs. Finally, Section 4 concludes the work and discusses future research opportunities.

2. ANALYSIS METHODOLOGY

We assume an offshore wind farm is operated under a PPA. At time t_0, K turbines are indicating RULs (while J turbines operate normally without RUL indications). Each RUL is predicted for some subsystem (e.g., for the gearbox or main shaft in cycles), and that subsystem will fail before the end of the year (called EOY) if the predictive maintenance is not implemented. Once the subsystem fails, the turbine will fail. From t_0 to EOY there are multiple discrete predictive maintenance opportunities, and the decision-maker wants to decide which predictive maintenance opportunity should be scheduled for all K turbines. If the predictive maintenance is not implemented, there will be a corrective maintenance event at EOY to fix all failed turbines and restore them to operation.

Using the wind speed historical data from the National Data Buoy Center (NDBC) Station 44009 (National Data Buoy Center, 2013), M buoy height wind paths can be simulated according to Lei et al. (2015), each of which represents a possible future wind profile for the whole wind farm.

For each turbine with a RUL indication, a unique triangular distribution is assumed to represent uncertainties in the subsystem RUL prediction as used in Sandborn and Wilkinson (2007). For each simulated wind path, Monte Carlo simulation can be used to obtain an actual RUL sample (called $ARUL_k$, e.g., in cycles) for turbine k, then time to failure for turbine k (TTF_k) can be obtained as the actual time to failure in calendar time according to Lei et al. (2015).[1] M TTF_k samples can be simulated for turbine k, and then this procedure is repeated for all K turbines.

2.1. Power Purchase Agreement (PPA) Modeling

A PPA is an outcome-based contract between a seller who generates electricity and the buyer who wants to purchase electricity. Wind farms are typically under PPAs for several reasons. First, although wind power can be sold directly into the local market, the average local market energy prices that vary daily and hourly tend to be lower than the contract prices defined in PPAs, (Stoel Rives Wind Team, 2014). Second, PPAs guarantee to the buyer and the seller that the energy generated and delivered will be paid for at the agreed price schedule. Third, as shown by Barradale (2008), utilities don’t

[1] For detailed calculation method TTF_k see Lei et al. (2015)

want to build and operate their own wind farms; they prefer to simply purchase power.

PPA terms are typically 20 years (Stoel Rives Wind Team, 2014). Barradale (2008) made the observation that PPAs often set annual energy delivery targets. The contract price can be either constant or escalated annually throughout the whole term. For each year, the buyer will generally agree to pay for all power generated and delivered to a specified transmission point. However, a maximum and a minimum annual energy delivery limit can also be set. Once the seller has delivered beyond the specified maximum limit, the buyer may choose to buy at a lower excess price or not to buy the excess energy at all, (Bonneville, 2007; Gloucester, 2011; Sonoma, 2014). The buyer may also have the right to adjust the annual target of the next year downward for the amount of energy over-delivered (Anaheim, 2003; Delmarva, 2008; World Bank, 2002; Xcel, 2013). If the seller is unable to reach the minimum limit, then the seller may have to compensate the buyer for the energy not produced at a predefined price (Delmarva, 2008; PacifiCorp, 2008; World Bank, 2002). The buyer may also adjust the annual target of the next contract year upward to compensate for the under-delivered amount (Anaheim, 2003).

As described in Lei et al. (2015), we assume in the PPA governing the wind farm, there is a constant annual energy delivery target (which is also the maximum/minimum annual energy delivery limit) set at the beginning of each year, reflecting the buyer's exact annual demand. During each year, if the delivery target is reached, the energy generated by the whole farm will be priced by a constant contract price; if it is not reached, a lower constant excess price applies for all power generated thereafter until the *EOY*. On the other hand, at *EOY*, if the target is not met, the buyer has to purchase energy from other sources with a price higher than contract price (called replacement price) to fulfill the demand, and the seller must pay the buyer a compensation equals to the shortfall amount of energy priced by the difference between the replacement and contract price.

The next step is to develop a PPA framed revenue and penalty calculation model. 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 on all K turbines at time t, the cumulative energy generated by the whole wind farm from the beginning of the year (*BOY*) to time t, $EC_{PM}(t)$ can be calculated as

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

where $EC(t_0)$ 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 without RUL indication) and k (the kth turbine indicating RUL), respectively, from time τ-1 to τ according to Lei et al. (2015).[2]

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

$$R_{PM,J}(\tau) = P_{PM}(\tau) \cdot \sum_{j=1}^{J} E_j(\tau) \tag{2}$$

$$R_{PM,K}(\tau) = P_{PM}(\tau) \cdot \sum_{k=1}^{K} E_{PM,k}(\tau) \tag{3}$$

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

$$P_{PM}(\tau) = \begin{cases} PC, \; EC_{PM}(\tau) \le ET \\ PE, \; EC_{PM}(\tau) > ET \end{cases} \tag{4}$$

where PC is the constant contract price, PE is the constant excess price, and ET is the annual energy delivery target for the wind farm.

