ABSTRACT

Title of Document: AN OPTIONS APPROACH TO QUANTIFY THE VALUE OF DECISIONS AFTER PROGNOSTIC INDICATION

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Safety, mission and infrastructure critical systems have started adopting prognostics and health management, a discipline consisting of technologies and methods to assess the reliability of a product in its actual life-cycle conditions to determine the advent of failure and mitigate system risks. The output from a prognostic system is the remaining useful life of the host system; it gives the decision-maker lead-time and flexibility in maintenance. Examples of flexibility include delaying maintenance actions to use up the remaining useful life and halting the operation of the system to avoid critical failure.

Quantifying the value of flexibility enables decision support at the system level, and provides a solution to the fundamental tradeoff in maintenance of systems with prognostics: minimize the remaining useful life thrown while concurrently minimizing the risk of failure. While there are cost-benefit models to quantify the value of implementing prognostics, they are applicable to the fleet level, they do not incorporate the value of decisions after prognostic indication (value of flexibility or contingency actions), and do not use PHM information for dynamic maintenance scheduling.

This dissertation develops a decision support model based on ‘options’ theory- a financial derivative tool extended to real assets - to quantify maintenance decisions after a remaining useful life prediction. A hybrid methodology based on Monte Carlo simulations and decision trees is developed. The methodology incorporates the value of contingency actions when assessing the benefits of PHM. The model is extended and combined with least squares Monte Carlo methods to quantify the option to wait to perform maintenance; it represents the value obtained from PHM at the system level. The methodology also allows quantifying the benefits of PHM for individualized maintenance policies for systems in real-time, and to set a dynamic maintenance threshold based on PHM information.

This work is the first known to quantify the flexibility enabled by PHM and to address the cost-benefit-risk ramifications after prognostic indication at the system level. The contributions of the dissertation are demonstrated on data for wind farms.

AN OPTIONS APPROACH TO QUANTIFY THE VALUE OF DECISIONS AFTER PROGNOSTIC INDICATION

By

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Dissertation submitted to the Faculty of the Graduate School of the
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Preface

Engineering systems are increasing in complexity. Servicing those systems has emerged as a key to competing globally. Prognostics and health management (PHM) has emerged as a promising discipline that allows maintenance contingent on the health state of the asset and to mitigate the system's risks.

PHM is an interdisciplinary field that merges together engineers, mathematicians, computer scientists, risk analysts and others to improve systems' safety and reduce life-cycle cost. PHM techniques have been successfully demonstrated on a number of applications such as jet engines, wind turbines, gas turbines, and locomotives.

I was fortunate to do an internship at CALCE in 2006, and work on the return of investment for the implementation of PHM in electronic systems. After all, new engineering technologies ought to be supported by business cases. In the years after, I got the opportunity to work on a number of PHM problems involving machine learning and decision support. While learning and working on those problems, I identified a gap that can potentially push the technology forward; maximizing the value of PHM by addressing the cost-benefit-risks ramifications after prognostic indication. My advisers, Professor Peter Sandborn and Professor Michael Pecht, supported this initiative and guided me through a research journey to address the problem of decision after prognostic indication and create methods to truly support what we envision a new maintenance paradigm.

This dissertation displays the ideas that I shaped through my internship at CALCE, my years in graduate schools (University of Maryland), and my two internships at GE Global Research. Having said this, the work does not reflect the ideas or thoughts of GE nor any industrial sponsor that I worked with during my years in graduate school.

Dedication

I dedicate this work to my mother (Jeannette), brother (Joseph), sister (Rita), and the greatest man I have known; my father- the late Nabil Youssef Haddad (1944-2011).

Acknowledgements

I am grateful for the support of my advisors; Professor Peter Sandborn and Professor Michael Pecht. They graciously provided coaching, academic advising, and financial support that allowed me to undertake this work. I thank them for giving me the opportunity to present at CALCE Consortium meetings, travel around the world to present cutting-edge research, and most importantly their mentorship. I would also like to thank my committee members; Professor Abhijit Dasgupta, Professor David Barbe, and Professor Linda Schmidt. I would also like to thank Professor Steven Gabriel and Professor Inbal Yahav for their invaluable feedback.

I would also like to thank the more than 100 companies and organizations that support research activities at the Center for Advanced Life Cycle Engineering (CALCE) at the University of Maryland annually and, specifically, the CALCE Prognostics and Health Management Consortium members.

I am grateful for the machine learning lab at GE, particularly: Dr. Piero Bonissone, Dr. Neil Eklund, and Dr. Anil Varma, for all the training and mentorship they provided me during the two internships in Niskayuna in 2010 and 2011.

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Nomenclature

BL	Binomial Lattice
B-S	Black-Scholes
CBA	Cost Benefit Analysis
CBM	Condition-Based Maintenance
DD	Data-Driven
DoD	Department of Defense
ISHM	Integrated Structural Health Monitoring
LSM	Least squares Monte Carlo
MC	Monte Carlo
MRO	Maintenance Repair and Overhaul
MU	Monetary Units
NFF	No-Fault-Found
NPV	Net Present Value
OEM	Original Equipment Manufacturer
O&M	Operation and Maintenance
PBL	Performance-Based Logistics
PHM	Prognostics and Health Management
PM	Preventive Maintenance
PoF	Physics of Failure

PSS	Product Service System
PV	Present Value
RCM	Reliability-Centered Maintenance
RFID	Radio-Frequency Identification
ROI	Return on Investment
RUL	Remaining Useful Life
TBM	Time Based Maintenance
VAG	Value at Gain
VAR	Value at Risk
VARG	Value at Risk and Gain

Symbols

A_{CR}	Annual cost reservation
C_{hd}	Cost of hiring per day
C_{CBM}	Cost of condition-based maintenance
$C_{Downtime}$	Cost of downtime
C_{EH}	Cost of energy
$C_{Failure}$	Cost of failure
C_{Ld}	Cost of loading
C_{M}	Cost of maintenance
C_{MT}	Cost of material
$C_{Penalty}$	Cost of penalty
C_{TP}	Cost of transportation
C_{USM}	Cost of unscheduled maintenance
C_{f}	Capacity factor
C_{old}	Cost of unloading
C_{t}	Cash flow at time t
F_{C}	Failure consequence
L_{RT}	Labor rate per hour

N_{dy}	Number of days
N_{pn}	Number of personnel
V_{At}	Tax
V_M	Value of cost avoidance opportunities and revenue from using the remaining useful life (RUL)
W_{hr}	Work hours per day
X_i	The value of V_M at current time
X_{i+1}	The value of V_M at time (current time + 1)
p_i	Probability of event
$\beta_{i,r}$	Least squares coefficients
$\phi_0, \dots, \phi_R$	Basis functions
CA	Cost avoidance opportunities
N	Support years
NT	Number of turbines
R	Revenue generated from using the RUL
TC_{AS}	Total cost of access
TC_{LB}	Total cost of labor
TC_{MT}	Total cost of material

TC_{PL}	Total cost of production lost when system is down
WT_{Pr}	Turbine power rating
X	Random variable
i	Discount rate
α	Failure rate
μ	Drift component in stochastic differential equation
σ	Variance component in stochastic differential equation

Chapter 1: Introduction

This chapter motivates the problem addressed in this dissertation and presents relevant background information for key topics. A summary of the research opportunities (gaps) is presented, the scope and objectives with the key questions addressed in this dissertation are presented, then an overview of the dissertation is provided.

1.1 Motivation

The value of safety, mission and infrastructure critical systems, such as aircraft, wind turbines, oil and gas drilling equipment, and airport monitoring systems, is associated with their availability. Availability is the ability of a service or a system to be functional when it is requested for use or operation (Jazouli and Sandborn, 2010); it is a function of reliability and maintainability. Commercial airlines go out of business if their planes are not available to fly; 911 systems are useless if they are not available when people need to call them; and wind farms cannot be depended on for energy generation if they are always down and waiting for maintenance.

To avoid unanticipated failures and ensure high availability, many safety, mission, and infrastructure critical systems have begun to employ prognostics and health management (PHM) techniques that warn users (and/or maintainers) before systems fail. PHM is a discipline comprised of technologies and methods designed to assess the reliability of a product in its actual life-cycle conditions to determine the advent of failure and mitigate system risks (Pecht, 2008), (Cheng et al., 2010). The PHM system gives information on the remaining useful life (RUL), which allows the decision-maker to take appropriate actions to manage the system's health prior (or sometimes upon) failure.

As an example of the actions that can be taken, consider an aircraft with prognostic capabilities flying between two locations: A and B, Figure 1. A prediction of the remaining useful life (RUL) of a critical system in the aircraft is obtained during a flight. In an ideal scenario, several contingency actions or options are available to the decision maker such as: 1) fly the aircraft to location B, but slow down so that less damage is accumulated, 2) return to location A, 3) land the plane at an alternative location, 4) continue operating the system until failure thus making use of the whole RUL. If the decision-maker chooses to continue to location B, new options arise: 1) maintenance can be performed at location B, 2) operation of the plane can continue as scheduled until a later time and/or alternative location for performing maintenance is reached, or 3) the flight schedule can be changed to route the plane to an alternative location for maintenance.

Although the example in Figure 1 is hypothetical, it would be ideal to be able to operate under such conditions whereby the decision-maker can choose among a host of options to manage the health of the system and maximize the value obtained from PHM.

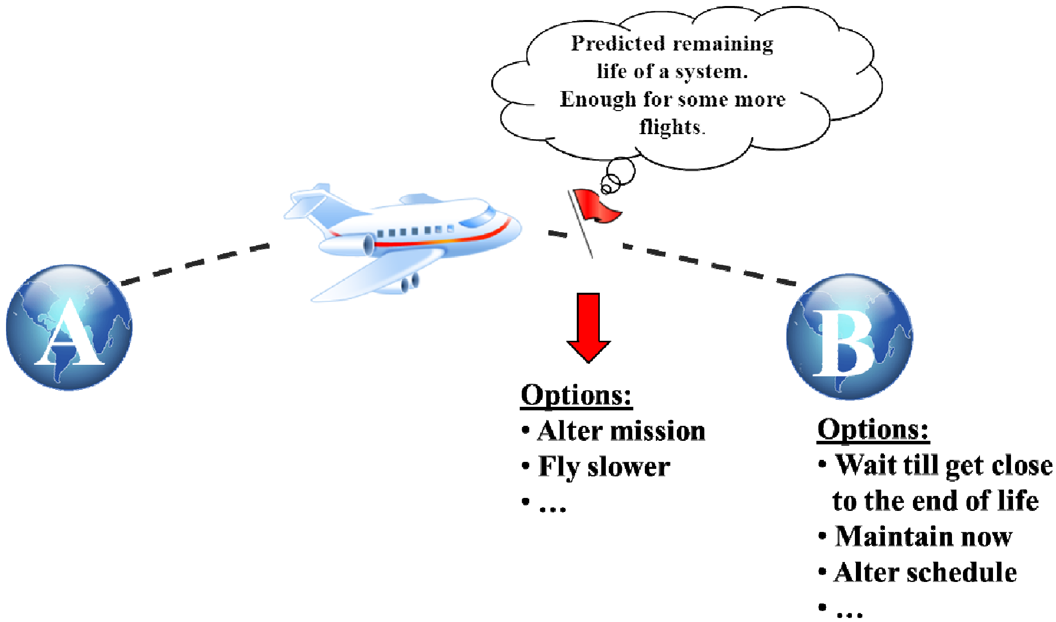

Figure 1- Hypothetical example of options arising after a prognostic indication

Considering another example, an offshore wind farm has 40 turbines. If each of the turbines (or subsystems in the turbines) has a unique remaining useful life (with its respective uncertainty), what is the best way to perform maintenance when the cost of performing maintenance on one or more turbines is significant? Figure 2 shows such scenario. A health index that measures the "risk" of failure for each turbine is shown along with a proposed threshold for maintenance.

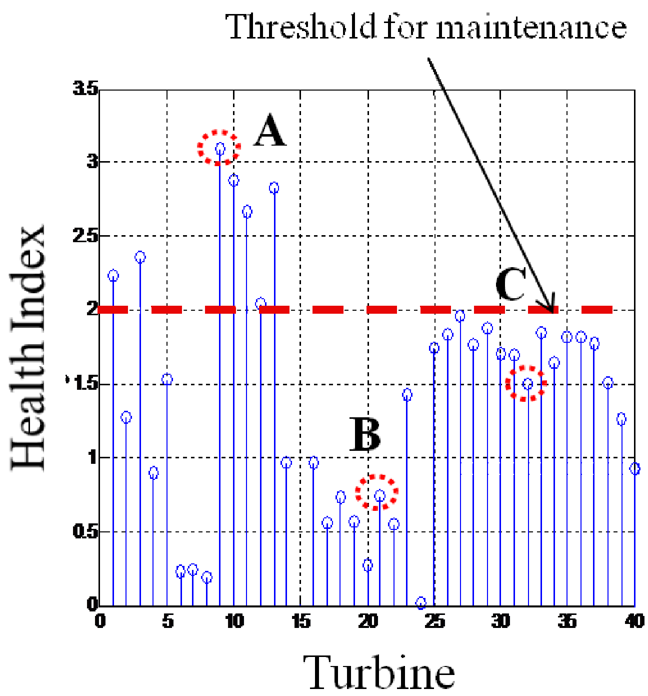

Figure 2- Illustration of the state of health of multiple wind turbines in a wind farm

If the wind turbines are offshore, for example, sending a maintenance vessel to the wind turbines is an expensive proposition and knowing which turbines need to be fixed when the maintenance vessel is on site is important – it may be significantly less expensive to throw away RUL in wind turbines than to risk having them non-operational or having to make special trips to maintain them. Consider the turbines A, B, and C in Figure 2. If a maintenance vessel is to be sent out, turbine A would be maintained given that is above the maintenance threshold. Turbine B would not be maintained since it is well below the threshold, but how about turbine C? Should it be maintained now? Or should we wait for next time the vessel is out for maintenance? The real issue is where should the threshold be? The threshold is not a constant, it varies depending on the when the maintenance vessel will return to the wind farm, the expected weather conditions, the availability requirement for the wind farm, and the maintenance options you have.

Waiting is one of the options that the decision-maker can take. Like any other option, it has a value associated with it; if the decision-maker waits until the gearbox of a turbine fails, then revenue is generated from producing power, but a high cost is incurred for replacing the gearbox.

To illustrate this point further, consider an example of wind turbine with a power rating, WT_{PR}, of 600KW. Based on the research and data published in (Andrawus et al. 2006), the revenue from a turbine can be calculated with the following equation:

$$Revenue = N_{dy}(24)WT_{PR}C_{EH}C_f \tag{1}$$

$Revenue$ corresponds to the revenue generated by a turbine (analogous to production loss, as identified by Andrawus et al. 2006) given a particular cost of energy C_{EH}. N_{dy} is the number of days considered in the calculation of the revenue generated, and C_f is the capacity factor; the ratio of how much power a turbine is generating over a period of time to the maximum theoretical power (it is considered representative of uncertainty in wind speed over a period of time). This factor is highly influenced by the properties of wind: if wind is blowing at a high speed constantly the turbine will generate more power. However wind speed has an uncertainty associated with it and is dependent on a number of factors including month of the year. Assume the uncertainty in wind speed is reflected in an uncertainty in the capacity factor. Consider two scenarios for maintenance: 1) scheduled maintenance is performed next month with a projected capacity factor of 33%; 2) wait for an additional month, and perform condition-based maintenance (CBM) in two months where capacity factor for the first month is 33% and there are three possibilities for capacity factor for the second month; 70%, 33%, and 5%; each with its respective probability of occurrence as seen in Figure 3.

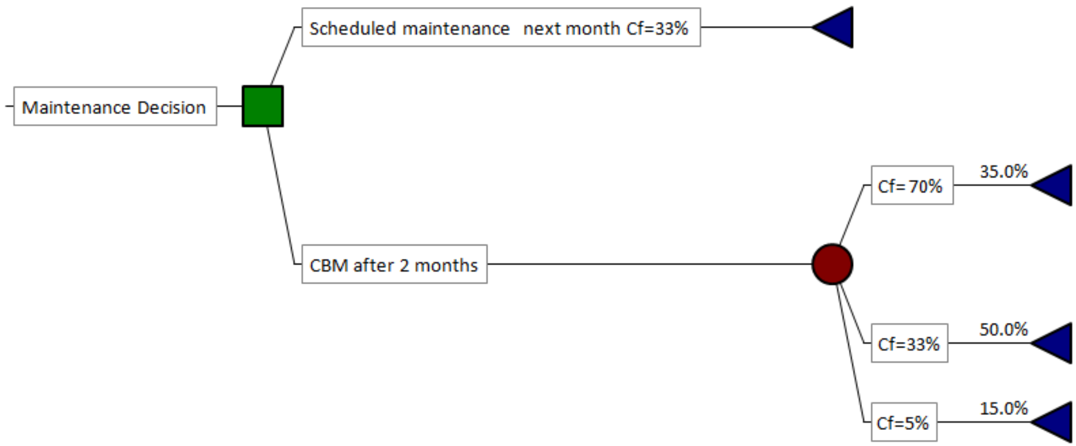

Figure 3- Waiting to perform maintenance

Assuming a cost of energy of $0.17/hour, the calculation using equation (1) for the two scenarios leads to revenue of $24,235 for scenario (1), and $54,896 for scenario (2). This implies that <u>waiting</u> for an additional month to perform maintenance will result in 13.2% additional value on the revenue. This is because of the uncertainties in the model, a high projected capacity factor in particular for scenario (2). In this hypothetical example, the decision-maker uses the RUL and harnesses the upside effect of the uncertainties by waiting to perform maintenance.

1.2 Background

This section introduces key-concepts used in this dissertation. The definitions provided in this section serve as background information for general understanding. Some concepts are explained more elaborately in subsequent chapters.

1.2.1 Prognostics and health management (PHM)

Prognostics and health management (PHM) is a discipline consisting of technologies and methods to assess the reliability of a product in its actual life-cycle conditions to determine the advent of failure and mitigate system risks (Pecht, 2008) (Cheng et al., 2010). PHM is an enabling technology that allows the industry to transition from traditional time- or cycle-based maintenance to condition-based maintenance. It also enables performance-based contracts (contracts where the user pays for the outcome of the asset instead of buying the asset), and reduces life-cycle costs (Vichare and Pecht, 2006) and (Jazouli and Sandborn, 2011).

A framework for PHM is shown in Figure 4. The health of the system is monitored continuously with sensor systems. Data is collected and analyzed. The first step in the analysis consists of preprocessing the collected data where outliers are removed, transformations are performed (if needed), gaps in the data are addressed, etc. The data is then used within a diagnostic algorithm; anomalies are reported when there is a change from a healthy state, then the root-cause of the anomaly is identified. A prognostic algorithm is then used to predict how much remaining life the component/system has. The remaining useful life (RUL) estimate can be used for on-board tactical control or off-board strategic planning. The RUL provides the decision-maker with the lead time to manage the health of the system and take the appropriate action prior to the failure.

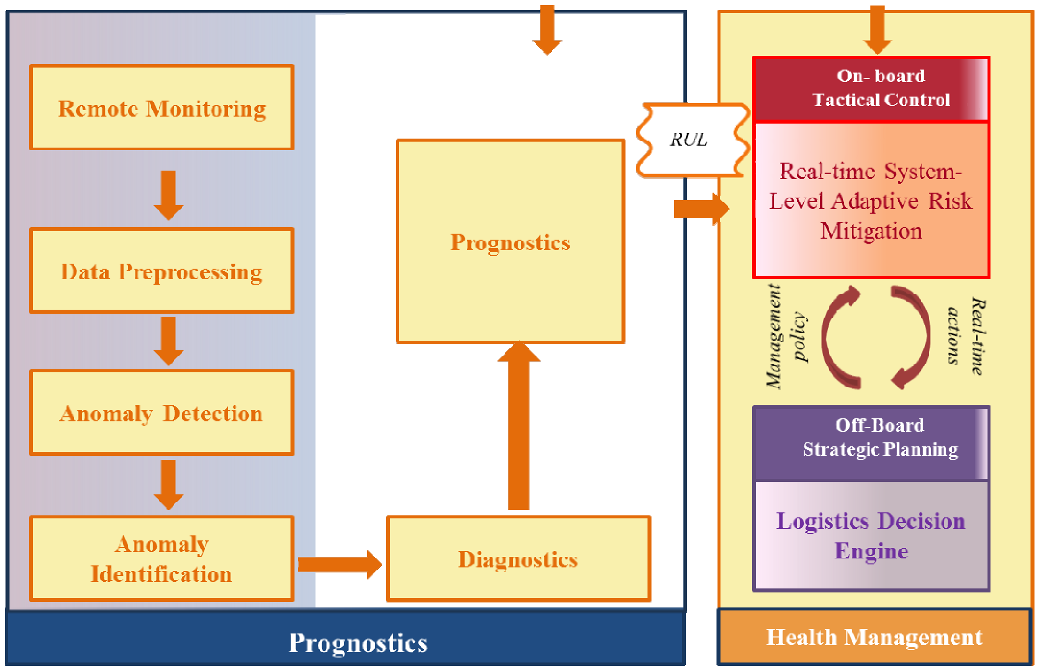

Figure 4- Framework for PHM

There are three main approaches to PHM: data-driven (DD), Physics of Failure (PoF), and fusion approaches. DD methods look at current and historical data to assess the health of the system and estimate the remaining useful life of a product using machine learning and statistical learning models. PoF approaches utilize the knowledge of a product's life-cycle loading conditions, geometry, material properties, and failure mechanisms to estimate its remaining useful life. Fusion, combines the benefits from DD and PoF for better prediction (Cheng and Pecht, 2009). The work proposed in this dissertation does not differentiate between the PHM methods used; it is applicable to any of them as long as the prognostic distance is obtained from them. Prognostic distance is the amount of time before the forecasted failure (end of the RUL).

For the remainder of the dissertation, we assume that there is an RUL that is output from the PHM system, and address the maintenance decision after the prediction is obtained.

1.2.2 Availability

Availability, the ability of a system to function when it is required (Jazouli and Sandborn, 2010), is a function of its reliability and how efficiently it can be maintained. The interest of this dissertation is operational availability which is given by the following relationship:

$$Availability = \frac{uptime}{uptime + downtime} \tag{2}$$

where uptime is the total operational time during that the system is up and running and able to perform the tasks that are expected from it. Downtime is generated when the system is down and not operating when requested.

Performance-based contracting is a contracting mechanism that allows the customer to pay only when the Original Equipment Manufacturer (OEM) has delivered outcomes, rather than merely paying for activities and tasks (Ng et al., 2009). PHM is an enabler of such contracts.

This contracting method is becoming popular for engineering systems especially costly assets such as avionics systems. Figure 5 shows an example of the Product-Service System (PSS) spectrum for a car. The spectrum extends from complete ownership of the car and its maintenance to simply purchasing a service that completely removes the customer from all maintenance activities. For system such as avionics, conventional practices are that the customer owns the avionics and obtains maintenance via a separate maintenance contract (Conventional Model in Figure 5). Outcome-based contracting would be analogous to renting the car and paying for its use.

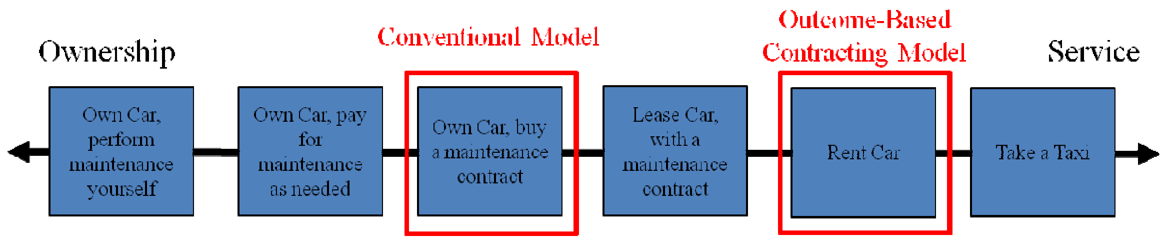

Figure 5- Product service system spectrum for a car

Availability-based contracts are a subset of performance-based contracts. Such contracts can include some form of cost penalty that could be assessed for failing to fulfill a specified availability requirement within a defined time frame (or a contract payment schedule that is based on the achieved availability) (Ng et al., 2009). An example of an outcome-based contract is for aircraft engines where the customer pays for the availability of the engine instead of paying for the engine itself. Performance-Based Logistics (PBL) is an example or performance-based contracts used by the Department of Defense (DoD) for the sustainment of their assets.

1.2.3 Maintenance optimization

There are multiple interpretations of maintenance optimization. Wang (2002) provides a survey of maintenance policies by broadly classifying the objective functions that are optimized in a maintenance problem as: age replacement policy, random age replacement policy, block replacement policy, periodic preventive maintenance (PM) policy, failure limit policy, sequential preventive maintenance policy, repair cost limit policy, repair time limit policy, repair number counting policy, reference time policy, mixed age policy, preparedness maintenance policy, group maintenance policy, and opportunistic maintenance policy among others.

When used in this dissertation, maintenance optimization means maximizing the value that can be obtained from maintenance by considering three alternatives: condition-based, scheduled, and unscheduled maintenance.

1.2.4 Fleet-level versus system-level risk mitigation

The information obtained from PHM can be used for system-level and fleet-level risk mitigation. The output from PHM can be used for real-time tactical control at the system level (to manage an individual instance of a system, e.g., an airplane), or for strategic planning for the fleet such as logistic decision making for the entire fleet (e.g., a whole airline); hence the distinction between system level and enterprise (or fleet level). In this dissertation, the terms fleet and enterprise are used interchangeably.

The distinction between the two levels is also based on availability. A system may not be available at a time when the fleet is still able to meet the required availability. For example, consider a wind farm: it may be able to produce enough power to meet its availability requirement, even if one turbine is not available (this is only an example; wind turbines may not be operating under availability contracts at this time).

1.2.5 Real options

A real option is an alternative or choice that becomes available as a result of a business investment opportunity; it is a right, but not an obligation, to take an action (e.g., defer, expand, contract, or abandon a project) at a predetermined cost called the exercise price, for a predetermined period of time- the life of the option (Copeland and Antikarov, 2001). Real options analyses are decision tools for addressing the value of investments under uncertainty.

Real options are the extension of financial options to real assets. Unlike financial options, real options are not securities and they can't be traded. A real option has an underlying asset, for example a project or a growth opportunity. For real options there's no need for a contract to specify the payoff, and the payoff can be a future cost avoidance (Wallace, 2010).

Adding PHM to a system enables flexibility in the decision-making process, and creates opportunities for the decision-maker to manage the health of the system. When a RUL is known, the decision-maker is faced with multiple options to choose from, each of which will lead to a different outcome and thereby a different value. These options are depicted in the example shown in Figure 1.

1.2.6 Difference between real and financial options valuation

There is a body of literature treating the valuation of real and financial options, which will be discussed in later chapters. It is however necessary to shed the light on the differences upfront. Valuate is the technical term used in the options literature as a synonym of quantify.

Cobb and Charnes (2007) state that a real option derives its value from the potential fluctuations of the cash flows generating the value of the investment project whereas financial options derive their values from potential price movements of the underlying financial asset.

This dissertation capitalizes on the real options literature and introduces the term maintenance options whose quantification must be concerned with determining both a value and an optimal exercise decision rule. The maintenance options derive their value from the PHM system whereby the knowledge of the RUL gives the decision-maker the flexibility to manage the system.

1.3 Evolution of maintenance paradigms

There are different approaches to maintenance, but, fundamentally, depending on if a system has failed, when we think it will fail, how it has failed, there are decisions that need to be made about how and when to maintain it. The goal is to maximize the value of maintenance. Figure 6 shows different maintenance paradigms with their respective maintenance values. The top graph indicates the system health as a function of time, and the bottom diagram shows the maintenance value as a function of time. System health describes the ability of a system to perform its intended functionality. For example, if a system is failed, it cannot perform its intended functionality and is considered unhealthy. The dashed line in the top graph represents the maintenance threshold; it is the threshold upon which maintenance should be performed.

