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Incorporation of Outcome-Based Contract Requirements in a Real Options Approach for Maintenance Planning

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Panel 2. Applications of Real Options Analysis in Defense Acquisition

Wednesday, May 4, 2016	
11:15 a.m. – 12:45 p.m.	**Chair: James E. Thomsen,** Former Principal Civilian Deputy, Assistant Secretary of the Navy for Research, Development, & Acquisition ***Acquiring Technical Data With Renewable Real Options*** Michael McGrath, ANSER Christopher Prather, Senior Associate Analyst, ANSER ***Incorporation of Outcome-Based Contract Requirements in a Real Options Approach for Maintenance Planning*** Xin Lei, Research Assistant, University of Maryland Navid Goudarzi, Postdoctoral Researcher, University of Maryland Amir Reza Kashani Pour, Research Assistant, University of Maryland Peter Sandborn, Professor, University of Maryland ***Measuring the Return on Investment and Real Option Value of Weather Sensor Bundles for Air Force Unmanned Aerial Vehicles*** Thomas Housel, Professor, NPS Johnathan Mun, Research Professor, NPS David Ford, Research Associate Professor, NPS Sandra Hom, Research Associate, NPS Dave Harris, NPS Matt Cornachio, NPS

Incorporation of Outcome-Based Contract Requirements in a Real Options Approach for Maintenance Planning

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Abstract

Performance-based logistics (PBL) is growing in popularity for both governmental and non-governmental acquisitions of critical systems. These contracts allow the customer to buy the performance of the system rather than purchase the system and/or to buy the availability of the system rather than pay for maintenance. Outcome-based contracts, which include PBL, are highly quantified "satisfaction guaranteed" contracts where "satisfaction" is defined by the outcomes received from the system (i.e., the specified performance level or availability).

Maintenance planning seeks to predict and optimize when maintenance for a system is performed. Condition-monitoring technologies such as Condition-Based Maintenance (CBM) and Prognostics and Health Management (PHM) provide Remaining Useful Life (RUL) estimates that can be used to plan maintenance. The challenge is how to use the predicted RULs (with their associated uncertainties) and the performance requirements imposed by the outcome-based contracts to optimally plan future maintenance.

This research addresses the incorporation of outcome-based contract requirements within a real options approach used to optimize maintenance planning. A simulation-based real options analysis (ROA) approach is used to determine the optimum predictive maintenance opportunity for a system managed via an outcome-based contract.

Introduction

Background and Motivation

While researchers have studied planning and decision making for outcome-based contracting in different areas (e.g., supply chain, logistics, and inventory management) and for different applications (e.g., defense, avionics, railroads, infrastructure, and energy), there is little formal work dedicated to contractual design and requirements optimization (Kashani-Pour & Sandborn, 2016).

The impact of contract oriented design processes on original equipment manufacturer (OEM) decision making for optimizing reliability in the post-production purchase period led to the development of integrated schemes with dynamic interdependencies of product and service, called product-service systems (PSSs; Meier, Roy, & Seliger, 2010). Procurement and system acquisition process efficiency and success across a system's life cycle requires the development and implementation of best-value, long-term, performance-based product support strategies that leverage performance-based agreements with both industry and government product support providers (Datta & Roy, 2010). Hence, an effective combination of technical and monetary approaches that includes the inventory, maintenance, and operational decisions together to form a unified model that provides visibility into the effect of different parameters is required (Arora, Chan, & Tiwari, 2010). PBL contracting is designed to incentivize this integration towards reducing life-cycle cost and improving design.

System-level PBL contracts were developed to connect system acquisition and logistics with a focus on acquiring a measurable performance outcome (such as the availability of a system), and they seek to optimize system readiness through logistics. Compared with contractor logistics support (CLS), where a contractor, rather than the government, is responsible for the integration of logistics support functions, an effective PBL requires a balanced contribution from both public- and private-sector providers. PBL contracts, as a group of strategies for system support, are intended to improve system performance at a cost similar to that previously achieved under a non-PBL approach or obtain the current system performance at a lower cost. The contract structure (defining the desired outcomes), performance measurements, and pricing (payment models) are key parameters in achieving performance-based contract goals throughout the complex legacy system support domain. System-level PBL contracts should address the operational availability time window, reliability, maintainability, supportability, operation and inventory cost, logistics footprint, total cost of ownership, and logistics response time for making program decisions.

