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Value Centric Approaches to the Design, Operations and Maintenance of Wind Turbines

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VALUE CENTRIC APPROACHES TO THE DESIGN, OPERATIONS AND MAINTENANCE OF WIND TURBINES

A Thesis

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"Knowledge can only be got in one way, the way of experience; there is no other way to know."

Swami Vivekananda

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NOMENCLATURE

VOE	Value of Energy
CM	Corrective Maintenance
PM	Preventive Maintenance
IPP	Independent Power Producer
CMS	Condition Monitoring System
CBM	Condition Based Monitoring
COE	Cost of Energy
DOE	Department of Energy
NREL	National Renewable Energy Laboratories
O&M	Operating and Maintenance
PPA	Power Purchase Agreement
PTC	Production Tax Credit
NDT	Non Destructive Testing
POD	Probability of Detection

$\boldsymbol{V_{CI}}$	Cut-in Wind speed
$\boldsymbol{V_{Co}}$	Cut-out wind speed
$\boldsymbol{V}$	Wind speed
$\boldsymbol{k}$	Shape parameter
$\boldsymbol{\rho}$	Density of air
$\boldsymbol{A}$	Area of rotor
$\boldsymbol{\lambda}$	Manual inspection detection level
$\boldsymbol{v}$	Virtual age
$\boldsymbol{R_t}$	Revenue at time step $\boldsymbol{t}$
$\boldsymbol{C_t}$	Cost at time step $\boldsymbol{t}$
$\boldsymbol{C_p}$	Coefficient of power
$\boldsymbol{\theta}$	Level of repair
$\boldsymbol{W_t}$	Wind speed at time $\boldsymbol{t}$
$\boldsymbol{C_i}$	Repair cost with respect to virtual age

ABSTRACT

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Wind turbine maintenance is emerging as an unexpectedly high component of turbine operating cost, and there is an increasing interest in managing this cost. This thesis presents an alternative view of maintenance as a value-driver, and develops an optimization algorithm to evaluate the value delivered by different maintenance techniques. I view maintenance as an operation that moves the turbine to an improved state in which it can generate more power and, thus, earn more revenue. To implement this approach, I model the stochastic deterioration of the turbine in two dimensions: the deterioration rate, and the extent of deterioration, and then use maintenance to improve the state of the turbine. The value of the turbine is the difference between the revenue from to the power generation and the costs incurred in operation and maintenance. With a focus on blade deterioration, I evaluate the value delivered by implementing two different maintenance schemes, predictive maintenance and scheduled maintenance. An example of predictive maintenance technique is the use of Condition Monitoring Systems to precisely detect deterioration. I model Condition Monitoring System (CMS) of different degrees of fidelity, where a higher fidelity CMS would allow the blade state to be

determined with a higher precision. The same model is then applied for the scheduled maintenance technique. The improved state information obtained from these techniques is then used to derive an optimal maintenance strategy. The difference between the value of the turbine with and without the inspection type can be interpreted as the value of the inspection. The results indicate that a higher fidelity (and more expensive) inspection method does not necessarily yield the highest value, and, that there is an optimal level of fidelity that results in maximum value. The results also aim to inform the operator of the impact of regional parameters such as wind speed, variance and maintenance costs to the optimal maintenance strategy. The contributions of this work are twofold. First, I present a practical approach to wind turbine valuation that takes operating and market conditions into account. This work should therefore be useful to wind farm operators, investors and decision makers. Second, I show how the value of a maintenance scheme can be explicitly assessed for different conditions.

CHAPTER 1. INTRODUCTION AND BACKGROUND

In recent years, it has become apparent that wind turbine operations and maintenance costs are higher than anticipated. In particular, wind turbine maintenance is emerging as an unexpectedly high component of turbine operating cost. For example, a typical blade replacement for a 2 MW turbine costs around $300,000 (Tretton et al, 2011). As a result, there is an increasing interest in managing maintenance costs. To help address this challenge, I demonstrate and refine here a value-based approach to optimize wind turbine maintenance. In contrast to the traditional cost-centric strategies, a value-driven perspective provides the decision maker with a deeper understanding of both the costs and benefits involved. In this thesis, I develop this concept and demonstrate its application to guide decisions about turbine blades using Condition-based Monitoring Systems (CMS) and Manual Inspection methods.

The thesis is organized as follows: Chapter 1 gives a brief introduction of wind energy along with the motivation and objectives of this work. Chapter 2 presents an overview of the Value Of Energy (VOE) approach and its mathematical formulation. Chapter 3 explains the approach used for the optimization of turbine maintenance strategies. Chapter 4 discusses the results from the application of optimal CMS and Manual

Inspection methods. Chapter 5 demonstrates a decision framework that has been developed to assist wind farm investors. Finally, Chapter VI concludes the thesis.

1.1 Motivation

The United States is amongst the largest producers of energy from renewable sources and is also the second largest producer of energy from wind in the world. Wind energy is a secure source of energy and is crucial to our energy independence and technological leadership. Energy production from wind protects the environment, and helps to reduce climatic impacts on the population. Additionally, increasing production of energy from wind can reduce costs associated with air pollution, both healthcare and environmental costs. There might be arguments that wind farms take up large areas of land, taking away productivity from farms, but essentially wind turbines require only a small area for foundation and hence do not significantly affect farm land (NREA, 2013).

Wind energy research has gained considerable momentum over the last couple of decades, owing largely to the rising oil prices and the global need for a more reliable and cleaner source of energy. Modern wind turbines can trace back their technological advancement to the large scale commercial wind turbine that NASA developed in collaboration with US government in the 1970s (Asmus, 2001). The first one of its kind, NASA's commercial wind turbine had a longer design life and could handle higher wind speeds in comparison to the other turbines of that period.

In its early days, wind energy was considered a highly risky investment, mostly because the associated technology was still very primitive. Additionally, the intermittent nature of wind posed several challenges such as its integration into the grid, and meeting power demand. See Jarass et al. (1981) for an extensive review. Studies focused on maximizing the energy extracted from a wind farm and thus numerous experimental and computational approaches led to the development of optimal wind farm layouts. The optimization models that were developed addressed conflicting issues such as turbine wake, cost, downtime and accessibility in order to maximize revenue from a wind farm (Lackner et al, 2007).

Another aspect that has been studied extensively are the effects of the temporal changes in wind speed at different locations (e.g., Fripp and Wiser, 2006), thus paving the way for research on the intermittency of wind, and how conventional sources must provide power to meet demands in these calm periods. However, integrating wind into the utility grids is difficult as most often these grids are designed for traditional energy sources like coal and gas. The intermittent nature of wind affects the balance between load and generation, economic and policy incentives, cost-effective storage, and robust and distributed control (Zehnder et al, 2011). This has led to the development of energy-based models that address the assimilation of wind energy sources in conventional generation systems (Billinton et al, 2006).

The advancement in research is encouraging, but several issues must be addressed before wind energy can become more favorable than traditional fossil sources. Issues such as reliability and maintenance plague the industry, and these factors in particular need to be understood better in order to integrate wind power into the national energy system and for making wind power an attractive investment. Currently, very little reliability and maintenance data is available in the United States, but recent estimates indicate that reliability levels are lower and maintenance costs are higher than anticipated (Asmus and Seitzler, 2010). Investors are faced not only with high capital requirements but also with uncertain maintenance and operating expenses that crop up during the lifetime of the project (Arvizu et al., 2011). A recent survey found that over 90% of respondents viewed cost as the biggest impediment to investment (Sovacool, 2009).

Some of the questions that must be answered are:

- Can improved reliability and maintenance strategies increase the return on investment?
- Would a higher maintenance technique with its added accuracy but higher initial costs contribute more value than the lower fidelity ones?
- How should maintenance strategy change, if at all, with varying weather conditions, turbine types and location?
- How would different forms of selling energy in the market affect the optimal maintenance strategies and the VOE?

Investors and operators do not have answers to these questions and thus often end up investing significant resources and funds into unnecessary and incorrect maintenance. This thesis specifically address the first two questions, and partially focuses on the third question.

Maintenance can be primarily divided into scheduled and unscheduled maintenance (Rausand and Hoyland, 2004). On average, scheduled maintenance is performed about twice per year on installed turbines and results in an average downtime of 24 hours per turbine, per inspection (Adams et al., 2011). In contrast, unscheduled maintenance is 500% more costly on average, and results in an average downtime of 130 hours per turbine per year for European turbines (Adams et al., 2011).

Currently, return on investments in the wind energy sector is unpredictable and highly dependent on the actions taken by the operator over the lifetime of the wind farm. By understanding this unpredictability, we can increase operator confidence and allow for better operating decisions.

1.2 History

Since early recorded history, people have tried to harness energy from the wind. Wind energy propelled boats along the Nile River as early as 5000 B.C. and, by 200 B.C., simple windmills were pumping water in China, while vertical-axis windmills were grinding grain in Persia and the Middle East (DOE, 2011). New ways of using the energy of the wind eventually spread around the world. By the 11th century, people in the Middle East used windmills extensively for food production. The Dutch refined the windmill and adapted it for draining lakes and marshes in the Rhine River Delta. When settlers took this technology to the New World in the late 19th century, they began using windmills to pump water for farms and later to generate electricity for homes and industry.

American colonists used windmills to grind wheat and corn, to pump water and to cut wood at sawmills. With the development of electric power, wind power found new applications in lighting buildings remotely from centrally generated power. Throughout the 20th century, small wind plants, suitable for farms and residences, and larger utility-scale wind farms that could be connected to electricity grids were developed. Figure 1 shows how the installed wind power capacity of the world has grown exponentially since 1980 (GWEC, 2012).