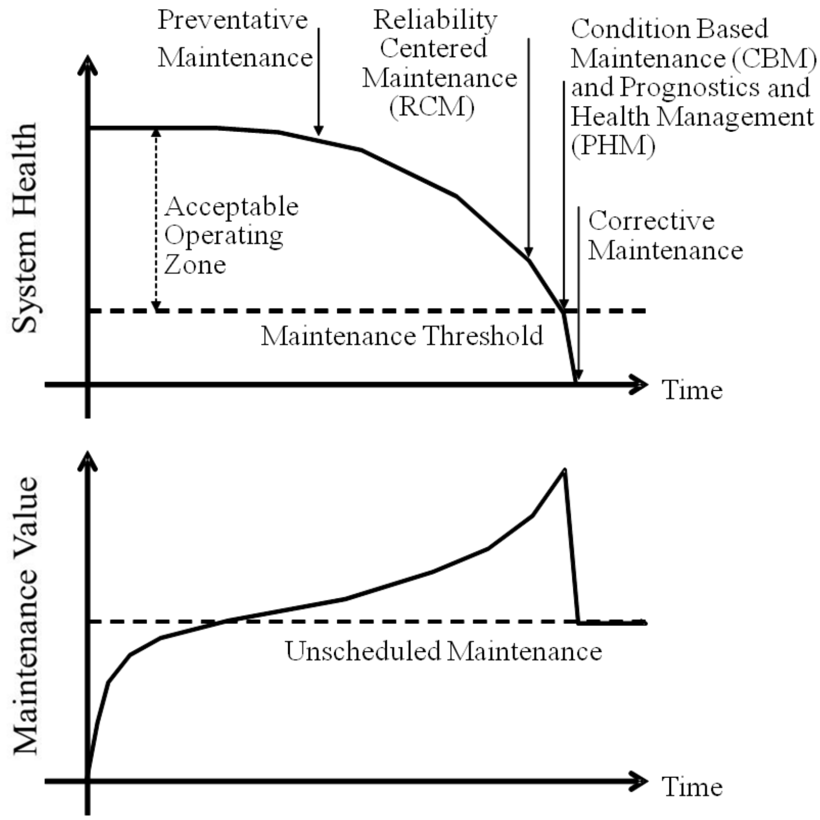

Figure 6- Evolution of maintenance paradigms

Corrective (unscheduled) maintenance consists of maintaining a system upon failure. This allows for the entire life of the system or component to be used. For many systems, corrective maintenance is inefficient, as it can result in long downtimes, catastrophic failures, and unpredictability, which lead to a low maintenance value. Preventive maintenance can be time-based or usage-based. It has a low maintenance value if the time or usage to failure is not well characterized because that throws away substantial RUL. Reliability Centered Maintenance (RCM) accounts for the reliability of the system and is more efficient than the first two paradigms. However, it does not account for the actual usage conditions of the system. Condition-based maintenance (CBM), enabled by PHM, allows the reliability of a system to be monitored in real-time, and is considered to be the paradigm with the highest value, since it minimizes the unused RUL, avoids failures, and presents a lead-time for logistics management, among other benefits.

The maintenance threshold is an important characteristic in Figure 6 and highlights the flexibility enabled by PHM. For unscheduled maintenance, the threshold is fixed, i.e., maintenance is performed upon failure. For CBM, the threshold is not fixed; the decision-maker has the flexibility to define the threshold based on the current and forecasted states of the system, resource availability, usage conditions, etc. An example of exercising this flexibility is to wait, use all the RUL, and maintain just before failure, but due to uncertainties in the RUL prediction, the closer to the end of the RUL one waits, the greater the risk of encountering an unanticipated system failure. This observation is key when assessing the value of PHM.

It is worthwhile to note that RCM, CBM, and PHM may have greater implementation and support costs than unscheduled maintenance – and each of these methods represents the best maintenance approach for particular types of systems. In this dissertation, our focus is on safety, mission and infrastructure critical systems, where the cost of failure and/or downtime is substantial. In such systems, the threshold must be adjusted to harness the benefits of PHM by using the maximum possible RUL and still avoiding failure.

1.4 Fundamental problem in maintenance of systems with prognostics

The fundamental tradeoff in maintenance problems with prognostics is finding the best time to perform maintenance that minimizes the combination of remaining useful life that is thrown away and the risk of expensive unscheduled maintenance (which increases as you use up the RUL). The cost avoidance[1] is an uncertain quantity, decreasing in value since the cost to maintain will increase as the system is used through the RUL. The cost to maintain will be equal to the cost of corrective maintenance if the system is run to failure. Figure 7 shows an illustration of the paths of cost avoidance and revenue opportunities. The cost avoidance is difference between the cost of non-detected failure and cost of detected failure. The diagram on the left in Figure 7 shows that when the prognostic indication is obtained, the cost avoidance is high under the assumption that the cost of a detected failure is smaller than the cost of undetected failure. As the system is used through the RUL, the severity of the failure is constant but the probability of failure will increase and eventually the system will fail and unscheduled maintenance has to be performed; hence the cost avoidance goes to zero. As for the revenue (shown in the diagram on the right in Figure 7), it is shown as an increasing function since the system is operating more and the RUL is used rather than thrown away.

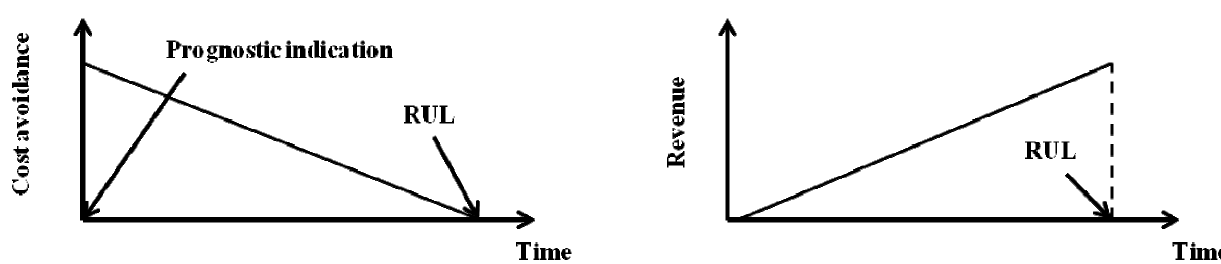

Figure 7- Trend of cost avoidance and revenue opportunities

[1] Cost avoidance is a reduction in costs that have to be paid in the future to sustain a system. Note, the reason that cost avoidance is used rather than cost savings, is that if the value of an action is characterized as a cost savings, then someone wants the saved money back. In the case of sustainment activities there is no money to give back.

1.5 Research opportunities

While there are cost-benefit models for PHM, there is a need for models that address the following gaps: 1) Cost-benefit-risk models for decision support after prognostic indication; life-cycle cost models make assumptions on the complete life cycle of a system, and do not incorporate the value of decisions from the time a prognostic indication is obtained to the end of the remaining useful life. 2) Cost-benefit-risk ramifications of maintenance decisions at the system level; life-cycle cost models tend to focus on decision support at the enterprise level (fleet of systems) and are targeted at strategic decisions, such as logistics planning. Such models evaluate one 'static' maintenance policy by assuming one prognostic distance (that may be optimal over the life-cycle) and compare it to a reference maintenance paradigm (scheduled or unscheduled). There is a need for a cost-benefit model that addresses the value of PHM for individualized maintenance policies for every system in a fleet. 3) A model accounting for all relevant uncertainties that can be updated in real-time for maintenance scheduling for system with prognostic capabilities. Such model can be used to set a dynamic maintenance threshold when requirements have to be met.

Table 1 provides a summary of the gaps in the literature with representative references. The gaps and will be discussed in detail in Chapter 2. Although there may be some attempts to address the gaps, the intent of the table is to highlight the research major research gaps and opportunities.

Table 1- Characteristics of relevant optimization problems

	Life-cycle cost models	Maintenance optimization models	Real options for maintenance applications
Cost/benefit/risk at system level		X	X
Cost/benefit/risk at enterprise level	X	X	
Technical uncertainty	X	X	
Non-technical uncertainty			X
Value of decisions after obtaining RUL prediction			
Options arising to the decision-maker			X
Outcome requirements	X		
Use PHM information for dynamic maintenance threshold			
Representative references	Feldman et al. (2009), Luna (2009), Saxena et al. (2010), Reimann et al. (2009), Grubic et al. (2009), Jazouli and Sandborn (2010 and 2011)	Dadhich and Roy (2010), Camci (2009), Keller et al. (2001), Naikan and Rao (2005)	Koide et al. (2001), Miller and Park (2004), Jin et al. (2009)

1.6 Scope and objectives of this dissertation

This work addresses three major gaps in health management for systems with prognostic capabilities. The objectives of this dissertation are:

1. Define a new class of maintenance options to frame the flexibility enabled by PHM. Quantifying the options allows the value of PHM to be established and use of PHM in systems to be improved.

2. Develop a methodology to represent the value of different options arising after a remaining useful life is obtained.
3. Develop an algorithm to quantify the wait to maintain option. The value of this option will represent the additional value obtained from the PHM system, and will present a solution to the fundamental tradeoff in the maintenance of systems with prognostics. The algorithm can be updated in real-time as new information is obtained.
4. Develop a methodology to define a dynamic maintenance threshold for systems with PHM in order to maximize maintenance value.
5. Apply the methodologies to the maintenance of wind farms to demonstrate the contributions of the dissertation.

1.7 Mathematical abstraction of the problem

After a prognostic indication is obtained, the decision-maker wants to know what the expected value of waiting to maintain is, as opposed to maintaining when the first opportunity arises. Answering this question will establish a system-level cost-benefit-risk model to show the value of PHM for individualized maintenance policies, and set a dynamic maintenance threshold based on PHM information.

If we let X_i be the value of the mission at the current time - a combination of cost avoidance opportunities and opportunities for revenue generated from running the system, it is desirable to know the expected value of X_i if the maintenance option of waiting is exercised (maintenance is delayed for a period of time). This relationship is expressed mathematically in equation (3):

$$E[V(X_{i+1})|X_i] \tag{3}$$

Equation (3) represents the value obtained from running the system through the RUL; hence represents the additional value obtained from PHM. This will help maximizing the benefit from PHM, quantify the value of waiting, and set a dynamic maintenance threshold. Maximizing (3) and expressing it in abstract form:

$$\begin{aligned} &\text{maximize}(\mathit{the\ value\ of\ waiting}) \\ &s.t \\ &value = f(cost\ avoidance, revenue) \\ &cost\ avoidance = f(reliability, maintainability) \end{aligned} \tag{4}$$

There are several steps enabling the solution of this problem; they will be discussed in the following chapters.

1.8 Dissertation overview

This dissertation is structured as follows: Chapter 1 provides the background and key-concepts associated with the value of maintenance options problem. The objectives and a mathematical abstraction of the problem are presented. Chapter 2 surveys relevant previous work on health management for systems with prognostic capabilities, and identifies research gaps. Chapter 3 presents maintenance options whose quantification represents the value of actions after prognostic indication, and a method to incorporate the value of flexibility when quantifying the benefits of PHM. Chapter 4 presents an algorithm based on the least squares Monte Carlo (LSM) method to put a value for the waiting option (one type of maintenance options). The contributions of the dissertation are demonstrated with a case study of wind turbines in Chapter 5. Chapter 6 concludes the dissertation, lists the contributions, the broader impact of the work, and suggests key topics for future work on the subject.

Chapter 2: Literature Review and Research Gaps

This chapter reviews: the work on health management for system with prognostic capabilities, relevant maintenance optimization problems, and real options for engineering and maintenance applications. The gaps in the literature are highlighted and will be addressed in subsequent chapters.

2.1 Potential benefits of PHM

Systems include PHM for a number of reasons (Pecht, 2008), (Feldman et al., 2009), and (Jazouli and Sandborn, 2010). The following is a list of the potential benefits of PHM:

- Failures avoided
    - Minimizing the cost of unscheduled maintenance
    - Increasing availability
    - Reducing risk of loss of the system
    - Increased human safety
- Minimizing loss of remaining life
    - Minimizing the amount of remaining life thrown away by scheduled maintenance actions
- Logistics
    - Better spares management (quantity, refreshment, locations)
    - Lead time reduction
    - Better use of inventory
    - Optimization of resource usage
- Repair
    - Better diagnosis and fault isolation
    - Reduction in collateral damage during repair

- Reduction in redundancy
- Reduction in no-fault-founds

2.2 Life-cycle cost models

A number of papers present proposals for adopting PHM to articulate an economic justification through life-cycle cost models, which are part of a business case. Examples of such models include return on investment (ROI), total value, and technical value. The following sections present models supporting the implementation of PHM. While some models may fit in more one category, the intent is to provide the objectives of using particular approaches.

Return on Investment (ROI) is a useful means of gauging the economic merits of adopting PHM. The determination of the ROI allows managers to include quantitative, readily interpretable results in their decision-making. ROI analysis may be used to select between different types of PHM, to optimize the use of a particular PHM approach (optimize the prognostic distance in this case), or to determine whether to adopt PHM versus more traditional maintenance approaches (Feldman et al., 2009). ROI is typically defined by:

$$\mathrm{ROI} = \frac{(\mathrm{Return} - \mathrm{Investment})}{\mathrm{Investment}} = \frac{(\mathrm{Avoided\ Cost})}{\mathrm{Investment}} - 1 \tag{5}$$

where the return in the case of PHM is generally a future cost avoidance.

ROI calculations are application specific as the breakdown of cost avoidance and investments can differ from one application to another. Research that address ROI for PHM includes the ROI associated with PHM ground vehicles, power supplies, telecommunication and electronics (Vohnout et al., 2008) (Tuchband and Pecht,

2007) (Wood and Goodman, 2006) and (Feldman et al., 2009). NASA proposed the ROI of prognostics in aircraft structures (Kent and Murphy, 2000). Banks and Merenich, (2007) expressed that ROI was maximized when the time horizon was the greatest, and when the number of vehicles and the failure rates were the largest.

Life-cycle cost models to support PHM implementation can be justified with metrics other than ROI. Banks and Mereneich (2007) provided a cost-benefit analysis of PHM for batteries within ground combat vehicles using the Trade Space Visualizer software tool. An analysis of PHM for JSF aircraft engines was developed using a methodology that employed Failure Modes, Effects, and Criticality Analysis (FMECA) to model hardware (Brotherton and Mackey, 2001).

Gurbic et al. (2009) proposed a Product-Service System (PSS), which offered a bundle of products and services where emphasis shifts from selling a product to selling the use of a product. This work was a move towards performance-based contracting; a contracting mechanism that allows the customer to pay only when the Original Equipment Manufacturer (OEM) has delivered the outcomes, rather than merely paying for activities and tasks (Ng et al., 2009). Leao et al. (2008) described a set of metrics developed to evaluate the performance of PHM and a cost benefit analysis (CBA) was included in their review. Yang and Letourneau (2007) proposed a method to quantify the cost savings expected from a given prognostic model that takes realistic inputs from the user. Wang and Pecht (2011) presented a cost model to: 1) show the economic merit for the implementation of canaries in electronic systems, and 2) the time to replace the line replaceable unit based on the information from the canary. A review of cost-benefit-risk metrics is also provided by Saxena et al. (2010).

2.3 *Maximizing maintenance value*

Another approach for supporting the application of health management for systems with prognostic capabilities are models to maximize maintenance value. These models consist of availability maximization, optimization of some benefit function, logistics optimization and others.

Jazouli and Sandborn (2010 and 2011) proposed a ‘design for availability method’ where they solve for system attributes that will result in a desired availability. The majority of previous work on subject tackled the problem from the opposite direction: given system attributes, generate the system’s availability. The design for availability model could be used to generate system reliability, operation, sparing, etc., for a specific availability, i.e., for a specific uptime and downtime.

A popular approach is to optimize an objective function while honoring the constraints on requirements and resources to arrive at a beneficial maintenance policy. Although some of the methods may be cost-benefit metrics or accounted for in the business cases for PHM, they can be used for optimal maintenance policy. Kacprzynski et al. (2001) discussed a prognostic modeling approach based on cost/benefit to optimize time for on-line waterwashing or crank washing for the LM2500 and Allison 501-K17 gas turbine. Khalak and Tierno (2006) proposed a joint optimization problem that is shown to be equivalent to a shortest path problem. Their work intended to give the tradeoffs in using damage prediction technologies in the overall health management solution. Luna (2009) discussed the impact of PHM on the maintenance policy and the benefit from condition-based maintenance (CBM) that is enabled by PHM, and the maintenance attributes and metrics for maintenance for systems with prognostic capabilities. Reimann et al. (2009) proposed a scheduling algorithm that leverages CBM data to determine when maintenance should be performed. The objective of their work is to reduce the cost associated with performance based contracts to improve profit margins. An example consisting of 50 aircraft was analyzed and the results indicated that significant cost savings can be achieved by utilizing a CBM scheduling algorithm. In addition, to the maintenance cost savings, the CBM scheduling algorithm is also able to identify potential resource limitations within the maintenance organization. Hoyle et al. (2007) proposed a cost-benefit analysis as a multiobjective optimization problem. One of the problems is to address the inspection interval. Khalak and Tierno (2006) presented a methodology that can be applied for the estimation of the supply chain benefits of prognostics applications. This methodology yields an optimal stock level for each node in the supply chain. The stock level is a function of the lead time provided by the prognostics, taking into account some restrictions and some prognostics design constraints. Wang and Hussin (2009) discussed a scheduling problem of condition based maintenance based on oil analysis where both monitored external and internal variables were considered.

MacConnell (2007) defined a set of scenarios made possible by the ideal integrated structural health monitoring (ISHM) system. These scenarios and the technologies associated with them were evaluated for their system impact, design impact, innovativeness and timeliness. Keller et al. (2001) proposed a method to estimate the benefits of prognostics in specific applications where the output is a life-cycle payoff as well and include an assessment of the technical risk of the application.

Drummond and Yang (2008) proposed a method to ‘reverse engineer’ the effective range of algorithms and estimate its potential cost savings. Drummond and Holte (2006) and (Drummond, 2007) proposed cost curves as a means to evaluate the effectiveness of classifiers and to choose among maintenance policies.

2.4 Other relevant optimization literature

Availability maximization is an important problem for many industries such as avionics, manufacturing, production among others. The objective is typically to maximize the availability of a system throughout a finite or infinite horizon accounting for some downtime events such as maintenance and sometimes accounting for reliability or the degradation of the systems that is often times depicted in Markov models. The decision variables are typically elements of the maintenance problem such as number of spares or crews, etc. Dadhich and Roy (2010) is a good example of availability optimization for preventive maintenance. Their objective is to maximize availability and a benefit function.

Other relevant optimization problems are real-time which optimization refers to evaluation and alteration of operating conditions of a process continually to maximize the economic productivity of the process. This optimization method is prevalent in the chemical engineering realm where the process is continuously monitored and optimized to generate maximum availability and profit. In an online decision problem, one makes a sequence of decisions without knowledge of the future. Each period, one pays a cost based on the decision and observed state (Groethschel et al. 2001).

Scheduling maintenance is a problem that has been studied for decades and was applied for different maintenance paradigms: scheduled, condition-based, opportunistic maintenance, and others. The most relevant scheduling problems are for condition-based and the opportunistic maintenance. In opportunistic maintenance, the problem is to choose the optimal number of subsystems to maintain when system is down for maintenance. In the scheduling problem, the decision is on the optimal time to perform maintenance give a set of constraint (degradation of system, logistics, etc.). Camci (2009) presented a model to use PHM information for scheduling condition-based maintenance.

Maintenance scheduling models are proposed in the reliability and operations research literature: Wang et al. (2010) used the delay time concept for scheduling inspection. Li et al. (2009) develop a reliability based dynamic maintenance threshold. Bouvard et al. (2011) presented a method for the maintenance optimization of vehicles. The model in Bouvard et al. (2011) addresses maintenance scheduling and grouping based on condition of system. Aissani et al. (2009) presented a reinforcement approach for the dynamic scheduling of maintenance tasks in the petroleum industry. Aissani et al. (2009) also provide a review of the state of the art in dynamic scheduling.

The inventory problem has been long studied and sometimes referred to as a the newsvendor problem. Generally speaking, a policy is to be derived to satisfy a demand that may be stochastic and constraints on the inventory and sometimes penalties. Inventory levels drops until a point where a reorder is executed. This is analogous to the availability being considered where availability has to always be maintained above a certain level. In such problems demand is considered stochastic.

Table 2 gives examples of some of the optimization problems listed in this section along with the objective function.

Table 2- Examples of relevant optimization problems

Problem	**Objective function**	**Author(s), year**
Availability optimization	$max(system\ availability)$	Dadhich and Roy, (2010)
Scheduling and maintenance optimization	$min\begin{pmatrix} failure\ and \\ maintenance\ risks \end{pmatrix}$	Camci, (2009)
Maximize benefit function	$\max\begin{pmatrix} benefit\ function\ for \\ individual\ systems \end{pmatrix}$	Kacprzynski et al. (2001)
Demand-based optimization	$\min_{x} x(inventory)$	Naikan and Rao, (2005)

2.5 Real options

Options are tools that originated in the financial world and then extended to real assets to solve capital budgeting problems where the decision-maker has the flexibility to invest in a project or growth opportunity. Formally, an option is defined as the right but not the obligation to take some action now, or in the future for a pre-determined price (Copeland and Antikarov, 2001). Since the dissertation extends to real options theory to maintenance problems, it is necessary to summarize the work done on real option.

Real options have been used for engineering applications. There is a body of literature that addresses the application of real options to engineering projects, Table

3 below summarizes some of the most common types of options, their description, and the industry where they are commonly used (Trigeorgis, 1993).

Table 3- Common real options (Trigeorgis, 1993)

Category	Description	Examples
Defer	Wait for a number of years before developing	Natural resources
Time to build	Abandon if new information is unfavorable	R&D industries (pharmaceuticals)
Alter: expand, contract	Expand if conditions are favorable	Mine operations
Abandon	Abandon actions permanently	Airlines
Switch option	Use different inputs	Consumer electronics

Real options are increasingly being used in decision support systems. Kim and Sanders (2002) develop a real options framework for strategic decisions in investment in information technology; the work emphasizes on competitor reaction and considers three options: growth, postponement and abandonment. Zhang and Babovic (2011) propose a real options framework that consists of real options methods, Monte Carlo simulations, decision analysis techniques and evolutionary algorithms to design and manage projects in the face of uncertainty. Zhang et al. (2008) study the dynamics of grid computing using a real options framework. The uncertainties in price and demand are the main motives for using this framework. Schober and Gebauer (2011) compare the value of flexibility using decision trees, real options, and an explicit assessment of uncertainties; real options is recommended as an attractive tool for such problems.

Real options analysis has also been used extensively in engineering technology applications such as RFID (Wu et al., 2009) (Lio and Lu, 2009). Past research has focused on cost benefit ratios, discounted cash flows, or net present values to support the decision. The motivation for using ROA in engineering decision making focuses on its ability to account for the uncertainties and the flexibility in the management/investment.

Real options have also been used for maintenance applications. For example, existing work includes the comparison of different maintenance strategies and their effects on the total costs for the maintenance and management of an existing bridge for thirty years (Koide et al. 2001). Real options have also been applied in the maintenance, repair, and overhaul (MRO) industry (Miller and Park, 2004). Miller and Park compare present value (PV) and RO. The PV analysis resulted in a no-go decision; however using the real options framework justified an investment. Jin et al. (2009) used an option-based cost model for scheduling joint production and preventive maintenance for a manufacturing industry when demand was uncertain. The option-based mathematical model in (Jin et al., 2009) provides recommendations for maintenance decision in the environment of uncertain demand.

2.6 Research gaps

While there is a body of literature on health management for systems with prognostic capabilities, a number of gaps have been identified.

Existing cost-benefit models do not incorporate the value of contingency actions (options) that are enabled by PHM. Furthermore, existing cost-benefit models do not present uncertainty management methods and quantify risks for contingency-management based on post-prognostics reasoning; this gap was also highlighted in (Saxena et al., 2010).

Existing cost-benefit models for showing the value of PHM are not applicable to individual systems. State-of the art models such as Sandborn and Wilkinson (2007) and Feldman et al. (2008) are implemented as discrete event simulators and are only applicable at the enterprise-level (to a fleet of systems). The models assume a population of systems and derive the economic merit of implementing PHM by finding the prognostic distance that minimizes the expected life-cycle cost of a maintenance policy, and compare the result to a reference maintenance paradigm (e.g., unscheduled). The single prognostics distance assumption (which may be optimal for the fleet over the support life of the fleet), represents a single maintenance policy. There is a need for a model to address the value of PHM at the system-level for all values of prognostic distance since systems in a fleet may have individualized maintenance policies.

There is a need for models that use PHM information to schedule maintenance. Such models should have the capability to be updated as new information is obtained. Very limited models in the literature address this point.

PHM is believed to be an enabler of outcome-based contracts, but quantification of this claim and its application within outcome-based contracts is in its infancy. Existing models supporting PHM as an enabler of outcome based contracts include Jazouli and Sandborn (2011) and Grubic et al. (2009).

2.7 Summary

This chapter surveyed the literature for the health management of systems with prognostic capabilities along with some publications that are relevant to the problems solved in this dissertation. The gaps in the literature are identified and will be addressed in the subsequent chapters.

Chapter 3: Maintenance Options to Manage Flexibility Enabled by PHM

This chapter starts by discussing risks and uncertainties in decision making. Maintenance options are then presented as means to manage the flexibility in systems, and a mapping from real options to maintenance options is then presented with the appropriate assumptions. Valuation methods and the limitations for their use in the PHM problem are discussed. A new hybrid methodology is presented. The methodology incorporates the value of the options when quantifying the benefits of PHM.

3.1 Risks and uncertainties in decision support

Uncertainty has long been identified as an important factor in the decision-making process for health management of systems. It is at the core of making realistic business cases or health management decisions. Uncertainty captions prediction error, customer demand, resources prices, environmental factors and others. For example, the speed of wind blowing through a particular location cannot be known before it is realized, and thus probabilistic models are needed. There are multiple classifications of uncertainties in capital and infrastructure intensive systems. One particular classification is proposed by (Miller and Lessard, 2001) who defined layers of uncertainty, a simplification of which is shown in Figure 8. The decision-maker's ability to influence uncertainty decreases as we move away from the smaller rings to the larger rings. The smallest ring is the technical risk. Those are the risks with the operation, technology, management. The second ring is less influenced by the decision-maker and corresponds to the uncertainties in the industry and the competition. If a competitor in the wind energy business introduced more reliable turbines, this will affect other companies' business and have less influence when reacting to it. The two outer rings' uncertainty (i.e., market, and natural) corresponds to exogenous uncertainty, which decision-makers can't directly influence, or control.

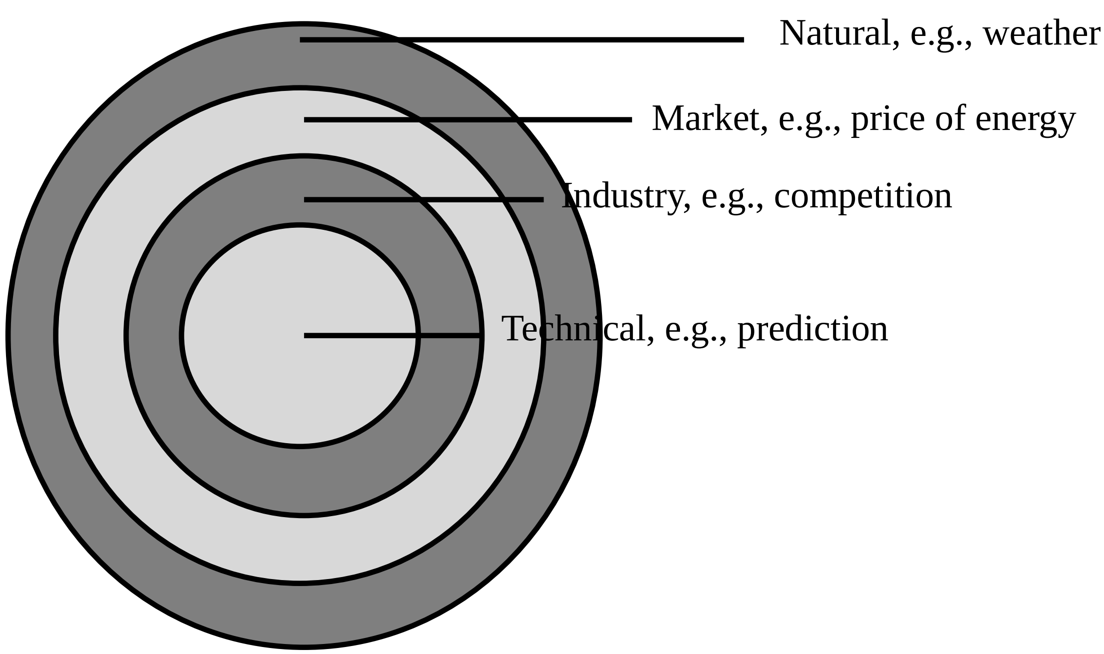

Figure 8- Classification of uncertainty, (Miller and Lessard, 2001)

The choice of uncertainties pertains to the problem under consideration. In some problems for instance, natural uncertainty may have a much bigger impact than other types of uncertainty. In the case of wind energy for instance; the outcomes of the project are highly dependent on wind speed and conditions at a particular site. Assessing the natural conditions and accounting for the uncertainties associated with weather at the site under consideration is of prime importance and are reflected in the decision-making analysis results.