An alternative outcome-based contract mechanism called public–private partnerships (PPPs) has been used to fund and support civil infrastructure projects. Availability payment models for civil infrastructure PPPs require the private sector to take responsibility for designing, building, financing, operating, and maintaining an asset. Under the "availability payment" concept, once the asset is available for use, the private sector begins receiving an annual payment for a contracted number of years based on meeting performance requirements (Sharma & Cui, 2012). The challenge in PPPs is to determine a payment plan (cost and timeline) that protects the public interest (i.e., does not overpay the private sector, but also minimizes the risk that the asset will become unsupported; Gajurel, 2014).

Discrete-event simulation (DES) techniques have been previously used in an integrated model to optimize the *payment* and *contract duration* by incorporating the effects of condition changes, uncertainties, and required availability of infrastructure for PPPs (Sharma, Cui, Chen & Lindly, 2010). This work resulted in obtaining an improved procurement and system acquisition model in which the system availability was chosen as the objective to meet contract requirements (Sandborn, Kashani-Pour, Zhu, & Cui, 2014). However, making decisions for specific future actions during pre-project planning (as DES, which is simply an implementation of discounted cash flow analysis, does) does not accurately address how uncertain conditions evolve because it does not model management flexibility. Real options analysis (ROA) is one means of organizing and valuing flexible strategies to address uncertainties throughout the life cycle of systems. ROA could be used to accommodate management flexibility and uncertainties in both design and monetary aspects of an outcome-based contract.

System Health Management

The maintenance planning that this paper focuses on is contingent on the presence and use of system health management technologies. System health management technologies such as Condition-Based Maintenance (CBM) seek to perform predictive maintenance based on the condition of the system. Prognostics and Health Management (PHM) uses the condition of the system coupled with the expected future environmental conditions (temperature, vibration, etc.) to forecast a Remaining Useful Life (RUL). The system management challenge is how to perform an accurate system risk allocation using the predicted RULs (with their associated uncertainties) to optimally plan when to perform maintenance and allocate maintenance resources. The optimal maintenance planning is modified by performance requirements imposed by the outcome-based contracts.

Maintenance Planning Using Real Options

ROA has been previously applied to maintenance modeling problems. An ROA model for offshore platform life-cycle cost-benefit 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) presented 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 cost of an existing bridge for 30 years is analyzed and minimized using ROA. Goossens, Blokland, and Curran (2011) developed a model to assess the differences in performance between different aircraft maintenance operations.

Haddad, Sandborn, and Pecht (2014) applied 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, 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 system run to failure). Haddad et al. (2014) demonstrated 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).

A Real Options Approach to Maintenance Planning describes a real options approach to maintenance planning when RULs are predicted for the system. The section titled Example—Wind Turbine With an Outcome-Based Contract presents a case study for a PHM enabled wind turbine with and without an outcome-based contract. In the Generalization of Predictive Maintenance Options With Outcome-Based Contracts (Non-Production Earning Systems) section, we discuss the generalization of the approach developed and demonstrated in the following two sections to systems subject to other types of outcome-based contracts.

A Real Options Approach to Maintenance Planning

This section starts with presenting the concept of PHM-enabled maintenance options. Then, it describes how the requirements from an outcome-based contract are incorporated into the option valuation process.

A real option is the right, but not the obligation, to undertake certain business initiatives, such as deferring, abandoning, expanding, staging, or contracting. For example, the opportunity to invest in an asset is a real "call" option. Real options differ from financial options in that they are not typically traded as securities and do not usually involve decisions on an underlying asset that is traded as a financial security. Unlike conventional net present value analysis (discounted cash flow analysis) and decision tree analysis, real options offer the flexibility to alter the course of action in a real asset decision, depending on future developments. Predictive maintenance options are created when in situ health management (i.e., PHM) is added to systems. In this case, the health management approach generates a remaining useful life (RUL) estimate that can be used to take proactive actions prior to the failure of a system. The maintenance option when PHM is used 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 performing 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 what the system would earn between the predictive maintenance event and the end of the RUL (if no predictive maintenance was done). Restated, this is the portion of the system's RUL that is thrown away when predictive maintenance is done prior to the end of the RUL. In reality, this cumulative revenue takes the form of loss in spare part inventory life (i.e., the revenue earning time for the system will be shorter because some inventory life has been disposed of).

