Development of a Maintenance Option Model to Optimize Offshore Wind Farm Sustainment

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This paper presents a method that uses a simulation-based real options analysis to determine the value of waiting after obtaining a remaining useful life (RUL) indication from prognostics and health management (PHM) structures within a wind turbine. This methodology potentially allows the threshold for maintenance to be optimized in real-time based on the state of health of the turbine, the anticipated future state of maintenance resources, maintenance flexibility (current and future), and market uncertainties (e.g., anticipated future price and demand for energy).

Nomenclature

CA	=	cost avoidance
C_{EH}	=	cost of energy
C_f	=	capacity factor
C_M	=	cost of maintenance
d	=	discount factor
R	=	cumulative revenue
P	=	number of paths analyzed
t	=	time
V_M	=	maintenance value
W	=	number of time periods corresponding to the maximum waiting time
WT_{PR}	=	turbine power rating
W_t	=	Brownian motion
X_t	=	the value of the quantity being simulated
μ	=	drift
σ	=	variance

I. Introduction

Offshore wind farms are capital intensive projects whose economic viability depends on many things including: the wind resources, the technology, the depth of the water, the price of energy, and the successful long-term sustainment of the turbines. Sustainment is the capacity of a system to endure; and its effectiveness is usually measured by assessing the life-cycle (or total ownership) cost of the system. Sustainment includes: reliability, maintainability, operational logistics, configuration control, obsolescence management and the ability to (and optimum frequency of) system upgrades and refreshes. Sustainment, also referred to as operation and maintenance (O&M) or operation and support (O&S), is projected to be the second largest contributor to the life-cycle cost of offshore wind turbines, representing 17-28% of the total levelized cost of offshore wind farms and more for farms that are more than 12 miles offshore (Ref. 1). These numbers are only an estimate, reality might be worse; without careful strategic planning, solid life-cycle cost estimations, and a realistic understanding of the sustainment resources required, the fervor to install wind turbines could be quickly replaced by derelict wind farms. In November 2011, NaturalNews.com estimated that over 14,000 wind turbines have been abandoned in the US due to high rates of failure and high maintenance costs, (Ref. 2).

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The prediction and optimization of maintenance activities provides a significant opportunity for wind energy cost reduction that benefits all stakeholders. Understanding the life-cycle sustainment requirements of offshore wind farms is an area that has received far less attention than wind turbine design, manufacturing, siting, etc.

II. Offshore Wind Farm Maintenance with PHM

Maintenance of offshore wind farms is challenging because the resources required to perform maintenance are expensive, not continuously accessible, and the capacity factor for the turbines is variable. For many types of infrastructure-critical systems, customers are transitioning to buying the availability of a system through "availability contracts," instead of actually buying the system itself (Ref. 3). Availability is the ability of a service or a system to be functional when it is requested for use or operation. Availability is a function of a system's reliability (how often it fails) and maintainability (how efficiently it can be restored when it does fail). Evaluating an availability requirement is a challenge for manufacturers and supporters of wind farms because determining what it will cost to deliver a specific level of availability is difficult. This paper will discuss an approach to implementing maintenance-optimized availability that will allow the valuation of maintenance options for individual turbines in the context of a wind farm managed using an availability (or similar) performance-based contract.

The specific challenge addressed is making business case for, and optimizing the use of, prognostics and health management (PHM) and condition-based maintenance (CBM) for determining which turbines to maintain when maintenance resources are available. PHM consists of technologies and methods to assess the reliability of a system in its actual life-cycle conditions to determine the advent of failure and the mitigation of system risks (Ref. 4). PHM-enabled means that the system is instrumented with sensors that measure either the environment stresses the system has encountered (indirect PHM), specific physical properties of the system (data-driven PHM), or both. The critical subsystems in many of today's wind turbines already have an array of such sensors. PHM is an enabler of availability-based contracts and potentially reduces life-cycle cost. A review of condition monitoring applied to wind turbines is provided by Hameed et al. (Ref. 5).