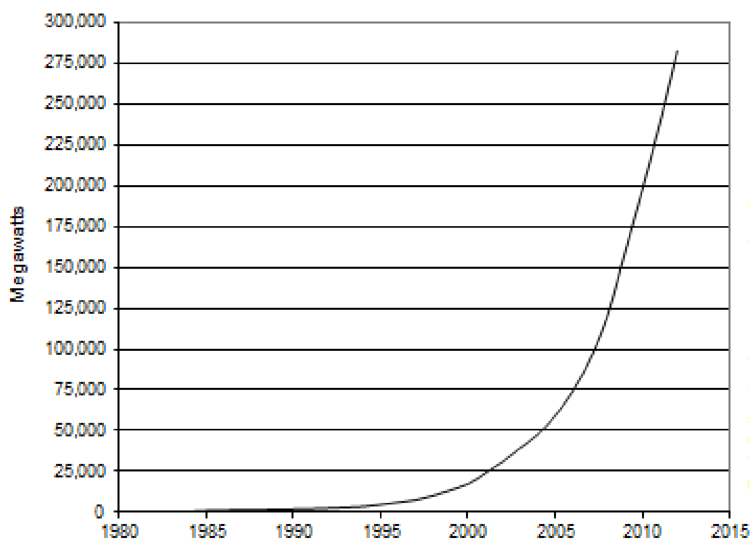

Figure 1: World Cumulative Installed Wind Power Capacity (GWEC, Worldwatch 2012)

Today, the wind energy industry continues to grow across the world, and particularly in the developed nations. This increasing interest in wind energy among the developed nations can be attributed to government regulations to provide energy security and an urgent requirement to reduce harmful emissions (IEA, 2002). Recently, the total U.S. wind power capacity surpassed 60 GW, which is enough to power more than 15 million homes (Figure 2). In South Dakota, Iowa and Kansas, wind power contributes more than 20% of electricity generation (Bolinger and Wiser, 2012).

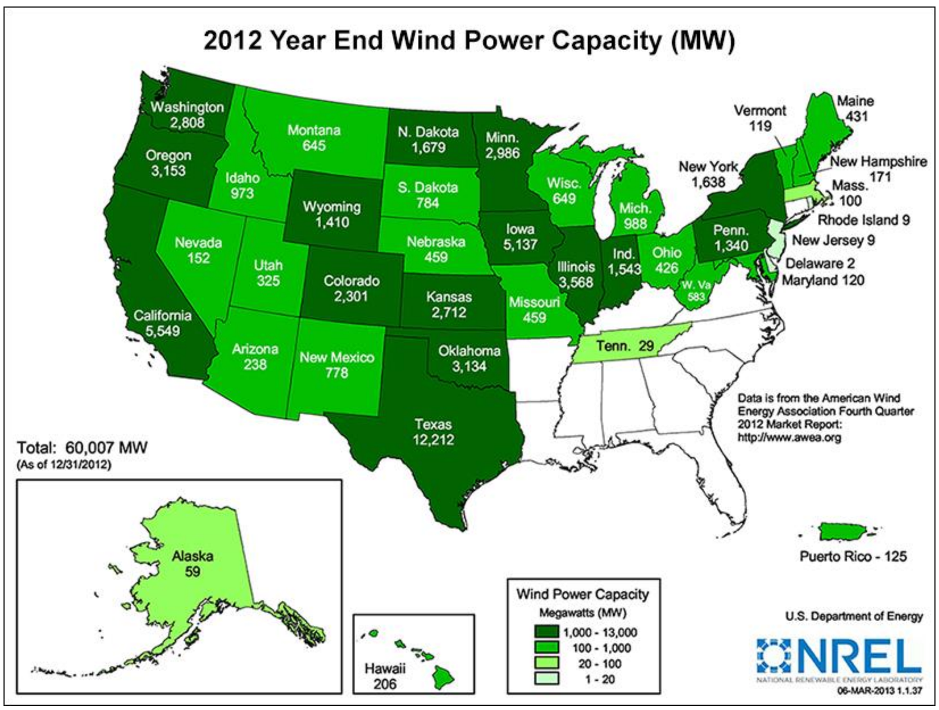

Figure 2: Wind power capacity of United States as of December 2012 (NREL, 2012)

This section provided a brief history of wind energy and its growth in the world. Next I discuss how energy is generated from wind and then move on to the economics behind selling this energy.

1.3 Generation

The process of wind-produced electrical generation begins when the force of the wind pushes against the turbine's blades, causing them to rotate, creating mechanical energy. The basic energy transformation that takes place at this step is the conversion of kinetic energy of the wind to mechanical energy. The following equations provide a deeper understanding of this transformation. First, Equation 1 gives the energy available in the wind by applying the definition of kinetic energy:

$$E = \frac{1}{2} \times m \times V^2 \tag{1}$$

Where m is the mass of moving air, and V is its velocity. Now substituting the mass of air travelling through the cross section of the rotor, the energy equation becomes:

$$E = \frac{1}{2} \times (AVt\rho) \times V^2 \tag{2}$$

Where ρ is the density of air, and A is the area of the rotor. Therefore AVt is the total volume of air passing through A during a period t (which is considered perpendicular to the direction of the wind); $AVt\rho$ is therefore the mass m passing during a period t.

The energy obtained from the wind then acts on the spinning blades, which are attached to the hub and a low-speed shaft, causing them to turn. The rotating low-speed shaft is connected to a gearbox that connects to a high-speed shaft on the opposite side of the gearbox (see Figure 3). Finally, the high-speed shaft connects to an electrical generator that converts the mechanical energy from the rotation of the blades into electric energy (Manwell, 2011).

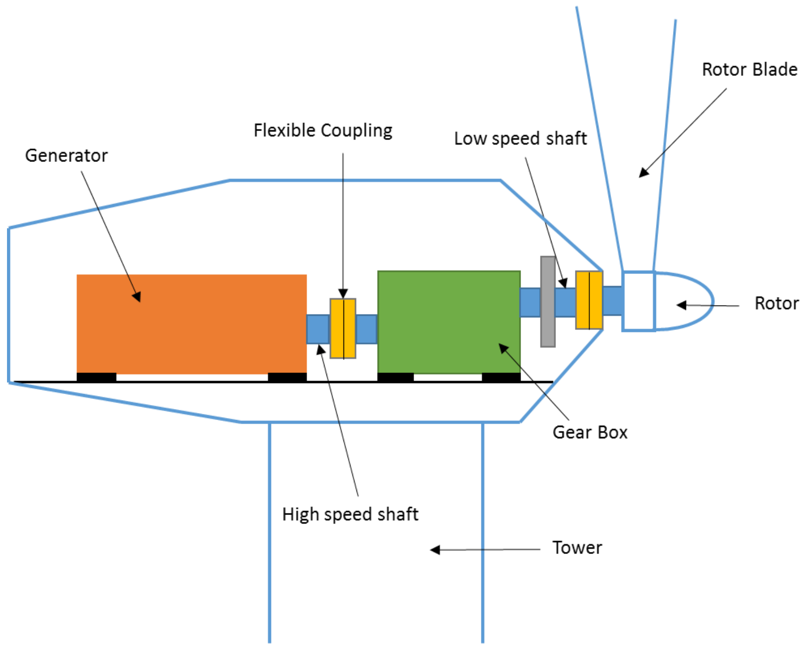

Figure 3: Typical Wind turbine generator assembly (adapted from (Manwell, 2011)).

Equation 1 shows that the energy output of a wind turbine depends on the amount of air that it can capture. The larger the blade, the larger the amount of air that is captured and thus more energy can be generated. Theoretically, the maximum amount of energy that can be extracted by a turbine from the wind is governed by the Betz law. It states that the maximum power coefficient is 0.593, i.e. a turbine can at most extract about 60% of the energy stored in the wind (Manwell, 2011). This limited efficiency of a wind turbine blade can be explained by the braking of the wind from its upstream speed *V1* to its downstream speed *V2*, while allowing a continuation of the flow regime (Ragheb and Ragheb, 2011).

However, the power coefficient for a practical wind turbine blade is much lower than the Betz limit. The reason is because for a practical wind turbine, there is a large amount of viscous and pressure drag on the rotor blades. Additionally, the swirl imparted to the air flow by the rotor also limits the power that can be captured from the wind. Therefore, considering the power coefficient, the relationship between wind speed and power generated can be represented as (Manwell, 2011):

$$P = {}^{1}\!/_{2}\, \rho \pi R^2 C_p(\lambda) V^3 \tag{3}$$

This equation applies only between the cut-in and cut-out speeds. The *cut-in speed* is the speed at which the turbine starts delivering power. It depends on the turbine design. On the other hand, the cut-out speed is the speed above which the rotor is locked and there is no generation of power. The rotor is locked to avoid damage to the wind turbine components due to excessive wind loading.

1.4 Wind Economics and the Market

Once this electricity is generated, there is a need to sell it to the consumer. Figure 4 shows a typical flow of electricity from manufactures to consumers in the U.S. wholesale market. Manufacturers such as GE, Vestas, and Acciona, produce wind turbines, which are acquired by developers such as Horizon and enXco. Developers are involved at various levels, from constructing and commissioning wind farms for sale, to operating and maintaining farms. The electricity generated by the wind farms is sold to utilities such as Duke Energy and Ameren. Finally, utilities sell the electricity to consumers.

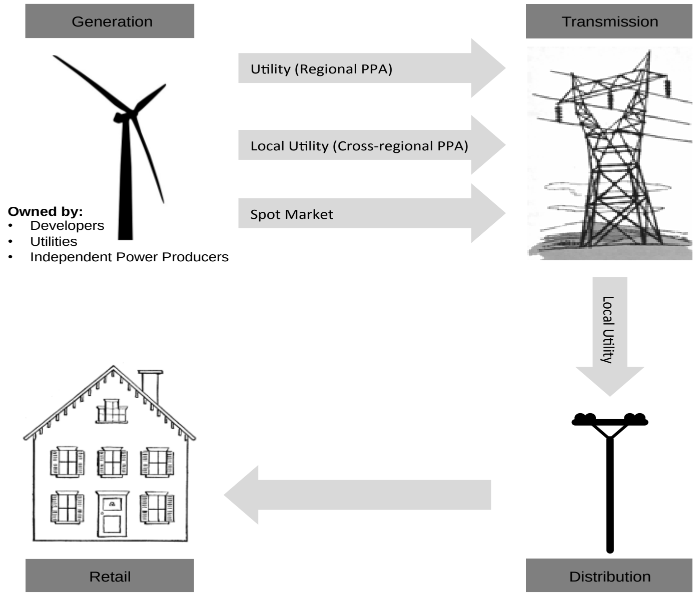

Figure 4: Renewable energy generation, transmission, distribution, and retail

In Figure 4, generators are the physical structures that are responsible for the production of electricity. Transmission refers to the flow of electricity across transmission networks via high voltage wires. Distribution includes the infrastructure and methods used to carry the generated electricity from transmission systems to consumers. Finally, retail deals with the purchase of electricity by the suppliers from wholesale market with subsequent sale to the customers.