Avoided corrective maintenance cost includes[1] the avoided corrective maintenance parts, service and labor cost, the revenue loss associated with corrective maintenance downtime, and the avoided under-delivery penalty due to corrective maintenance (if any).

Figure 1 illustrates the construction of the maintenance value. The cumulative revenue[2] loss is the largest on day 0 (the day the RUL is forecasted). This is because the most remaining life in the system is disposed of if predictive mainenance is performed the day that the RUL is predicted. As time advances, less RUL is thrown away (and less revenue is lost). The avoided corrective maintenance cost is assumed to be constant.

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[1] This is not the difference between the predictive and corrective maintenance actions, but rather the cost of just a corrective maintenance event. The predictive maintenance event cost is subtracted later when the real option value is determined (i.e., in Equation 1).

[2] The value construction in this section assumes that the system is revenue earning (e.g., a wind turbine or an airplane used by an airline). In Generalization of Predictive Maintenance Options With Outcome-Based Contracts (Non-Production Earning Systems), a generalization of the model that applies to non-production systems is discussed.

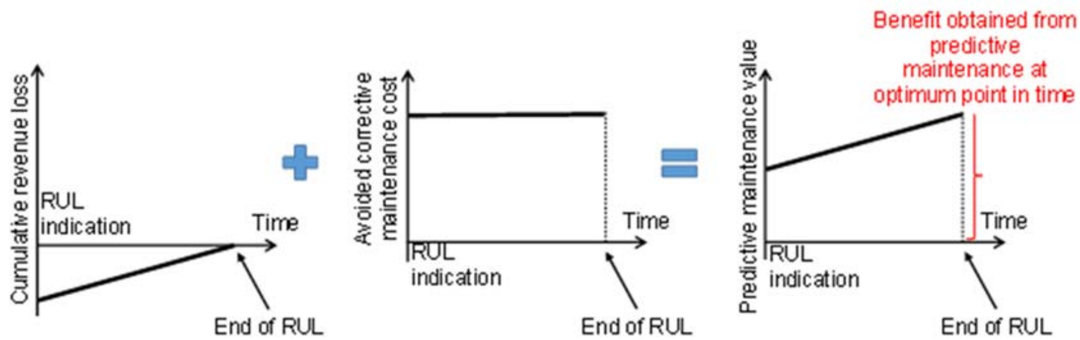

Figure 1. Predictive Maintenance Value Construction
(Lei, Sandborn, Goudarzi, & Bruck, 2015)

The predictive maintanance value is the summation of the cumulative revenue loss and the avoided corrective maintanance cost (Figure 1). If there were no uncertainties, the optimum point in time to perform maintenance would be at the peak value point (at the RUL), which is the last moment before the system fails. Unfortunately, everything is uncertain.

The primary uncertainty is in the RUL prediction. The RUL is uncertain due to inexact prediction capabilities and uncertainties in the environmental stresses that drive the rate at which the RUL is used up. A "path" represents one possible way that the future could occur starting at the RUL indication (Day 0). The cumulative revenue loss paths have variations due to uncertainties in the system's availability or uncertainties in how compensation is received for the system's outcome.[3] The avoided corrective maintenance cost paths represent how the RUL is used up and vary due to uncertainties in the predicted RUL. Each path is a single member of a population of paths representing a set of possible ways the future of the system could play out.

Due to the uncertainties described above, there are many paths that the system can follow after an RUL indication, as shown in Figure 2. Real options analysis lets us evaluate the set of possible paths to determine the optimum action to take.

Consider the case where predictive maintenance can only be performed on specific dates.[4]

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[3] For example, if the system is a wind turbine, path uncertainties could be due to variations in the wind over time.
[4] This could be due to the limited availability of maintenance resources.