In this paper we will use real-options analysis to value options to: maintain now, and wait and maintain later.. The methodology allows the effective threshold for maintenance to be optimized in real-time based on the state of health of the turbines, the anticipated future state of maintenance resources, maintenance flexibility (current and future), and market uncertainties (e.g., anticipated future price and demand for energy).

III. Using Real Options Analysis (ROA) to Valuate Maintenance Options

When an anomaly is detected in a PHM-enabled system (e.g., a wind turbine), and the remaining useful life (RUL) of the system is estimated with associated uncertainties, the decision maker has multiple choices called options, which can be exercised (or not exercised) to manage the health of the system.

Real Options Analysis (ROA) is used to estimate the "value" the maintenance options arising from the implementation of PHM.[3] The valuation (quantification of the value) of the options under uncertainty represents a system management optimization problem. In the case of wind farms, when a prognostic-indication is obtained for a turbine the decision-maker has the option to turn the turbine off in order to avoid further damage, modify the wind turbine's operation in such a way as to reduce the loading, or continue normal operation (i.e., do nothing). Market risks and technical risks are relevant to ROA decision making. As an example the price of power produced by wind turbines may be regarded as market risk because it is contingent on the price of other energy sources. An example of technical risk is the risk associated with the efficiency at which the technology operates, e.g., capacity factor, which is the ratio of the turbines actual output over some period of time to its potential output.

The investment in implementing PHM within a system is considered the purchase price of the "option". If an RUL produced by the PHM results in a maintenance activity prior to the failure of the system, then the option is exercised; if the RUL is not acted upon prior to failure than the option expires. The fundamental tradeoff in maintenance problems with prognostics is finding the time to perform maintenance that minimizes the combination of remaining useful life that is thrown away (which decreases as you use up the RUL) and the risk of expensive unscheduled maintenance (which increases as you use up the RUL). For options valuation we restate this as: find the time to perform maintenance that maximizes the combination of the revenue that can be generated by the system during its RUL and the cost of unscheduled failure that can be avoided. In Fig. 1, the longer the maintainer waits after the prognostic indication to replace a failing part, the more revenue can be made with the part (i.e., less remaining life of the part is thrown away); however, the longer one waits after a prognostic indication, the less cost

[3] The valuation of options associated with performing maintenance has been done in the past, e.g., Refs 6-8, however, the use of maintenance options where the option being purchased is the inclusion of PHM within the system has not appeared previously.

avoidance is realized due to the increased risk of failure. The sum of these two effects is the value of exercising the

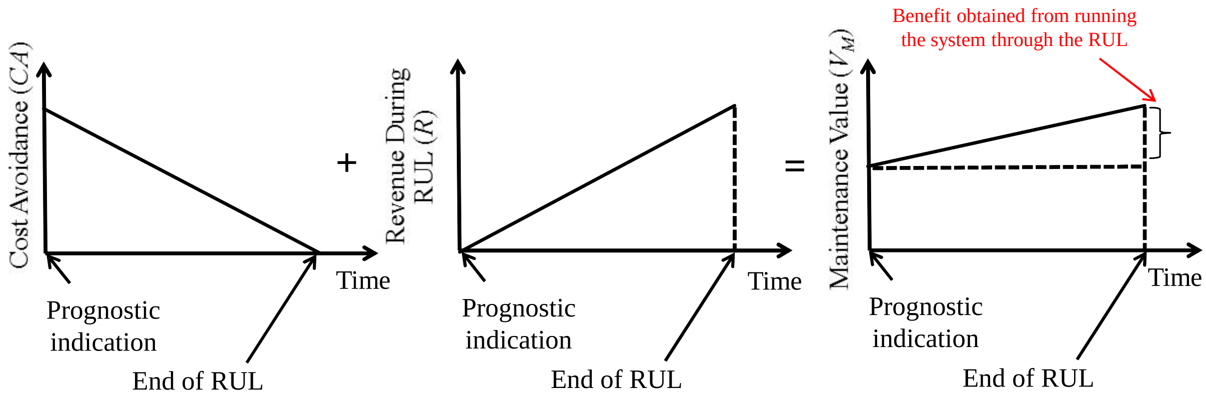

Figure 1. Value of waiting to maintain. This simple representation assumes that the severity of the failure is constant but the probability of failure increases as the RUL is used up. This figure does not address uncertainties in the RUL.