The cumulative revenue earned from time t_1 to t_2 by all K turbines and by the whole wind farm $RC_{PM,K}(t_1,t_2)$ and $RC_{PM}(t_1,t_2)$, respectively, can be calculated as

$$RC_{PM,K}(t_1, t_2) = \sum_{\tau=t_1+1}^{t_2} R_{PM,K}(\tau) \tag{5}$$

$$RC_{PM}(t_1, t_2) = \sum_{\tau=t_1+1}^{t_2} R_{PM,J}(\tau) + RC_{PM,K}(t_1, t_2) \tag{6}$$

If ET hasn't been met at *EOY*, there will be under-delivery compensation UP_{PM} paid by the seller to the buyer calculated as

$$UP_{PM} = \begin{cases} \big(ET - EC_{PM}(EOY)\big) \cdot (PR - PC), \\ \qquad EC_{PM}(EOY) < ET \\ 0, \; EC_{PM}(EOY) \ge ET \end{cases} \tag{7}$$

where PR is the constant replacement price.

Similarly, if the predictive maintenance is not going to be implemented on all K turbines before *EOY*, the corrective maintenance will fix all failed K turbines at *EOY*. The cumulative energy generated by the whole wind farm from *BOY* to time t, $EC_{CM}(t)$ can be calculated as

$$EC_{CM}(t) = EC(t_0) + \sum_{\tau=t_0+1}^{t} \sum_{j=1}^{J} E_j(\tau) + \sum_{\tau=t_0+1}^{t} \sum_{k=1}^{K} E_{CM,k}(\tau) \tag{8}$$

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

$$E_{CM,k}(\tau) = \begin{cases} E_{PM,k}(\tau), \; t_0 < \tau < TTF_k \\ 0, \; TTF_k \le \tau \le EOY \end{cases} \tag{9}$$

When turbine k fails at TTF_k, it will be down for the corrective maintenance event at *EOY*.

[2] For detailed calculation method for $E_j(\tau)$ and $E_{PM,k}(\tau)$ see Lei et al. (2015).

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

$$R_{CM,J}(\tau) = P_{CM}(\tau) \cdot \sum_{j=1}^{J} E_j(\tau) \quad (10)$$

$$R_{CM,K}(\tau) = P_{CM}(\tau) \cdot \sum_{k=1}^{K} E_{CM,k}(\tau) \quad (11)$$

where $P_{CM}(\tau)$ is the energy price at time τ with predictive maintenance not implemented before EOY, defined as

$$P_{CM}(\tau) = \begin{cases} PC, & EC_{CM}(\tau) \le ET \\ PE, & EC_{CM}(\tau) > ET \end{cases} \quad (12)$$

The cumulative revenue earn from time t_1 to t_2 by all K turbines and by the whole wind farm $RC_{CM,K}(t_1,t_2)$ and $RC_{CM}(t_1,t_2)$, respectively, can be calculated as

$$RC_{CM,K}(t_1, t_2) = \sum_{\tau=t_1+1}^{t_2} R_{CM,K}(\tau) \quad (13)$$

$$RC_{CM}(t_1, t_2) = \sum_{\tau=t_1+1}^{t_2} R_{CM,J}(\tau) + RC_{CM,K}(t_1, t_2) \quad (14)$$

The under-delivery compensation UP_{CM} paid by the seller to the buyer at EOY can be calculated as

$$UP_{CM} = \begin{cases} \big(ET - EC_{CM}(EOY)\big) \cdot (PR - PC), \\ \qquad EC_{CM}(EOY) < ET \\ 0, \ EC_{CM}(EOY) \ge ET \end{cases} \quad (15)$$

2.2. Predictive Maintenance Value Simulation

If predictive maintenance is implemented on all K turbines at time t, the cumulative revenue earned by all K turbines from t_0 to t is $RC_{PM,K}(t_0,t)$; if corrective maintenance is implemented on all K turbines at EOY, the cumulative revenue earned by all K turbines from t_0 to t is $RC_{CM,K}(t_0,t)$.