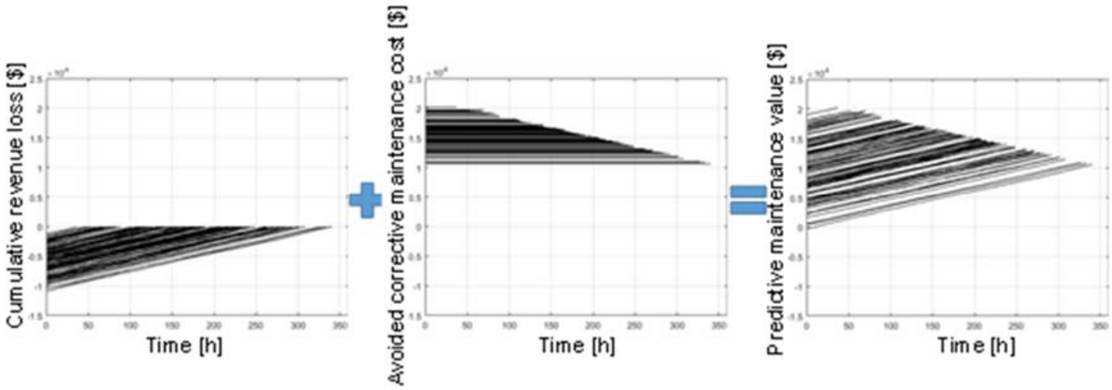

Figure 2. Example of the Simulated Paths After an RUL Indication

On each possible maintenance date, the decision-maker has the flexibility to determine whether to implement the predictive maintenance (exercise the option) or not (let the system run to failure [i.e., let the option expire[5]]). This makes the option a sequence of "European" options that can only be exercised at specific points in time in the future. The left side of Figure 3 shows two example predictive maintenance paths (diagonal lines) and the predictive maintenance cost (the cost of performing the predictive maintenance). Real Option Analysis (ROA) is performed to valuate the option where the predictive maintenance option value is given by

$$O_{PM} = Max(V_{PM} - C_{PM}, 0) \quad (1)$$

where V_{PM} is the value of the path (right most graph in Figure 2 and the diagonal lines in Figure 3) and C_{PM} is the predictive maintenance cost. The values of O_{PM} calculated for the two example paths shown on the left side of Figure 3 are shown on the right side of Figure 3. Note that there are only values of O_{PM} plotted at the maintenance opportunities (not in between the maintenance opportunities). Equation 1 only produces a non-zero value if the path is above the predictive maintenance cost (i.e., the path is "in the money").

Each separate maintenance opportunity date is treated as a European option. The results at each separate maintenance opportunity are averaged to get the expected predictive maintenance option value of a European option expiring on that date. This process is repeated for all maintenance opportunity dates. The optimum predictive maintenance date is determined as the one with the maximum expected option value. The detailed mathematical formulation of the solution can be found in Lei et al. (2015).

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[5] The decision-maker may also have the flexibility not to implement the predictive maintenance on a particular date but to wait until the next possible date to decide, which makes the problem an American option style as has been demonstrated and solved by Haddad et al. (2014). 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 maximum "wait to date." Unfortunately, in reality, maintenance decision-makers for critical systems face a somewhat different problem: given that the maintenance opportunity calendar is known when the RUL indication is obtained, on what date should the predictive maintenance be done to get the maximum option value. This makes the problem a European option style.

Incorporating Outcome-Based Contract Requirements Into the Predictive Maintenance Option

The "paths" described in Figures 1 and 2 are based on a non-outcome-based contract (e.g., an "as-delivered" energy delivery contract for a wind farm that defines a single fixed price for each unit of the energy delivered). When a system is managed via an outcome-based contract (like a PBL), the paths will be impacted. The outcome-based contract influences the combined predictive maintenance value paths due to changes in the cumulative revenue loss and the avoided corrective maintenance cost paths. These cost paths will be influenced by the outcome target, prices before and after that target is reached (generally the latter is lower than the former), penalization mechanisms, the outcome already produced, and the operational state of the other systems in the population. For example, assume that the cumulative outcome produced by a population of systems is close to the outcome target. All systems are operational while some are indicating RULs. The population of systems can meet the outcome target without the members indicating RULs. Then the cumulative revenue loss of the systems with RULs will be lower than when they are managed under a non-outcome-based contract, since the cumulative revenue loss will be lower (because the price paid for the outcome is lower after the outcome target is met). Assume a different scenario where the cumulative outcome from the population of systems is far from the outcome target and many systems are non-operational. In this case, running the systems with RULs to failure and performing corrective maintenance causing long downtimes may result in the population of the systems not reaching the outcome target. In this case, the under-delivery penalty will occur, and the avoided corrective maintenance cost will be higher than the non-outcome-based contract (as delivered) case that doesn't have any penalization mechanisms.

Under an outcome-based contract, the optimum predictive maintenance opportunity for individual systems in a population (e.g., a fleet) is generally different than for an individual system managed in isolation. These two cases would have the same optimum if an as-delivered contract was used.