option,

$$V_M = CA + R \tag{1}$$

where V_M is the maintenance value, R is the revenue obtained during the RUL and CA is the cost avoided.

In reality, there are many possible paths (given uncertainties in both revenue and cost avoidance) that the value could take over time starting when the RUL is forecasted by the PHM system. The revenue and cost avoidance that appear in Fig. 1 are time-dependent uncertain quantities that can be modeled with dynamic forecasting models such as geometric Brownian motion. The following stochastic differential equation is used to propagate uncertainty with time for the generation of the dynamic quantities,

$$dX_t = \mu X_t dt + \sigma X_t dW_t + X_t dq_t \tag{2}$$

where X_t is the value of the quantity being simulated at time t, μ is a drift component, σ is a variance component (also called shock or volatility), W_t is a Brownian motion ($\sqrt{dt}$), and dq_t is an independent process that represents a "jump" to zero. Figure 2 shows the cost avoidance, revenue and value for a pitch control mechanism in a wind turbine. In Fig. 2, the horizontal axis represents time in days; at time 0 a prognostic indication is obtained, and uncertainty is propagated for 100 days in one-day time steps. The cost avoidance starts at a value of \$6984 (60% of the cost of a new pitch control mechanism) with μ = -0.6 and σ = 0.25. The daily revenue for the turbine is calculated using,

$$R = 24 WT_{PR} C_{EH} C_f \tag{3}$$

Where we have assumed a 600KW turbine (WT_{PR}) with a capacity factor of C_f = 0.33 and a cost of energy C_{EH} = \$0.05/KWh. From (3) the cumulative revenue of the turbine starts at \$237 with μ = 0.18 and σ = 0.5. Finally the value is the summation of the cost avoidance and the cumulative revenue. The values for drift (μ) and volatility (σ) are estimated from the variation in the power curve for the revenue and from historical data for cost avoidance. In the case shown in Fig. 2, a jump in the cost avoidance at 80% of the forecasted RUL is assumed and represents the risk of the system failing prior to reaching the forecasted RUL. Note, a negative cost avoidance represents potential collateral damage.

Using the set of possible value paths for the system as a function of time, we wish to evaluate the value of waiting to perform maintenance after an RUL estimation is received. To value the paths we first need to determine a cost of maintenance (C_M) to compare the maintenance value (V_M) to,