The predictive maintenance value $V(t)$ at time t, representing the extra value obtained by carrying out the predictive maintenance on all K turbines at time t rather than waiting for the corrective maintenance at EOY, is defined as

$$V(t) = \Big(RC_{PM,K}(t_0, t) - RC_{CM,K}(t_0, EOY)\Big) + CA(t) \quad (16)$$

where $t_0 < t < TTF_{min}$, and TTF_{min} is the shortest TTF_k of all K turbines. It is assumed that all K turbines will be maintained predictively together before TTF_{min}. Therefore once the first turbine failure happens, the predictive maintenance option expires, and the value path simulation will be stopped. The first item in parentheses reflects the revenue lost or the value of the RUL thrown away due to predictive maintenance. The earlier the predictive maintenance is scheduled, the more revenue will be lost (more of RUL will be wasted). The second item represents the cost avoidance by replacing corrective maintenance with predictive maintenance, can be calculated as

$$CA(t) = \sum_{k=1}^{K} C_{CM,k} + (UP_{CM} - UP_{PM}) + RL \quad (17)$$

Figure 1 shows a graphical representation of Eq. (16).

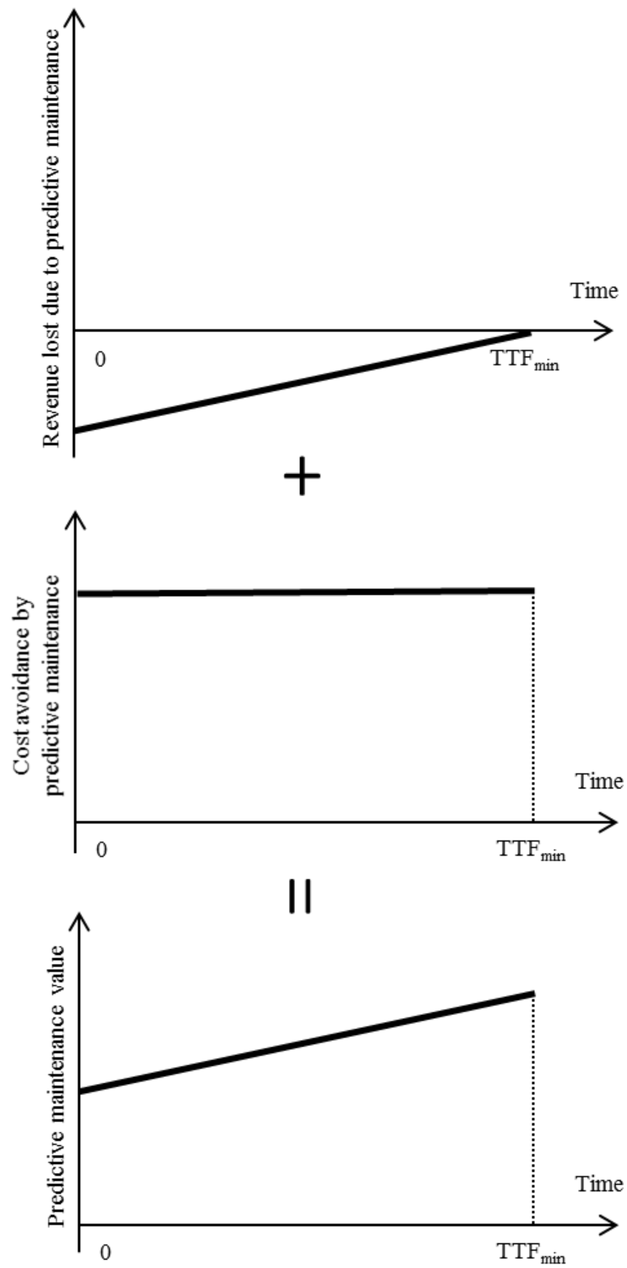

Figure 1. Simple predictive maintenance value formulation.

In Eq. (17), $C_{CM,k}$ is the corrective maintenance cost for turbine k at EOY, which includes the cost of parts, equipment and facilities and labor. The second item in parentheses is the under-delivery penalty due to corrective maintenance, and RL is the revenue lost during downtime for corrective maintenance at EOY, can be calculated as

$$RL = RC_{PM}(t, EOY) - RC_{CM}(t, EOY) \quad (18)$$

2.3. Stochastic DCF Approach

The predictive maintenance can be seen as an investment, and the predictive maintenance value can be treated as its gross profit. If we assume that the predictive maintenance will always be implemented at some selected opportunity, the optimum predictive maintenance opportunity can be determined by optimizing the net profit of the predictive maintenance as

$$NPV(t) = \begin{cases} V(t) - \sum_{k=1}^{K} C_{PM,k}, \\ \quad t_0 < t < TTF_{min} \\ 0, \ TTF_{min} \le t \le EOY \end{cases} \tag{19}$$

where $NPV(t)$ is the net present value (called NPV) at t_0 of the predictive maintenance implemented on all K turbines at t, and this is called the stochastic DCF approach. $C_{PM,k}$ is the predictive maintenance cost for turbine k at time t, including cost of parts, equipment and facilities, and labor. The discount rate is ignored assuming the time period from time t_0 to t is short. When $t_0 < t < TTF_{min}$, $NPV(t)$ can also be expressed as