Example—Wind Turbine With an Outcome-Based Contract

In this section, the predictive maintenance option model is implemented on a single turbine, and then a wind farm with multiple turbines is managed via an outcome-based contract. A Vestas V-112 3.0 MW offshore wind turbine (Vestas, 2013) was used for this study.

Maintaining offshore wind turbines requires resources that are not continuously available. These resources include ships with cranes, helicopters, and trained maintenance personnel. These resources are often onshore-based (which may be as much as 100 miles from the wind farm) and may be maintaining more than one wind farm. Therefore, maintenance is only available on scheduled dates (maintenance opportunities) that may be weeks apart. The availability of maintenance is also dependent on weather and ocean conditions, making the timing of future maintenance visits uncertain.

Figure 4 shows an example result for a single wind turbine. In this example, the ROA approach is not trying to avoid corrective maintenance, but rather to maximize the predictive maintenance option value. In this example, at the determined optimum maintenance date, the predictive maintenance will be implemented on only 65.3% of the paths (the paths that are "in the money"). Thirty-two percent of the paths, which are "out of money," will choose not to implement predictive maintenance, and in 2.7% of the paths, the turbine has already failed prior to that date.

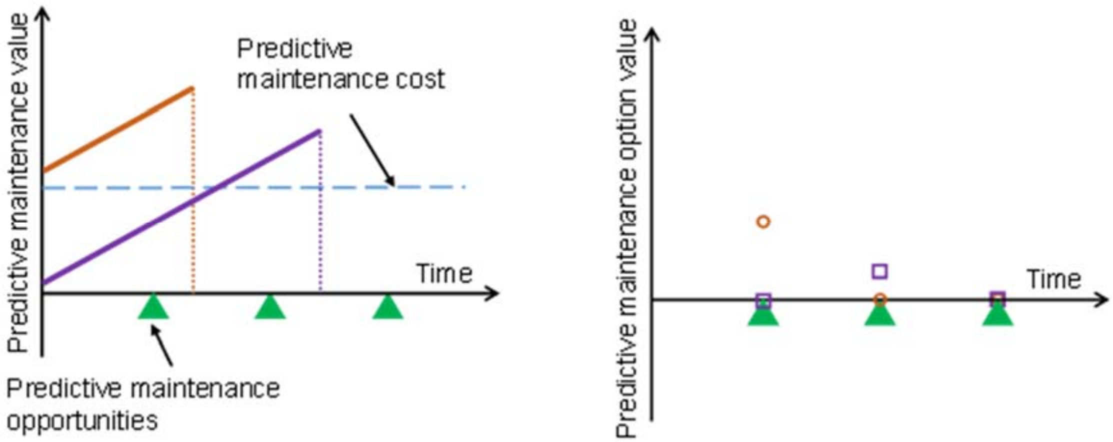

Figure 3. Real Options Analysis (ROA) Valuation Approach
Note. In the right graph, circles correspond to the upper path and the squares correspond to the lower path in the left graph.