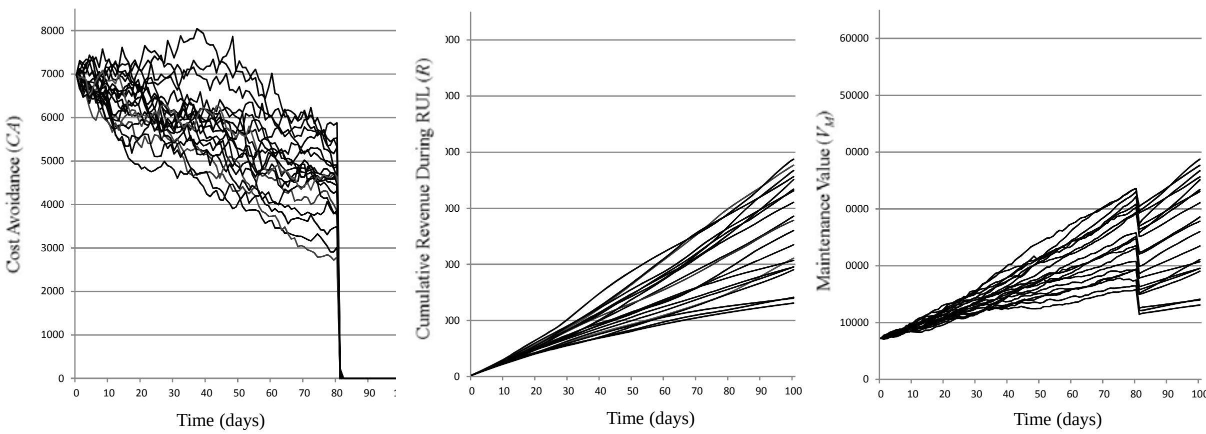

Figure 2. Propagation of the properties in Figure 1 in time with uncertainties. In this example, the RUL is 100 days and 20 paths are shown. Note, the properties also include a jump to zero in the cost avoidance at 80% of the RUL.

$$C_M = C_{Failure} + C_{Downtime} + C_{Penalty} \tag{4}$$

where $C_{Failure}$ is the cost of a system failure, $C_{Downtime}$ is the cost of downtime and $C_{Penalty}$ is the penalty cost. The penalty cost is the cost incurred if the turbine's downtime results in the wind farm not meeting its required availability. The penalty may take the form of the cost incurred by having to buy or produce energy via alternative means to supplement the wind farm in order to meet the availability requirement. The cost of maintenance represents the cost of an unscheduled maintenance activity, i.e., run to failure.

The valuation of the option to wait for specific periods of time is performed using a simulation method called least-squares Monte Carlo (LSM) developed by Longstaff and Schwartz (Ref. 9).[4] The LSM approach starts at the end date (a selected waiting time), and works backwards in time through the value paths. At each possible time that maintenance could be performed, the algorithm determines the values of performing maintenance (the option's exercise value) and the expected value of continuing for another period of time (not exercising the option). The expected value of continuing is determined using a least-squares fit of the value of exercising at the current time versus the difference between the value of exercising at the next time period and C_M discounted to the current time. The least-squares fit only considers paths that are "in the money" at the current time step, i.e., $V_M > C_M$. This process is repeated all the way back to zero time (the prognostic indication point). We then work forward in time from 0 to the waiting time in every path and stop at the first maintenance opportunity in each path where the current value is greater than the continuation value. Analyzing each path forward in time identifies the optimum stopping point (prior to the selected waiting time) for each path and the path's associated value.

The basic premise of the analysis is that at any possible exercise time (maintenance opportunity), the expected payoff from immediate exercise is compared against the expected payoff from continuation without exercising, and then exercises if the immediate payoff is higher. This is performed for each path separately; however, all paths are needed to accurately evaluate the expectation values. The possible exercise points are determined by the availability of maintenance resources.

The overall value corresponding to a particular waiting time is given by,

$$Value = \frac{1}{P} \sum_{i=1}^{P} \sum_{j=1}^{W} V_{M_{P,j}} d_j \tag{5}$$

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[4] Tutorial examples of the LSM algorithm appear in Longstaff and Schwarz (Ref. 9) for an American "put" option and in Haddad et. al. (Ref. 10) for an American "call" option. The option analyzed in this paper is an American call option.

where, P is the number of paths analyzed, W is the number of maintenance opportunities (time periods) corresponding to the maximum waiting time considered, d_j is the discount factor corresponding to the jth time period, and $V_{M_{P,j}}$ is the maintenance value corresponding to the jth time period of the Pth path (note, $V_{M_{P,j}}$ is only non-zero at the optimum exercise point in the path).

Equation (5) gives the value associated with a particular waiting time, i.e., it is the value of each path stopping at its optimum point up to the maximum waiting time considered. The analysis is repeated for waiting times that range from zero to the RUL to determine the optimum amount of time to wait (that maximizes value) after a prognostic indication for a particular RUL.