$$\begin{aligned} NPV(t) &= \left(RC_{PM,K}(t_0, t) - \textstyle\sum_{k=1}^{K} C_{PM,k} - UP_{PM}\right) \\ &\quad - \left(RC_{CM,K}(t_0, EOY) - \textstyle\sum_{k=1}^{K} C_{CM,k} - UP_{CM} - RL\right) \end{aligned} \tag{20}$$

where the first item in parentheses is the present net profit of predictive maintenance on all K turbines at time t, and the second item in parentheses is the present net profit of corrective maintenance on all K turbines at time EOY.

Equations (19) or (20) can be used to valuate the NPVs of all possible maintenance opportunities after t_0, then the optimum predictive maintenance opportunity can be selected that generates the maximum NPV.

2.4. European ROA Approach

There is an implicit assumption in Eqs. (19) and (20) that the predictive maintenance will be implemented at the selected optimum maintenance opportunity whether the NPV is positive, zero or negative. According to Eq. (20), if the present net profit of predictive maintenance is lower than corrective maintenance, a negative NPV will be generated. In other words, replacing corrective maintenance with predictive maintenance will not always be beneficial, which is the limitation of the stochastic DCF approach.

It is reasonable to assume that the decision-maker is willing to schedule a predictive maintenance only if it is more beneficial than corrective maintenance (a positive NPV is generated from Eq. (19) or (20)), otherwise it is better to have all K turbines run to failure for corrective maintenance. Therefore, as demonstrated in Lei et al. (2015), the predictive maintenance opportunities that follow PHM prediction for wind turbines can be treated as real options, and on each opportunity, a European ROA can be applied to valuate the predictive maintenance option as a "European" style option

$$OV(t) = \begin{cases} max\left(V(t) - \sum_{k=1}^{K} C_{PM,k}, 0\right), \\ \quad t_0 < t < TTF_{min} \\ \quad 0, \ TTF_{min} \le t \le EOY \end{cases} \tag{21}$$

where $OV(t)$ is the present option value at t_0 of the predictive maintenance implemented on all K turbines at t. The risk free rate is ignored for the short time period from time t_0 to t.

By applying the European ROA approach, we assume before TTF_{min} on each predictive maintenance opportunity, if the predictive maintenance value is higher than the predictive maintenance cost, it will be implemented on all K turbines; otherwise, all K turbines will be run to failure, and the option value is 0. After TTF_{min}, the option expires and the option value is 0.

An ROA process can be implemented to valuate the option values of all possible maintenance opportunities after t_0 as a series of European options. The optimum predictive maintenance opportunity can be selected as the opportunity with highest predictive maintenance option value.

It is worth mentioning that the decision-maker may also want to schedule predictive maintenance for each of the K turbines individually, in that case the predictive maintenance value paths can be generated for each of the K turbines till its own TTF. Then the European ROA can be applied to each turbine to determine its own optimum predictive maintenance opportunity, which may be different from each other. Due to the harsh environment and limited availability of the maintenance resources, in reality the decision-maker may prefer to maintain multiple turbines during a single visit to the farm, as assumed in the presented model.

During the valuation process for each predictive maintenance opportunity, the stochastic DCF approach has to carry out the predictive maintenance, while the European ROA approach has the flexibility and may choose not to carry out the predictive maintenance if corrective maintenance is more beneficial.

3. CASE STUDY

In this section, the European ROA and stochastic DCF approaches are applied to a single turbine and a wind farm managed via a PPA. The optimum predictive maintenance opportunities obtained from the two approaches are compared.

1000 wind paths are simulated from t_0 to EOY by using the method described in Section 2. The wind turbines under study are Vestas V-112 3.0 MW offshore turbines, with cut-in, cut-out and rational speeds of 3 m/s, 25 m/s and 12 m/s, respectively, and a nominal rotational speed of 14 RPM (Vestas, 2013).

3.1. Predictive Maintenance Optimization for Single Turbine

We assume there is a single offshore wind turbine operated under a PPA, ET is 8000 MWh, PC, PE and PR are \$20/MWh, \$10/MWh and \$40/MWh, respectively. At t_0 = 8400 hrs when $EC(t_0)$ is 7800 MWh, a PHM indication is triggered and a RUL of 100,000 cycles is predicted for a key subsystem (e.g., the main shaft). The width of the RUL triangular distribution is 200,000 cycles. Using Monte Carlo simulation, 1000 *TTF* samples are obtained.