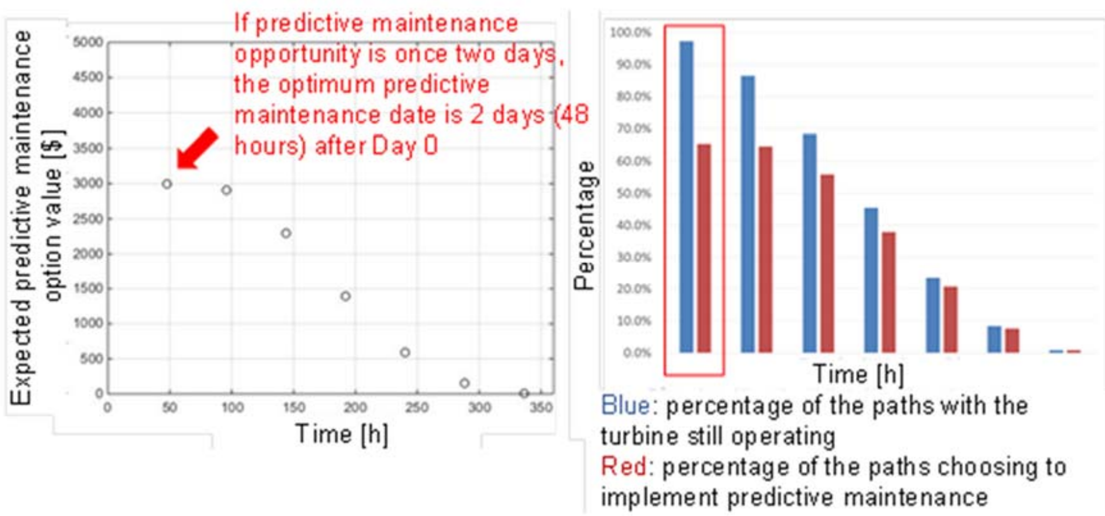

Figure 4. Optimum Maintenance Date After an RUL Indication for a Single Wind Turbine

The result in Figure 4 assumes that all the power generated by the turbine can be sold at a fixed price. There are many wind farms (and other renewable energy power production facilities) that are managed under outcome-based contracts called power purchase agreements (PPAs). A PPA defines the energy delivery targets, purchasing prices, output guarantees, etc. Wind farms are typically managed via PPAs for several reasons (Bruck, Goudarzi, & Sandborn, 2016). First, though wind power can be sold into the local market, the average local market prices tend to be lower than long-term PPA contract prices. Second, lenders are not willing to finance wind projects without a signed PPA that secures a future revenue stream. Third, wind energy buyers prefer simply purchasing power to building and operating wind farms by themselves.

PPA terms are typically 20 years for wind energy, with either a constant or escalating contract price defined through the whole term. At the beginning of each year, a PPA often requires the seller to estimate how much energy they expect to generate during the whole year, based on which an annual energy delivery target may be defined. For each year, a maximum annual energy delivery limit can be set, beyond which a lower excess price may apply. The buyer may also have the right not to accept the excess amount of energy or adjust the annual target of the next contract year downward based on how much has been over-delivered. A minimum annual energy delivery limit or output guarantee may also be set, together with a mechanism to determine the liquidated damages. For example, the seller must compensate the buyer for the output shortfall that the buyer is contracted to receive, multiplied by the difference between the replacement energy price, the price of the energy from sources other than wind paid by the buyers to fulfill their demands, and the contract price. The buyer may also adjust the annual target of the next contract year upward to compensate for how much has been under-delivered.

Assume a 5-turbine-farm managed via a PPA, turbines 1 and 2 indicate RULs on Day 0, turbine 3 operates normally, and turbines 4 and 5 are non-operational. Predictive maintenance value paths of all turbines with RULs need to be combined together because maintenance will be performed on multiple turbines on each visit (see Xin et al. [2015] for details on how the paths are combined for multiple turbines). Cumulative revenue loss, avoided corrective maintenance cost, and predictive maintenance value paths for turbines 1 and 2 are shown in Figure 5.

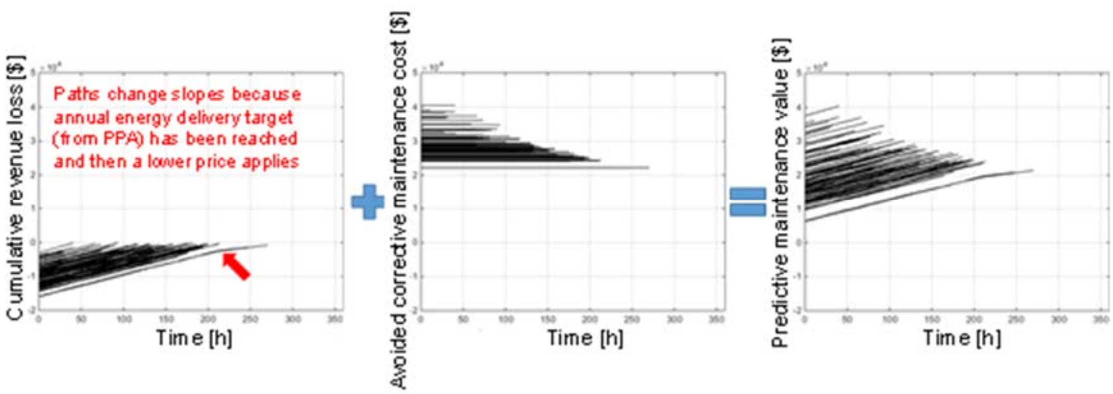

Figure 5. Combined Value Paths for Turbines 1 and 2 in a 5 Turbine Farm Managed by a PPA

Note. Some paths (as indicated by the arrow) change slopes because the annual energy delivery target defined by the PPA has been reached, after which a lower price for the power applies.