IV. A Case Study Result

This section demonstrates the wait-to-maintain option on one turbine subsystem that is indicating a remaining useful life, a more detailed description and discussion of this example appears in Haddad et al. (Ref. 10). Uncertainties are at the heart of maintenance options valuation. In fact, if there was no uncertainty, it would be trivial to determine the value of the option. Including these uncertainties is a central element of the analysis that causes the multiple stochastic paths after prognostic indication as discussed in Section III. This example case analyzes 100 paths, and assumes that C_M is the cost of unscheduled maintenance ($11,640, the cost of a pitch mechanism in 2006 dollars (Ref. 11)).

The example considers one failure mode with a remaining useful life forecasted to be 37 days. The cost avoidance and revenue are assumed to be as modeled in Fig. 2 except that we assume that at 80% of the RUL (80% of 37 days rather than 100 days shown in Fig. 2). The jump models an increase in the risk of collateral damage if the turbine fails, which results in a cost of failure that is larger than the cost of the failure of the subsystem under consideration (the one that indicated an RUL). An example of collateral where a failure of one subsystem can lead to a cost that is larger than the subsystem that failed is discussed by Ragheb and Ragheb (Ref. 12).

Figure 3 shows the value of waiting to perform maintenance after a prognostic indication for the subsystem in the turbine under consideration where a remaining useful life of 37 days is assumed. The horizontal axis on Fig. 3 is the waiting time; at time 0 a prognostic indication is obtained. The vertical axis on Fig. 3 is the value of the waiting option. Note that this is not the value of PHM (the value of PHM is better captured by an ROI model, e.g., Ref. 13), but rather it is the additional benefit from capturing the upside effect of uncertainties (such as the probability of high wind speeds). Figure 3 shows the value of waiting from 5 days to 37 days.

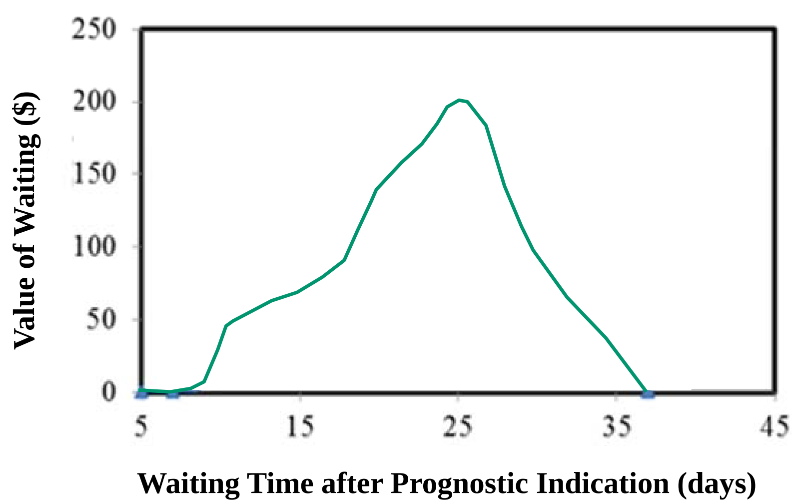

Figure 3. Value of waiting for a 37 day predicted RUL.

The value of waiting in Fig. 3 is 0 for the first 7 days. This means that waiting for 7 days will not generate additional value from PHM. This is due to the fact that the cumulative revenue generated in 7 days will not compensate for the cost of failure. However, after 7 days, the cumulative revenue generated from running the turbine compensates for the risk of failure; this is when the value of waiting starts to increase. The value of waiting has a peak at approximately 25 days, with a value of waiting slightly larger than $200. The value from waiting is the additional benefit that the decision-maker obtains from PHM (knowledge of the remaining life and running the system through the RUL). The magnitude of the values in Fig. 3 may seem small compared to the system's cost. However, this example calculates the value of the waiting option for one particular subsystem experiencing one failure. In reality, the PHM system will generate the waiting option over the lifetime of the turbine (many possible failures), i.e., it is a "staging" option. Moreover, there are more maintenance options beyond waiting that can potentially create more value. Finally this example is for one turbine only; in reality, the turbine is part of a fleet of turbines (i.e., a wind farm) and the value would be aggregated for the lifetime of the fleet.