Technical uncertainty is at the core of the maintenance management problem as it significantly influences the outcome of the decision. Any prediction has uncertainties associated with it, which can influence the maintenance costs. Technical uncertainty can be broken down to aleatory and epistemic. Aleatory uncertainty is inherently random, new experiments and more data cannot eliminate this type of uncertainty, and it is usually modeled by distributions. Epistemic uncertainty is due to the lack of knowledge and can be reduced by further data collection and experimentation (Ayyub and Klir, 2006). Figure 9 shows how the uncertainty relates to levels of knowledge.

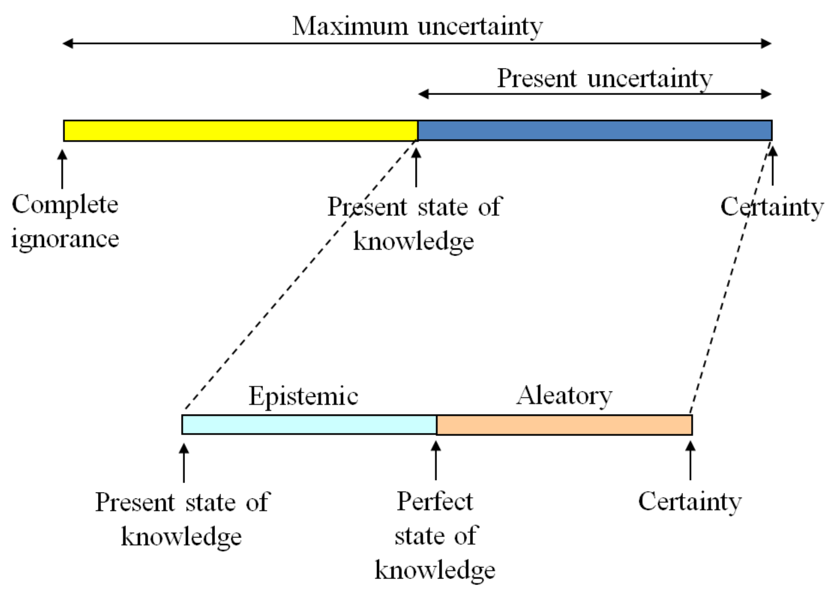

Figure 9- Uncertainty and levels of knowledge, (Aughenbaugh and Paerdis, 2005)

Various modeling techniques have been presented for management uncertainty such as simulations while assuming some stochastic process, decision trees, binomial lattices (BL), tree analysis, etc.

Generally speaking, depending on the characteristics that can be associated with the problem at hand, the choice of method to account for uncertainty is dictated. If uncertainties can be represented by a set of probabilities, then decision tree or similar methods can be appropriate. Rule and fuzzy logic can also represent some types of uncertainties associated with domain knowledge and experts' opinion (Ayyub and Klir, 2006). When distributions can be associated with uncertainties, then simulations may be a preferred way of assessing the effect of uncertainty.

3.2 The flexibility enabled by PHM: maintenance options

A number of the benefits (cost-avoidance opportunities) inherent to PHM are derived from the knowledge of the RUL. After a prognostic indication, the decision-maker is faced with several actions that can be taken to manage the health of the system. Examples of the actions that can be taken are fault accommodation, changing loads, and tactical control. Bonissone (2006) proposes a temporal segmentation for decisions for systems with PHM, where the tactical and operational decisions at the object level are examples of options after prognostic indication. Hence the decision-maker has a set of options among which they can choose. *The term options will be used in the remainder of the dissertation to denote a choice or action the decision maker can take after a prognostic indication*.

Figure 10 shows an example of general categories of options. Note that the options post-prognostic indication can be system specific, but the intent here is to provide a general framework for understanding the options. The decision-maker can choose among a host of options. For instance, maintenance can be carried out immediately after the prognostic indication, or it can be delayed in order to use up the RUL. Alternatively, the mission can be abandoned completely if it is judicious to do so.

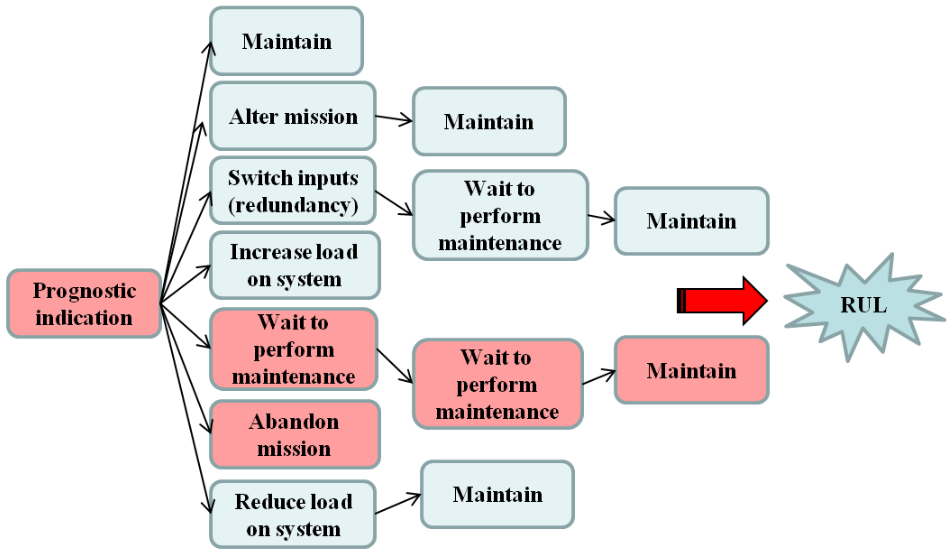

Figure 10- Options arising after a prognostic indication

For a fleet of systems, it is desirable to know the maximum value from PHM that can be generated. Choosing the options with highest values for individual systems will result in a choice of maintenance threshold based on maximum revenue. This concept is illustrated graphically in Figure 11.

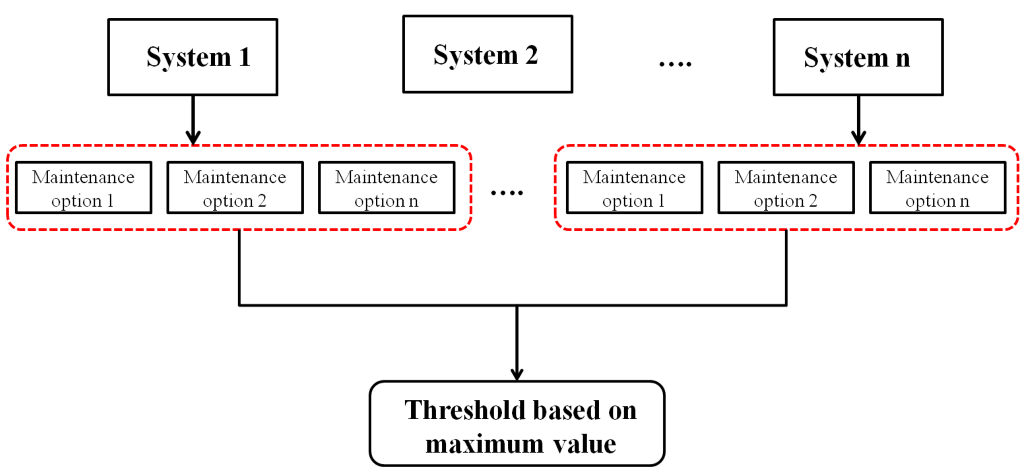

Figure 11- Options acting on a fleet of systems

The key property of an option is the asymmetry of the payoff, an option holder can avoid downside risks and limit the loss to the price of getting the option, while being able to take advantage of the upside opportunities (Adner and Levinthal, 2004). The components that make up real options problems are the following (Copeland and Antikarov, 2001) (Dixit and Pindyck, 1994) (Adner and Levinthal, 2004) and (Greden, 2005): 1) Management flexibility; 2) Uncertainties affecting the decision; 3) Time and resource restrictions on making and implementing a decision; and 4) Cost of acquiring (and sustaining) flexibility.

PHM installed on a system enables condition-based maintenance where the option holder can perform maintenance contingent on the condition of the asset. If the option is not exercised, the option can expire without being used and unscheduled maintenance has to be performed. In the latter case, the option-holder would have invested in PHM but did not use it, hence the asymmetry of the payoff.

Risks and uncertainties are part of any engineering problem. PHM assess the reliability of a system in real-time and enables risk mitigation. This makes real options an attractive tool for assessing the return from a PHM system or algorithm and its effect on the overall management of the system.

For options the action can be taken only within a specific period of time. In systems with PHM capabilities, maintenance can be performed at any time up to the end of RUL where the system fails.

Finally, options have a cost associated with them. In maintenance problems, the investment in implementing and sustaining PHM gives rise to maintenance options. It is worthwhile noting that one investment in PHM gives the decision-maker an infinite number of options. Waiting is one option but can be exercised at many points in time. This is analogous to American option in the finance or real options space.

3.3 Mapping from real to maintenance options

Kodukula and Papudesu (2006) propose a mapping from financial to real options. This dissertation extends the mapping to maintenance option which will lay the ground for methods enabling building cost-benefit-risk models. Table 4 shows the mapping between real and maintenance options.

Table 4- Mapping from real to maintenance options

Real Options	Maintenance Options
Asset/project	System (asset/project)
"Value" of underlying uncertainties	"Value" of underlying uncertainties, cost avoidance opportunities, and revenue from operation of the system
Premium to buy the option	Sunk cost to implement and sustain the PHM system
Cost to carry out the real option	Cost to support maintenance action
Time by which the real option has to be carried out	Prognostic distance

The value of waiting (and related options such as abandoning) are the key to applying options theory to the PHM problem. Hence, we consider the option to wait and the option to abandon and analyze further in the dissertation.

3.4 Methods for quantifying flexibility in projects

Different methods for quantifying flexibility (real options) have been presented in the literature. Some of them have their roots in finance and are the application of financial options pricing methods to real options. Others are specific to real options. Borison (2005) presents a review of the most common methods used for quantifying flexibility with the assumptions made in each method. The paper provides a great comparison of different valuation methods for the same example. The major take-away from the paper is that one ought to be careful about the assumptions made for the valuation of options in order for the analysis to culminate in realistic and meaningful results.

Quantifying flexibility with models borrowed from financial options is the most commonly used approach in the literature. Models include the Black-Scholes (B-S) formula, and binomial lattices. When the problem is dominated with market risk (such as the valuation of an oil company's decision to acquire land and drill for oil, with oil price being the only uncertainty considered) the methods used for financial option analysis can be appropriate. For projects dominated with technical risk, project management methods such as decision trees represent the value of the flexibility better (Borison, 2005). For projects including both market and technical risks, a combination of methods from the financial realm and decision sciences represent the value of the project better (Smith and Nau, 1995) and (Borison, 2005). Stochastic dynamic programming has also been used to deal with flexibility in projects involving technical risks Eckhaus et al. (2009) and Wallace (2010).

Besides the types of risks in the problem, path dependence is a strong influential factor for the choice of method to value flexibility in engineering projects. Engineering projects are typical path dependent in that the value of the project depends on the actions taken by project managers that will change the value of the project. This is not problematic in financial options or projects where there's an asset that can be traded and the price is dictated by the market.

Monte Carlo simulations is the preferred method for valuating flexibility (de Neufville and Scholtes, 2011) because of its versatility in modeling the value of the project with and without flexibility. This dissertation presents a hybrid method consisting of Monte Carlo simulations and decision trees to encompass the path dependence of engineering projects, and the lack of traded assets that diverts the choice of methods inherited from finance.

3.5 Hybrid simulations and decision trees

We introduce a hybrid methodology that combines simulations and decision trees to incorporate the flexibility enabled by PHM in the valuation process. In a traditional cost-benefit analysis, the timeline is first identified. Then the costs, cost avoidance, and uncertainties are identified and represented on the timeline. A cost-benefit analysis is performed by using some metric such as net present value (to discount all cash flows to time 0), and then sensitivity analysis. The hybrid methodology is added to such cost-benefit analysis and aims at including the options arising over the timeline. For example, in the case of a wind turbine; if the cost of downtime is smaller than the cost of failure, then the decision-maker may be better off exercising the abandon option and lose avoid an increase in the cost of failure on the expense of losing power production. Figure 12 is a flowchart for the methodology. Once an RUL is predicted, the options are identified and selected to be included in the model.

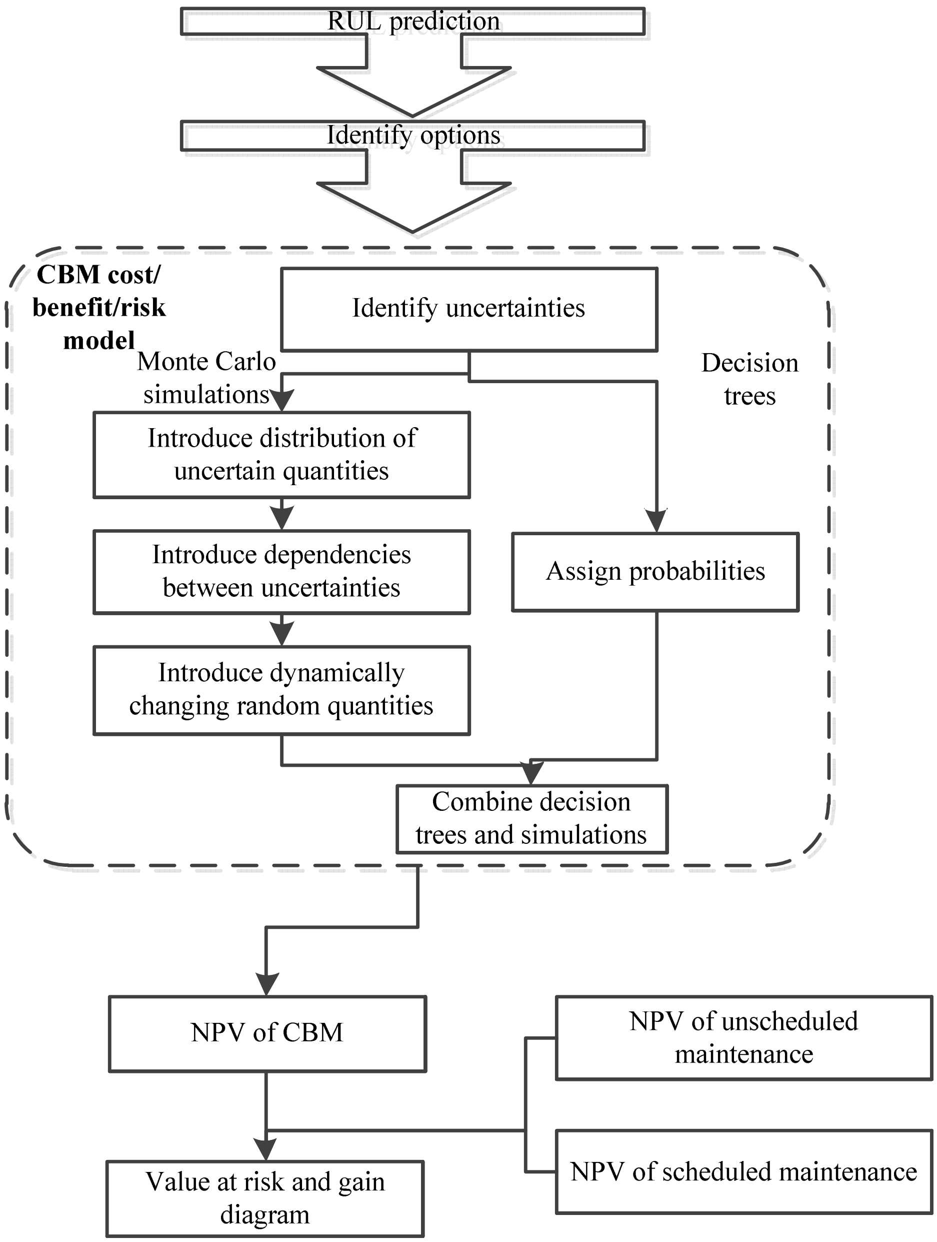

Figure 12- Procedure for quantifying flexibility

Uncertainties are first identified and then split between Monte Carlo simulations and decision trees. Uncertainties that have probability distributions associated with them can be represented in Monte Carlo simulations. Uncertainties that can be described with discrete probabilities are best represented in decision trees.

3.6.1 Uncertainties in Monte Carlo simulations

Monte Carlo (MC) simulations are suitable for analyzing the range of possible outcomes for maintenance policy alternatives. They calculate the performance of each alternative mathematically, considering the joint distribution of the uncertainties. First, they sample from the distributions of possible circumstances, and then the MC process repeats the sampling process many times, giving each possible future circumstance an appropriate chance of being sampled. It thus creates a distribution of the performance of the policy that is consistent with the joint distribution of possible circumstances de Neufville and Scholtes (2011). The CBM policy takes options as input, which differentiates it from the traditional cost-benefit analyses. This accounts for the cash flows generated from exercising the option. For instance, waiting to perform maintenance will generate more revenue from the system (although maintenance cost may increase).

In a valuation methodology, quantities may be associated with uncertainties. A number of those uncertainties can be represented with probability distributions. Some of the distributions are obtained from fitting distributions to historical data, or by assuming some distributions. Distributions are generally represented by a probability density functions.

An example of a probability density function of an uncertain quantity with a triangular distribution is defined by three parameters: minimum (a), maximum (b), and mode (c). The distribution has the following probability density function:

$$f(x) = \begin{cases} 0, & x < a \\ \frac{2(x-a)}{(b-a)(c-a)}, & a \leq x < c \\ \frac{2}{b-a}, & x = c \\ \frac{2(b-x)}{(b-a)(b-c)}, & c < x \leq b \\ 0, & b < x \end{cases} \tag{6}$$

Dependencies can be assumed through relationships between the different variables in the equations considered. For a number of methods to introduce dependencies between uncertain quantities the readers are referred to (Vose, 2000).

Time-dependent uncertain quantities can be modeled with a stochastic differential equation (de Neufville and Scholtes, 2011, and Oskendal 2000); an equation where one or more term is a stochastic process. Such equations are used to model uncertainties and their propagation with time. An example of a differential equation to propagate uncertainty with time is:

$$dX_t = \mu X_t dt + \sigma X_t dW_t \tag{7}$$

where X_t is the value of the quantity being simulated at time *t*, μ is a drift component, σ is a variance component, and W_t is a Brownian motion (also known as a Weiner process). An example of propagating uncertainty with such a method is presented later in this dissertation.

3.6.2 Uncertainties in decision trees

To solve a decision tree, let *A* be an event and *X* a random variable. Denote *{A|S}* the probability assigned to the event *A* on the basis of a state of information *S,* and *{x|S}* the probability that the random variable assumes the value *X*, i.e. the probability mass function given a state of information S. We use mass function here since there is a discrete set of probabilities. We shall assume the random variable takes on some value, so the probabilities sum to 1:

$$\sum_{x} \{x|S\} = 1 \tag{8}$$

The expected value of the random variable over its probability distribution is:

$$< x|S > = \sum_{x} x\{x|S\} \tag{9}$$

An example of a decision tree is shown in Figure 13. The expected value of the cost of maintenance is calculated as following:

$$< x|S > \; = Cost_1 p_1 + Cost_2 p_2 + Cost_3 p_3$$

$$< x|S > \; = 1{,}000(0.65)+15{,}000(0.1)+2{,}000(0.25)$$

$$< x|S > \; = 2{,}650$$

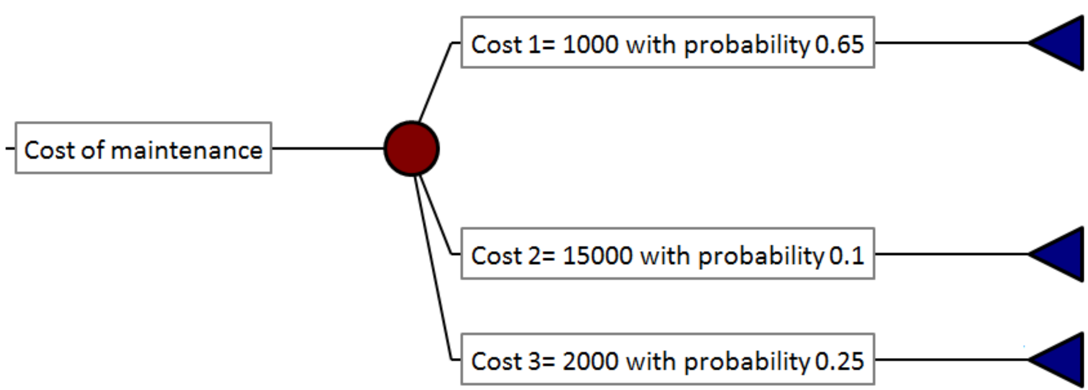

Figure 13- Example of a decision tree

3.6.3 Combination of decision trees and simulations

After accounting for both types of uncertainties, simulations and decision trees are combined. The simulations and decision tree will result in one distribution: let A_i be the area of the probability density function for a scenario i; let $A_i = 1$. Let p_i be the objective probability of scenario i:

$$\sum_{i=1}^{n} p_i A_i = \sum_{i=1}^{n} p_i(1) = \sum_{i=1}^{n} p_i = 1 \quad (10)$$

$$\sum_{i=1}^{n} p_i = 1 \quad (11)$$

3.6.4 Value at risk and gain

The net present value (NPV) takes into consideration the time value of money and discounts all future cash flows to the current time using a discount rate. NPV can be calculated using the following equation:

$$NPV = \sum_{t=0}^{N} \frac{C_t}{(1+i)^t} \quad (12)$$

where t is the time of the cash flow, N is the total time, i is the discount rate and C_t is the cash flow at the point in time.

Incorporating the flexibility in the valuation process will enable the determination of the value provided by PHM when using the system through the RUL. In the valuation of the maintenance of wind farms (treated in Chapter 5), the decision-maker has options to delay maintenance when high wind speeds are forecasted or to stop operation when the cost of failure is high; the value of delaying the maintenance and stopping the operation is incorporated within this methodology.

The distribution for the outcomes is represented by the target curve (de Neufville and Scholtes, 2011), which is also known as the Value at Risk and Gain (VARG) diagram. The VARG diagram shows the probability that a realized outcome will be lower than any specified level or target. The VARG diagram graphs the cumulative value associated with any possible policy. It builds upon the Value at Risk (VAR) concept from finance that identifies the risk of losses that may be incurred.

Figure 14 shows a hypothetical VARG diagram. The horizontal axis is the net present value (in terms of monetary units (MU)), and the vertical axis is the cumulative probability. The diagram shows a number of useful quantities: 1) The range of results, reflecting the dispersion in outcomes. 2) The risk of the downside of any specified level (referred to as the Value at Risk). For example, there is a 20% chance of losing more than 2 MU. This is the value at risk and is read by reading 0.2 on the vertical axis and checking the corresponding point on the curve. There is an 80% chance that the results will be less than a gain of 4.5 MU. This is the 80% value at risk (complement of the 20% value at gain) and is read by taking a horizontal line intersecting the curve from 80% on the vertical axis. 3) The difference between the median value at a cumulative probability of 50% and the average value caused by the asymmetry (which can reflect the asymmetry in penalties). The expected net present value (ENPV) is found by taking the reading on the curve corresponding to the 0.5 probability on the vertical axis.

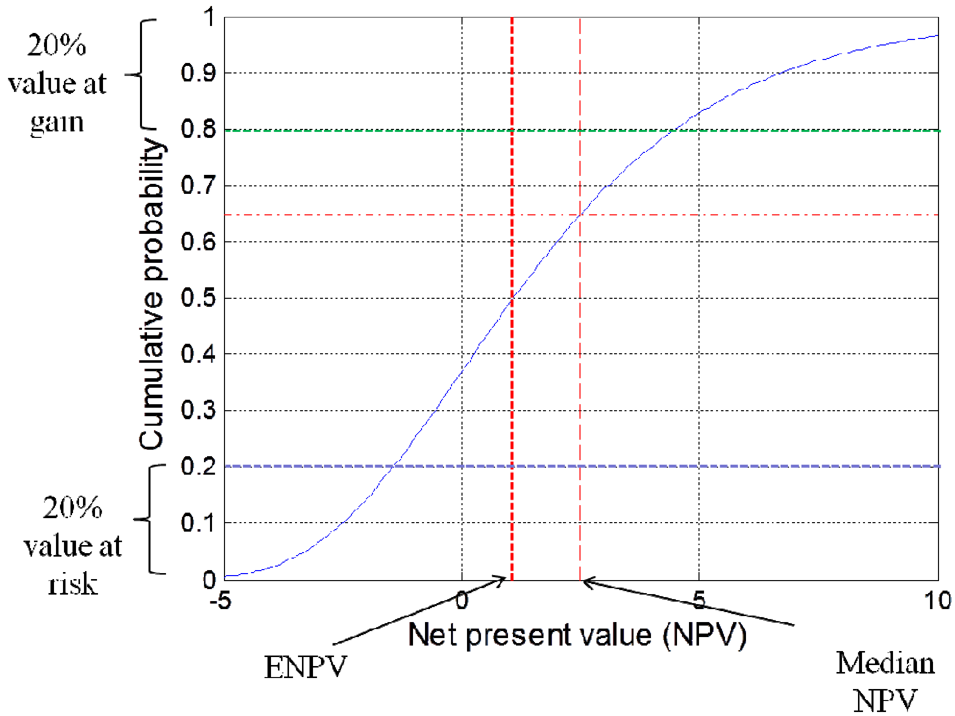

Figure 14- VARG diagram

Under traditional decision analysis, at the chance nodes one multiplies the expected NPVs by the corresponding probabilities to obtain an expected value for the chance node. In this hybrid method, instead of multiplying one single value (i.e., the expected NPV for each scenario), one multiplies the entire VARG distributions of NPVs by the corresponding objective probability and combines the distributions into one VARG that describes the chance node.

3.6 Volatility estimation

Volatility is a measure of the total value of the underlying asset or mission over its lifetime. It signifies the uncertainty associated with the cash flows that comprise the underlying asset value (Kodukula and Papudesu, 2006). The volatility of a project can be observed from the cone of uncertainty (Figure 15): it consists of several paths within the boundaries of the cone. Each path corresponds to a particular project payoff.

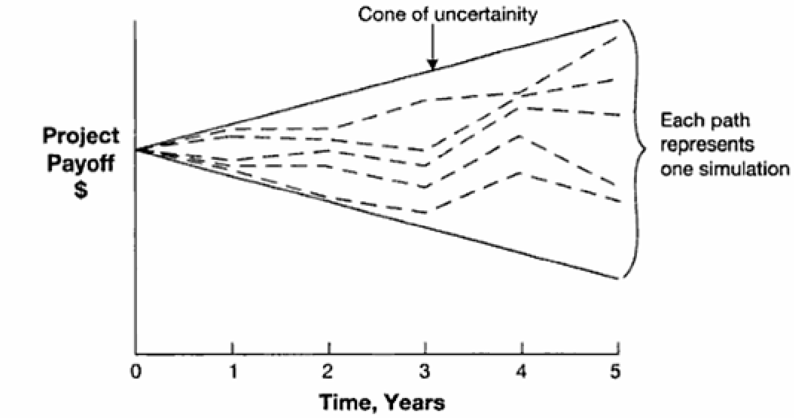

Figure 15- Cone of uncertainty (Kodukula and Papudesu, 2006)

Copeland and Antikarov (2001) propose a method for estimating the volatility that is based on a discrete event simulator. The method consists of using simulation to develop a hypothetical distribution of one-period returns in lieu of the unavailable historical distribution of returns. Then on each simulation trial, the value of the asset is estimated at two different points in time. The ratio of these two estimated values produces an estimate of the rate of return. Compiling the rate of return estimates from all simulation trials creates a rate of return distribution.

Although volatility is not used directly in the valuation methodology proposed in this dissertation, but it provides the intuition about the change of value in a project with time and uncertainty. It can also be useful for modeling uncertainties for some projects.

3.7 Summary

This chapter discussed the uncertainties and their importance in decision support problems. Maintenance options are introduced as means to quantify the flexibility enabled by PHM. A mapping from real to maintenance options is presented and a review of the quantification methodologies is presented. Finally, a hybrid valuation methodology is presented and is used for the quantification of the flexibility enabled by PHM.

Chapter 4: The Value of the Waiting to Maintain Option

Chapter 3 proposed maintenance options as a means to define and quantify the flexibility enabled by PHM. In the time frame from the prognostic indication to the end of the RUL, the decision maker is concerned with the best waiting time to maintain in order to maximize the use of RUL and minimize the risk of failure. In this chapter the wait to maintain option is proposed as a solution to this fundamental problem. We quantify the waiting time using least squares Monte Carlo methods. The value of the option indicates if the decision-maker is better off maintaining immediately or waiting to perform maintenance. It is also the value obtained from PHM at the system level. This capability analyzes individualized maintenance policies for system as opposed to one maintenance policy (based on one optimal prognostic distance over the life-cycle). The value of the wait to maintain option is extended to set a dynamic maintenance threshold based on PHM information.