Real options analysis run on the wind farm with a PPA demonstrates that the maximum maintenance value varies with the number of turbines that are down (non-operational). Figure 6 shows the results. The result that corresponds to Figure 5 is the right most result in Figure 6.

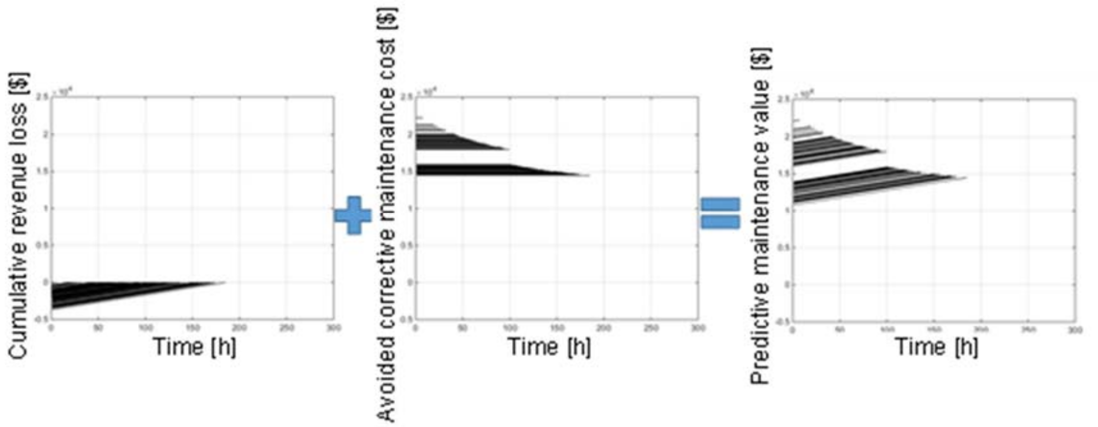

Figure 6. Example of the Simulated Paths After an RUL Indication for a Single Non-Production System Managed Under an Outcome-Based Contract

Generalization of Predictive Maintenance Options With Outcome-Based Contracts (Non-Production Earning Systems)

The real options approach for the predictive maintenance planning described in the sections A Real Options Approach to Maintenance Planning and Example—Wind Turbine With an Outcome-Based Contract assumes that the system is revenue earning (e.g., a wind turbine or aircraft engine). In this section, a generalization of the model is developed and applied to the non-production systems. For example, the hourly rate (e.g., per available hour) in PBL contracts is a fixed number. Hence, it creates a different challenge than selling the energy, which produces a variable amount of revenue.

To start with, we assume a single system (e.g., an aircraft engine) with PHM embedded. This system is managed under an outcome-based contract between a contractor (e.g., the OEM of the engine) and a customer (e.g., an airline), in which the availability is the contracted-for measurable performance outcome. The customer pays a fixed contract price to the contractor for each unit of time the system is operating; the contractor compensates the customer for each unit of time the system is down (non-operational). The contractor is responsible for all the maintenance activities. On Day 0, an RUL is predicted by the PHM, and the contractor needs to decide if and when to implement the predictive maintenance; alternatively, the system will be operated until failure, at which point corrective maintenance will be performed (we assume that safety is not compromised). It is reasonable to assume the predictive maintenance will cause a lower cost (part, service, labor, etc.) and shorter downtime than a corrective maintenance.

Integrated PHM and Inventory Management

The decision to act on PHM indications (RUL predictions) will be influenced by the inventory of spares (for the system) that are available. An integrated model to address both PHM and inventory is described here. This integration clarifies how PHM should be used to make maintenance and logistics decisions and how it impacts inventory management. Here, the primary focus is on individual component prognosis (e.g., an aircraft engine in considered to be an individual component for the purpose of this discussion) and the system-level maintenance support and management decision.

Inventory modeling is an important part of the integration of PHM and inventory management. For example, Fang Tu et al. (2007) have used a multi-state Markov network to model different levels of inventory. However, this model does not consider the best time to perform maintenance (it only considers the inventory size). The model discussed here addresses the best time to perform maintenance. The goal of this model is “when-to-act” rather than “how many spare parts to order.” This assumption allows this model to be extended to the case of multiple systems using a single shared inventory (e.g., a fleet of aircraft all drawing engines from the same inventory).