In the early 1900s, most electric utilities operated under state and federal regulations and a single utility provided service to each particular geographic area (state, county or city) (NEED, 2005). The price electricity was sold at was determined by the state. In the aftermath of the oil embargo in the 1970s, stricter environmental regulations were enacted and Independent Power Producers began making a major impact on the industry.

After the passing of the Energy Policy Act in 1992, transmission lines were opened to all producers. Three main types of markets exist currently in the United States for wind: 1) Power Purchase Agreement market (PPA), 2) Utility-owned market, and 3) Merchant market.

1.4.1 The PPA market

The basis for a PPA market is an agreement which requires the power purchasers to buy a specified portion of the energy produced by the wind farm (Lantz, 2007). This energy is bought by the power purchasers for a fixed flat rate over a specified period of time. The duration of the agreement is decided by the wind farm developer and typically runs for an average of 20 years. In this way, the purchaser is guaranteed a steady flow of energy with no fluctuation in price. The developer benefits from the fact that it enables financing options as it ensures that reliable revenue will be generated to repay debts and eventually strike a profit. An important advantage of the PPA market is the security it provides to developers and utilities by assuring the former a steady revenue stream and the latter a steady supply of energy at fixed predetermined price. For further interest to the reader, a detailed explanation of the PPA market and its classification is provided by Fernandes (2012).

1.4.2 Utility owned market

The utility owned market was developed after utilities realized that considerable reduction in costs could be achieved from owning and operating a wind farm themselves.

In doing so, they do away with the PPA and trade on the open *spot market*. A spot or cash market is one in which commodities are bought and sold for immediate delivery. Independent utility companies are generally well funded and hence developing a wind project on their own is generally not financially risky. Regulated utilities have the additional security of increased rate to recover their cost.

1.4.3 The Merchant Market

A merchant market is a market where wind facilities are owned by Independent Power Producers (IPP) which have the leverage to sell electricity to utilities, consumers, or industries (RAP, 2011). Electricity is sold on the open market and is influenced by real time pricing. In this way, developers are not constrained by the fixed price of the PPA market and are able to reap the potential benefits of trading in the spot market. An additional benefit of such a market is the increase in the number of buyers that enter the wholesale market. As a result developers have access to a large variety of potential buyers which stimulates competition providing leverage to the developers. A major disadvantage of this type of market is the risk associated with the energy prices going down.

1.5 Wind Turbine Maintenance

The historical approach to maintenance in wind turbines was to run them to failure, which is corrective maintenance. As wind turbines increased in capacity and become more expensive, run to failure became less feasible because of the higher costs associated with replacement. Another issue with running these turbines to failure was the loss in revenue due to the long downtimes observed during maintenance (Hyers et al, 2006). Today, with help from modern technology, newer practices of maintenance have been developed to tackle these issues. These newer forms of maintenance fall under the category of preventive maintenance. Preventive maintenance techniques differs from corrective maintenance in the sense that they are employed before a failure occurs. Preventive maintenance can be further classified as condition-based maintenance (CBM) and scheduled maintenance (Figure 5). CBM uses condition monitoring systems (CMS) to optimize and schedule maintenance tasks effectively, while scheduled maintenance involves routine checks of the system for failures and deterioration.

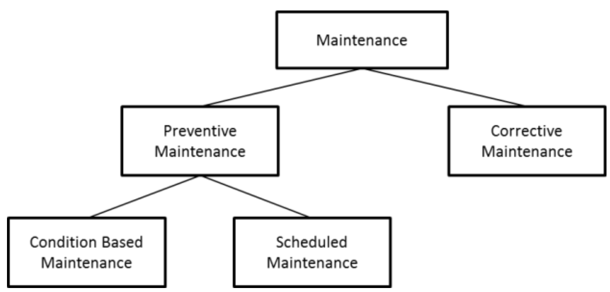

Figure 5: Maintenance activity classification (Nillson and Bertling, 2007)

The current industry practice is to schedule maintenance activities usually once or twice a year for a turbine, based on guidelines set by the manufacturer (Nillson and Bertling, 2007). As a result, scheduled maintenance is usually incapable of addressing unexpected failures and often results in unnecessary visits. This raises the pressing issue that more effective maintenance strategies are needed to reduce unnecessary service visits as well as turbine downtime. Moreover, the operating environment of wind turbines is highly stochastic in comparison to that of traditional power plants and thus the feasibility of both new repairs and the continuation of ongoing repairs is affected by uncertain weather conditions. The majority of wind turbines are installed in remote windy sites or offshore locations with the hope to harvest the maximum amount of wind energy. Due to the remoteness of wind farms' locations, access to turbines for maintenance can be restrictive during harsh weather seasons, and repair actions are very expensive. Compounded with these complexities, newly established wind farms usually house hundreds or more turbines that spread over a large geographical area. This makes O&M even more challenging and costly. Walford (2006) evaluated how much O&M costs contribute to the total cost of energy (COE). COE is a key metric to evaluate the marketability of wind energy, and it consists of the power production cost per kWh, O&M costs and installation costs (See Section 2.1). Walford based his study on a report by Vachon (2002) and concluded that O&M costs account for about 10 to 20 percent of the COE. Most recently, Asmus's (2010) extensive analysis of O&M data from wind turbine manufacturers and operators revealed even higher O&M costs. Asmus estimated that the average O&M cost the wind industry is facing is around $0.027/kWh, which accounts for half of the COE.

Hill et al. (2008) discuss the relationship between wind turbine reliability and O&M costs and identify four objectives for the optimization of O&M: improvement of crew deployment; reduction of failure rates; fault tolerant operations; and improvement of accessibility. Note how these objectives are a combination of design improvements and operating changes. Rademakers et al. (2003) describe a Monte Carlo simulation model for maintaining offshore wind farms. The model simulates the operation aspects over a period of time, considering multiple critical factors for performing repair actions, such as turbine failures and weather environments. The model further categorizes different failure modes and the corresponding repair actions. For example, the first category of failure modes requires replacement of the rotor and nacelle using an external crane; the second failure mode requires replacement of large components using an internal crane, and so on. The failure rates of the individual components are distributed over four maintenance categories. Rademakers et al.'s model only considers corrective maintenance, and their simulation results indicate that the revenue losses during such corrective repairing account for 55% of the total maintenance. Walford (2006) reviews approaches to reducing O&M costs by improving reliability and reducing the costs of the remaining maintenance activities. In particular, he focuses on Condition Monitoring Systems (CMS), which are coming into the foreground as one way to reduce O&M costs by shifting the burden from corrective to preventive maintenance. To highlight the benefit of preventive maintenance, Walford discusses the unpredictable nature of corrective maintenance and its majority share (30-60%) of the total maintenance costs. Further, McMillan and Ault (2008) evaluate the cost-effectiveness of CBM via Monte Carlo simulations. They compare a six-month periodic maintenance policy with CBM taking into consideration annual power production, capacity factor, availability, revenue and failure rates. Simulating various scenarios with different weather patterns, down-time durations, and repair costs, they show for land-based turbines that a CBM strategy could provide the operators economic benefits. Therefore a shift towards preventive maintenance will not only decrease overall costs, but also increase predictability of downtime. Nilsson and Bertling (2007) performed life-cycle cost analysis of a single onshore turbine and an offshore wind farm and found that CMS are justified from a lifecycle cost perspective when their cost is offset by a decrease in corrective maintenance.

1.6 Thesis Objectives and Aims

1.6.1 Thesis Objectives:

1) To study the value and risk of investments in wind energy by considering both engineering and financial aspects.
2) Increasing the investment value and reducing its risk by developing an understanding of the benefits of Condition Based Monitoring and Manual Inspection techniques under different conditions.

1.6.2 Aims:

1) To demonstrate the use of a metric which measures the value of an investment, Value of Energy (VOE).
2) To provide an understanding into the deterioration and maintenance of Wind turbines.
3) To develop an optimization algorithm that incorporates deterioration and optimal maintenance strategies to determine the value of an investment.

CHAPTER 2. A VALUE OF ENERGY APPROACH

Systems provide a service, and associated with that are cost and revenue. People have long considered cost as an important factor in making engineering decisions, but in recent years “value”, which captures both the revenue and the cost and provides a much more comprehensive perspective is also being considered. This chapter proposes an approach to capturing the value of wind farms.

The first section provides the definition and calculation for Cost of Energy (COE). Section 2.2 introduces VOE and distinguishes it from COE. Section 2.3 elaborates on the factors that affect VOE. Finally, Section 2.4 concludes the chapter.

2.1 Cost of Energy

The US National Renewable Energy Laboratory (NREL) has suggested the “Cost Of Energy” (COE) as a way of comparing different energy generation methods (Shreck et al., 2005). The levelized COE in $/kWh is defined as:

$$COE = \frac{(FCR * ICC) + AOE}{AEP_{net}} \tag{4}$$

where FCR is the fixed charge rate, which reflects finance charges, debt or equity repayment, construction financing, and the cost of capital. ICC is the initial capital cost ($), equal to the sum of the turbine cost and the balance of station cost (e.g., site development and preparation, installation), and AEP_{net} is the net annual energy production (kWh/yr). AOE is the annual operating expenses, given by:

$$AOE = \frac{O\&M + LRC}{AEP_{net}} \tag{5}$$

where O&M is the operations and maintenance cost and LRC is the levelized replacement/overhaul cost.