By applying Eqs. (1) to (5), 1000 cumulative revenue paths are simulated if predictive maintenance is implemented. Similarly, using Eqs. (8) to (13), 1000 cumulative revenue paths with corrective maintenance are obtained.

Predictive and corrective maintenance costs are assumed to be $10,000 and $9000, respectively. Using Eqs. (6), (7), (14), (15), (17) and (18), 1000 cost avoidance paths are simulated. Using Eq. (16), the predictive maintenance value paths are obtained, as illustrated in Figure 2.

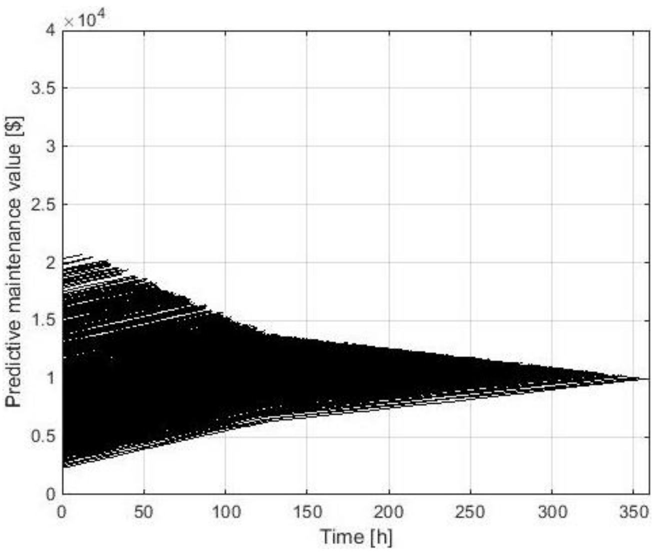

Figure 2. Predictive maintenance value paths for one turbine. 1000 paths are shown.

As shown in Figure 2, while the cost avoidance is staying constant (see Figure 1), since the revenue lost due to predictive maintenance decreases over time, all value paths are ascending. Each path terminates at a different time point when the RUL is used up, which represents the uncertainties in the predicted RUL and wind speeds. The earlier the RUL is used up, the higher the path's initial value is; it is because the revenue lost during downtime for corrective maintenance is also larger. The change in slopes of some paths indicate that *ET* is reached and then the *PE* is applied.

For offshore wind turbines, predictive maintenance opportunities are not continuously available. We assume the predictive maintenance is available every 2 days. For the simulated 1000 predictive maintenance value paths, using Eq. (23), 1000 option value paths are obtained. At each predictive maintenance opportunity, all option values are averaged to get the expected option present value as shown in the left graph of Figure 3. In order to compare it to the expected NPV obtained from DCF method, the stochastic DCF approach is also applied to get the expected NPV as a comparison, and the results are shown in the right graph of Figure 3.

As can be seen in Figure 3, the optimum predictive maintenance opportunity predicted by the European ROA approach is 4 days (96 hours) after t_0, with a higher expected value of $1,563 when 13.5% turbine samples have failed. Stochastic DCF approach suggests 6 days (144 hours) after t_0 with a lower expected NPV of $1,363 when 31.6% turbine samples have already failed. Since The European ROA approach is an asymmetric approach that only captures the upside value (when predictive maintenance is more beneficial) while limiting the downside risk (when corrective maintenance is more beneficial), it suggests to implement predictive maintenance earlier. Also, because of this asymmetric characteristic, at each maintenance opportunity, the expected option value from the European ROA approach is always greater than or equal to the expected NPV from the stochastic DCF approach. The difference is the additional value provided by the flexibility that the real option approach correctly models.

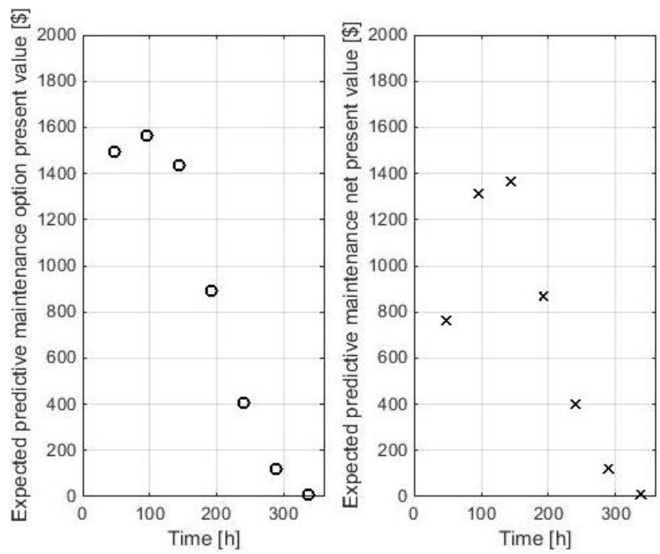

Figure 3. Left – expected predictive maintenance option present value (from European ROA approach) and right - expected predictive maintenance net present value (from stochastic DCF approach) for one turbine.