4.1 The value of waiting

With the knowledge of the RUL, it is desirable when is the best time to maintain while maximizing the benefits from PHM. In the case of wind turbines, it is desirable to know when to maintain, or exercise maintenance options to allow when the decision-maker to realize the largest cost-avoidance opportunities while harnessing the most from wind power generation. Figure 16 shows a schematic of the degradation of three hypothetical systems (the schematic is not specific to a particular system; it is intended to represent the degradation).

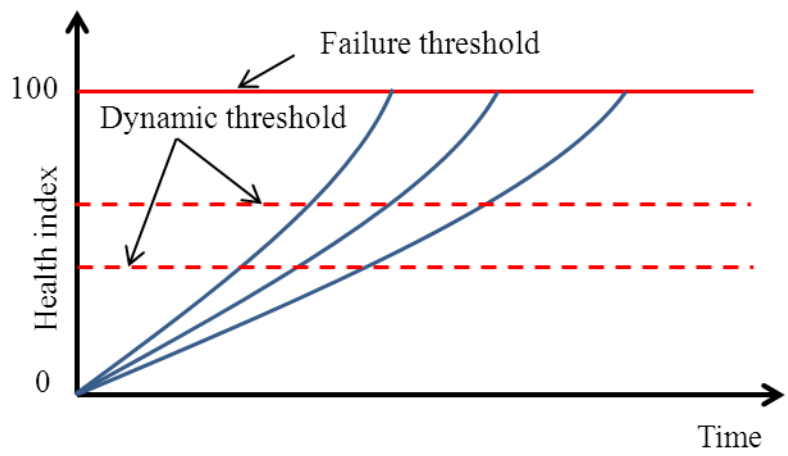

Figure 16- Stochastic degradation of a system

The health index is a measure of the health of the system and is plotted versus time. If the performance measure reaches 100%- the failure threshold, then unscheduled maintenance has to be performed. The decision-maker has the right to exercise maintenance options any time before the end of life of the system. Waiting options are depicted by the dashed lines labeled dynamic threshold.

The fundamental objective of system maintenance with prognostics is to maximize the use of the remaining useful life while concurrently minimizing the risk of failure. This tradeoff was discussed in Chapter 1 and represented in Figure 7. The cost avoidance is an uncertain quantity, decreasing in value since the cost to maintain will increase as the system is used through the RUL. The cost to maintain will be equal to the corrective cost of maintenance if the system is run to failure.

Decision-makers are concerned with the value of delaying an investment in maintenance given the flexibility enabled by PHM. This is essentially the knowledge of the time when waiting is no longer beneficial. We start by defining the maintenance value (V_M) as the value of the summation of cost avoidance opportunities (*CA*) and revenue generated from operating the system (*R*) up to the end of the RUL. It can be expressed as:

$$V_M = CA + R \tag{13}$$

The cost avoidance opportunities are expressed as the difference of the cost of non-detected failure (C_{NDF}) and the cost of detected failure (C_{DF}):

$$CA = C_{NDF} - C_{DF} \tag{14}$$

The maintenance value (V_M) consists of a summation of uncertain quantities, hence it is stochastic. It is worthwhile noting that the cost avoidance is obtained from historical data. However the uncertainty in this quantity may be time-dependent as the confidence in the prediction may increase as we get closer to the end of the remaining life.

Consider the following example: a system indicates an RUL of 3 time units, and V_M has an initial value of 1. A Monte Carlo simulation that follows 8 possible time histories for this example system is shown in Figure 17. When uncertainty in the value is propagated, the result will be stochastic paths; some paths have a value greater than 1 (1 is the initial value) and some have a smaller value when uncertainty is propagated. If we consider all the possible values at any particular time step, the result will be a distribution (cross-sectional information at a time step).

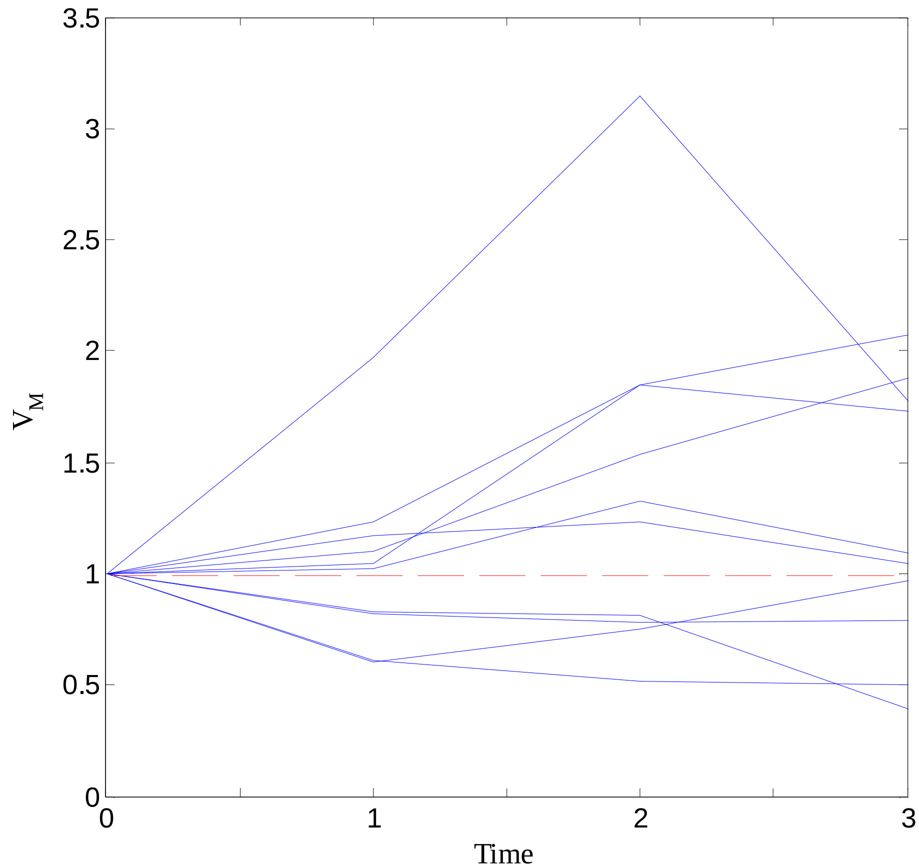

Figure 17- Simulated value (cost avoidance and revenue opportunities), where 0 is the time of the prognostic indication

At every time step, the value is compared with the cost of maintenance, C_M, which accounts of cost of failure, $C_{Failure}$, and cost of downtime $C_{Downtime}$:

$$C_M = C_{Failure} + C_{Downtime} \tag{15}$$

Comparing C_M to V_M at every time step provides means to assess the benefit from running the system through the RUL. For example if C_M is larger than V_M, then the cost of failure, downtime, and penalty is larger than the benefit of running the system.

We assume that the decision-maker can maintain at discrete times 1, 2, or 3. At every time, we need to examine the value of continuation of system operation (no maintenance) and compare it to the value of maintaining at the time step. We start by defining some terms for the analysis:

X_i: the value obtained from operating the system at the current time.

X_{i+1}: the value obtained from running the system until the next instance when maintenance can be performed.

$F(X_{i+1})$: the value of waiting for an additional time step to maintain the system. In other words, this is the value of the cost avoidance opportunities and the revenue generated from the system, and is derived from waiting to perform (invest in) maintenance. While X_i represents V_M at a point in time, $F(X_{i+1})$ represents the gain obtained from waiting till time *(i+1)* to maintain. This gain derives its value from the change in V_M and the ability to wait to maintain.

In order to find the best time for maintenance, we define the stopping rule as a rule to exercise the option if the value of continuation without maintenance is smaller than the value of exercising the option at the current time. The stopping rule is based on finding the expectation of the option's value at time t_{i+1} conditional on the value of revenue at time t_i given by the following equation:

$$E[F(X_{i+1})|X_i] \tag{16}$$

The function gives the expectation of the value of waiting conditioned on the value at the current state. If the expectation function becomes 0 or negative, then waiting is not beneficial. If the expectation function is positive, then PHM is providing additional value, and waiting is beneficial.

4.2 Decision rule using the least squares Monte Carlo approach

At each exercise date (the time when maintenance can be performed) the decision-maker has the choice to maintain or to wait until the next exercise date (the next time maintenance resources are available). The most notable work on optimal stopping time for simulation of options can be seen on Longstaff and Schwartz (2001) where the authors propose an algorithm based on least squares method that uses cross-sectional data and approximates the conditional expectation function in (16). The algorithm is known as the LSM algorithm and has been used by numerous authors. Longstaff and Schwartz (2001) briefly outline a convergence proof for the algorithm.

Since at the current time step, the decision-maker does not have knowledge of the future value of opportunities, the LSM algorithm approximates the conditional expectation at each time step using a set of basis functions $\phi_0, \dots, \phi_R$

$$E[F(X_{i+1})|X_i] \cong \sum_{r=0}^{R} \beta_{i,r}\phi_r(X_i) \tag{17}$$

Function approximation consists of approximating complex functions with simpler ones. In the current work, we approximate the expectation function in (16) with defined polynomials. For a review of mathematical functions that can be used for approximation, the readers are referred to (Abramowitx and Stegun, 1964).

The approximation with basis functions allows the problem of exercising to be reduced to comparing the immediate exercise value with the conditional expectation function in (16). When the value of immediate exercise is positive and greater than or equal to the conditional expectation, the option is exercised. We chose the set of the weighted Laguerre polynomials, from Longstaff and Schwartz (2001), for function approximation, defined as:

$$\phi_0(x) = e^{\left(-\frac{x}{2}\right)} \tag{18}$$

$$\phi_1(x) = e^{\left(-\frac{x}{2}\right)}(1 - x) \tag{19}$$

$$\phi_2(x) = e^{\left(-\frac{x}{2}\right)}\left(1 - 2x + \frac{x^2}{2}\right) \tag{20}$$

$$\phi_r(x) = \frac{e^{\left(-\frac{x}{2}\right)}e^x}{r!}(d^r/dx^r)(x^r e^{-x}) \tag{21}$$

In the LSM algorithm, the objective is to minimize the expected squares error in the approximation, with respect to the coefficients $\beta_{\mathrm{i,r}}$ in (17). From (Glasserman, 2004) and (Thom, 2001):

$$E\left[\left(E[F(X_{i+1})|X_i] - \sum_{r=0}^{R} \beta_{i,r}\,\phi_r(X_i)\right)^2\right] \tag{22}$$

Differentiating equation (22) with respect to $\beta_{i,r}$ and setting the result equal to zero, leading to:

$$E[E[F(X_{i+1})|X_i]\phi_r(X_i)] = \sum_{r=0}^{R} \beta_r E[\,\phi_r(X_i)\phi_s(X_i)] \tag{23}$$

$$E[E[F(X_{i+1})|X_i]\phi_r(X_i)] = \sum_{r=0}^{R} \beta_r E[\,\phi_r(X_i)\phi_s(X_i)] \tag{24}$$

Using matrix notation for the terms in (23) and (24):

$$\left(M_{\phi\phi}\right)_{r,s} = \mathrm{E}[\phi_r(X_i)\phi_s(X_i)] \tag{25}$$

$$\left(M_{V\phi}\right)_{r,s} = E[E[F(X_{i+1})|X_i]\phi_r(X_i)] \tag{26}$$

$\phi_r(X_i)$ can be expressed as:

$$\left(M_{V\phi}\right)_r = E[E[F(X_{i+1}\phi_r(X_i)|X_i]] \tag{27}$$

using the Tower rule[2] will result:

$$\left(M_{V\phi}\right)_r = E[F(X_{i+1}\phi_r(X_i)] \tag{28}$$

and then inverting:

$$\beta = M_{\phi\phi}^{-1}M_{V\phi} \tag{29}$$

In order to find the coefficients, we perform Monte Carlo simulations with N paths:

$$\left(\widehat{M}_{V\phi}\right)_r = \frac{1}{N}\sum_{n=0}^{N} V(X_{i+1}^{(n)})\phi_r(X_i^{(n)}) \tag{30}$$

$$\left(\widehat{M}_{\phi\phi}\right)_{r,s} = \frac{1}{N}\sum_{n=0}^{N} \phi_r(X_{i+1}^{(n)})\phi_s(X_i^{(n)}) \tag{31}$$

The coefficients are used in the decision rule of stopping or continuation and are discussed in the algorithm. With this representation, the problem reduces to comparing the immediate exercise value with this conditional expectation, and then

[2] For two random variable X and Y, the tower rule states that the expected value of the conditional expected value of X given Y is the same as the expected value of X.

exercising as soon as the immediate exercise value is positive and greater than or equal to the conditional expectation.

4.3 Choice of basis functions

Basis functions are used in the LSM algorithm for function approximation. Function approximation uses a number of functions to approximate an unknown function. For the LSM algorithm, the Laguerre polynomials are used and Longstaff and Schwartz (2001) provide the convergence proof for the method. Other types of basis functions include: Chebychev, Hermite, Gegenbauer, and Jacobi polynomials. For detailed discussion on function approximation using polynomials, the readers are directed to Abramowitx and Stegun (1964).

Longstaff and Schwartz (2001) discuss in their paper (2001) that the least squares Monte Carlo algorithm is robust against the choice of basis functions, and that the Laguerre polynomials work quite well. It should be kept in mind that the functions include an exponential term so normalization may be necessary.

4.4 Algorithm

The algorithm for obtaining the value of the option to wait to maintain is shown in Figure 18. The end of the remaining useful life is denoted by $t_{k.}$

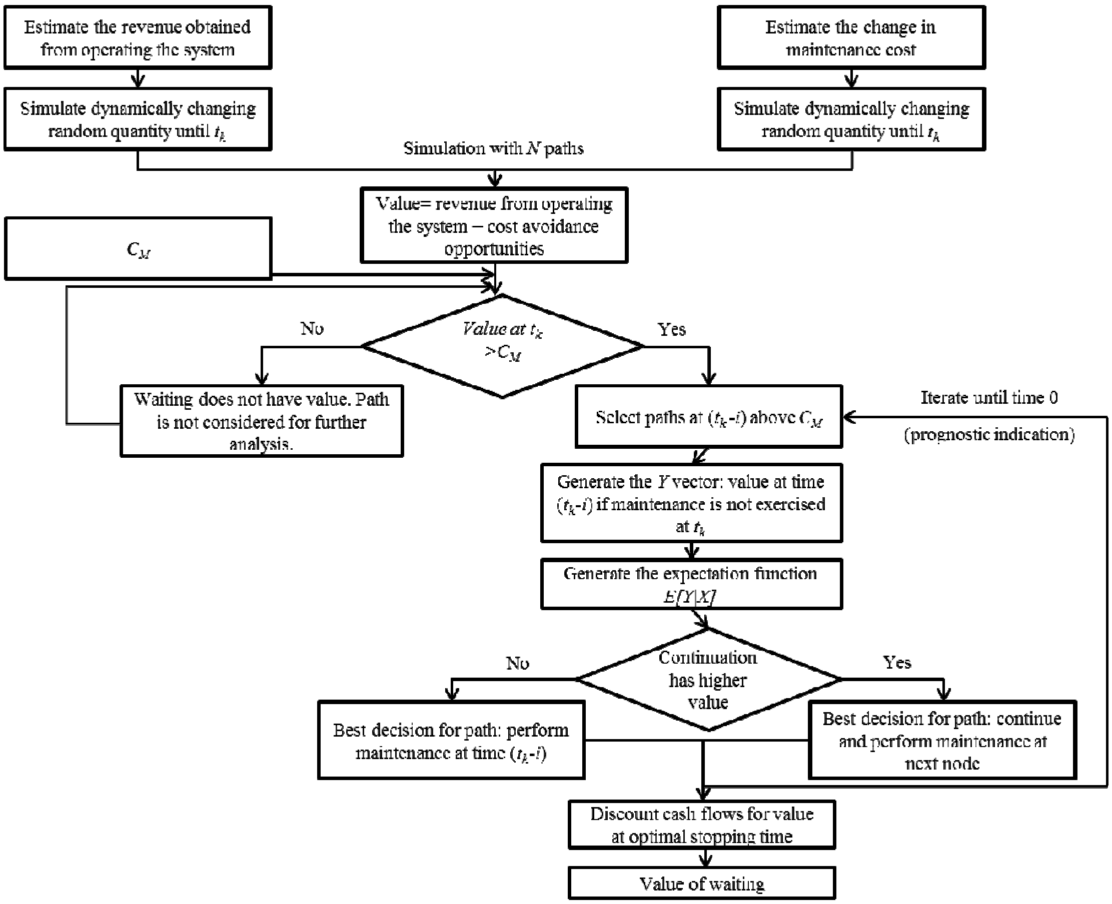

Figure 18- Algorithm to quantify the value of wait to maintain option

The cost avoidance and revenue from operating the system are simulated using N paths (following N independent time lines for the system) with the appropriate distributions or random processes. The decision timeline is divided into different time steps, where maintenance can be carried out at . The paths at the terminal nodes are considered first; if the value is higher than the baseline, then the path is called "in the money" and considered for further analysis. If the value at the terminal node is not in the money, then it is discarded. A value that is not in the money signifies that waiting does not have value.

The LSM approach uses least squares to approximate the conditional expectation function at $t_{k-1}, t_{k-2}, \ldots, t_1$. The index *i* is used to iterate in the time steps in the algorithm. It then works backward, since the path of the cash flows produced by cost avoidance and revenue generation is defined recursively. For all the paths that are in the money, we generate the expectation function using least squares and use three basis functions (although the number of basis functions can be considered in a sensitivity analysis). At every time step, a new expectation function is generated and then used for comparing the value of immediate exercise to the value of waiting. After iterating recursively to the first time step, we have the best decision for each path. The value at the best exercise time of each path is discounted to time 0 and averaged, resulting in the value of the option to wait to perform maintenance. If the value is larger than 0, the waiting option has a value and represents the additional benefit obtained enabled by PHM.

4.5 Example

We consider a hypothetical example to illustrate the steps for obtaining the decision rule and quantify the maintenance option. We go through the process step by step and explain the assumptions when necessary.

We consider a system with prognostic capabilities that indicates a RUL of 3 time units and the decision-maker can maintain at times 0, 1, 2, or 3. The problem here is to find the value of the waiting to perform maintenance given that the decision-maker can decide to maintain anytime from time 0 to time 2. The other option is to let the option expire and perform unscheduled maintenance at time 3 thus not using the information from the PHM system. The value of maintenance, V_M (equation (13)) is shown in Figure 19.

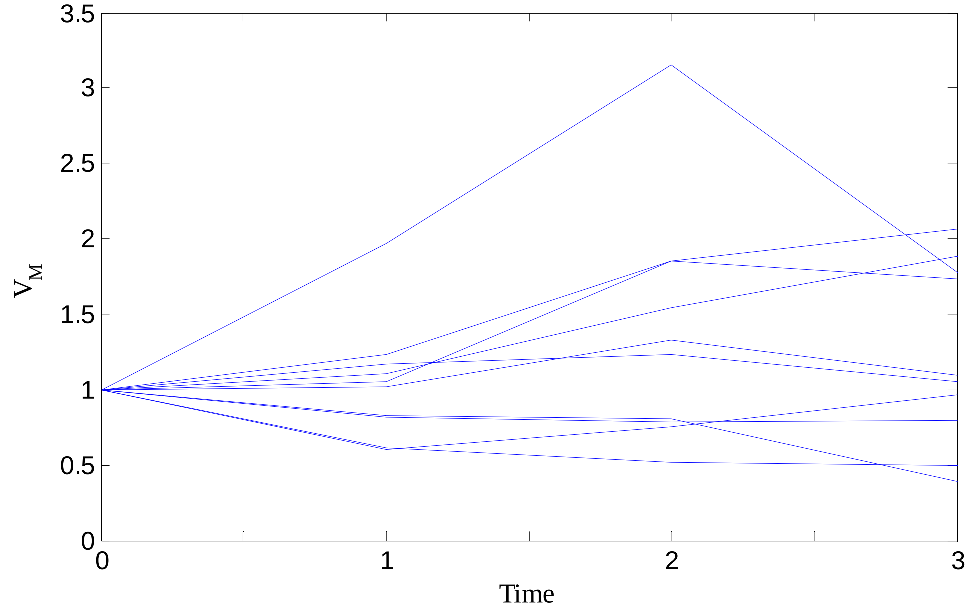

Figure 19- Simulation of option value

Following are the assumptions for the example:

$$X_0 = 1: value\ of\ V_M\ at\ time\ 0$$

$$C_M = 1.1: assumed\ cost\ of\ unscheduled\ maintenance$$

$$t_1, t_2, t_3: times\ at\ which\ decision - maker\ can\ maintain$$

In this example, the term C_M consists of the cost of unscheduled maintenance for the purpose of illustration. 10 time histories (paths) for the value of maintenance are simulated in the example. Some paths have values higher than the initial starting point 1, and some are lower; this is an effect of accounting for uncertainty in the model. Cost avoidance opportunities will decrease with time as there is a higher risk of failure on the system, but the system will generate more revenue as it is used through the end of the RUL. The idea would be to wait to perform maintenance even if the cost if slightly higher to maintain at the end. We define an option to be in the money if its value at a particular time step is higher than the cost of unscheduled maintenance.

At the final exercise date, the best exercise strategy is to exercise the option if it in the money. Prior to the final date, the best strategy is to compare the immediate exercise value with the expected cash flows from continuing, and then exercise if immediate exercise is more valuable. Hence the key here is to identify the conditional expected value of continuation.

The value of V_M from the simulation can be obtained from Table 5.

Table 5- Value of V_M over time

Path	t=0	t=1	t=2	t=3
1	1	1.05	1.85	1.73
2	1	1.97	3.15	1.78
3	1	0.61	0.52	0.50
4	1	1.02	1.33	1.09
5	1	0.82	0.78	0.79
6	1	1.10	1.54	1.88
7	1	0.60	0.75	0.97
8	1	1.23	1.85	2.07
9	1	0.83	0.81	0.39
10	1	1.17	1.23	1.05

The objective is to determine the stopping rule that maximizes the value of the wait to maintain option at each point along each path. Several intermediate steps need to be considered before quantifying the option.

Conditional on not exercising the option before the final expiration date at *t*=3, the cash flows realized by the option holder from following the best strategy are given in Table 6.

Table 6- Cash flow at *t*=3 if the option is not exercised

Path	*t*=0	*t*=1	*t*=2	*t*=3
1	-	-	-	0.63
2	-	-	-	0.68
3	-	-	-	0
4	-	-	-	0
5	-	-	-	0
6	-	-	-	0.78
7	-	-	-	0
8	-	-	-	0.97
9	-	-	-	0
10	-	-	-	0

The values for *t*=3 in Table 6 are obtained by subtracting 1.1 from the value a *t*=3 if the option is in the money.

If the option is in the money at *t*=2, the option holder must then decide whether to exercise the option immediately or continue until next time maintenance can be supported. From Table 5, there are 6 paths where the option is in the money at *t*=2 (where the value is more than 1.1). Note that only the paths that are in the money at *t*=3 are considered for the analysis at previous times. We denote by X the value of V_M at *t*=2, for those paths, and Y, the corresponding discounted cash flow received at *t*=3 if the option is not exercised at *t*=2.

Table 7- X and Y at *t*=2

Path	X	Y

1	1.85	0.59
2	3.15	0.64
3	-	-
4	1.33	0
5	-	-
6	1.54	0.73
7	-	-
8	1.85	0.91
9	-	-
10	1.23	0

The *Y* values are obtained by discounting the cash flow at *t*=3 if the option is not exercise at *t*=2. For instance; if the option is not exercised at *t*=2 for path 1, then *Y* is calculated using:

$\mathrm{Y} = (1.73 - 1.1)0.9418 = 0.59$ where 0.9418 is used to discount for one time period with a discount rate of 6%.

To estimate the expected cash flow from waiting (continuing the option's life) conditional on the value at *t*=2, we regress *Y* on the basis functions. For the purpose of the example we choose a constant, *X*, and X^2 (this choice is for the ease of representation. In the algorithm we use Laguerre polynomials). This will result in the expectation function that approximates the value of continuation:

$$E[Y|X] = -0.7679\, X^2 + 3.7020X - 3.4082 \tag{32}$$

With the conditional expectation function we can now compare the value of immediate exercise at *t*=2 with the value from continuation which can be seen in the table below:

Table 8- Value of exercise and continuation at *t*=2

Path	Exercise	Continuation
1	0.75	2.01
2	2.05	5.83
3	-	-
4	0.23	0.49
5	-	-
6	0.44	1.11
7	-	-
8	0.75	2.01
9	-	-
10	0.13	0.2

The exercise value is obtained by *(X-1.1)* and the continuation value is obtained by substituting X in the conditional expectation function. This comparison implies that it is better to continue as the value of continuation is higher than the exercise value at t=2; the conditional expectation function evaluated is higher than the current exercise value.

The next step is to generate the cash flow matrix in Table 9, which depicts the cash flows received by the option holder conditional on not exercising prior to t=2.

Table 9- Cash flow at *t*=2

Path	*t*=1	*t*=2	*t*=3
1	-	0	0.63
2	-	0	0.68
3	-	-	-
4	-	0	-
5	-	-	-

6	-	0	0.78
7	-	-	-
8	-	0	0.97
9	-	-	-
10	-	0	0

Continue recursively until we get to *t*=1. We note that in defining Y, we use the actual realized cash flows along each path and not the conditional expected value of *Y* estimated at the next time step because this will introduce bias. For a discussion on the topic, the reader is referred to Longstaff and Schwartz (2001).

The vectors *X* and *Y* for time 1 are given in Table 10. Where cash flows obtained at *t*=3 are discounted for 2 time periods (multiplying by 0.8869) and cash flows obtained at *t*=2 are discounted for one period.

Table 10- X and Y at *t*=1

Path	**X**	**Y**
1	-	-
2	1.97	0.6
3	-	-
4	-	-
5	-	-
6	-	-
7	-	-
8	1.23	0.86
9	-	-
10	1.17	0

We regress again and obtain:

$$E[Y|X] = -18.35X^2 + 58.38X - 43.18 \quad (33)$$

Then we compare the value of the option at *t*=1 to the value of continuation by using the regressed function and obtain the results in Table 11.

Table 11- Value of exercise and continuation at *t*=1

Path	Exercise	Continuation
1	-	-
2	0.87	0.61
3	-	-
4	-	-
5	-	-
6	-	-
7	-	-
8	0.13	0
9	-	-
10	0.07	0

From Table 11, we see that it is better to and maintain at *t*=1 for paths 2, 8, and 10. Having identified the strategies at *t*= 1, 2, and 3 the stopping rule can be represented using the following matrix:

Table 12- Stopping rule matrix

Path	*t*=1	*t*=2	*t*=3
1	0	0	1
2	1	0	0
3	0	0	0
4	0	0	0
5	0	0	0
6	0	0	1
7	0	0	0
8	1	0	0
9	0	0	0
10	1	0	0

With the stopping rule obtained, we then determine the cash flows realized by following the rule and exercising at the dates where there's a one in the above matrix. This will lead to the following cash flow matrix:

Table 13- Wait to maintain option cash flow matrix

Path	***t*=1**	***t*=2**	***t*=3**
1	0	0	0.63
2	0.87	0	0
3	0	0	0
4	0	0	0
5	0	0	0
6	0	0	0.78
7	0	0	0
8	0.13	0	0
9	0	0	0
10	0.07	0	0

To calculate the value of the option, we discount each cash flow in the option to time 0 and average all the paths to obtain:

$$Value = (0.63(0.8353) + 0.87(0.9418) + 0.78(0.8353) + 0.13(0.9418) + 0.07(0.9418))/10 = 0.2185$$

Where, 0.8353 is used to discount 3 periods and 0.9416 is sued to discount for 1 period.

In this example, if the decision-maker waits to maintain, an expected additional 0.2853 MU is obtained. If the decision-maker decides not to wait and maintain immediately after obtaining the prognostic indication, a value of 0.2185 may be missed. Although this example uses fictional data, it demonstrates the use of the LSM algorithm for obtaining the value of maintenance options. Without accounting for the option to wait for three time steps to maintain, one would compare the value at t=3 with 1.1 and discount to time 0. This would result in a value of 0.18. Hence, when accounting for flexibility in the decision-making (wait when it is favorable), the result show that the value of waiting is 58% higher than the value obtained without accounting for flexibility. The result from this example represents the additional value obtained from PHM. Waiting, an option that is enabled by PHM is a representation of the benefit obtained from using the system through the RUL.

4.6 Dynamic maintenance threshold and penalty impacts

The algorithm for quantifying the value of the wait to maintain options provides the value obtained from PHM at the system-level. This methodology can be extended to the fleet level where it is desirable to know when the best time to maintain is based on maximum value obtained from the PHM system. This will lead to a dynamic maintenance threshold and a methodology to support outcome-based contracts.