2.2 Value of Energy

Although COE provides a useful way of comparing designs of turbines and wind farms, it does not provide any indication of the value of the energy generated. For example, if the COE is low but there is no market for the energy generated, the investment will have no value. To capture such scenarios, we propose the concept of "Value Of Energy" (VOE). VOE allows us to analyze the benefits as well as the costs to better understand the investment environment.

The overall value of the system to an investor is given by the total benefits less costs over the lifetime of the system. In general, the present value of a flow of service can be calculated as follows:

$$Value = \sum_{t=0}^{T} \frac{Revenue(t)}{(1+r)^t} - \sum_{t=1}^{T} \frac{Cost(t)}{(1+r)^t} \tag{6}$$

where *T* is the assumed system lifetime, and *r* is the discount rate indexed to the time step *t*. The revenue generated is calculated based on the amount of energy sold and the type of contract used to sell energy. Thus the revenue generated at time step *t* can be calculated as:

$$R_t = P_t \cdot E_t \tag{7}$$

where P_t is the price per unit of energy at time step *t* ($/kWh); and E_t is the energy generated at time step *t*. Here, P_t is dependent on the energy contract and market demand and E_t is a function of wind conditions and state of the turbine.

$$P_t = f(C, D_t) \tag{8}$$

$$E_t = f(W_t, G_t) \tag{9}$$

where C is the type of energy contract, D_t is the market demand in kWh, W_t is the wind speed in m/s and G_t is the maximum available generating capacity in kWh at time *t*, which depends on the designed capacity of the turbine and on the operating conditions.

Energy generation costs can be divided into construction, grid connection, operating, and decommissioning costs. While various financing arrangements are available, we assume for this discussion that construction and grid connection costs are incurred at project onset (i.e., $t = 0$), and that decommissioning costs are incurred at project termination (i.e., $t = T$). Thus the cost incurred at time step t can be expressed as:

$$C_{t_0} = Construction + Connection \tag{10}$$

$$C_{t_a} = Operating\ Costs(t) \tag{11}$$

$$C_T = Decommissioning \tag{12}$$

Thus the net present value can be represented as:

$$Value(T) = \sum_{t=0}^{T} \frac{R_t - C_t}{(1+r)^t} \tag{13}$$

Finally, by analogy to the COE, the value of energy is defined as the net present value of the system over its design lifetime normalized by the systems generating capacity.

$$VOE = \frac{Value(T)}{Capacity * time} [\$/\mathrm{MWh}] \tag{14}$$

2.3 Factors affecting VOE

The VOE of a wind turbine is affected by several factors such as power generation capacity, revenue generation capability, component reliability, and costs associated with turbine operations and decommissioning activities. Figure 6 presents an overview of these factors and their inter-relations.

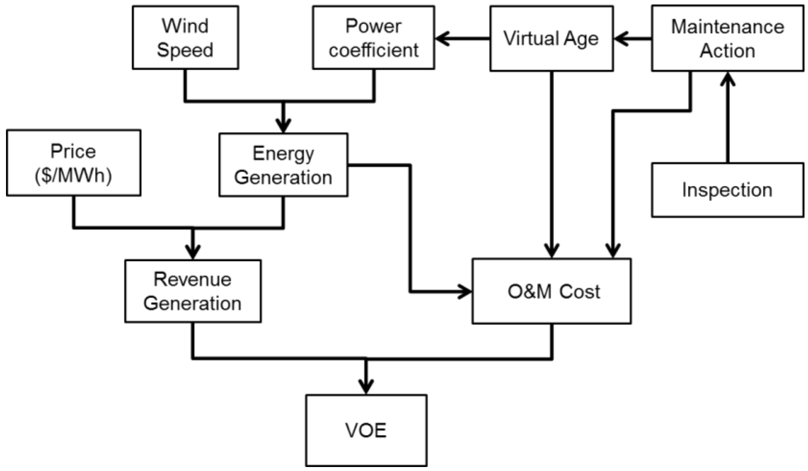

Figure 6: Factors affecting VOE

Fernandes (2012) used historical wind data to calculate VOE based on a repair and replace maintenance plan. In his thesis, Fernandes calculated these maintenance actions assuming failure has occurred at inspection. He used a simple repair/replace as maintenance actions and observed that the VOE would be higher for the following scenarios, 1) lower repair cost, and 2) lower failure rate. Some of the limitations of this work is that it fails to provide a more accurate repair action depending on the deterioration of the wind turbine and also fails to capture realistic trends of these repair costs.

The present work considers the deteriorating mechanism of wind turbines and makes a comprehensive effort to capture the benefits of using detection techniques in providing value. Further, this thesis also provides the reader a comparison of different detection techniques and how they bring value to an investment.

2.4 Summary

This chapter looked at how the VOE concept differs from the COE metric, and the way in which it captures a two-dimensional aspect to the cash flow. Additionally, it also highlights the factors that contribute to this flow and provides an understanding as to how they contribute. In the next chapter, I will explain how I simulate the operation of a wind turbine to see the application of this concept.

CHAPTER 3. A MODEL TO ESTIMATE WIND FARM VOE

Several parameters impact the Value of Energy (see Figure 6). In this section, I briefly describe these parameters and explain their formulation in the model. For ease of explanation, I broadly divide these factors into the following categories: (1) revenue (including energy generation, wind speed, power co-efficient, and price), (2) costs (includes operating and maintenance costs), (3) system state, (4) condition monitoring system, and (5) manual inspection technique.

3.1 Energy generation

The revenue generated by a wind turbine depends upon the power generated, which in turn depends upon the wind and the condition or, state, of the turbine. I use a Weibull distribution (Carta et al, 2009) with scale parameter *c* and shape parameter *k* to generate an average wind speed *u* for each day:

$$W(u) = 1 - exp\left[-\left(\frac{u}{c}\right)^k\right] \tag{15}$$

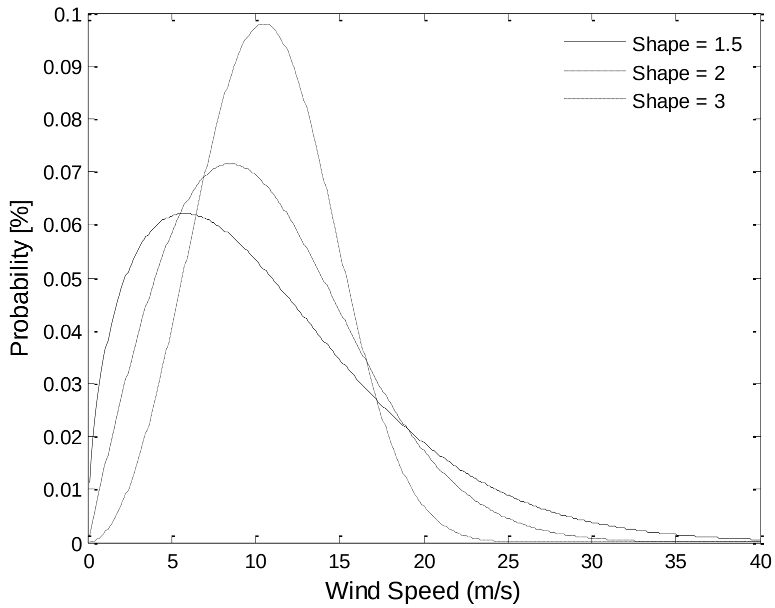

Figure 7: Weibull distribution of wind speed (m/s)

The scale parameter c corresponds to the average wind velocity and the shape parameter k is generally between 1 and 3 (Van Donk et al, 2005). The flexibility and convenience of the two parameter Weibull distribution to model variable wind speeds have made it one of the most widely used distributions in simulating wind speeds (Carta et al, 2009). Figure 7 shows how the wind speed distribution varies for shape parameters 1.5, 2, and 3.

Table 1: Vestas 1.8 MW turbine Parameters (Vestas, 2013)

Name	**Nominal value**	**Units**
Cut in speed (V_{ci})	3	m/s
Rated speed (V)	12	m/s
Cut out speed (V_{co})	25	m/s
Turbine radius (R)	50	m
Turbine height	90	m
Rated Power	1.8	MW

The analysis is based on the Vestas V100 1.8MW turbine; Table 1 summarizes its relevant features. These characteristics, along with the wind speed model described above, determine the power produced by the turbine (Manwell et al, 2009), as shown in Equation 16. The turbine outputs zero energy below the cut-in speed (3 m/s) and above the cut-out speed (25 m/s).

$$P = {}^{1}/_{2}\, \rho \pi R^2 C_p(v) V^3 \tag{16}$$

where v represents the system's virtual age (Section 3.3 discusses virtual age in detail) .

I capture deterioration in turbine functionality with age or use by decreasing the power coefficient (C_p) of the wind turbine as follows:

$$C_p = 0.35 \times e^{-m \cdot v} \tag{17}$$

where m determines the rate of decrease of the power coefficient with respect to the virtual age (v) and 0.35 is the power coefficient at the rated power of the turbine.

I estimate the revenue generated for a given power output using a simple power purchase agreement (PPA) as follows (Emerging Energy Research, 2011):

$$Revenue = PPA\,price \left(\frac{\$}{MWh}\right) * Power\ Generated * 24(hrs) \tag{18}$$

Here, the PPA price was estimated to be US$ 65 from average countrywide PPA pricing as of January 2010 (Emerging Energy Research, 2011).

3.2 Costs

Costs incurred during the operation of a wind turbine include operating costs and maintenance costs and depend on the operator, maintenance activities, and location of the wind turbine.