If the predictive maintenance value is higher than the predictive maintenance cost at all predictive maintenance opportunities due to high revenue lost, under-delivery penalty or expensive corrective maintenance cost, then there will be no differences between the results from the European ROA and stochastic DCF approach. As it is shown in Figure 4, under the assumption of having a high corrective maintenance cost of $50,000 and keeping all other parameters the same, both approaches suggest the same result for the predictive maintenance: 2 days (48 hours) after t_0.

Therefore, unless the predictive maintenance value is much higher than the predictive maintenance cost, the European ROA approach offers a more conservative opportunity to schedule predictive maintenance. This means that when the maintenance crew arrives on the suggested maintenance date, the probability that the turbine has failed is lower, which also means a higher probability for the predictive maintenance to be implemented successfully. The European ROA approach also leads to an expected option value higher than the expected NPV from stochastic DCF approach.

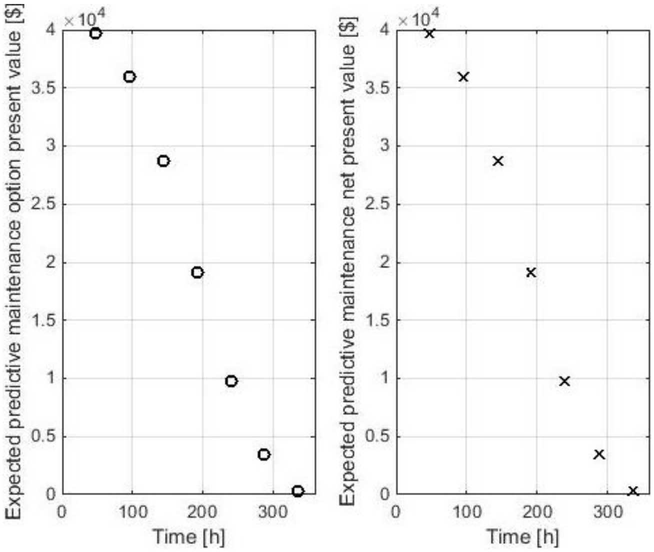

Figure 4. Left - expected predictive maintenance option present value (from European ROA approach) and right - expected predictive maintenance net present value (from stochastic DCF approach) for one turbine with expensive corrective maintenance.

3.2. Predictive Maintenance Optimization for a Wind Farm

We assume there is an offshore wind farm with 5 turbines managed via a PPA with the *ET* of 40,000 MWh, *PC*, *PE* and *PR* are assumed to be the same as the one turbine case. At t_0 = 7800 hrs when $EC(t_0)$ is 39,000 MWh, RULs are predicted for turbine *1* to be 80,000 cycles (with 160,000 cycles width triangular distribution) and for turbine *2* to be 100,000 cycles (with 200,000 cycles width triangular distribution). Assume at the same time, there are two turbines in the wind farm that are not operating. The predictive maintenance value paths can be generated for turbine *1* and *2* in Figure 5.

Assuming the predictive maintenance opportunity is once every 2 days, the expected predictive maintenance option present value and predictive maintenance net present value can be determined as shown in Figure 6. The optimum predictive maintenance opportunity according to European ROA approach is 2 days (48 hours) after t_0, and by stochastic DCF approach it becomes to 4 days (96 hours) after t_0. Again, the European ROA approach provides a more conservative opportunity with the expected option value higher than the expected NPV from stochastic DCF approach. Figure 7 shows the results when the corrective maintenance cost assumed to be $50,000; both approaches suggest optimum maintenance opportunity as 2 days (48 hours) after t_0.

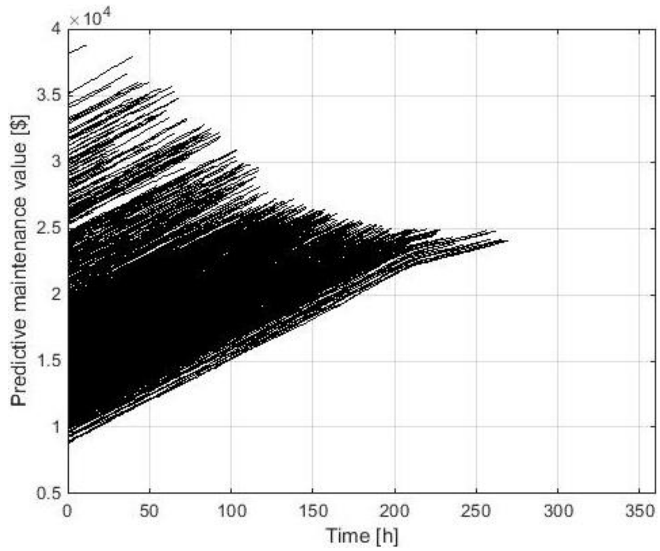

Figure 5. Predictive maintenance value paths for turbine *1* and *2*. 1000 paths are shown.