When extended the models to the fleet it is necessary to account for availability impacts especially when supporting outcome-based contracts. A system in a fleet may not be operational but the fleet may still be able to deliver a required availability. But when the required availability is not met, then penalty has to be imposed on the cost of maintenance term in equation (15) by adding a penalty term.

For example, consider a hypothetical wind farm consisting of 40 turbines shown in Figure 21. It is desirable to know where to place the dynamic maintenance threshold given that systems may have different performance measure (analogous to health state). The figure shows that some systems will have a performance measure above the threshold and some below.

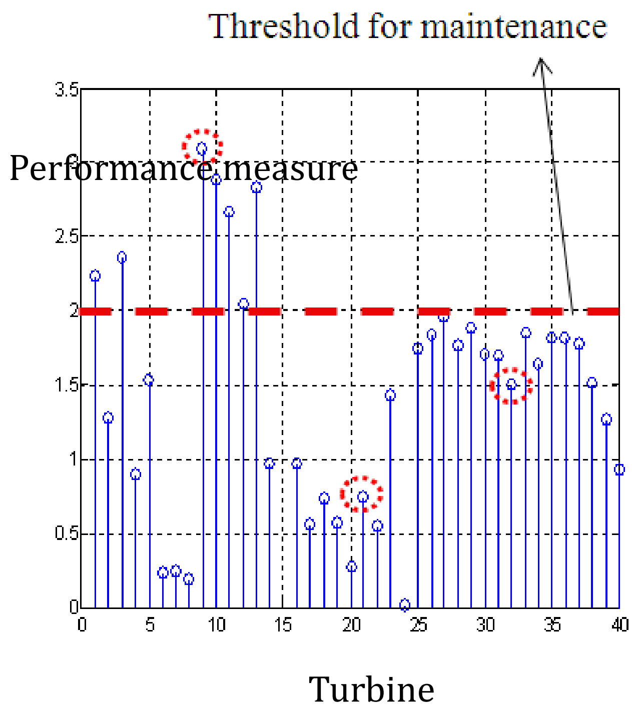

Figure 20- Hypothetical wind farm with prognostic capabilities

For a fleet of *n* systems, the maintenance threshold can be defined based on the time that maximizes the value of waiting:

$$\arg\max_t\left(\sum_1^n c_{t_n} X_0\right) \tag{34}$$

where *t* is the time argument (time when maintenance can be supported), *n* is the number of systems, c_t is the value of the wait to maintain option, and X_0 is the maintenance decision (X_0 =0: wait, X_0 =1: maintain).

Equation (34) maximizes the value of waiting for all the turbines that indicate a prognostic distance and solves for the time that maximizes this function. This contribution will be highlighted in the case study. Note that the dynamic maintenance threshold is not dictated by the summation of values of the waiting option on different subsystem. The reason is that the value of waiting for each system is compared to a cost of unscheduled maintenance, cost of downtime, and cost of penalty. When two or more systems are considered together, these costs should be carefully considered. Furthermore, when the systems indicate prognostic distance at different times, it is important discretize the time and apply the costs avoidance, the revenue, and the costs for comparison appropriately. This point will be elaborated in the case study.

4.7 Summary

This chapter presented a system-level cost model that quantifies the value of the option to wait to maintain (one kind of contingency actions). The value of waiting represents the benefits obtained from PHM which cannot be accounted for in life-cycle cost models. Quantifying the value of the option to wait to maintain, is means to quantify the benefit of PHM for individualized maintenance policies. An algorithm to quantify the option is presented and demonstrated on a simple example. The model is then extended to a fleet of system to set a dynamic maintenance threshold based on PHM information. Such model can be used to schedule maintenance and support outcome-based contracts.

Chapter 5: Case Study: Decision Support for Maintaining Wind Farms

This chapter demonstrates the methodologies developed in this dissertation using a case study on wind farms. The choice of wind farms for case study is motivated by: the large number of turbines that are going out of warranty, the importance of PHM for wind turbines, and the potential for cost avoidance in the maintenance of turbines.

The case study is based on data that is obtained from the General Electric Company, a leading North American manufacturer of turbines.

The Chapter starts by discussing the sustainment problem for wind farms then presents the data used for the case study. An analysis of the service data is presented, and then a life-cycle cost model is established. The hybrid methodology is then presented and compared to the life-cycle cost model. The wait to maintain option and dynamic maintenance threshold are then analyzed for different failures in the farm.

5.1 Sustainment of wind farms

Alternative energy sources have increasingly gained the interest of governments, research institutes, academia, and industry in order to reduce the dependency on traditional energy sources such as coal and oil. Wind energy stands at the forefront of these energy sources; the United States Department of Energy (DoE) and the National Renewable Energy Lab (NREL) for instance, under the '20% Wind Energy by 2030' plan, announced that the US could feasibly increase the wind energy's contribution to

20% of the total electricity consumption in the United States by 2030 (U.S. DoE, 2008).

Wind energy sources face numerous challenges that could hinder their competitiveness with traditional sources. Wind energy has not been operational over a sufficient amount of time to assess its long term viability. Furthermore, the reliability of wind turbines has turned out to be different from what was originally predicted. Another major challenge with wind energy is intermittency, i.e., their energy generation is dependent on intermittent sources, as can be seen in Figure 21, which shows the wind capacity factor for Kansas wind farms from July 2007 (labeled month 1 on the plot) to June 2008 (KCC, 2011)).

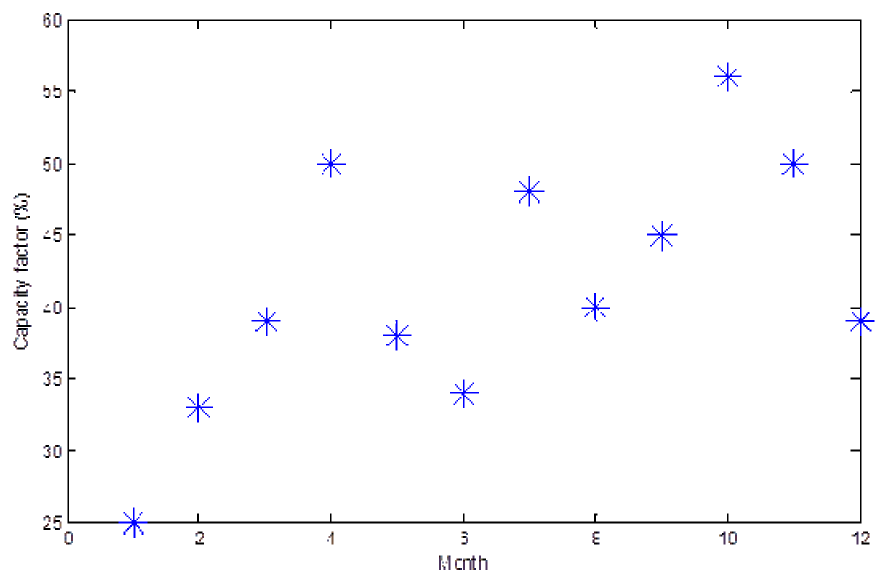

Figure 21- Capacity factor in a Kansas wind farm July 2007 to June 2008

The Wind Energy Operations & Maintenance Report was recently published (Asmus and Seitzler, 2010) and included a discussion highlighting the challenges with wind energy systems. Some of the most notable conclusions are that the operation and maintenance (O&M) costs for wind power are double or triple the figures originally projected, they are particularly high in the United States. Another interesting fact is that many gearboxes, designed for a 20-year life, are failing after 6 to 8 years of operation.

These challenges indicate that reliability, maintainability, and availability stand among the key challenges to the economic viability of wind turbines and their ability to compete with traditional energy sources. The remainder of this section summarizes these challenges.

5.1.1 Reliability

Ideally, the turbines would behave in the field just as they perform under testing of stated conditions. However, most fielded turbines are relatively new and have not been subject to sufficient testing and qualification. This resulted in a dramatic difference in the actual life of the system in the field from what is stated on the specification sheet.

Simulating the actual conditions where the system will be implemented is challenging and may not be properly accounted for in the testing phase for wind turbines. However, reproducing the actual conditions may be challenging - reproducing harsh weather conditions and the interaction with other environmental factors may be impossible to account for in a lab testing environment.

Figure 22 adopts the data from Arabian-Hoseynabadi et al. (2010) to show the failure rate of different sub-assemblies in wind turbines. The plot shows that multiple subassemblies have a significant yearly failure rate.

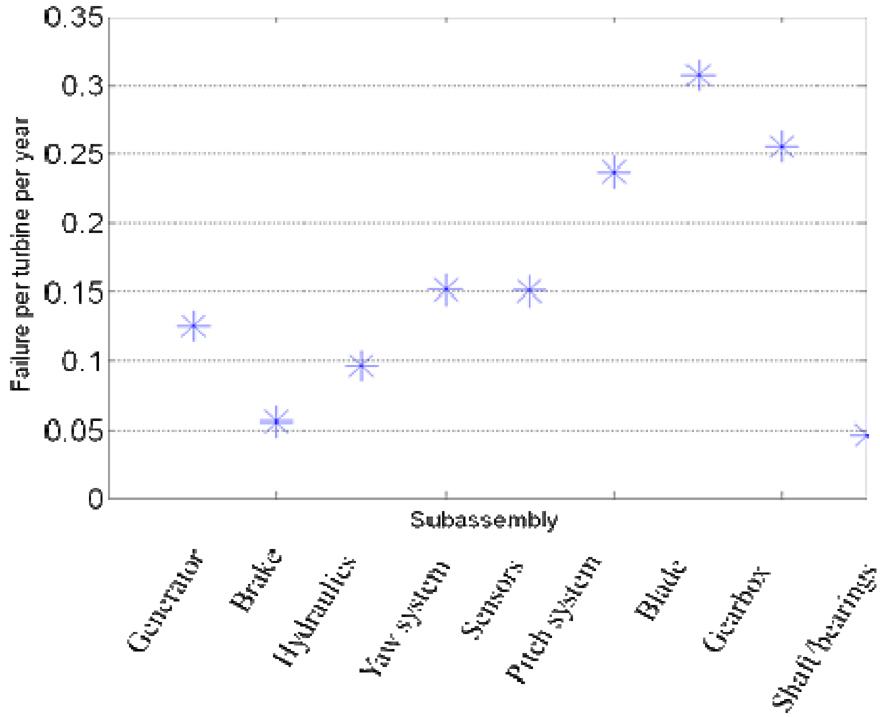

Figure 22- Reliability of wind turbines

5.1.2 Maintainability

The maintainability of wind turbines emerged as a major challenge to their economic viability. For an offshore wind turbine for instance, the projected operation and maintenance cost accounts for the second largest share of the turbine's life-cycle cost as seen in Figure 23 (Musial and Ram, 2010).

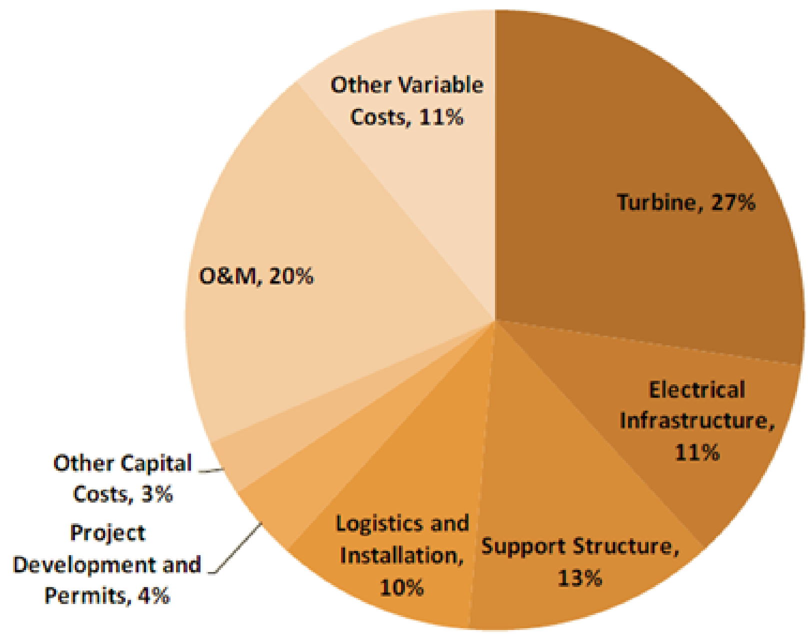

Figure 23- Projected life-cycle cost breakdown for offshore wind turbines (Musial and Ram, 2010)

Figure 23 shows the projected cost for offshore wind turbines in the United States. With the operations maintenance cost being 20% of the total cost, if the turbine is not maintained as it is originally intended to be then the cost is going to rise even more and pose more challenges on the economic viability.

Furthermore, wind turbines require special workforce that is trained to maintain the particular system, and require non-traditional resources such as vessels and cranes.

5.1.3 Availability

Availability of turbines will actually determine their energy impact. In other words, if the system is unreliable and always unavailable because it is subject to maintenance and repairs, or if the cost of maintenance is high, then the potential profit from the source will drop drastically.

Another aspect of availability is the need of nontraditional resources for maintenance. Offshore wind farms require vessels with cranes that may only be able to perform maintenance a couple times a year. If one turbine broke right after a maintenance action has been performed on it, then it will not be available until next time the vessel is on-site for maintenance.

Kuhn (2007) studied the failure rates of 235 small wind turbines and assessed the annual frequency rate and the corresponding downtime for different subassemblies. The results can be seen in Figure 24.

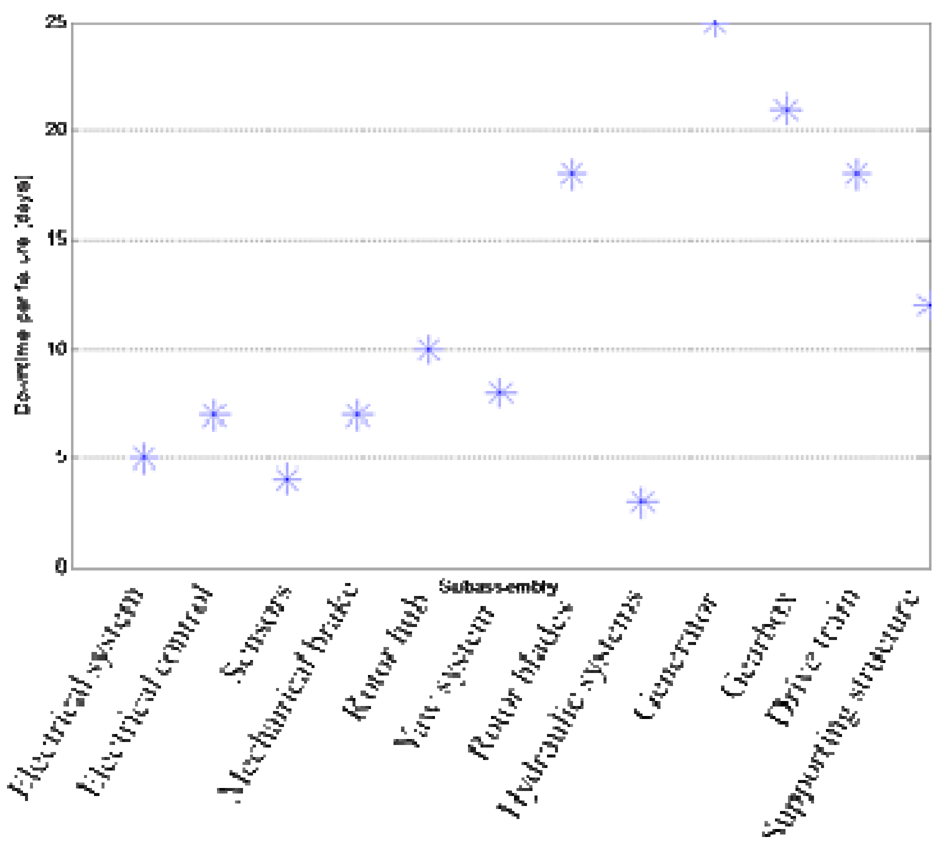

Figure 24- Downtime for wind turbines (Kuhn, 2007)

The availability of wind turbines (and wind farms) will determine the energy impact they are able to have. In other words, if the system is unreliable and always unavailable because it is subjected to maintenance and repairs, then the potential profit from the wind farm will drop because the system is not able to produce the required energy. This can be even worse if the costs of the energy that has to be produced using alternative means (e.g., burning coal or oil) to make up for turbine downtime due to maintenance of the system outweigh the profit obtained if the system is in operation.

5.2 Description of the wind farm for the case study

Data for the case study is from General Electric and consists of a wind farm in the United States that has more than 100 land-based turbines. The farm was completed in the early 2000's. Power and maintenance data was obtained from this farm, and cost data was obtained from the literature. Note that the costs appear in different currencies due to the source of the data.

Power data consists of the performance of the individual turbines, and consists of parameters such as wind speed, power output from the turbine, the rotor rpm, the generator rpm, the blade angle and other performance parameters. The data was recorded every 10 minutes: it is the average of the measured quantity over 10 minutes. Service data pertains to maintenance actions and consists of a database of all maintenance actions reported for the turbines since they were installed.

Power data is obtained for the year 2009, and service data is obtained for all years since turbines were installed (approximately 10 years). Scheduled maintenance occurred in February and July in 2009. Seven turbines were chosen from the farm.

The choice is based on the failure modes they exhibit; the seven turbines had the most common failure modes for wind turbines presented in Figure 22. The faults or failure that occurred include: pitch mechanism, hub, generator bearing, IGBT, rotor faults, and gearbox. The turbines are assumed to be representative of the whole population.

Power versus wind data is obtained for the seven turbines and used to generate the power curves. Data is split into subsets corresponding to increments of 2 m/s and marginal and joint distributions are fitted to the data. The original wind indices are used to reconstruct a new time series with the exact order of the original time series. Data is then scaled to 600KW. This transformation does not affect the power-wind relationship. The following steps were used to generate the simulated data set:

- Generate the power curve (power versus wind speed) for different turbines
- Fit distributions to the data using the function copulafit in Matlab
- Sample from the fitted distributions
- Reconstruct the power time series.[3]

Figure 25 is an actual power curve of a wind turbine and shows the power produced as a function of wind speed for 50,000 data points. Figure 26 shows the reconstructed power curve (with 2,000 data points corresponding to one subset). It can be seen that the marginal distributions in the two cases are similar.

[3] General Electric only allowed their data to be used within this dissertation under the conditions of reconstructing the data as described in this section.

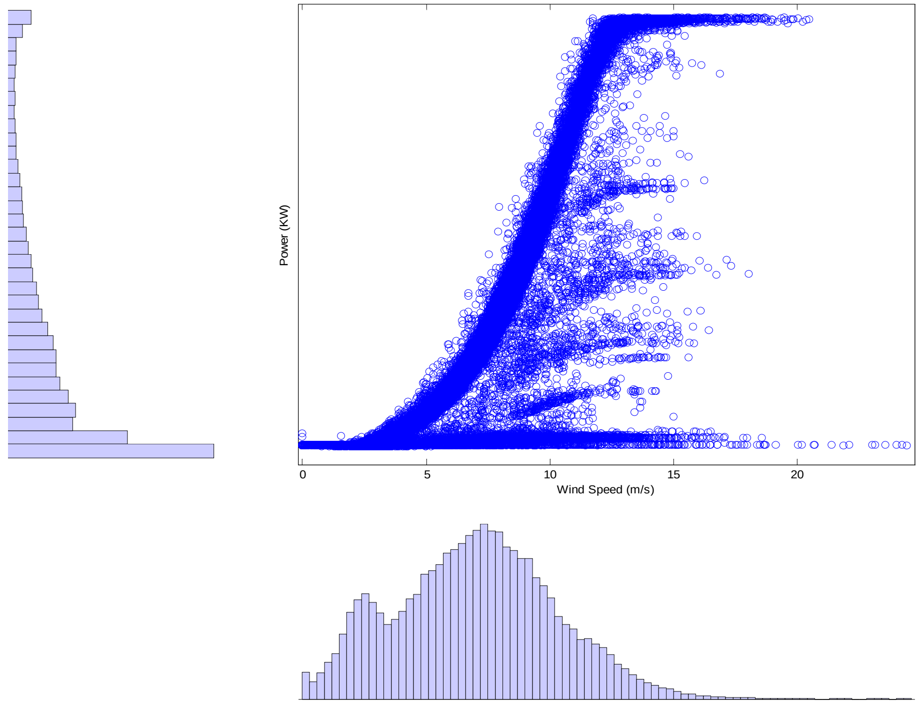

Figure 25- Actual power curve (50,000 points)

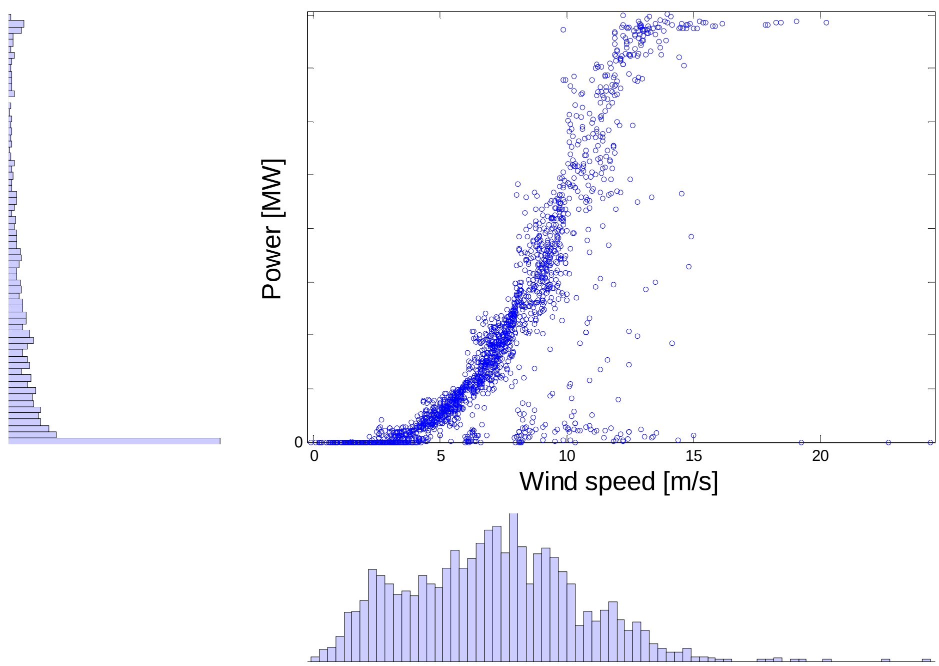

Figure 26- Reconstructed power curve (2,000 points)

In the remainder of the dissertation, the 7 turbines chosen for the case study will represent the farm unless otherwise stated. 5 turbines in the farm exhibited failures during the year 2009, and 2 turbines did not have maintenance events outside of the routine scheduled maintenance. The failures are represented on the timeline in Figure 27.

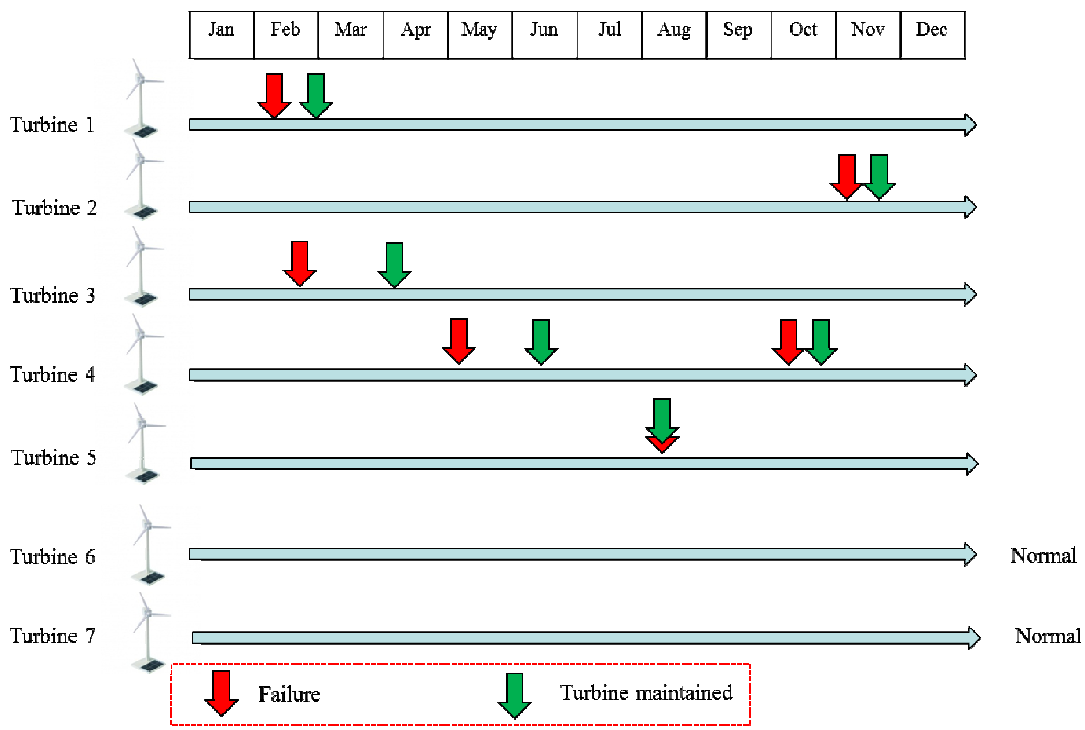

Figure 27- Illustration of the wind farm

Figure 27 illustrates the time where a failure or fault occurred and when it was maintained. In some cases, the failure lasted for more than a month (Turbine 3). Turbine 5 has the failure and the maintenance event represented at the same point in the time line, it corresponds to a no-fault-found (NFF) [4]. The actual failure modes are not indicated on Figure 27 because of confidentiality of the data.

The cost of maintenance for the failure modes can be seen in Table 14. The order of the failures in the table is not representative of the failures Figure 27. Table 14 shows the component where failure occurred, the cost of unscheduled maintenance, and the cost of condition-based maintenance (under the assumption that it is 40% of the cost of failure; an assumption made for gearboxes in (EPRI, 2006)). Note: the costs from Andrawus were converted to 2006 US dollars using a conversion factor of 1.89785.

Table 14- Cost of maintenance for different failure modes

Failure	Cost unscheduled	Cost CBM	Reference
Pitch mechanism	$11,640	$4,656	Kahrobaee and Asgarpoor (2011)
Main bearing	$42,462	$16,985	Andrwaus et al. (2006)
Bad generator bearing	$68,254	$27,302	Andrwaus et al. (2006)
Control system	$7035	$2,814	Kahrobaee and Asgarpoor (2011)
Gearbox failure	$148920	$59,568	Andrawus et al. (2006) and

The costs in the table correspond to the cost of material, cost of labor to maintain the turbines, the cost of access (e.g., cranes), and cost of downtime.

There are 6 failures that are represented on the timeline in Figure 27, and costs for 5 failures in Table 14. The NFF is not included in the costs as the actual costs were

[4] Note that NFFs do not always take very small time to get resolved. They may take longer to resolve than actual maintenance events.

not obtained in the data set. Note that NFFs can sometimes cost more than the actual failure of a system.

5.3 Scheduled maintenance for the sustainment of wind farms

The data in this section is reported as obtained (and not subject to any transformation: only power data used in following sections was transformed). The labels on the y-axis have been removed for confidentiality of the data.

Figure 28 shows the cumulative maintenance cost for the farm under consideration for the years 2007 to 2010.

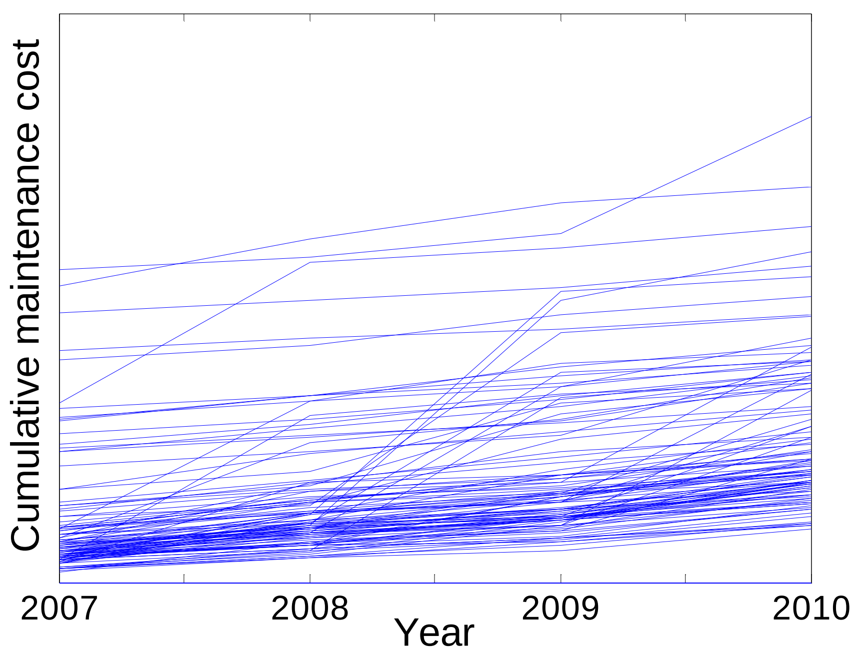

Figure 28- Cumulative maintenance cost for 4 years for the real farm (more than 100 turbines)

Although this farm is operating with a scheduled maintenance, one would expect that the cumulative maintenance cost would be increasing steadily (corresponding to routine maintenance). However the jumps in the cumulative maintenance cost curve indicate that there are components failing in some turbines and leading to an increase in cost. Gearboxes are examples of such components. Gearboxes are not supposed to fail during 10 years of operation. This infers that scheduled maintenance may not be the most efficient paradigm for such expensive assets.