3.2.1 Operating costs

Operating costs are the costs associated with the daily functioning of the wind turbine. Operating costs may include costs associated with insurance, administration, regular maintenance electricity and rent. The operating costs are based on Horizon Wind Farm operating and maintenance (O&M) data as shown in Figure 8 (Horizon Wind Data, 2011).

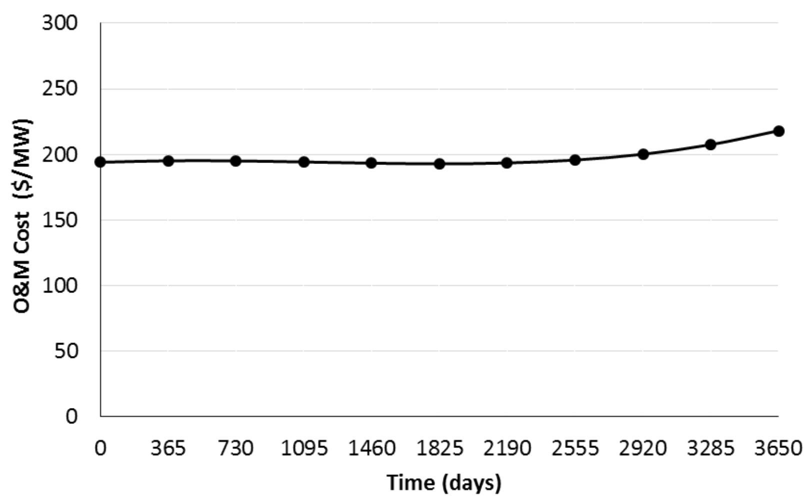

Figure 8: Operating Cost (Horizon, 2011)

Since the simulation has a time interval of a day, the yearly O&M was divided equally among the days of the year, which resulted in an estimated daily O&M cost per MW.

Finally, I fitted a line to the data in Figure 8 and estimated the operating costs to be 60% of the O&M costs (WindStats, 2006):

$$Operating\ Cost = 0.6 \times (-7 \times 10^{-6}t^2 + 0.0055t + 194) \times Power \qquad (19)$$

3.2.2 Maintenance Costs

Maintenance costs are incurred as a result of maintenance actions performed on the deteriorated system, (for example the wind turbine blade). The specific costs associated with maintenance depend on the particular repair and replacement activities. In the case of replacements, the corresponding costs depend on the part to be replaced. For example, the estimated replacement costs for a Vestas 1.8 MW turbine blade are shown in Table 2. This cost includes the cost of procuring a new turbine blade along with the labor and crane costs incurred for the replacement. In contrast, costs associated with repairing a part depends on degree of deterioration experienced by the particular component. The most common forms of deterioration seen in wind turbine blades is the erosion of leading and trailing edges, followed by crack growth due to hidden manufacturing flaws. Typical maintenance actions carried out in the case of erosion is to apply resin coating or any other waterproof sealant. For more serious cases of erosion it is best to carry out an entire structural repair or replacement. In the case of smaller crack formations, the most common repair action is to arrest crack growth by applying gel coating to fill the entire length of the crack.

In this thesis, I consider three levels of repair that can restore the system's state to different levels of performance. I provide a detailed description of how the costs associated with these three repair levels vary with level of deterioration in the next section.

Table 2: Replacement cost (C_0) tabulation (Tretton et al, 2011)

Item	**Cost ($)**
Blade	223 000
Crane cost	72 000
Labor cost	33 000
Total cost	318 000

In response to the level of deterioration observed, we can choose one of the following three activities: 1) Do nothing 2) Perform the different repair actions or 3) Replace the blade. As mentioned above, the replacement cost depends on the part to be replaced, while the repair costs depend on the deterioration observed and the level of repair chosen. Operating costs incurred and the revenue generated by the system depend on the specific state of the system. Table 3 shows the operating, revenue and repair/replacement costs derived for the different maintenance activities.

Table 3: Operating and repair costs based on activity

Activity	**Operating and repair costs [$]**
Do nothing	$-C_{op.cost(v)} + C_{op.rev(v)}$
Repair	$-C_i - C_{op.cost(v')} + C_{op.rev(v')}$
Replace	$-C_0 - C_{op.cost(0)} + C_{op.rev(0)}$

C_0 is the replacement cost, C_i are the repair costs for the different repair levels (i = 1, 2, 3), $C_{op.cost}$ is the operating cost, and $C_{op.rev}$ is the operating revenue. These cash flows depend on the state or virtual age of the turbine, which is represented by v. The gain in virtual age brought about by repair and replace activities is represented by v' and 0, respectively.

3.3 Modeling system state using virtual ages

Typically maintenance optimization models consider maintenance as improving the failure rate or reliability of the system (Pham and Wang, 1996). In some models, this effect is modeled by reducing the failure rate of the system. Perfect maintenance therefore reduces the failure rate of the system to that of a brand new system. This improvement of failure rate due to maintenance is usually estimated from historical data or expert judgment. In this work I consider maintenance as an activity that reduces the system's virtual age (Kijima et al, 1989). This virtual age increases concurrently with clock age, but can increase faster than clock age if the system is subjected to harsh conditions, and conversely, can be reduced by performing maintenance or replacement.

I use Kijima's Type I model to model the impact of repair on the virtual age of the system as follows (Marais, 2013). Let v_n be the system's virtual age after the nth repair, $x_n$the additional age incurred between the (n – 1)th and nth repair, and θ_n the level of repair. In the Type I model, the nth repair cannot remove the damages incurred before the (n – 1)th repair. Thus, after the nth repair, the virtual age of the system becomes:

$$v_n = v_{n-1} + \theta_n x_n \tag{20}$$

Therefore, perfect maintenance corresponds to a repair level of zero, and no maintenance corresponds to a repair level of 1.

3.3.1 Modelling the deterioration

For each virtual age, I estimate the distribution of the deterioration, as shown in Figure 11. When the virtual age is low, the probability of deterioration is low, and if deterioration does occur, it is more likely to be minor. As the virtual age increases, the probability and expected extent of deterioration increase.

I use two different approaches to model this deterioration because CMS and manual inspection work in fundamentally different ways. Condition monitoring systems (CMS) use sensors and data acquisition units to continuously monitor and detect both internal and external deterioration, such as cracks, fiber dis-bond, and edge erosion, of a wind turbine blade. To evaluate CMS, I therefore model deterioration using an exponential model that accounts for different modes of deterioration.

In contrast, manual inspection techniques such as visual inspection can only detect cracks that occur on the outer surface of the turbine blade. Thus, the deterioration that can be detected by CMS is modeled using an exponential curve, while that which can be detected by manual inspection is modeled using a fatigue crack growth model, as some manual inspections techniques such as visual inspection can only identify external cracks (see Figure 9).

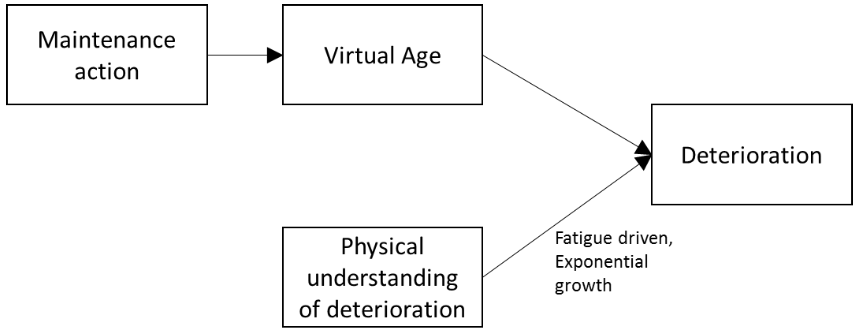

Figure 9: Deterioration modelling

Both deterioration models are modelled such that higher virtual ages have a higher likelihood of higher deterioration. For the more general deterioration process that I use for CMS, I model deterioration using an exponential equation with respect to virtual age (see section 3.3.2). On the other hand, for the crack growth model, I use the Paris law (discussed further in Section 3.3.3) to propagate the crack growth deterioration in a wind turbine blade.

For both deterioration models two steps are followed: first, I estimate the probability that deterioration has occurred (i.e., the deterioration rate), and second, I estimate the extent of this deterioration. The first step is common to both deterioration models and is discussed below, while the second step is specific to each model, general exponential and crack growth models, and is described in Sections 3.3.2 and 3.3.3 respectively.

For the first step, a modified bathtub curve is used to model the blade deterioration rate with respect to virtual age, as shown in Figure 10. The bathtub curve captures a steeply decreasing rate of deterioration at the beginning of the product lifetime, a low constant deterioration rate throughout most of the usable lifetime of the product, and an increasing deterioration rate near the end of the usable lifetime. Based on operational wind turbine data, Kaldellis et al. (2002) found that wind turbines' reliability is characterized by early failures until the third operational year after which follows a longer period (around 10 years) of "random failures" before the failure rate due to wear and damage accumulation increases with operational age. Since infant mortality is primarily due to initial manufacturing defects (Rausand et al, 2004), I gradually remove the infant mortality portion of the curve as time progresses, as shown in Figure 10. The conditional probability of deterioration with respect to virtual age is determined as follows (Rausand, 2004):

$$P_{deteriorate}(v) = \frac{F(v + \Delta v) - F(v)}{1 - F(v)} \tag{21}$$

where v is the current virtual age and Δv is the virtual age for the next deterioration instance. The probability that the product will deteriorate once a maintenance action has taken place is denoted as $P_{det\,|replace}$ and $P_{det\,|repair}$ for replacement and repair respectively. The pdf, $f(v)$, of the deterioration is given by (Rausand, 2004):

$$f(v|a,b) = \frac{b}{a}\left(\frac{v}{a}\right)^{b-1} e^{-(v/a)^b} \tag{22}$$

where v is the virtual age, and a = 50 and b = 3.5 are the scale and shape parameters selected suitably to build the bathtub curves.