If there are less turbines not operating at time t_0, the optimum predictive maintenance opportunity will shift to 4 days (96 hours) after t_0 by using the ROA approach as shown in Figure 8. When two turbines are down, considering the significant revenue loss and under-delivery penalty due to corrective maintenance, the selection of optimum predictive maintenance opportunity will tend to be conservative.

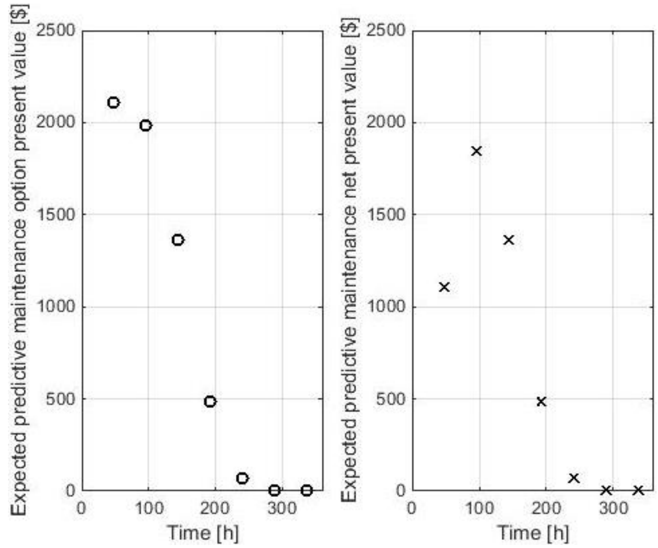

Figure 6. Left - expected predictive maintenance option present value (from European ROA approach) and right - expected predictive maintenance net present value (from stochastic DCF approach) for turbine *1* and *2*.

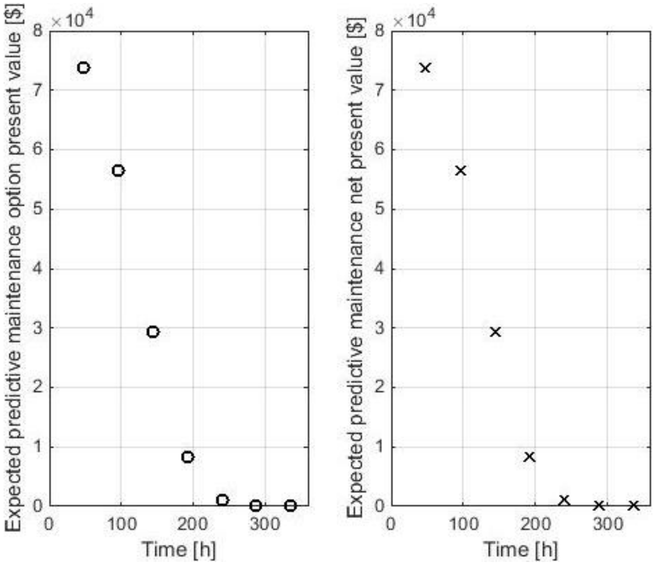

Figure 7. Left - expected predictive maintenance option present value (from European ROA approach) and right - expected predictive maintenance net present value (from stochastic DCF approach) for turbine *1* and *2* with expensive corrective maintenance.

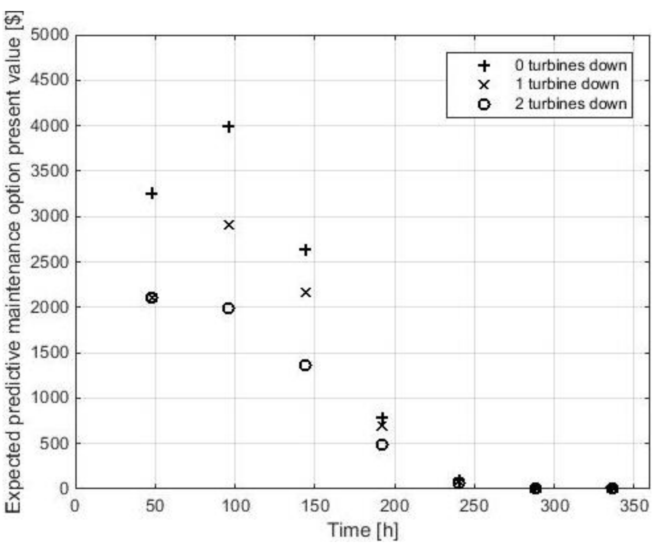

Figure 8. Predictive maintenance option present value for turbine *1* and *2* when the number of turbines down is varying.