Figure 29 shows a plot of the power for a turbine that had more than one failure over the year 2009. The fluctuations are due to the intermittency of the wind source.

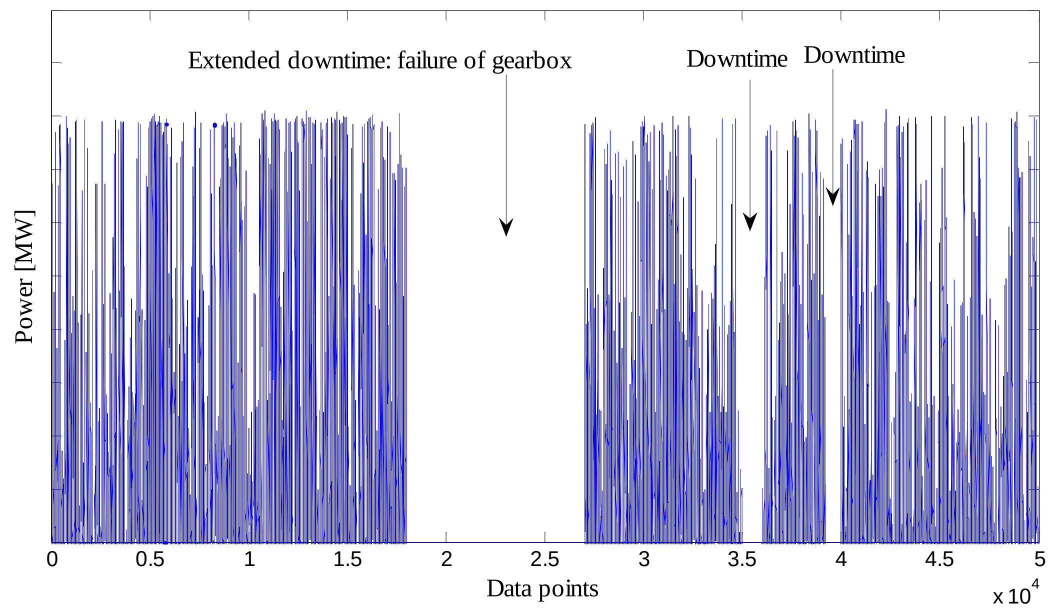

Figure 29- Power over a year period for one turbine

There are 3 unusual downtimes for the turbine shown in Figure 29. The first downtime is for an extended period of time and is caused by the failure of a gearbox. The cost of maintenance in this case is high due to the cost of failure and cost of downtime since the turbine is not generating any power. Figure 29 shows that there are 2 other downtimes for the turbine, which also increases the cumulative cost (cranes and labor have to be provided).

There are 4 types of service types: 1) non-functional turbine, 2) operating with problem, 3) preventive maintenance, and 4) scheduled preventive maintenance. Service type indicates the state of the turbine when maintenance was requested. A 'non-functional turbine' indicates that a service was requested for a turbine that was not operational. Preventive maintenance is the request for all maintenance actions happening during preventive maintenance, and scheduled preventive maintenance occurs twice a year. Preventive maintenance is performed for some components such as gearbox. It is performed at a different time than preventive maintenance.

Figure 30 shows the frequency of request service types for all the turbines. A non-functional turbine can be either down before the scheduled maintenance, during or after. If the turbine is down right after the maintenance cycle, then the turbine will either be down for an extended period of time until the next scheduled maintenance cycle or a crew is called for maintenance.

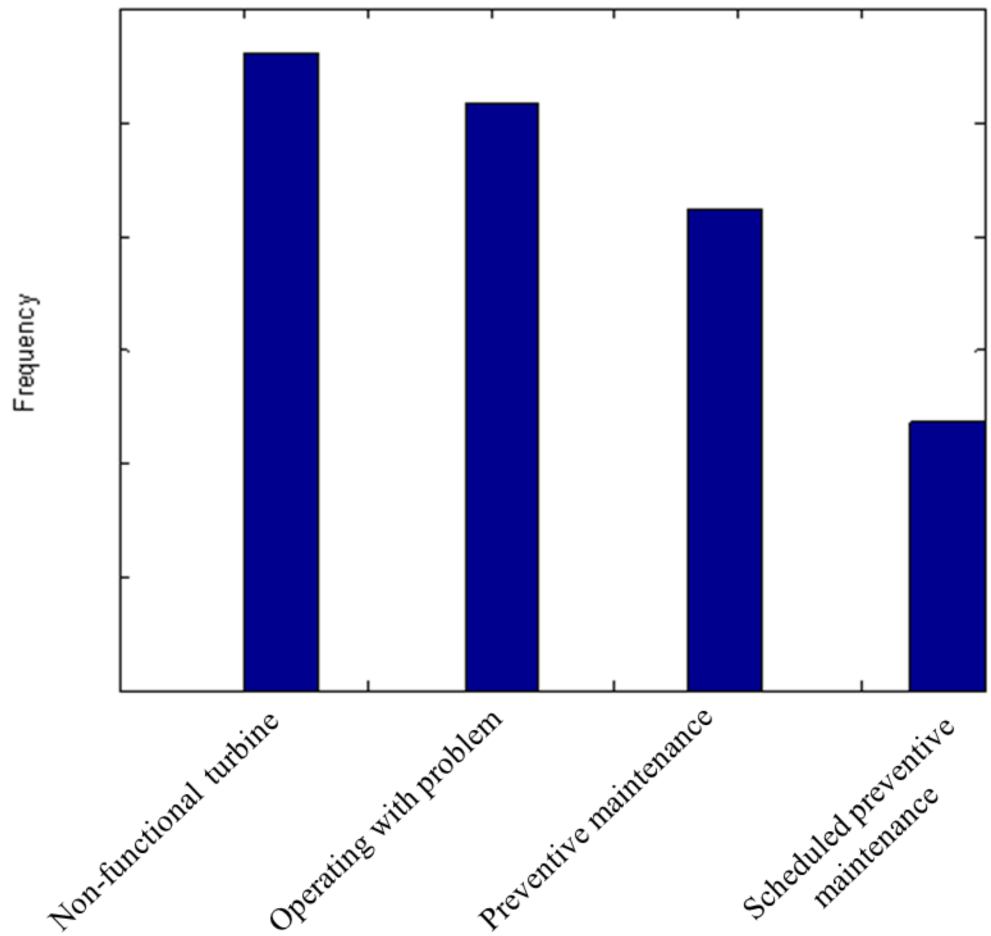

Figure 30- Frequency of service requests by type

Figure 30 shows that the frequency of ‘non-functional turbine’ request types is larger than all other types. ‘Operating with problem’ ranks second in the service request type. If the turbine is non-operational or operating with problem, the turbine may not produce as much power as it should, and the life-cycle cost will increase.

For service request ‘non-functional turbine’, the number of days elapsed between the service request and the repair date of the turbine can be seen in Figure 31. The histogram shows a high frequency for days between 0 and 20; this is due to the fact that a number of faults are resolved by resetting the turbine or some other subsystem in the turbine or occurring during scheduled maintenance. There is a substantial amount of service requests however that took more than 20 days to resolve; 300 of those cases took between 40 and 60 days.

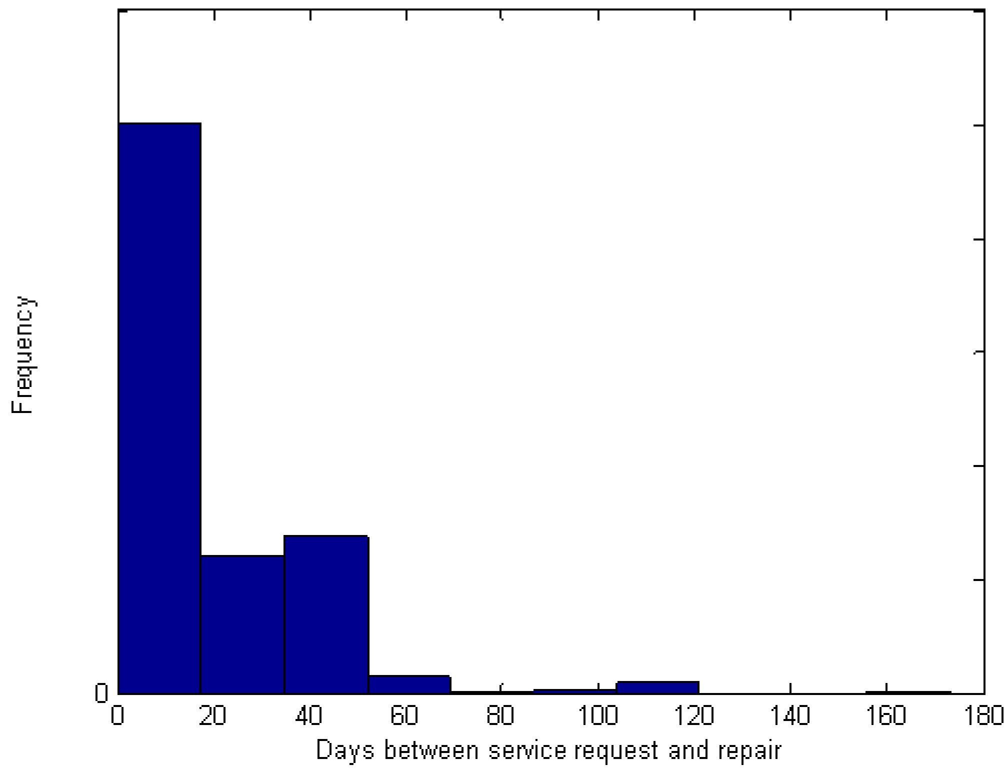

Figure 31- Time between service request and repair for non-functional turbine service requests

Some turbines in Figure 31 have more than 100 days elapsed between the service request and the time when the turbine is repaired. If a downtime lasts for 100 days, the turbine is down for almost a third of the year and not generating power. This has a negative effect on the economics of the wind farm.

Since scheduled maintenance is performed twice per year, it is worthwhile looking at the times when failures are occurring and check whether they coincide with the scheduled maintenance or not. Figure 32 shows the days elapsed between repairing the problem and the closest maintenance cycle for type 'non-functional turbine'.

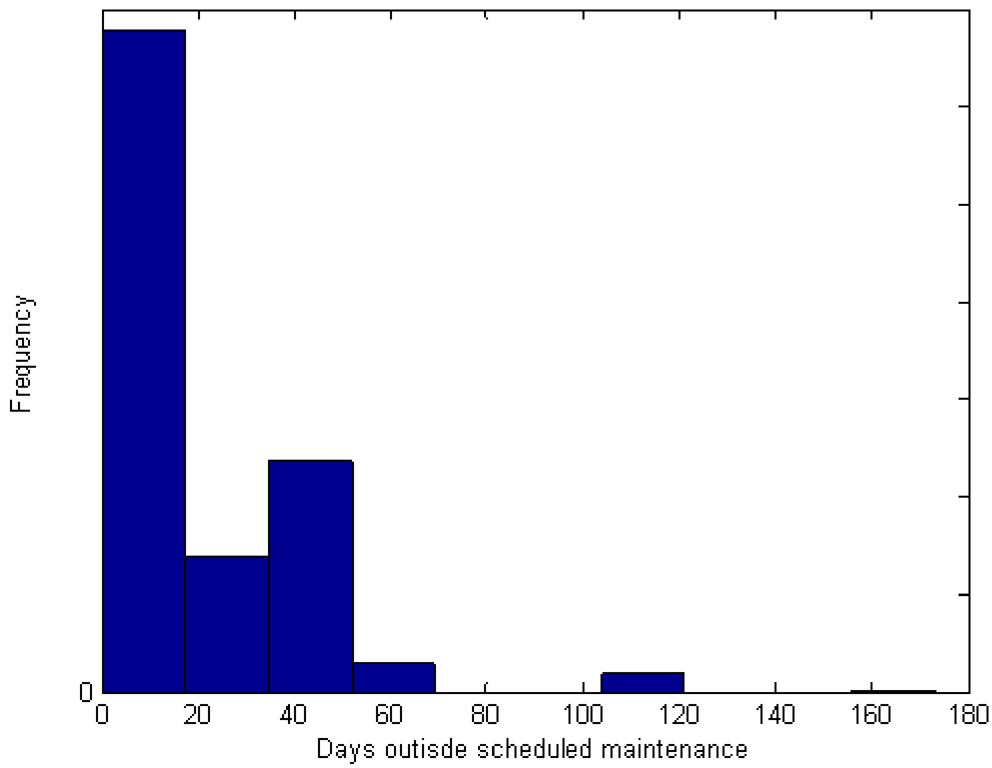

Figure 32- Time elapsed from fixing problem to maintenance cycle for non-operational turbine service requests

The first bin in the histogram in Figure 32 exhibits the largest count since it may be associated to the proximity to the start or end of scheduled maintenance cycles. However, there is a high frequency of events happening more than 40 days outside the maintenance cycle. Some events happen more than 100 days outside maintenance cycle. Figure 32 is fundamentally different than Figure 31 in that it represents the proximity of the failure to the maintenance cycle. A failure can occur 30 days after the closest maintenance cycle; and the turbine has to wait non-operational. Figure 31 on the other had represents the time elapsed between the failure and the maintenance action to fix it.

The wind farm also exhibits a number of no-fault-found (NFF). This is an indicated fault that is resolved by actions such as reset; functionality is then restored to normal. Figure 33 shows the count of no fault found as a function of the number of days it took to repair them. The largest number of NFF can be seen closer to 0, which indicates that NFF can be resolved quickly with a reset or similar actions. There are however NFFs that took more than 30 days to resolve. Some turbines were down for almost a month for a NFF.

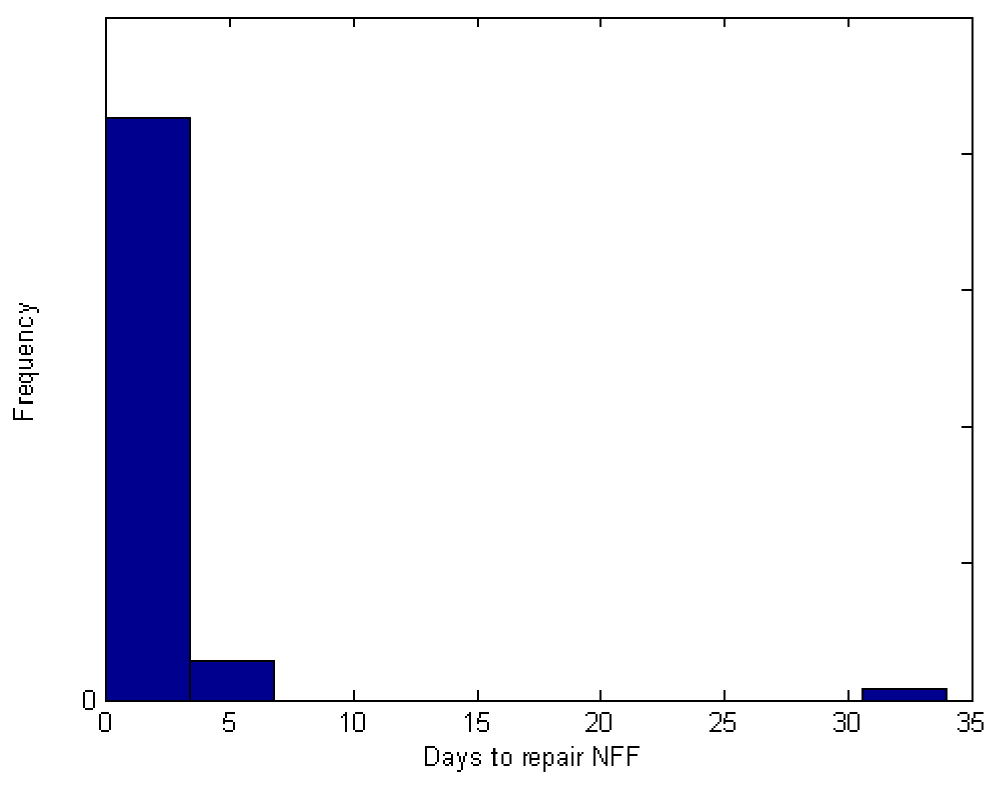

Figure 33- Days to resolve the no-fault-founds (NFFS)

Scheduled maintenance for this wind farm is resulting in a number of scenarios that can decrease the value obtained from the wind farm. Prognostics can increase the maintenance value of such systems, avoid failures and increase the impact of such renewable energy source.

5.4 Life-cycle cost model for wind turbines: ROI

Haddad et al. (2011) established a life-cycle cost model (based on Feldman et al. (2009)) for the implementation of PHM on blades of wind turbines. Although blades are not among the failure in Table 14, the intent is to highlight the differences between the life-cycle cost models and the methodologies presented in this dissertation (demonstrated in the following sections). For data and the details of the analysis, the readers are referred to Haddad et al. (2011) (note the results in the paper and in this section are presented in Euros).

To enable the calculation of ROI, the analysis first determines the optimal prognostic distance when using a data-driven PHM approach (see Figure 34). Prognostic distance is the amount of time before the forecasted failure (end of the RUL) that maintenance action should be taken. Small prognostics distances cause PHM to miss failures, while large distances are overly conservative and throw away lots of remaining life. For the combination of PHM approach, implementation costs, reliability information, and operational profile assumed in this example, a prognostic distance of 470 hours yielded the minimum life-cycle cost over the support life of the turbine. Similar analysis was conducted to determine the optimum fixed-interval scheduled maintenance interval. A fixed maintenance interval of 8,000 hours yielded the minimum life-cycle cost over the support life. Again, small fixed maintenance intervals miss failures, while large intervals are overly conservative.

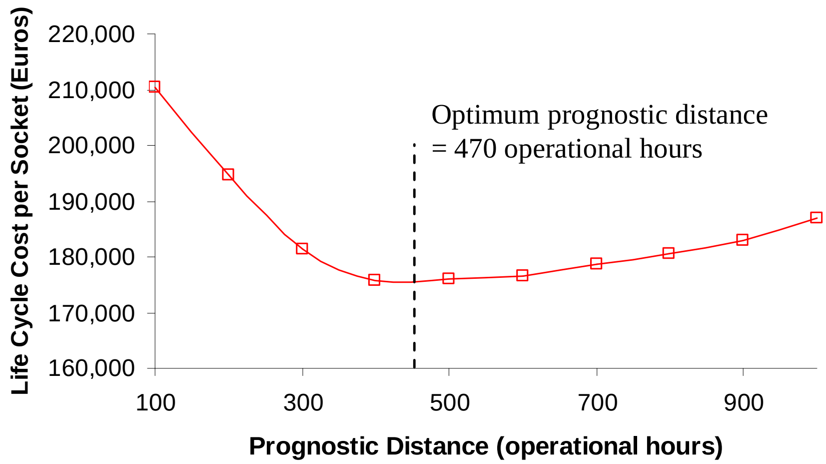

Figure 34- Variation of mean life-cycle cost with a fixed maintenance interval (1000-socket population)

The accumulation of the life-cycle cost per socket for both data-driven PHM and fixed-interval scheduled maintenance case are shown in Figure 35 and Figure 36. A socket is a location in a system (in the wind turbine) where a single instance of the item being maintained (a blade) is installed. The socket may be occupied by one or more items during the lifetime of the system. The time history of costs for each of 1000 sockets is shown in Figure 35 and 36. The data-driven PHM case resulted in an overall lower life-cycle cost (mean = €173,213) compared to the best fixed-interval scheduled maintenance case (mean = €356,999). The data-driven PHM case requires fewer spares throughout the support life of the system. This is primarily due to maximizing the useful life of the blades, i.e., early warning of failures in the data-driven PHM case provided an opportunity to schedule and perform maintenance events closer to the actual failures, thus, avoid failures while maximizing the useful life. Alternatively, the fixed-interval scheduled maintenance case resulted in either throwing-away more useful-life (early intervention). In both cases, some unscheduled maintenance events (intervention that is too late) occurred.

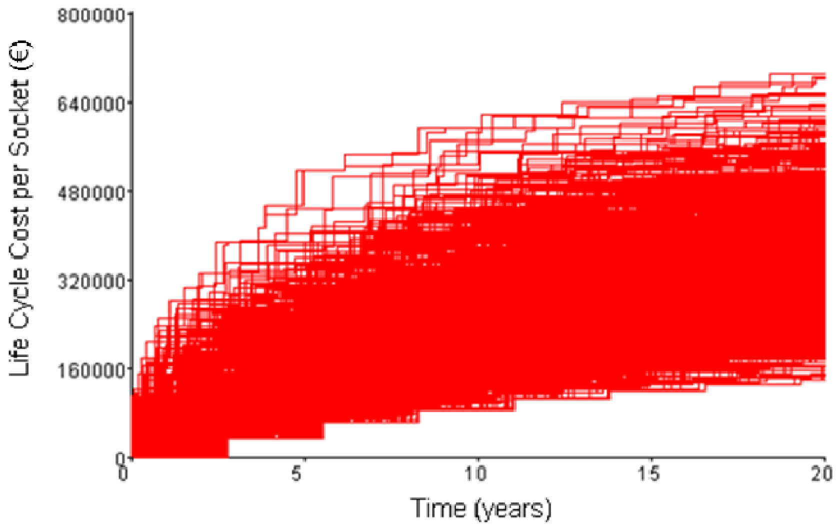

Figure 35- Life-cycle cost accumulation for scheduled maintenance

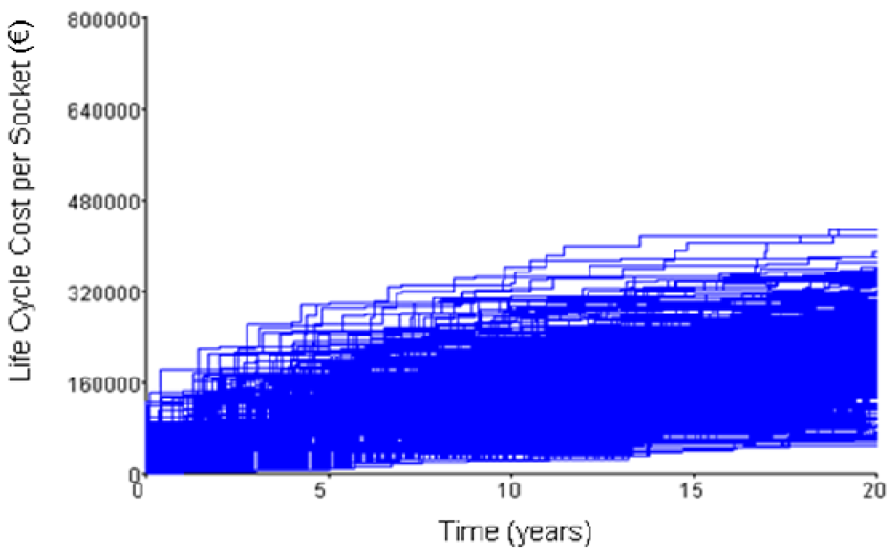

Figure 36- Life-cycle cost for PHM

The mean total life-cycle cost per blade, for a data-driven PHM approach, was €173,213 (mean), with an effective investment cost per blade of €25,408 (mean), representing the cost of developing, supporting, and installing PHM in the blade. This cost was compared to the fixed-interval scheduled maintenance approach, where the total life-cycle cost per blade was €356,999 (mean). Note that the investment cost for the fixed-interval scheduled maintenance policy is by definition zero; since the ROI is computed to support an economic justification in investing in PHM, as opposed to the fixed-interval scheduled maintenance case where there is no investment (i.e., zero investment) in PHM.

Figure 37 shows the histogram of the computed ROIs for 1000-socket population (due to uncertainties in all quantities, each socket in a population will have a unique ROI). In this example, the computed mean ROI of investing in a data-driven PHM approach for the population of blades was 7.43. Notice that some of the ROI values in Figure 37 are negative. This means that there is a risk that implementing a data-driven PHM approach for the blades could result in an economic loss, i.e., you could end up being worse off than fixed-interval scheduled maintenance. Based on Figure 37, this example predicts that a data-driven PHM approach would result in a positive ROI (cost benefit) with a 94.4% confidence.

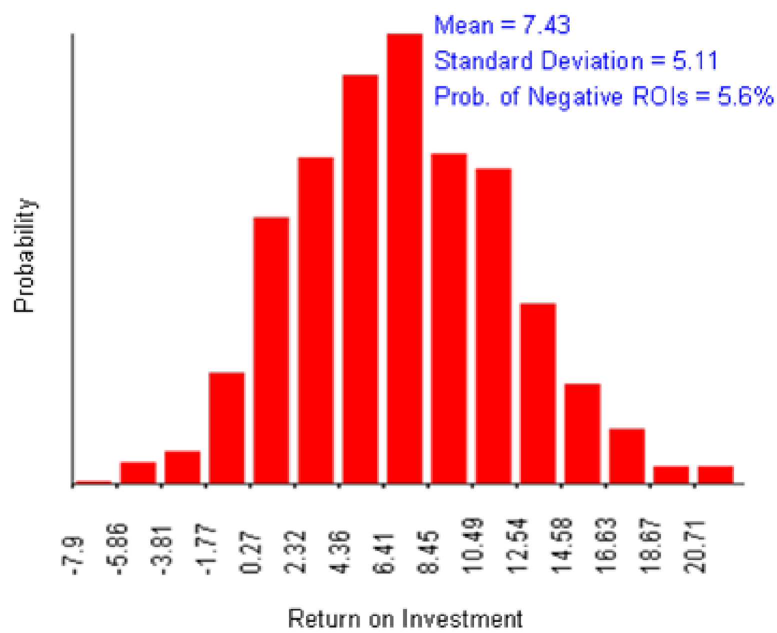

Figure 37- Distribution of return on investment

In Figure 34, an optimal prognostic distance is obtained and is used over the support life to obtain the economic merit of using PHM when compared to other maintenance paradigms. Although this approach shows the value of PHM, it does not account for the value of options that the decision-maker could have made when predicting a failure. The other drawback of such models is that they assume one prognostic distance, hence one maintenance policy over the support life. These drawbacks will be addressed in the following sections for the failure modes observed in the wind farm of the case study.

5.5 Hybrid methodology to value the flexibility enabled by PHM

The previous section considered a life-cycle cost model to show the economic merit of implementing PHM on wind turbines. This section shows a net present value analysis for implementing PHM on gearbox and generators and then incorporates uncertainties and flexibility enabled by PHM to show that the value of PHM increases when flexibility is accounted for. The choice of gearbox in this section is driven by the availability of the data. The contributions however are applicable to any failure mode. The cost data is based on Andrawus et al. (2006). The uncertainties are obtained from the farm discussed in Section 5.2.

The data considers a wind farm with 7 600KW land-based turbines, and compares the net present value (NPV) of scheduled maintenance (called inspection) and CBM. We reproduce the NPV analysis for the 7 turbines by using the costs from Andrawus et al. (2006), rescaling the farm to 7 turbines, and discounting over a period of 18 years (support life of the turbines after they go out of warranty) with a discount rate of 8.2%. This analysis results in a NPV of 32,869£ for inspection, and 64,374£ for CBM. This result indicates that inspection is more beneficial than CBM.

Andrawus et al. (2006) consider that the PHM system avoids failures of the following subsystems: blade, bearing, main shaft, gearbox, and generator. The frequency of failure α, indicates the probability of failure. When the PHM system avoids this failure, cost avoidance, called failure consequence (F_c) will result. Andrawus et al. (2006) identify these cost avoidance opportunities by annual cost reservation, A_{CR}, which is the product of the frequency of failure α, the failure consequence *(F_c)*, and the number of turbines in the farm NT:

$$A_{CR} = \alpha F_c NT \tag{35}$$

Where the failure consequence (F_C) consists of total production lost when turbine is not operating (TC_{PL}), the total cost of material to maintain the turbines (TC_{MT}), the total cost of labor to maintain the turbines (TC_{LB}), and total cost of accessing the turbines (TC_{AS}) (the variables in the equations are defined in the Symbols section at the beginning of the dissertation):

$$F_C = TC_{PL} + TC_{MT} + TC_{LB} + TC_{AS} \tag{36}$$

$$TC_{PL} = 24N_{dy}WT_{PR}C_{EH}C_f \tag{37}$$

$$TC_{MT} = (C_{MT} + C_{TP} + C_{Ld} + C_{Old})\left(1 + \frac{V_{AT}}{100}\right) \tag{38}$$

$$TC_{LB} = (N_{Pn})(N_{dy})(W_{hr})(L_{RT}) \tag{39}$$

$$TC_{AS} = (C_{hd}N_{dy}) + (C_{hd}N_{dy}\frac{V_{AT}}{100}) \tag{40}$$

Consider the case of the generator with a frequency of failure α of 0.00641, a cost of lost production TC_{PL}, of 1663.2£, a cost of material $TC_{MT,}$ of 23,441.25£, a cost of labor TC_{LB}, of 2,400£, and a cost of access TC_{AS}, of 8,460£. These numbers are obtained from the last row of Table 15. This will result in a failure consequence F_C, of 35,964£. And an annual cost reservation A_{CR}, of 1,613£ when multiplied by the failure frequency. This result can be seen in the fifth row of Table 16.