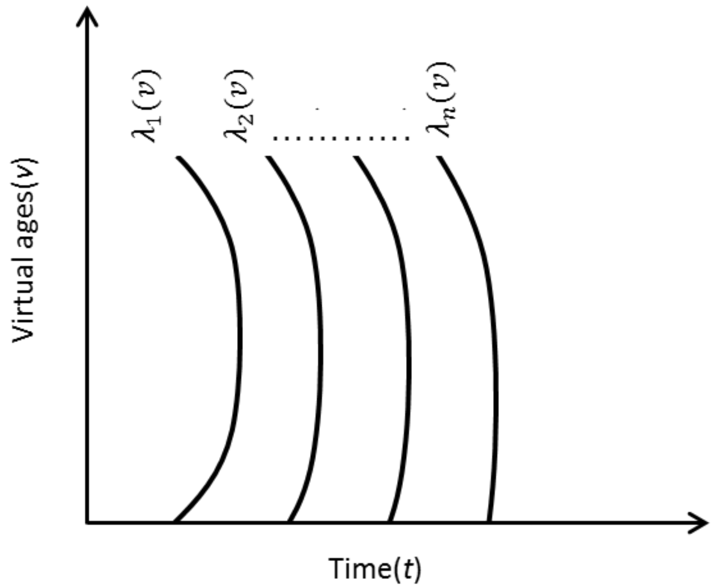

Figure 10: Deterioration rate modeling with virtual ages (v)

3.3.2 Exponential deterioration model

Here, I capture the extent of deterioration using a simple exponential approach. Modeling this deterioration extent in composite wind turbine blades is difficult because turbine blades are made up of multiple composite materials that have an extremely complex geometry and also vary in thickness. I model that as the blade ages, the expected level of deterioration for any given failure increases using Equation 23. The deterioration level (φ) is expressed as a measure between 0 (no detectable deterioration) and 1 (complete or catastrophic failure):

$$\varphi(t) = m(t) * e^{c(t)*v} \tag{23}$$

Where $\varphi(t)$ is the deterioration level with respect to time, and v is the virtual age. Here $m(t) = 0.5t + 0.004$ and $c(t) = 0.5t - 0.004$ are both varied with time to ensure that deterioration ranges from 0 to 1 (complete failure).

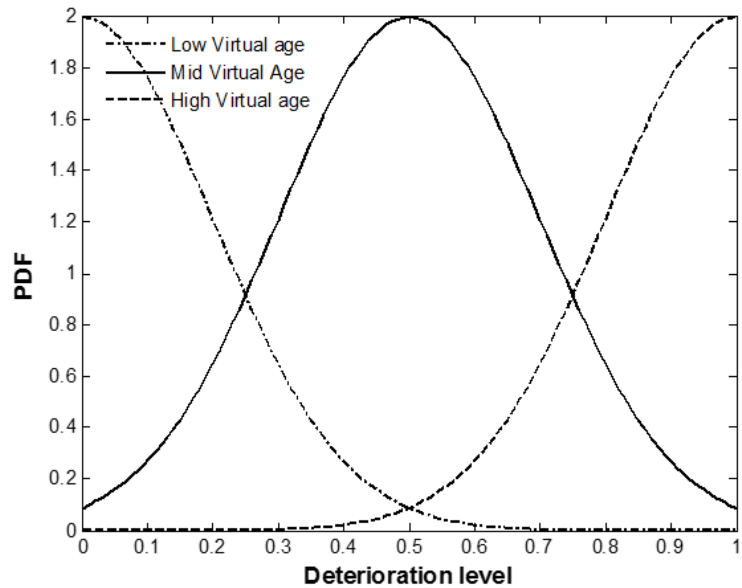

Figure 11: Deterioration level (φ) distribution with virtual ages

Then I model that at high virtual ages, the system experiences a higher likelihood of greater deterioration, as shown in Figure 11. In contrast, at low virtual ages, the system is more likely to experience lower deterioration levels.

3.3.3 Fatigue driven deterioration model

Here, I consider a fatigue driven approach to modelling the extent of deterioration. Extensive studies have been done to understand fatigue driven damage in wind turbine blades and many of them are based on computational and experimental setups. Dutton et al. (2010) models fatigue failure in wind turbine blades using a Parametric FE model. He assesses the effect of unidirectional loading on a sub section of the wind turbine blade. This work however fails to capture comprehensively the effect of varying loads and materials configurations on the fatigue damage modelling of the wind turbine blade. Computational modeling shows significant promise. For example, Nair et al. (2006) explains how multi-scale physical models are becoming capable of integrating the damage process from the atomic scale to the scale of the part, giving an accurate picture of the kinetics of damage evolution. Such models are approaching maturity for metals, but need further development for reinforced polymers. For reinforced polymers and multi-scale composites, the physical mechanisms of failure are not well understood. More research is required both on experimental determination of the dominant physical mechanisms and on the appropriate multi-scale models to predict the behavior of these composites under service conditions.

To model damage to a wind turbine blade, we need to first understand the type of loads that act on a wind turbine blade. The loads are usually classified as aerodynamic, gravity, and centrifugal loads. Out of these, aerodynamic loads have a greater effect on the stress acting on the blade. Aerodynamic loads are a function of wind speed, turbulence, rotational speed, airfoil shape, and aero elastic effects. Sorensen et al. (2011) discuss typical realizations of damage accumulation as function of time for (1) a linear damage mode, e.g. damage proportional with mean wind velocity; and (2) a fatigue driven model, used to model damage accumulation imitating the way cracks form. To reduce the computational complexity of modelling damage, I modelled accumulation of damage based on the fatigue driven model described by Sorensen.

The differential equation in this case is given by the Paris law. The deterioration of the blades is assumed to be dependent on the average wind speed. Therefore, the rate of deterioration is given by:

$$\frac{dD}{dt} = \frac{dN}{dt} \times C \times \Delta K^m \tag{24}$$

Where C and m are material constants for a wind turbine blade. ΔK is the change in the damage intensity factor, which depends on the current deterioration size D and is given by:

$$\Delta K = \beta \times \Delta s \times \sqrt{\pi \times D} \tag{25}$$

Where, β is the geometry factor and Δs is the cyclic damage that is considered to be proportional to the average wind speed:

$$\Delta s = W_s \times x_s \tag{26}$$

Here, x_s is the proportionality factor, which models the uncertainty in estimating the cyclic damage Δs and W_s is the average wind speed. The damage parameters used in the calculations are assumed to follow the distributions as shown in the Table 4 (Sorensen et al, 2011). The mean values have been calibrated to ensure appropriate damage growth for the virtual ages such that higher virtual ages experience greater deterioration similar to the approach used in Section 3.3.2 (refer to Figure 11).

Table 4: Damage parameters (Sorensen et al, 2011)

Symbol	Mean	COV	Distribution
$\boldsymbol{m}$	2	-	Deterministic
$\boldsymbol{\beta}$	1	-	Deterministic
$\boldsymbol{C}$	9.26×10^{-10}	0.2	Lognormal
$\boldsymbol{x_s}$	10	0.1	Lognormal
$\boldsymbol{D_0}$	0.02	0.02	Exponential

3.3.4 Repair cost with deterioration

Repair ranges continuously from minor to complete overhaul; to make the modeling tractable I consider three levels of repair for the blade: minor, medium, and significant. The virtual age benefit and the corresponding costs increase with repair level, and the costs of repair increase with respect to the deterioration level, as shown in Figure 12 and by:

$$C_i = R_i exp^{\alpha\varphi} \tag{27}$$

Where as before φ indicates the deterioration level ranging from 0 to 1, and α is the rate parameter which determines how rapidly the repair cost increases with deterioration level (estimated as 0.5 to represent a relatively slow increase in cost with deterioration).

The repair costs for each repair level, R_i (i = 1, 2 and 3) are based on 2010 NREL data (Tretton et al., 2011), using which an estimate was made for R_1 as \$4000, R_2 as \$30,000 and R_3 as \$65,000. Although repair cost for a given deterioration may have a stochastic component (due for example to changes in labor cost), this component is likely to be small and dwarfed by the stochastic variation in deterioration level. Therefore I disregard this variation here. Replacement cost (C_0) has been established in Table 2.

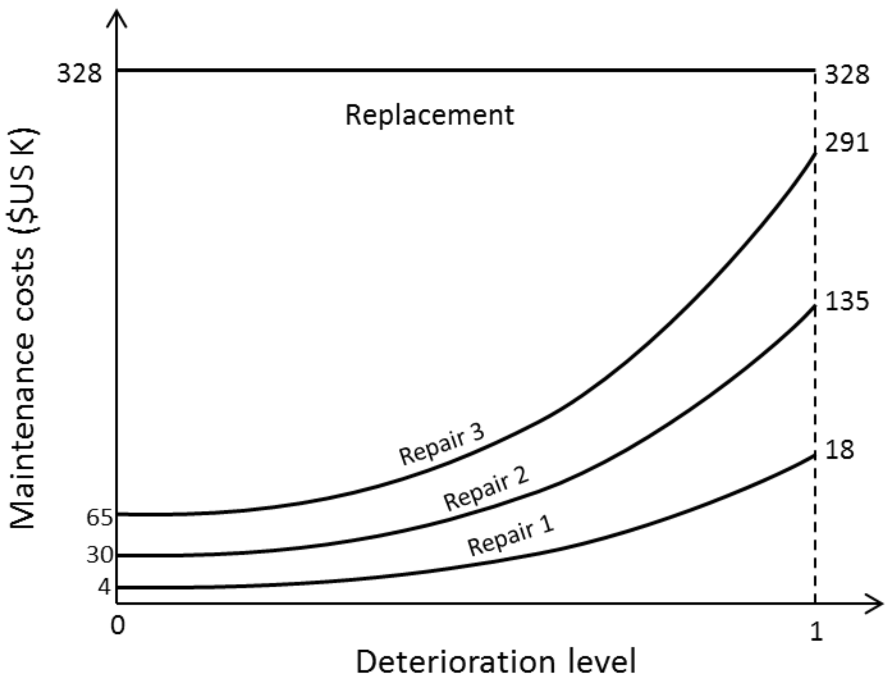

Figure 12: Repair cost variation with deterioration level (φ)

3.4 Detection by CMS

Condition based maintenance (CBM) recommends maintenance actions based on the state of the system (Lee et al., 2004). Typically, sensors such as strain gauges and accelerometers are used to facilitate the real time measurement of the system deterioration and alert the operator of any imminent failures (overview shown in Figure 13). A CMS can help avoid unnecessary maintenance tasks by enabling operators to take maintenance actions only when there is evidence of system deterioration. However, these systems do have accompanying costs such as the capital associated with initial deployment of the system, and maintenance costs of the individual sensors.