4. CONCLUSION

The objective of the work presented in this paper is to determine the optimum predictive maintenance opportunity for wind farms managed under PPAs when multiple turbines are indicating RULs. Uncertainties in the wind speed and the RUL predictions from PHM are considered, and both ROA and stochastic DCF approaches are applied. This work demonstrates that the predictive maintenance option's flexibility to expire if the predictive maintenance value is not enough to cover the predictive maintenance cost, results in the ROA approach always having an expected option value higher than the expected NPV from stochastic DCF approach. For the same reason, the ROA approach always suggests an optimum maintenance opportunity that is earlier than the stochastic DCF approach. However, the results from two approaches are the same when the predictive maintenance value is higher than the predictive maintenance cost at all predictive maintenance opportunities.

For a wind farm managed via a PPA with multiple turbines indicating RULs concurrently, the predictive maintenance value for each turbine depends on the operational state of the other turbines, the amount of energy delivered and to be delivered by the whole wind farm. When there are many turbines not operating in the wind farm, the revenue lost and under-delivery penalties due to corrective maintenance will be significant; therefore, the selection of the optimum predictive maintenance opportunity by ROA approach tends to be more conservative.

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

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

$ARUL_k$	simulated actual *RUL* for turbine *k*
BOY	beginning of the year
$C_{CM,k}$	corrective maintenance cost of turbine *k*
$C_{PM,k}$	predictive maintenance cost of turbine *k*
$CA(t)$	cost avoidance obtained if predictive maintenance is implemented on *K* turbines at time *t*
$E_j(t)$	energy generated by turbine *j* from *t*-1 to *t*
$E_{CM,k}(t)$	energy generated by turbine *k* from *t*-1 to *t* with turbine *k* running to failure
$E_{PM,k}(t)$	energy generated by turbine *k* from *t*-1 to *t* if predictive maintenance will be implemented
$EC(t_0)$	cumulative energy delivered by the whole wind farm from *BOY* to t_0

$EC_{CM}(t)$	cumulative energy generated by the whole wind farm from *BOY* to *t* by running *K* turbines to failure
$EC_{PM}(t)$	cumulative energy generated by the whole wind farm from *BOY* to *t* if predictive maintenance will be implemented on *K* turbines
EOY	end of the year
ET	annual energy delivery target of the wind farm
J	number of turbines operating normally at time *t* in the wind farm
K	number of turbines indicating *RULs* at time *t* in the wind farm
M	number of simulation paths
NPV(t)	expected predictive maintenance net present value at t_0 if predictive maintenance scheduled at time *t*
OV(t)	Expected predictive maintenance option present value at t_0 if predictive maintenance scheduled at time *t*
PC	contract price in PPA
PE	excess price in PPA
PR	replacement price in PPA
$R_{CM,J}(t)$	revenue earned by *J* turbines from *t*-1 to *t* with *K* turbines running to failure
$R_{CM,K}(t)$	revenue earned by *K* turbines from *t*-1 to *t* with *K* turbines running to failure
$R_{PM,J}(t)$	revenue earned by *J* turbines from *t*-1 to *t* if predictive maintenance will be implemented on *K* turbines
$R_{PM,K}(t)$	revenue earned by *K* turbines from *t*-1 to *t* if predictive maintenance will be implemented
$RC_{CM}(t_1,t_2)$	cumulative revenue earned by the whole wind farm from time t_1 to t_2 with *K* turbines running to failure
$RC_{CM,K}(t_1,t_2)$	cumulative revenue earned by *K* turbines from time t_1 to t_2 with *K* turbines running to failure
$RC_{PM}(t_1,t_2)$	cumulative revenue earned by the wind farm from t_1 to t_2 if predictive maintenance implemented on *K* turbines
$RC_{PM,K}(t_1,t_2)$	cumulative revenue earned by *K* turbines from time t_1 to t_2 if predictive maintenance will be implemented
RL	revenue lost during downtime for corrective maintenance at *EOY*
RUL	nominal remaining useful life in cycles
t, τ	time of the year
t_0	time of the year when *RULs* are predicted and predictive maintenance decision needs to be made
TTF_k	simulated time to failure of turbine *k*
TTF_{min}	smallest TTF_k of *K* turbines
UP_{CM}	under-delivery compensation if corrective maintenance implemented at *EOY*
UP_{PM}	under-delivery compensation if predictive maintenance scheduled at time *t*
V(t)	predictive maintenance value for *K* turbines at time *t*

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