Table 15- Failure consequence (Andrawus et al. (2006))

	Failure consequence F_C (£)				
Failure modes	TC_{MT}	TC_{LB}	TC_{AS}	TC_{PL}	Total
Blade failure	34,545	2,400	8,460	1,663.20	47,068
Main bearings failure	9,851.49	2,400	8,460	1,663.20	22,375
Main shaft failure	11,133.36	4,800	11,280	1,900.80	29,114
Gearbox failure	61,687.50	3,600	11,280	1,900.80	78,468
Generator failure	23,441.25	2,400	8,460	1,663.20	35,964

Table 16- Calculation of annual cost reservation (Andrawus et al. (2006))

	Number of events	$\boldsymbol{\alpha}$	$\boldsymbol{F_C}$	$\boldsymbol{A_{CR}}$

Bearing failure	0	0	25,993	
Main shaft failure	0	0	32,234	
Gearbox failure	2	0.01282	78,468	6,682
Generator failure	1	0.00641	35,964	1,613

Similar results are obtained for the gearbox. The other systems are not included in the analysis as they are assumed to have a frequency of failure of 0. The annual cost reservation is realized over the 18 years of support life. This cost is discounted to year 0 and results in a net present value of 80,091£. This value is added to the net present value of inspection (or time based maintenance (TBM), and results in a total of 112,960£ which is the real cost of inspection. To assess the value of PHM, the difference in NPV of inspection and CBM is calculated and results in 48,585£. This value compares the net present value accounting for the cost and cost avoidance derived from inspection and CBM over the life-cycle.

This standard method to quantify the benefits of PHM does not account for the value of options that the decision-maker can take after prognostic indication. Furthermore, it is necessary to account for uncertainties. If there are forecasts for wind speed, then the decision-maker may decide to run the system while there is probability of high wind speeds and harness the upside effect of uncertainty. Another uncertainty that needs to be accounted for is the uncertainty within the PHM system (i.e., its RUL predictive capability is not perfect).

Figure 38 shows the capacity factor for Turbine 6 on a monthly basis over the year 2009. Power data for Turbine 6 is averaged for every month and divided by 600KW to obtained the ratio of the actual power produced in a given time to the theoretical maximum power. The capacity factor turns out to vary drastically over the months of the year, and basing the results on an average may affect the valuation of the problem under consideration. The capacity factor result affects the maintenance planning for the turbines whereby decision-maker is better off having the turbine down for maintenance.

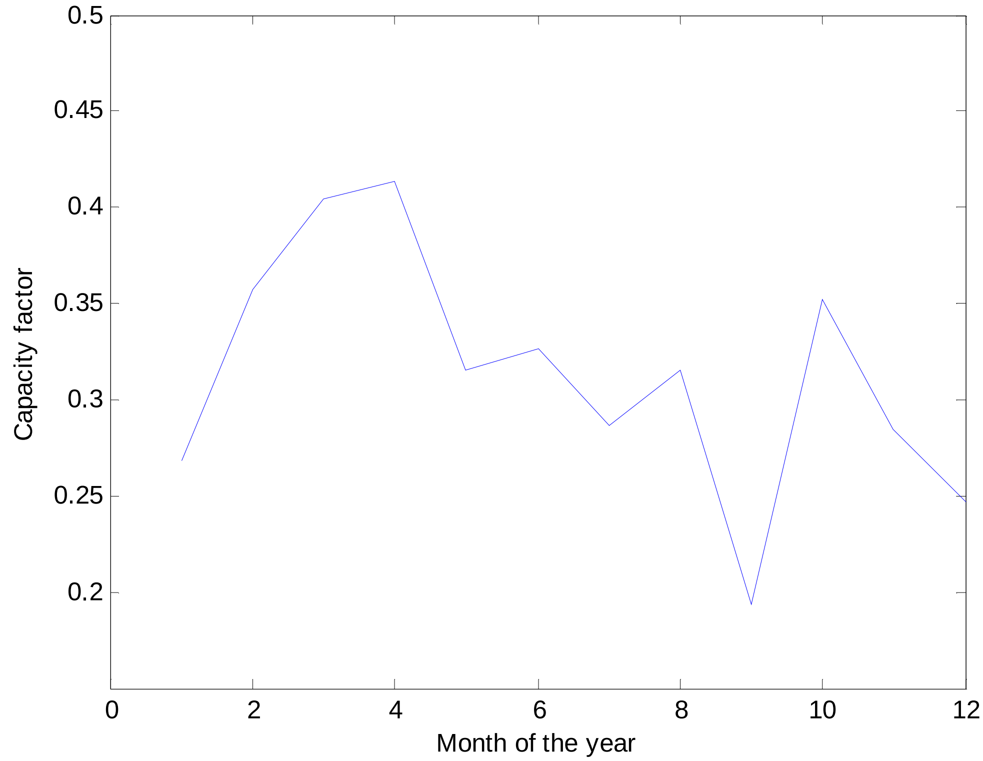

Figure 38- Monthly capacity factor

To estimate the uncertainty in capacity factor, we consider the power from Turbine 6, a healthy turbine (a turbine that did not have failures over the course of the year). The power output is averaged every day, and divided by 600KW, which is the maximum theoretical power the turbine can produce. The data is imported to @RISK and a distribution is fit according to the Chi-square test. A Beta distribution (Figure

39) with the following density function and parameters α of 0.734 and β of 2 fits the data the best:

$$f(x;\ \alpha,\beta) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{\int_0^1 u^{\alpha-1}(1-u)^{\beta-1}du} \tag{41}$$

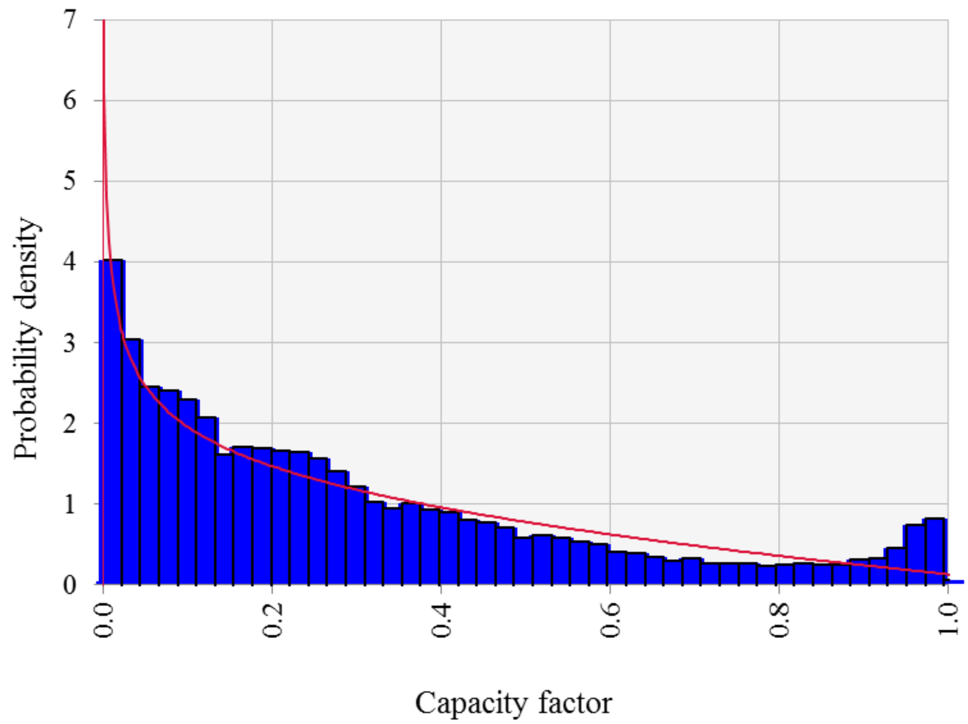

Figure 39- Distribution fitting for the capacity factor over a year

The uncertainty in the capacity factor is an integral part of the production lost. Production lost (TC_{PL}), is expressed as the product of number of days the turbine is down (N_{dy}), the number of hours in a day (24), the power rating of the turbine (WT_{PR}), the cost of energy (C_{EH}), and the capacity factor (C_f):

$$TC_{PL} = (N_{dy})(24)(WT_{PR})(C_{EH})(C_f) \tag{42}$$

To incorporate flexibility in the model, we assume that the decision-maker can turn the turbine off when there is a prognostic indication for the gearbox. The cost of CBM for the gearbox is assumed to be 40% of the cost of failure and the cost of scheduled maintenance is 70% of the cost of failure (EPRI, 2006). The cost of loss production from Table 17 for a gearbox is 1900.8£, and 1663.2 for generator. Using (42) (with a power rating of 600KW, cost of energy of 0.05 £/KW, and a capacity factor of 0.33) we can calculate the number of days the turbine is down for each system: 7 for gearbox and 8 for generator. Now we use this number and calculate an updated production loss when accounting for the uncertainty in the capacity factor. The net present value of the difference in the two maintenance paradigms demonstrating the value of PHM can be now represented as a distribution. We scale the cost data for time-based maintenance and condition-based maintenance from Andrawus et al. (2006) from 26 to 7 turbines (this is an assumption on the total cost of TBM and CBM).

Now we consider the second uncertainty associated with the PHM system. We assume a misclassification rate of 0.05 associated with the PHM system. This implies that the PHM system will not predict a failure 5% of the time. Figure 40 shows a decision tree for uncertainty associated with PHM.

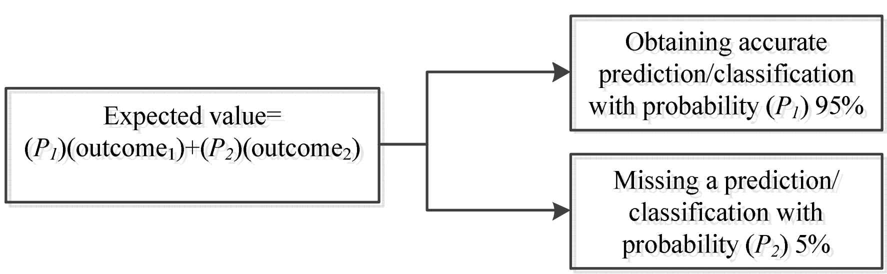

Figure 40- Decision tree for uncertainty within the PHM system

Furthermore, we assume that there is the same number of events (same α) that is predicted by CBM and by inspection. However, when predicted by CBM, the decision-maker has the option to abandon and halt the operation. This will result in a 30% cost saving in supporting maintenance (under the assumptions listed earlier: cost of CBM is 40% of the cost of failure and cost of scheduled maintenance is 70% of the cost of failure).

The expected value is obtained by multiplying the probability of occurrence by the outcome of each branch in the decision tree. In the case of correct prediction, the PHM system will predict all the failures and result in a cost avoidance of 73,842£, which was shown earlier. When the PHM system fails to predict the failures, we replace the failure frequency with 0 and calculate the NPV of annual cost reservation using (35)-(40).

So far we consider two types of uncertainties, and included the flexibility (option to abandon) when addressing the value of implementing PHM. Now we complete the steps of the hybrid methodology and represent them in a VARG diagram. 500 Monte Carlo simulations were run, combined with the decision trees are represented in Figure 41. We assume that the decision-maker can exercises the abandon option 50 days prior to the failure.

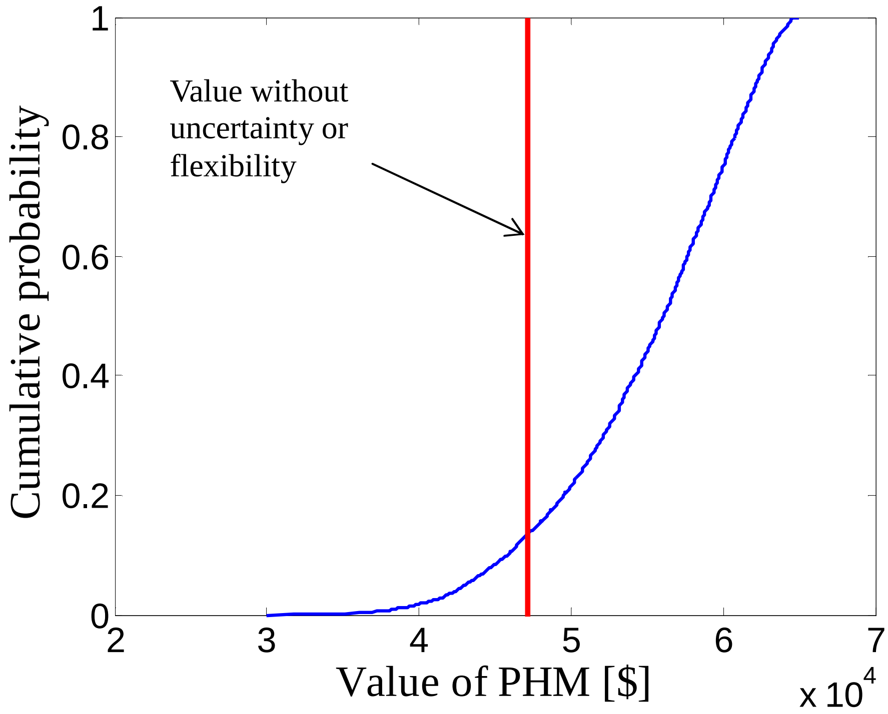

Figure 41- VARG diagram for model accounting for real capacity factor and option to turn turbine off 50 days before failure

Figure 41 shows the results from the analysis with flexibility and the one that does not account for flexibility or the uncertainties. Figure 41 shows that the 18% value at risk is $48,850. This result indicates that there is a 18% chance that the value of PHM on the gearbox and generator is smaller than the value obtained from the analysis that does not account for flexibility and uncertainties. The 50% value at gain is $56,096. This result means that there is a 50% chance that the value of PHM will be greater than $56,096. The additional value in Figure 41 is a result of accounting for the uncertainty in the capacity factor, and the cost-avoidance of turning the turbine off to avoid failure (leading to a lower maintenance cost).

Figure 42 shows the sensitivity analysis on the expected net present value of PHM when changing the number of days the turbine is turned off before failure, ranging between 20 and 100, the misclassification rate (error in PHM system) ranging between 0.95 and 0.5, and the discount rate ranging between 0.05 and 0.11.

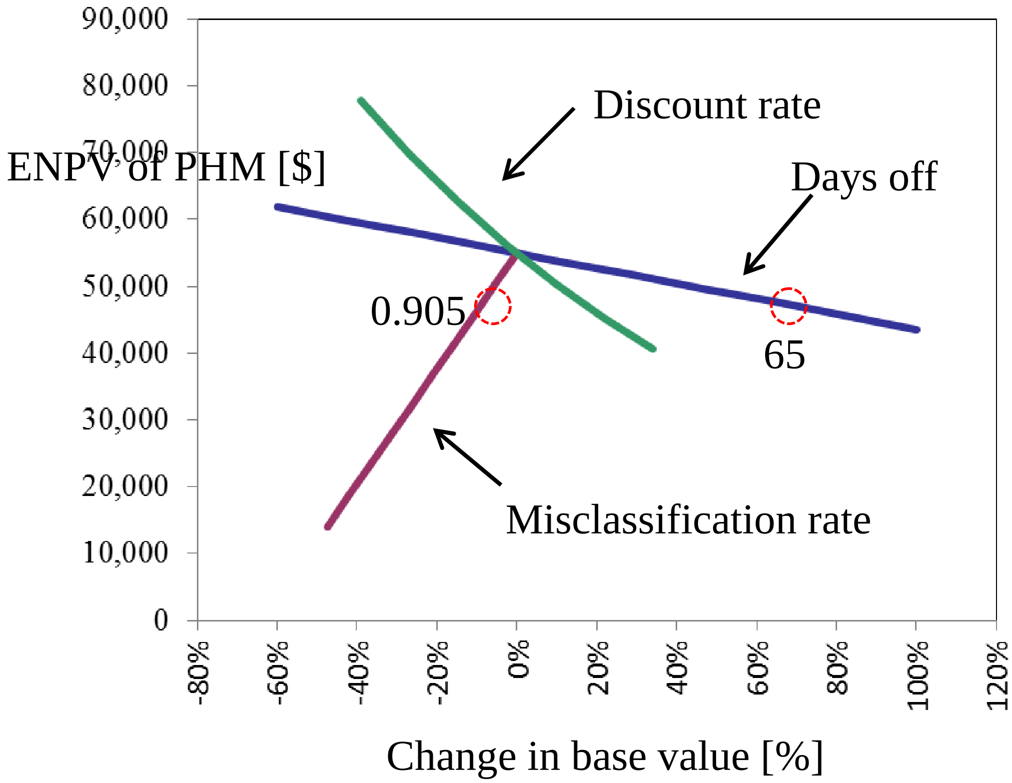

Figure 42- Sensitivity analysis for the value of PHM

Figure 42 shows that the value of PHM is highly affected by the performance of the PHM system. If the misclassification rate of the PHM system decreases to less than 90.5% , the value of implementing PHM is no longer justified even if the decision-maker has the option to turn the system off and avoid failure. The reason is that although the decision-maker has the option to turn the turbine off, the failure is happening before an indication of RUL by the PHM system is obtained. Figure 42 also shows the effect of exercising the option up to 100 days before the indicated predicted failure. Turning the turbine off to avoid failure comes on the expense of a cost of downtime. However that turning the turbine off for up to 65 days before the failure is beneficial. The last part of Figure 42 is the discount rate: since the analysis is performed over 18 years, it is important to analyze the effect of discount rate.

This section included uncertainties and flexibility in the quantification of the benefit of PHM using the hybrid methodology. We consider the support life and show that exercising flexibility can result in a higher value from PHM. The next section considers the time frame from the prognostic indication to the end of the RUL and uses the hybrid methodology to represent uncertainties to show the value of PHM at the system level.

5.6 Quantifying the wait to maintain option

This section highlights the value of waiting after prognostic indication for the different failure modes in the case study. Quantification of the value of waiting is a representation of the additional benefit that the user of the PHM system obtains. It provides means for analyzing the benefits at the system-level and compares a large number of maintenance policies. The method can be done in real-time and updated whenever new information about uncertainties is obtained.

5.6.1 Model description

The value of maintenance is a summation of two uncertain quantities; the cost avoidance (difference in cost of performing condition based maintenance and cost of failure), and the production loss (which is influence by the capacity factor). The value is described in Equations (16)-(18).

Production loss is affected by the capacity factor, and we model it with a geometric Brownian motion that is represented with the following stochastic differential equation:

$$dTC_{PL} = \mu TC_{PL}dt + \sigma TC_{PL}dW_t \tag{43}$$

where TC_{PL} is the production loss being simulated at time t, μ is a drift component, σ is a variance component, and W_t is a Brownian motion. This is a stochastic differential equation that represents production loss as a dynamically changing uncertain quantity. For a capacity factor of 0.33, the production loss per day is 236.7£. This number is the production lost in 1 day with a turbine rating of 600 KW and a cost of energy of 0.05 £/KWh. Simulating the production loss using with a drift of 0.5, a variance of 0.1, and a starting value of 236.7£, we get the result in Figure 43. Figure 43 also shows a histogram for the cross-sectional data at time 50; i.e., it represents the distribution of the production loss on the 50^{th} day.

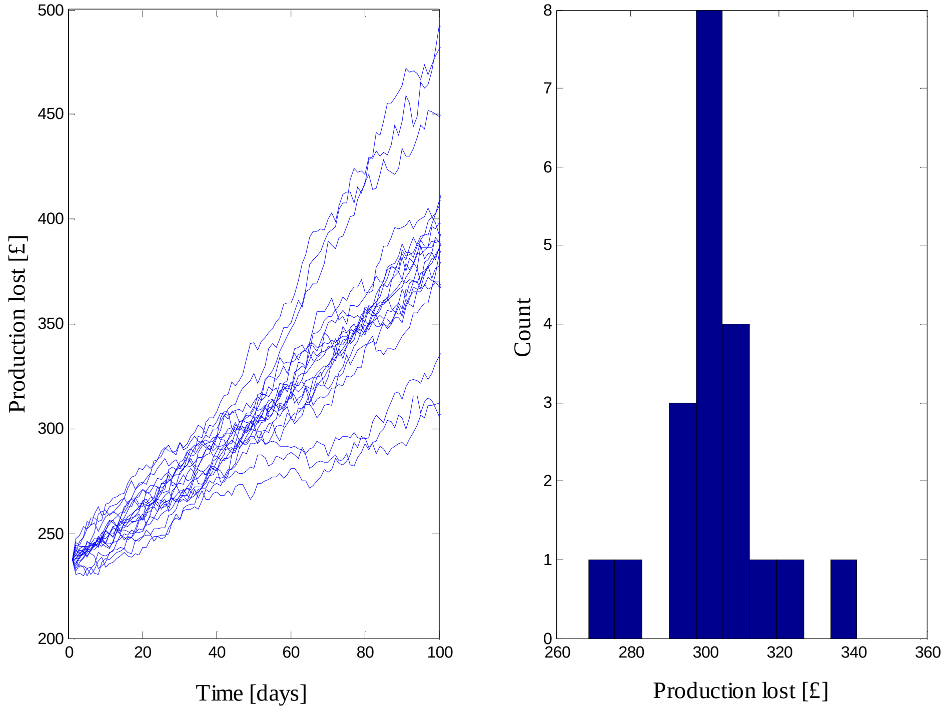

Figure 43- Evolution of production loss

In a recent report by the Electric Power Research Institute (EPRI, 2006), the cost of performing CBM on the gearbox of a wind turbine was assumed to be 40% of the cost of failure, the cost of performing scheduled maintenance on the gearbox was 70% of the cost of failure, and the cost of failure was 100% of the cost of failure. The uncertainty in the cost of maintenance is modeled by a stochastic random process with a geometric Brownian motion using (actual numbers can be estimated from historical data):

$$dC_M = \mu C_M dt + \sigma C_M dW_t \qquad (44)$$

To represent the value of maintenance graphically, we model the production loss with geometric Brownian motion with a drift rate of 0.5, and a variance of 0.1. The cost avoidance is simulated with a starting value of 47,080£ (60% of the cost of failure of a gearbox (EPRI, 2006)), a drift of -0.8, and a variance of 0.25. These two quantities along with the value of maintenance (summation of cost avoidance opportunities and cumulative revenue generated from running the system) are represented in three plots in Figure 44. The first plot is the simulated cost avoidance. The value of cost avoidance starts at 60% of the cost of failure and decreases with time. The second plot is the cumulative revenue obtained from running the system to the end of the RUL. The right most plot in Figure 44 is the value of waiting, which is the summation of the quantities in the left two plots. The simulations consist if 20 paths. Figure 44 shows that the value of waiting decreases initially then increases (right most plot). As the system is used through the remaining useful life, the system will degrade and the cost of maintenance will increase according to our assumption. The turbine will however generate power. If there is a high probability of high wind speeds, then the cumulative revenue will be even higher than considering the case of average capacity factor.

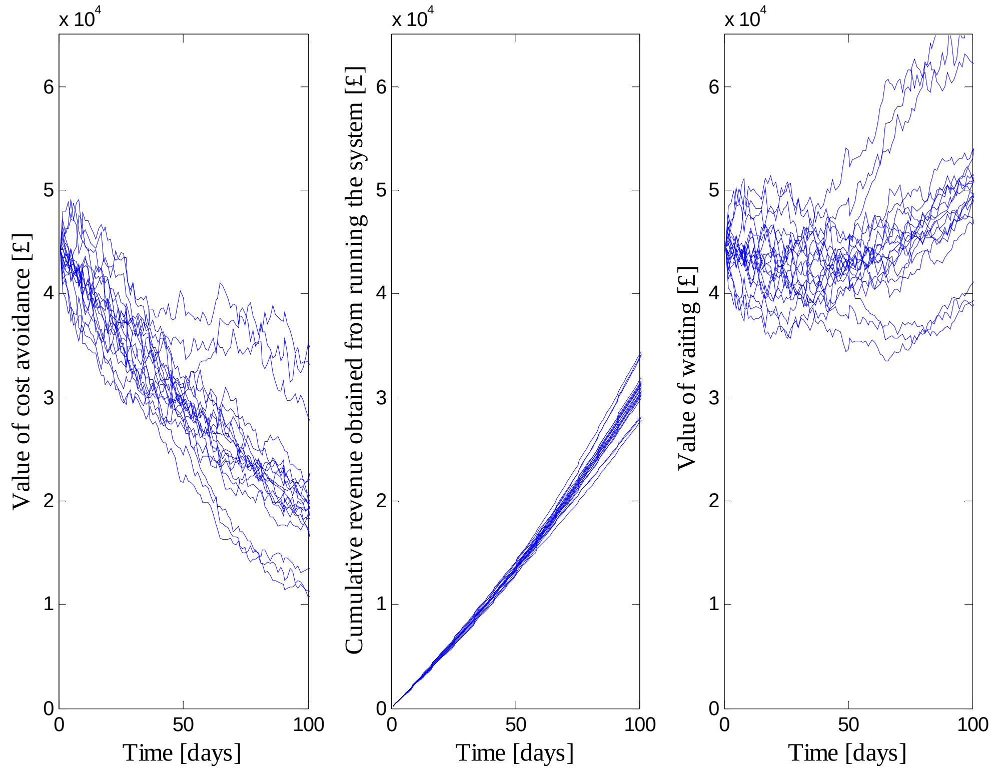

Figure 44- Value of maintenance after prognostic indication

The cost avoidance opportunities are obtained from historical data and follow the trend of the degradation of the system. They can be obtained from historical data and the maintainer of the system. Cost avoidance is not necessarily a function decreasing with a constant drift. Subsystems in turbines (and other systems as well) may be interrelated; a failure in one system can cause a failure in another system and cause an increase in the maintenance cost; or a decrease in the cost avoidance.

5.6.2 Modeling uncertainties

In order to quantify the value of waiting, the uncertainties are first estimated. The uncertainty in the capacity factor is estimated from historical data, and the uncertainty in the cost avoidance is assumed to follow a degradation model. The starting point is known (difference between the cost of unscheduled maintenance and the cost of condition-based maintenance).

The uncertainty in the capacity factor is considered over multiple time horizons: one year for the healthy turbine, one month for Turbines 1 and 3 (the failure occurred in February and no prior data), 2 months prior to failure for all other turbines, and monthly capacity factor for the healthy turbines. The power is averaged every day (since it is 10 minutes data), and divided by 600KW to obtain the capacity factor. A time series for Turbine 6 averaged every day is show in Figure 45.

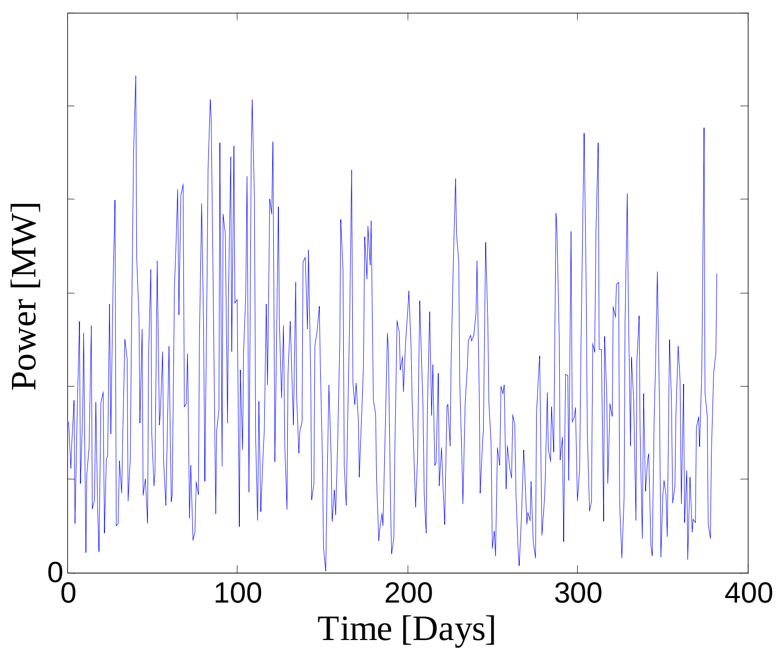

Figure 45- Power time series for Turbine 6

The parameters for the stochastic differential equation of the time series are estimated using the SDE toolbox in Matlab (Picchini, 2007), which uses simulated maximum likelihood estimation (Durham and Gallant, 2002). The estimates of the parameters in stochastic differential equation for Turbines 1 to 5 can be seen in Table

17. The table shows the mean value and the confidence interval (lower bound (LB 95% CI) and upper bound (UB 95% CI)). Confidence in estimation increases with more data.