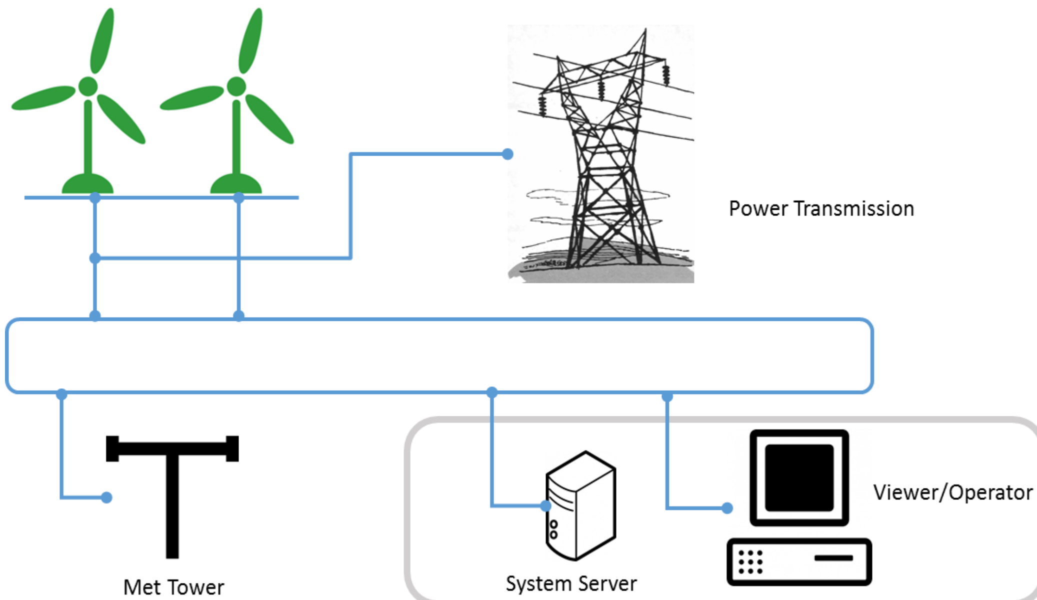

Figure 13: Condition Monitoring System Layout

Condition monitoring systems differ in their accuracy and sensitivity. Here, I compare CMS according to the level of deterioration that they can detect, as shown in Figure 14. I assume that the CMS have a minimum damage level below which they cannot detect damage. The dotted green line represents a "good" CMS (one that can detect deterioration levels as low as 0.2) as compared to the solid red line, which represents a "poor" CMS (one that can identify only after the system deteriorates to a 0.5 level). Note that only two extremes are considered: either the CMS detects the deterioration, or it does not. Generally, the condition monitoring analysis is based on correlation between the measured values and the operating threshold values. If the threshold is exceeded, a warning allows the operator to make a decision on the implementation of a maintenance action (LeBlanc, 2007).

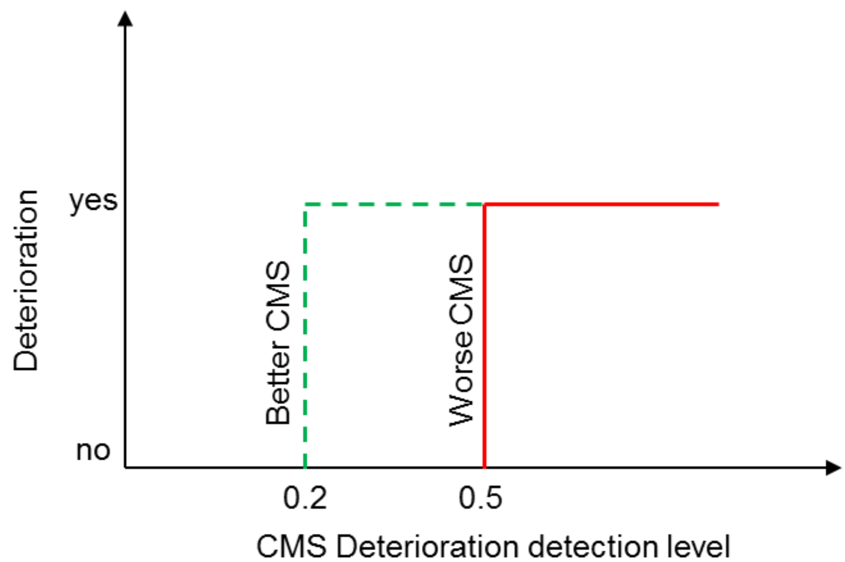

Figure 14: CMS deterioration detection level

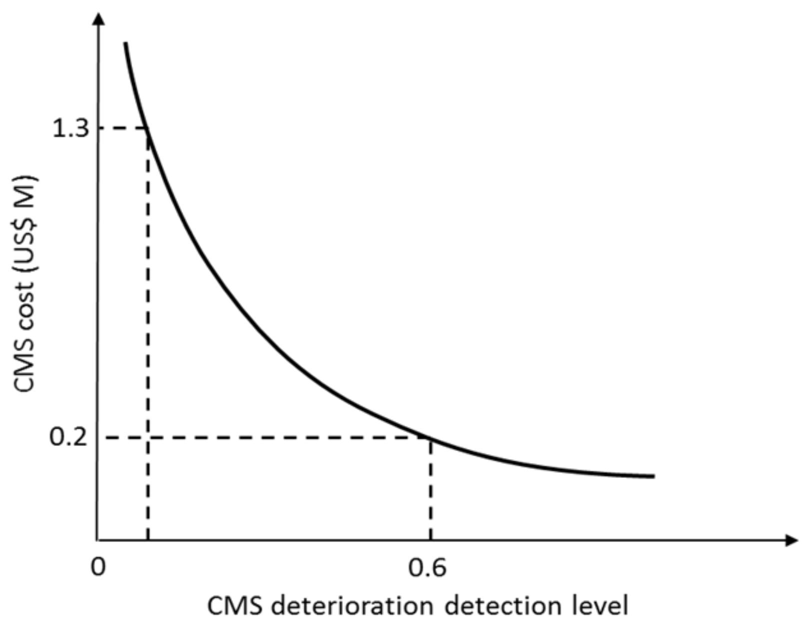

Figure 15: Cost of CMS in relation with CMS deterioration detection level

Solid data on CMS cost is hard to come by and often "business sensitive", therefore here I model the CMS cost as a decreasing exponential curve (see Figure 15):

$$C_{cms} = (1.3 \times 10^6) \times e^{-0.3 \times L} \tag{28}$$

where L is the CMS deterioration detection level and C_{CMS} is the cost of the condition monitoring system corresponding to the deterioration detection level. In other words, the more sensitive the CMS, the more expensive it is.

The parameters have been selected by estimating the cost of a perfect state of the art CMS as US$M1.3 (Hyers et al, 2006). From (Sheng, 2011) I estimated the CMS cost as $200,000 spread over 10 years for a moderately functioning CMS detection level of 0.6.

3.5 Detection by Manual Inspection Method

In this section, I elaborate on the manual inspection techniques that have been studied in the thesis and provide the mathematical approach as to how the inspection and detection was modeled. The first section discusses the various inspection methods being used in the industry today and then, the second section provides the mathematical formulation of a manual inspection approach.

3.5.1 Manual inspection techniques

In this section, I discuss some of the non-destructive techniques (NDT) currently in use in the wind turbine industry (Drewry et al., 2006). In particular, I elaborate on visual inspection, thermography and ultrasound inspection. These three types of techniques represent different fidelities of inspection and also have different costs. This understanding is important here as I use fidelity and cost of inspection as important parameters to study the benefit of manual inspection techniques later in my modeling.

3.5.1.1 Visual inspection

The methods employed include penetrant testing and visual inspection with the use of miniature cameras or endoscopes. Typical equipment also includes the use of telescopes and dye penetrants. Telescopes are used from the base of the turbine to detect flaws on the turbine blade. On the other hand, the penetrant testing method involves the use of ropes and harnesses to allow for close up inspection of the blades. Visual inspection is generally the least expensive and least reliable of all the inspection methods for detecting flaws in wind turbine blades (Kapadia, 2010).

3.5.1.2 Ultrasonic NDT

An ultrasonic test is a fast and efficient way to investigate if any damage is present in a wind turbine blade. Ultrasonic inspection reveals these flaws quickly, reliably and effectively and is the most often used non-destructive composite inspection method in industry (Kapadia, 2010). The main advantage of ultrasound scanning is that it enables us to see beneath the surface and check the laminate for dry glass fiber and delamination.

A typical ultrasonic inspection system consists of several units, such as the pulser/receiver, transducer, and display devices. A pulser/receiver is an electronic device that can produce high voltage electrical pulses. Driven by the pulser, the transducer generates high frequency ultrasonic energy. The sound energy is introduced and propagates through the materials in the form of waves. When there is a discontinuity (such as a crack) in the wave path, part of the energy will be reflected back from the flaw surface. The reflected wave signal is transformed into an electrical signal by the transducer and is displayed on a screen. From the signal, information about the reflector location, size, orientation and other features can be obtained. The ultrasound inspection technique is the most reliable and accurate manual inspection method that is used in the wind turbine industry.