This model simulates the case where upon RUL indication, the spare part is not available and it takes some time t_s for it to become available. If the maintenance starts at a time point before the spare part arrives, a penalty on the contractor will occur (e.g., to expedite the spare order). In practice, t_s is coming from a probability distribution that models the arrival of the spare part.

The cumulative revenue loss, the avoided corrective maintenance cost, and the predictive maintenance value paths can be simulated as shown in Figure 6. The avoided corrective maintenance cost in the middle plot and the predictive maintenance value paths in the right plot separate into two groups where the penalty for implementing corrective maintenance before ts occurs to the upper group of paths and not in the lower.

By applying the ROA approach, the optimum predictive maintenance date can be determined, as shown in Figure 7. Similar to a wind farm managed under a PPA, when we consider a fleet of systems under an outcome-based contract, both the cumulative revenue loss and the avoided corrective maintenance cost paths for the systems with RULs are influenced by the contract price, availability requirement, penalization mechanisms, and the operational state of the other systems in the fleet.

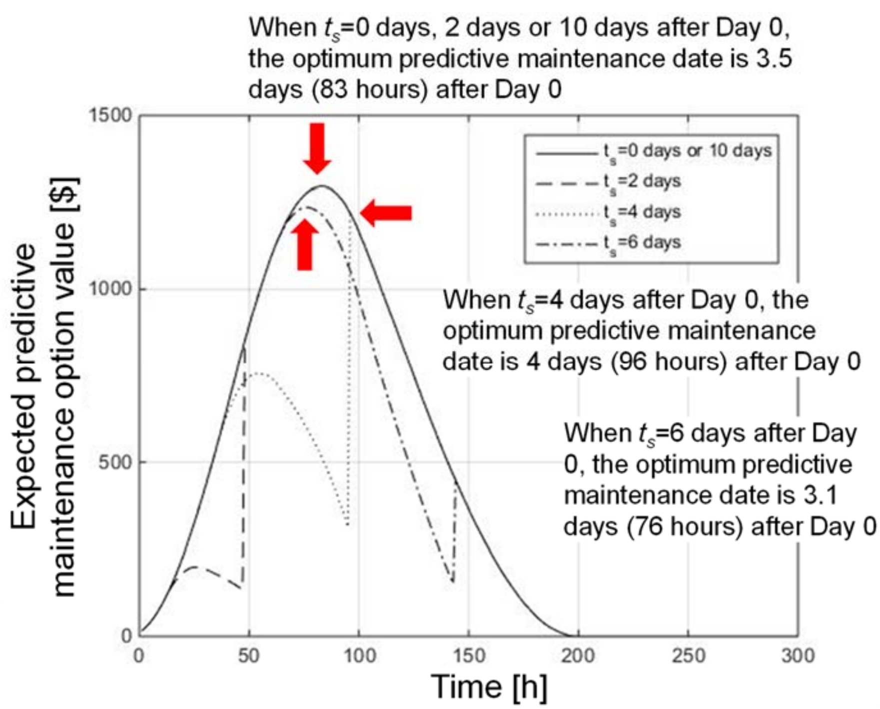

Figure 7. Optimum Maintenance Date Determined by the ROA Approach (Pointed to by the Arrows)

Note. When t_s changes, the optimum date may also change.

Conclusions

The objective of this work is to find the optimum predictive maintenance opportunity for systems managed under outcome-based contracts. Uncertainties in the RUL predictions from PHM and other sources are considered. This work demonstrates that the optimum action to take when a system presents an RUL depends on whether the system is an individual or is part of a larger population of systems managed via an outcome-based contract.

When considering non-production systems, the availability of a required spare part in the inventory is added to the model, and both the inventory and PHM are taken into account when making the decision on best time to perform maintenance.

Our vision is to develop a multidisciplinary outcome-based real options pricing model for supply chain and logistics design to determine the optimum performance metrics and an optimum payment plan (amount, term, incentive fees, and penalties) during the total life cycle of critical systems in PBL contracts. The proposed integrated PBL contract would address public policy and management in the field of government acquisition as well as have applicability to many types of non-governmental performance-based contracts. It includes economics, financial management, risk management, marketing, contracting, logistics, test and evaluation, and systems engineering management.

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