V. Discussion and Conclusions

The value determined using the method described in this paper cannot be negative because we are representing the opportunity of the upside effect generated from waiting. If the cost of failure is larger than the revenue, then waiting has no value; in other words, we are not representing the difference in cost of failure and revenue, but instead the additional value we get from the option (i.e., waiting). Note that the value in the case study example decreases after 25 days (and eventually goes to 0) because of the assumptions made that the cost of failure increases at 80% of the RUL. Had this assumption not been made (i.e., if there was no effect of collateral damage on cost), the value of waiting would have increasing until the end of the RUL. When the cost of maintenance and failure is available from historical data, this assumption can be relaxed and estimates from actual data can be used to define the distributions that are assumed in this example.

A part instance centric assessment of value is assumed in this paper, i.e., we are looking at the value attached to particular turbine subsystems because the analysis presented here does not account for revenue that is earned after the maintenance event. In the case study provided in this paper, we assumed that maintenance could be performed each day up to the end of the RUL; in reality, especially for offshore wind farms, maintenance resources will not be available every day and their availability will depend on weather and other factors. This will define a set of specific dates on which maintenance can occur.

The algorithm for quantifying the value of the wait to maintain options as demonstrated here provides the value obtained from PHM at the system-level. This methodology can be extended to the fleet level (wind farm level) where it is desirable to know when the best time to maintain is based on the value to the whole farm not the individual turbine, i.e., the optimum maintenance when the farm is managed via an availability contract.[5] Consider the following problem: when the maintenance resources are available, which of the turbines in a wind farm should be maintained? An individual turbine's maintenance threshold depends on the current state of the turbine, the expected future conditions for performing maintenance (e.g., when will maintenance resources be available?), the state of health of the other turbines in the farm, and the management options that are available. The threshold is not constant; it changes depending on all the factors already mentioned. An extension of the real options approach demonstrated here will allow availability requirements to be mixed with market and technical risks to optimize the maintenance thresholds for offshore wind farms. Note, the highest valuation (optimum) option for an individual turbine will not necessarily be the highest valuation for the turbine in the context of a farm that must meet a specific availability required or be penalized. The penalty could take the form of having to burn coal or oil to make up for electricity that cannot be generated by the farm. Current maintenance practice for wind farms consists primarily of scheduled maintenance, corrective maintenance, and preventive maintenance, (Refs. 5 and 16). Researchers have addressed the optimization of maintenance for wind farms, however, the previous work is not availability driven. PHM has been shown to be an effective way to approach the health management wind farms. However, a drawback of PHM is that it assumes that the threshold for maintenance is a constant.

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[5] Availability contracts (Ref. 3) are a subset of "outcome-based contracts" where the customer purchases an outcome from a system, rather than purchasing the system. In the defense community (US and Europe) these contracts are known as Performance-Based Logistics (PBL). Outcome-based contracts pay for effectiveness (availability, readiness and/or other performance measures) at a fixed rate, penalize performance shortcomings, and/or award gains beyond target goals. Availability contracts are becoming popular for sustainment-dominated systems such as aircraft, ships, and military systems because they force the designer and manufacturer of the system to take responsibility for the entire life cycle of the system thus breaking the traditional model of purchasing an asset and then separately purchasing maintenance.

A recent IHS emerging energy research report on North American wind power (Ref. 14) states: "production-based availability contracts - which tie O&M compensation to project output - are becoming more prevalent and are anticipated to begin replacing traditional uptime availability guarantees." From Ref. 15: "attention is shifting towards smart energy grids that incorporate dispersed green electricity suppliers and new types of consumers that move from all time power contracts to reduced power availability contracts at lower cost."

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