Table 17- Estimates of uncertainty parameters before failures with 95% confidence intervals

Turbine		Start time	End time	Mean	LB 95% CI	UB 95% CI
1	Mean	1/1/2009	2/7/2009	1.80E-01	3.28E-02	3.27E-01
	Shock			5.00E-01	4.21E-01	5.80E-01
2	Mean	9/1/2009	11/1/2009	1.98E-01	7.51E-02	3.20E-01
	Shock			5.98E-01	5.24E-01	6.72E-01
3	Mean	1/1/2009	2/23/2009	1.32E-01	4.14E-02	2.22E-01
	Shock			6.37E-01	5.82E-01	6.92E-01
4	Mean	3/7/2009	5/7/2009	7.21E-03	-1.63E-02	3.07E-02
	Shock			2.07E-01	1.94E-01	2.19E-01
	Mean	8/2/2009	10/2/2009	7.11E-03	-2.10E-02	3.52E-02
	Shock			1.99E-01	1.85E-01	2.13E-01
5	Mean	6/14/2009	8/14/2009	3.09E-02	-1.56E-02	7.73E-02
	Shock			3.46E-01	3.22E-01	3.70E-01

Tables 18 and 19 summarize the parameters for modeling uncertainty obtained from data with the 95% confidence interval (LB for lower bound and UB for upper bound) for the healthy Turbines 6 and 7 respectively.

Table 18- Uncertain parameters in healthy Turbine 6

Month	Mean	LB 95 CI	UB 95 CI	Shock	LB 95 CI	UB 95 CI
1	9.12E-02	9.01E-03	1.73E-01	4.69E-01	4.28E-01	5.11E-01
2	7.24E-02	1.29E-02	1.32E-01	4.41E-01	4.04E-01	4.77E-01
3	1.19E-01	5.44E-02	1.84E-01	4.62E-01	4.23E-01	5.02E-01
4	9.22E-02	6.55E-03	1.78E-01	5.06E-01	4.63E-01	5.49E-01
5	6.52E-02	2.48E-02	1.06E-01	3.45E-01	3.11E-01	3.79E-01
6	-4.90E-03	-4.04E-02	3.06E-02	2.62E-01	2.43E-01	2.81E-01
7	2.80E-02	-1.71E-02	7.30E-02	3.36E-01	3.03E-01	3.70E-01
8	8.24E-02	4.58E-02	1.19E-01	3.14E-01	2.86E-01	3.42E-01
9	6.23E-02	5.00E-03	1.20E-01	4.15E-01	3.76E-01	4.54E-01
10	1.60E-01	8.24E-02	2.38E-01	5.92E-01	5.41E-01	6.43E-01
11	-2.31E-01	-2.99E-01	-1.63E-01	4.89E-01	4.46E-01	5.31E-01
12	1.83E-01	1.17E-01	2.50E-01	4.78E-01	4.41E-01	5.15E-01

Table 19- Uncertain parameters in healthy Turbine 7

Month	Mean	LB 95 CI	UB 95 CI	Shock	LB 95 CI	UB 95 CI
1	1.43E-01	5.01E-02	2.36E-01	5.23E-01	4.84E-01	5.61E-01
2	2.14E-01	1.39E-01	2.89E-01	5.80E-01	5.36E-01	6.25E-01
3	-9.50E-03	-8.32E-02	6.42E-02	5.52E-01	5.10E-01	5.94E-01
4	5.08E-02	-3.36E-02	1.35E-01	5.01E-01	4.41E-01	5.62E-01
5	1.79E-01	1.14E-01	2.44E-01	4.86E-01	4.33E-01	5.40E-01
6	-2.69E-03	-7.53E-02	6.99E-02	4.81E-01	4.47E-01	5.16E-01
7	5.22E-02	1.46E-02	8.99E-02	3.72E-01	3.53E-01	3.91E-01
8	4.72E-02	-6.71E-03	1.01E-01	3.56E-01	3.22E-01	3.90E-01
9	1.38E-01	7.23E-02	2.03E-01	4.39E-01	4.11E-01	4.66E-01
10	4.61E-01	3.14E-01	6.08E-01	7.72E-01	6.94E-01	8.49E-01
11	2.06E-01	9.96E-02	3.12E-01	5.87E-01	5.32E-01	6.41E-01
12	2.03E-01	1.07E-01	3.00E-01	5.97E-01	5.23E-01	6.71E-01

When the information from the PHM system or sensors on the wind turbine are obtained, the uncertainty can be updated and new drift and shock can be generated on the updated time series. In the case study, the uncertainty parameters are estimated after the failure happened, but all these parameters can be updated in real-time.

5.6.3 Value of waiting

The uncertainties in the capacity factor are summarized in the previous section. The least squares Monte Carlo algorithm is applied to quantify the value of waiting for different components. The prognostic distance considered is not the same for all turbines in the case study (because data is obtained for 1 year only). The assumed prognostic distance can be seen in Table 20.

Table 20- Assumed prognostic distance

Turbine	1	2	3	4	5
Prognostic distance	37	60	53	60	60

Figure 46 shows the value of waiting for Turbine 1 for 37 days. It is observed that the value is initially 0, and starts increasing on day 8. On day 25 the value of waiting starts decreasing because of the risk of failure which may also induce failure in other components as well. Figure 47 and Figure 48 show the value of waiting for Turbines 2 and 4 respectively. The uncertain capacity factor is sued in equation (37) to generate the production of the turbine. The cumulative production is obtained by summing the power every day. The cost avoidance is obtained from the costs of failure from Table (14) and assumes a drift component of -0.6 and shock of 0.25. At 80% of the RUL, we model an increase in the risk of failure by inducing a jump in the cost avoidance that is simulated by a sharp drop in mean of cost avoidance. In other words, when calculating the value of waiting towards the end of the remaining useful life, the cost avoidance is small or negative (because of risk of collateral damage). The choice can be obtained from historical and degradation models along with expert opinion. It is however assumed in this dissertation.

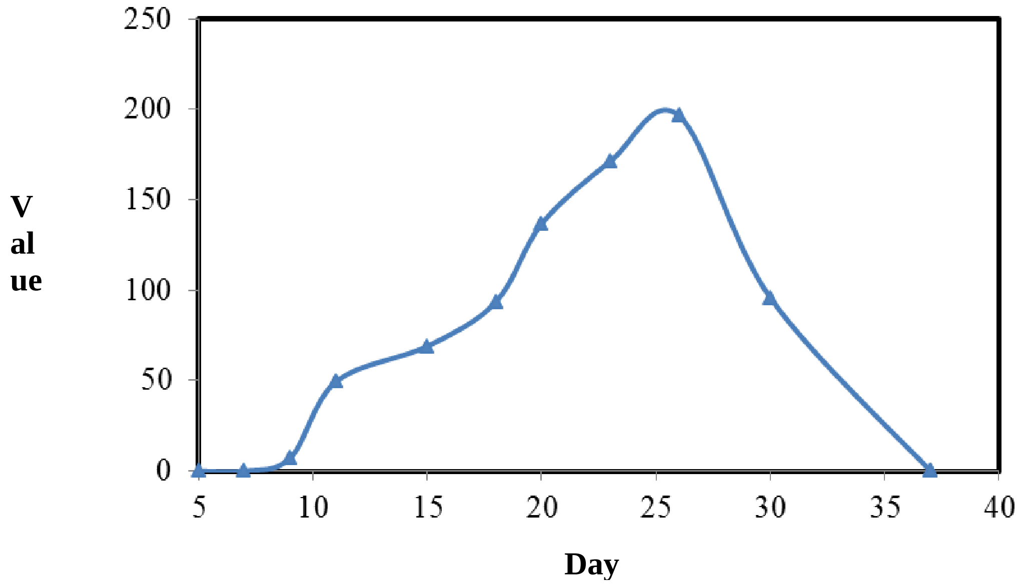

Figure 46- Value of waiting for 37 days for Turbine 1

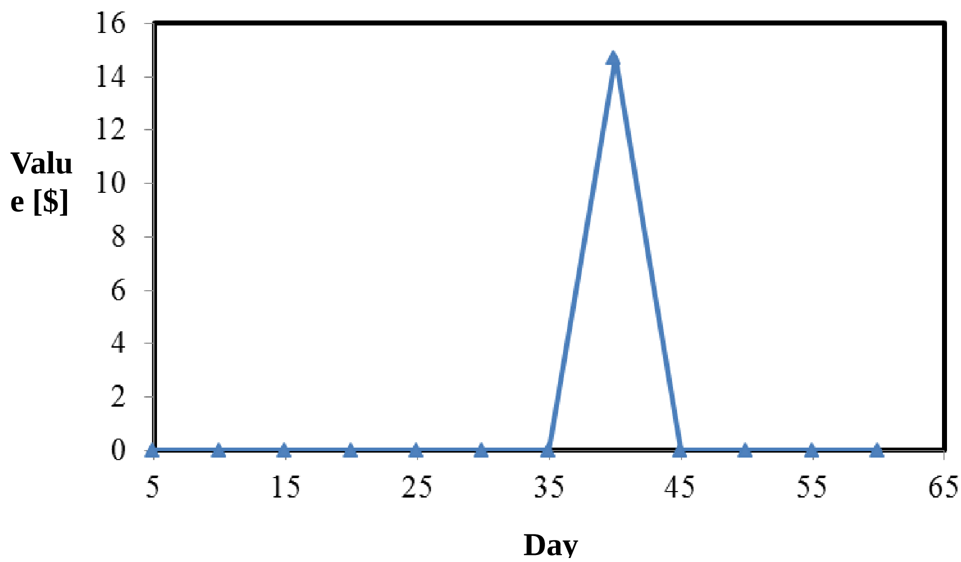

Figure 47- Value of waiting for 60 days for Turbine 2

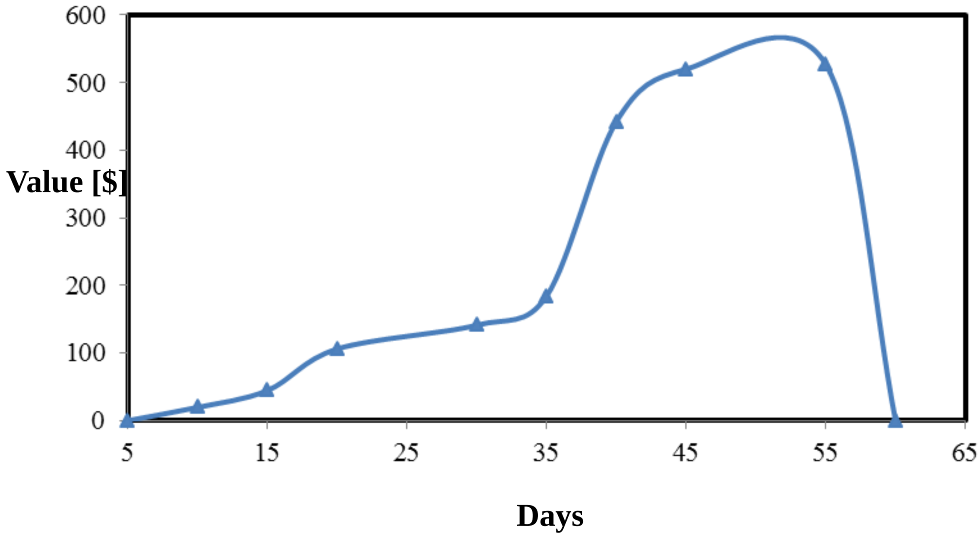

Figure 48- Value of waiting for 60 days for Turbine 4

Figure 47 shows that the value is 0 until day 35 where it starts increasing but then drops again. It is worthwhile noting that the value only increases slightly and then the risk of failure overcomes the value and takes it back to 0. Figure 48 shows the value of waiting for Turbine 4, and shows the waiting has a value and starts decreasing on day 54. The best time to maintain in this case is day 54; which is the time with the highest waiting value. Turbines 3 and 5 have a value of $0 throughout the RUL and are not plotted. A value of 0$ indicates that the decision-maker is better off maintaining immediately. This is fundamentally different than the value of PHM in cost-benefit models. Such models prove the economic merit of PHM when accounting for all the costs and cost avoidance over the life cycle and summarizing with some metric such as ROI. The options cost model indicates how much additional value, the user/decision-maker can obtain from running the system through the RUL; a capability enabled by PHM.

Now we assume that all the turbines have a RUL of 100 days, and estimate the uncertainty in the capacity factor from the healthy Turbine 7 for the whole year. Results show a drift component of 0.0983 and a variance component of 0.46. The value of the option to wait up to 100 days can be seen in Figure 49 (labels are failure modes and not turbines to in this figure: one turbine exhibited multiple failure modes).

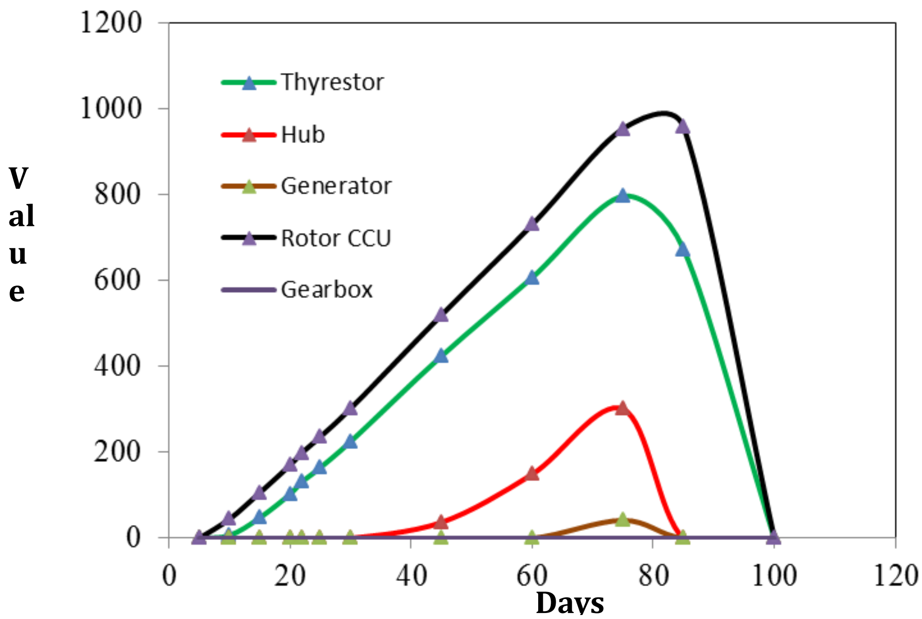

Figure 49- Value of waiting for 100 days

The value of waiting for the 5 observed failure modes in the turbines is shown in Figure 49. The value of waiting indicated the benefit that the user of the PHM system obtains from running the system through the RUL. The curves show that the value starts at 0, for all failure modes and increases at some point except for failure mode 5. This failure mode corresponds to a gearbox failure. When a failure for a gearbox is predicted, the decision maker is better off maintaining at the earliest convenience as the revenue obtained from running the system will not compensate for the risk of failure. This is of course for the uncertainties assumed in this case study. These numbers can vary depending on the uncertainties assumed.

Consider the thyrestor for example, the value of waiting starts increasing on day 8 and peaks on day 74 before it starts decreasing again. The decrease is associated with an increase in the risk of failure. The value of $820 on day 74 is the benefit obtained from the PHM system that allows the decision-maker to wait and maintain at any point until the end of the RUL. The values are dependent on the assumptions of costs made and can be much higher if the turbines had a higher power rating. For the hub (or main bearing), the value starts increasing on day 28 and peaks on day 76 before it starts decreasing again. The decision-maker is better off waiting until day 76 to maintain to obtain the largest value from PHM.

The $0 waiting value for the gearbox does not mean that PHM has no value; it means that waiting does not generate any additional benefit. In the Section 5.5, we demonstrated the economic merit of implementing PHM on a gearbox. In this part of the case study, we derive the additional benefit (value of contingency action: waiting to perform maintenance). A value of $0 is a recommendation for the decision-maker to maintain when the first opportunity arises.

Another point worthwhile highlighting in this section is that the least squares Monte Carlo algorithm quantifies the benefit of PHM at all points up to the end of the RUL. This is in contract to the life-cycle cost model in Section 5.4 that assumes one optimal prognostic distance throughout the life-cycle. The methodology demonstrated in this section is applicable to individual system (individual turbines exhibiting different failure modes), and quantifies the additional benefit that the PHM system provides. The analysis in this section considers individualized maintenance policies; condition-based maintenance at any point until the end of the RUL.

Finally, we note that the model is based on uncertain quantities that can be updated in real-time as new information is obtained regarding the uncertain quantities; a capability that did not exist for cost-benefit models for quantification of the benefits of PHM.

5.7 Placing the dynamic maintenance threshold

Finally we demonstrate the value of waiting by considering two turbines exhibiting prognostic indications for different components at different times. Considering a timeline from 0 to 53, the first turbine has a failure on day 37, and the second one on day 53. The prognostic indication is assumed to be obtained 37 days prior to failure for both turbines. When the prognostic indication of the first turbine is obtained, the decision-maker does not have any information about the time when the second turbine will fail. The value of waiting is first obtained from the least squares Monte Carlo algorithm for the data of Turbine 1. The uncertainty parameters are estimated for 37 days prior to for turbine 1 (drift of 0.198 and shock of 0.58). The value of waiting starts increasing on day 9. On day 16 (37 days before the end of life of turbine 2), a prognostic indication for Turbine 2 is obtained. After the failure of Turbine 1, a penalty equivalent to the cost of production lost by 1 turbine is imposed. The decision-maker is interested in knowing when to maintain given the prognostic information and the uncertainties associated with the operation of the system. The value of waiting with the annotation of different events can be seen on Figure 50.

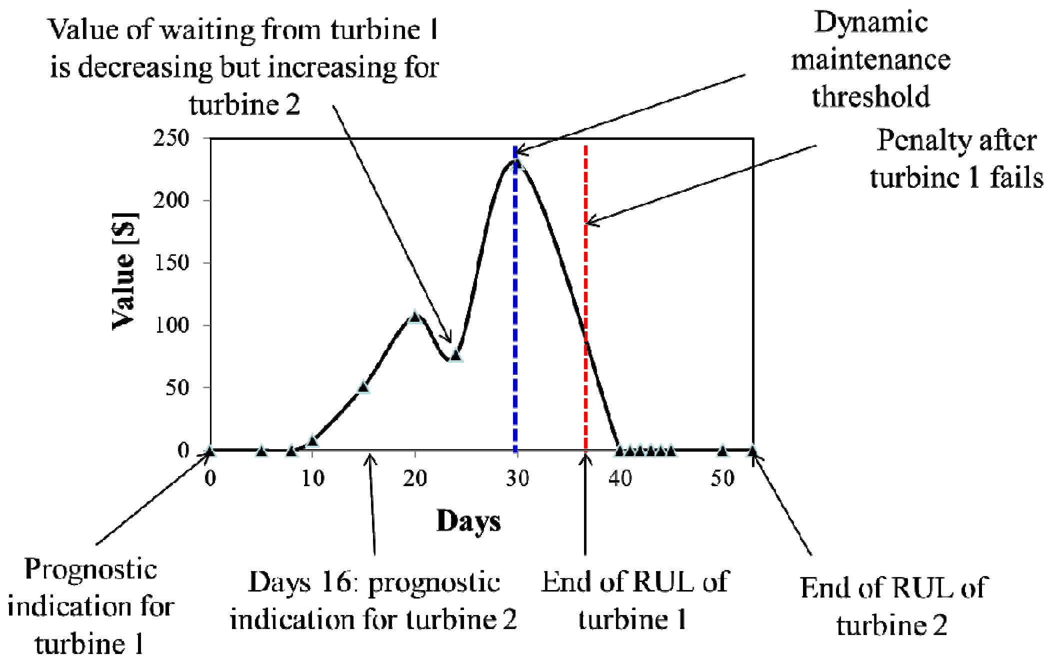

Figure 50- Dynamic threshold based on the value of the option to wait

The value of waiting exhibits two local maxima in Figure 50, the first one is influenced by the maximum waiting value for Turbine 1. But when the second Turbine indicates an RUL, the result show that dynamic threshold that maximizes the value of waiting correspond to day 30. This is 7 days before the failure of Turbine 1 where penalty starts to accrue.

The methodology is applicable to multiple systems and is able to set a threshold based on the uncertainties and prognostic information. As new information about the degradation or the uncertainties associated with the operation, the model can be updated and the threshold can be set dynamically to maximize the value obtained from the PHM system.

5.8 Summary

This chapter demonstrates the methodologies presented in this dissertation on a wind farm case study. The chapter first highlights the importance of sustainment of wind farms, then explains the data used for the case study. A life-cycle cost model is proposed to show the value of PHM on blades of turbines, then a net present value analysis is presented to show the value of PHM on gearboxes and generators. The hybrid methodology is demonstrated and includes the option to abandon which increases the value of PHM. The value of the waiting option is demonstrated on the 7 turbines obtained from the wind farm, and a dynamic maintenance threshold is presented. The value of waiting is a representation of the benefit that is obtained from PHM at the system when running the system through the RUL.

Chapter 6: Summary, Contributions and Future Work

This chapter summarizes the research performed in this dissertation, discusses the contributions and proposes directions for future work.

6.1 Summary

This dissertation adds to the body of knowledge on health management for systems with prognostic capabilities contributions supporting the advancement and penetration of PHM technologies. Maintenance options are presented to define the flexibility enabled by PHM, and valuation methods based on a least squares Monte Carlo methods are presented. The wait to maintain option is presented with an algorithm to quantify it. This provides a new system-level cost model that quantifies the value of PHM for individualized maintenance policies and enable maintenance planning in real-time based on PHM information.

Chapter 1 motivated the problem, presented a mathematical abstraction of the problem, and presented the outline of the dissertation. Chapter 2 provided a literature review on health management for systems with prognostic capabilities, relevant optimization problems, and real options work relevant to the problem solved in this dissertation. Chapter 3 introduced maintenance options and tools to frame the flexibility enabled by the PHM system. The proposed methodology integrates multiple sources of uncertainty in order to present the distribution of the net present value of the option in a diagram called value at risk and gain diagram (VARG). The VARG diagram is a cost-benefit-risk representation of the value of implementing PHM on a system that can account for flexibility. Chapter 4 presented a least squares

Monte Carlo algorithm to quantify the value of waiting options. An example is provided to showcase the detailed step-by-step process of the algorithm and the methodology used to get a price for the options. Chapter 5 demonstrates the methodology on a case study of wind farms in the United States from the General Electric Company.

6.2 Contributions

The research work in this dissertation presents the following contributions that are applicable to systems with prognostic capabilities:

1) Formalizing maintenance options within the real options framework and the development of the first cost-benefit model that incorporates the value of flexibility (contingency actions or options). Maintenance options are introduced as means to represent the flexibility enabled by PHM, and a hybrid methodology based on Monte Carlo simulations and decision trees was established to incorporate the value of flexibility.
2) The development of the first system-level cost-benefit model to quantify the benefits of PHM from a user's perspective. The benefits of PHM are measured by quantifying a new kind of options, the option to wait to perform maintenance. The model evaluates individualized maintenance policies for different system instances, and quantifies the value of PHM at all points from prognostic indication to the end of the remaining useful life.
    a. The model can be updated in real-time and can generate a value of the waiting to maintain option at any time.

b. The model provides a solution to the fundamental maintenance problem of systems with prognostics.

c. The methodology allows the value of PHM to be established and the use of PHM in systems to be improved when an availability requirement has to be met.

3) The development of a maintenance threshold methodology that uses the information from PHM to set a dynamic maintenance threshold. The model is applicable to multiple systems that may not have the same prognostic distance or the same failure mode. The maintenance threshold is based on maximizing the value of waiting across a fleet of systems. The methodology can also be used to support outcome-based contracts.

6.3 Potential broader impacts of this work

The maintenance options methodology applied to PHM systems is the first reported work that puts the flexibility enabled by PHM in a quantifiable framework. It provides significant new capabilities to: a) perform real-time pro-active cost-benefit-risk decision support; b) determine the optimal maintenance strategy for a fleet of systems; and c) maximize the value of maintenance. The methodology can be extended to incorporate availability requirements as constraint, and support availability contacts.

The methodologies of this dissertation are versatile and applicable to many types of systems. Although the focus of the dissertation is on a limited number of maintenance options, there is theoretically a much larger (maybe infinite number of maintenance options) that may be application dependent.

6.4 Future work

Future work can extend the maintenance options approach to include the valuation of multiple options arising in engineering systems. This dissertation addressed two types of options, waiting and abandoning. However there may be a larger number (maybe infinite) number of options. The decision-maker can prioritize among the options. A global optimization method such as genetic algorithms can be used to choose the best option for each system in a fleet of systems.

Another extension of the current work is to incorporate logistics parameters and models in the options valuation in order to estimate the uncertainties in logistics and how they affect the value of the options.

The least squares Monte Carlo algorithm considered one type of polynomial for function approximation; the Laguerre polynomials. This class for polynomials has been proven to enable convergence in the literature. There are however other choices for polynomials for function approximation (discussed in Chapter 4). A study to compare different polynomials and the number of paths can be conducted to show the effect on the value of waiting.

The cost avoidance considered in the wait-to-maintain option are obtained from historical data. The goal was to find a balance between risk and additional revenue. A loss function can be added to the model to visualize this balance. An example of a loss function is the Taguchi loss function that measures the financial impact when a process deviates from its target.

Although it is not addressed in this dissertation, valuation of staging options can give the true value that should be invested in the PHM system or in improving its performance. Staging options in real options theory are options that arise after the execution of a first option. For example, a PHM system for monitoring a gearbox for a wind turbine would ideally predict the advent warning of failure for failures throughout the life cycle of the gearbox. Exercising one maintenance option in one maintenance cycle gives rise to maintenance options in the next cycle. Valuation of the staging options gives the true value that should be charged for the PHM system.

Glossary

This glossary presents the definition for key terms that are used throughout the dissertation. The terms may have been used in different contexts in the scientific community; the definition presented here is the key one for the work.

- **Availability**: the ability of a system to be operational when it is required for operation.
- **Brownian motion:** a continuous time stochastic processes.
- **CBM**: condition-based maintenance is the maintenance of an asset contingent on its health condition or use.
- **Contingency actions**: actions taken after prognostic indication.
- **Discount rate**: the interest rate that an eligible depository institution is charged to borrow short-term funds directly from a Federal Reserve Bank.
- **Enterprise**: fleet of system. Availability at the enterprise level is usually different than availability at the system level.
- **Flexibility**: RUL is the remaining useful life that a system has and it effectively represents the lead time (subject to appropriate uncertainties) for the decision-maker or other maintenance entities to take preventive actions prior to a failure. This can be described as a flexibility phenomenon whereby entities involved with the operation, management, and maintenance of a system have the flexibility to take actions at any time up to the end of the RUL.
- **Health index**: The system-state at time can be summarized by a random aging variable. In the absence of repair or replacement actions, is an increasing

stochastic process. The system fails when the aging variable is greater than a fixed threshold.

- **Net present value**: The difference between the present value of cash inflows and the present value of cash outflows. NPV is used in capital budgeting to analyze the profitability of an investment or project. NPV analysis is sensitive to the reliability of future cash inflows that an investment or project will yield.
- **Option**: the term option is used in the context of a choice arising to the decision maker. An option or choice is a strategy that can be carried out to manage the health of the system in order to meet some requirement.
- **Post-prognostic indication**: After a prognostic indication. Typically the decision making is addressed after a prognostic indication.
- **Prognostic distance**: it is the amount of time before the forecasted failure (end of the RUL).
- **Prognostic indication**: Indication of an anomaly by a prognostic system. It is typically a prediction that a fault or failure will happen after a certain time.
- **Real option**: is the right but not the obligation to take an action within a period. Real options analysis is a capital budgeting tool that quantifies flexibility in systems.
- **Remaining useful life (RUL)**: the remaining life the system has before failure.
- **Requirement**: performance measurement or outcome required by an entity involved in the use, management, operation or maintenance of a system.

- **Stochastic process**: it is a statistical process involving a number of random variables depending on a variable parameter (which is usually time). Stochastic processes are used to model uncertainties.
- **Sustainment**: The capacity of a system to endure. The key elements of sustainment are: reliability, maintainability, availability, upgradability, affordability.
- **System level**: an individual instance of a system. This can be one aircraft, one engine, one turbine, etc.

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Awards

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Related Publications

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