3.5.1.3 Infrared thermography

Thermo-graphic inspection refers to the nondestructive testing of parts, materials or systems through the imaging of the thermal patterns of the object's surface. There are two approaches in thermo-graphic inspection: (1) passive, in which the features of interest are naturally at a higher or lower temperature than the background, for example: the generator in a wind turbine; and (2) active, in which an energy source is required to produce a thermal contrast between the feature of interest and the background, for example: a wind turbine blade with external and internal flaws. When compared with other classical nondestructive testing techniques such as ultrasonic testing or radiographic testing, thermo-graphic inspection is safe, nonintrusive and noncontact, allowing the detection of relatively shallow subsurface defects (a few millimeters in depth) under large surfaces and in a fast manner.

3.5.2 Mathematical Approach

In the manual inspection detection technique, I use the fatigue driven deterioration model as discussed in Section 3.3. I modelled different inspection techniques to detect deterioration based on a probability of detection. The reliability of inspections themselves may be subject to significant uncertainty, and this must also be taken into account in the planning of inspections, e.g. by using probability of detection (POD) curves (Ginzel, 2005). POD curves have been produced for a range of Non-Destructive Testing (NDT) methods (e.g. ultrasound, radiography, magnetic particle inspection, liquid penetrants, visual and others). In this case I assume that such data is made available to a wind turbine operator in order to make his choice of inspection. It is reasonable to assume that different NDT methods will produce different POD curves (even when applied to the same flaws), and therefore here I formulate a POD curve for varying fidelities of detection techniques. The probability of detection formula is given by:

$$POD = \phi(1 - e^{\left(\frac{-D}{\lambda}\right)}) \tag{29}$$

Where ϕ is the maximum probability of detection, D is the deterioration level at the time step and λ is the expected smallest detectable deterioration parameter. I use the expected detectable deterioration parameter (λ) as a measure of the fidelity of the inspection procedure and from here on I call this parameter the 'Manual Inspection Detection Level'.

Figure 16 shows how the POD varies with respect to manual inspection detection level. From the graph, it can be seen that a higher fidelity inspection corresponds to a lambda (λ) value of 0.2 as it has better detection probabilities for all values of deterioration.

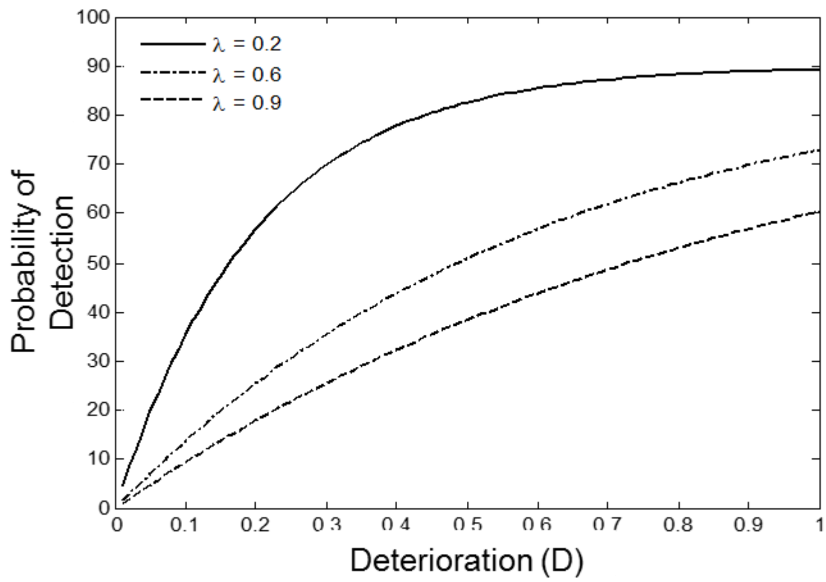

Figure 16: Probability of detection curves with respect to deterioration

Next, to understand the value derived from an inspection technique, I take into account the cost of different levels of inspection. The cost of the inspection C_{insp} varies with the fidelity of the inspection. The cost of inspection for high fidelity inspection technique which detects a 0.1 deterioration level is estimated to be 50,000 USD (Isaksson et al., 2011). From this report I also estimated the cost of a thermographic inspection procedure as \$20,000. I associate thermographic inspection as a moderate form of inspection procedure capable of detecting 0.6 level of deterioration to help build my inspection cost equation. Equation 30 shows how C_{insp} is varied with the manual inspection detection level (λ) (see Figure 17).

$$C_{insp} = 50000 \times e^{-\lambda} \tag{30}$$

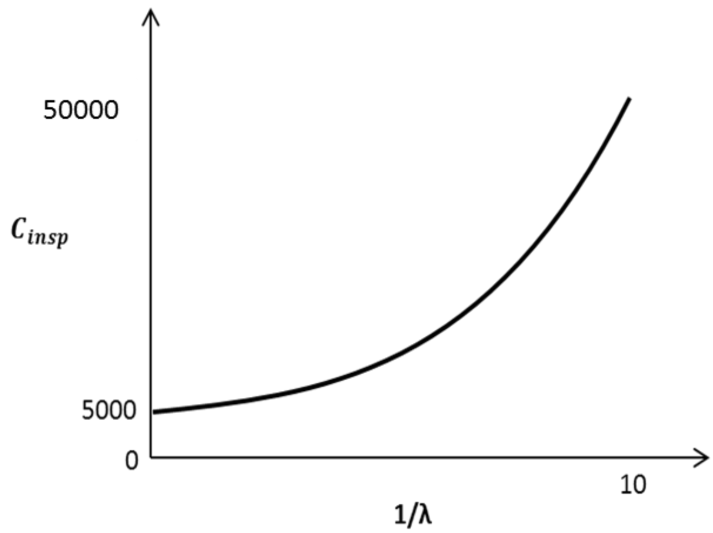

Figure 17: Inspection cost variation with the Manual Inspection Detection Level, λ (lambda)

3.6 Summary

This chapter illustrated the model I have used to estimate the VOE of a wind turbine. I have also explained how I incorporated detection techniques in the form of 1) Condition Monitoring Systems and 2) Manual Inspection methods. In the next chapter, I discuss the optimization technique and the results that I obtained by the application of an optimal CMS and a Manual Inspection procedure.

CHAPTER 4. APPLICATION OF OPTIMAL CMS AND MANUAL INSPECTION

In this section, I explain how the optimization is carried out and then go on to discuss the results of applying this method to a condition monitoring and a manual inspection technique. Table 5 shows the input parameters used for the optimization. I conclude this chapter by discussing the results obtained by applying these techniques for inspection purposes.

Table 5: Parameters used for the Optimization

Name	Nominal Value	Unit
Wind turbine		
Cut in speed (V_{ci})	3	m/s
Rated speed (V)	12	m/s
Cut out speed (V_{co})	25	m/s
Turbine radius (R)	50	M
Turbine height	90	M
Rated Power	1.8	MW
Maximum Power Coefficient	0.35	
Wind Speed		
Avg. Wind Speed	12	m/s
Shape factor	2	
General		
Wind Farm lifetime	10	Years
Time Slice	365	Days

4.1 Maintenance Optimization

The model elements described thus far enable us to estimate the VOE. In this section, I add an optimization loop to determine the value-maximizing maintenance strategy over a given finite time period. I use a simple backwards recursion incorporating discounting to account for the time value of money (Winston, 2004; Marais 2013).

I define $W(n, v, i)$ as the optimal expected net present value looking forward from time step $\boldsymbol{i}$ to the last time step $\boldsymbol{i_{max}}$. Note that a finite time horizon is assumed. In the case of a wind farm, this time horizon would correspond to for example the time over which the operator intends to operate the farm. Here n denotes the number of failures and v represents the virtual age of the system. At each deterioration instance, I seek a general repair policy such that:

$$W(n, v, i) = \max \begin{cases} -C_0 + PV(C_{op.rev}(0) - C_{op.cost}(0), \beta) + \beta P_{det|replace} W_{optimal\ldots} \\ \qquad \ldots + \beta\big(1 - P_{det|replace}\big) W_{not\ deteriorated} \\ -C_i + PV(C_{op.rev}(v') - C_{op.cost}(v'), \beta) + \beta P_{det|repair} W_{optimal\ldots} \\ \qquad \ldots + \beta\big(1 - P_{det|repair}\big) W_{not\ deteriorated} \end{cases} \tag{31}$$

where *v'* is the virtual age after a repair action, $PV(.)$ is the present value of the cost and revenue stream and β is the discount factor scaled to the time interval size. In each case the repair cost varies stochastically since the deterioration level is stochastic. Since, for simulation purposes *W* is needed at each time step, when no failure has occurred *W* is updated according to:

$$W(n, v, i)_{no\ deterioration} = PV\left(C_{op.rev}(v) - C_{op.cost}(v)\right) + \beta W_{optimal} \tag{32}$$

The optimal policy is found by setting *W* to zero for $i \geq i_{max}$ and then working backwards to $i = 0$. Begin at time step $i = i_{max} - 1$. For each virtual age, calculate the value looking forward, assuming that the system has failed, for the case where maintenance is performed, the case where the system is replaced, and the case where nothing is done. The virtual ages depend on the chosen repair level as discussed earlier. Select the option that gives the maximum value. Also calculate the value looking forward assuming the system has not deteriorated; this is shown by Equation 32. Note that the next step expected W's ($W_{optimal}$ and $W_{no\ deterioration}$), are set to zero for the final time step. Thus the optimal expected value of each node is given by:

$$W_{optimal} = P_{deteriorate} W(n, v, i)_{deterioration} \dots$$
$$\dots + (1 - P_{deteriorate}) W(n, v, i)_{no\ deterioration} \quad (33)$$

Now, step back one more time step. Repeat the previous calculations for the failed and functioning cases, using the next step W's just calculated. Repeat the process until the first time step is reached.

Figure 18 shows a sample graphical representation of the model output for a turbine with a 10-year lifetime. The x-axis represents time in years and the y-axis the virtual age. As shown by the black dot, in the 5th year a turbine having a virtual age of 3 should be maintained by a repair level 3 to maximize VOE. However, as the program approaches the end of life, it is better to be maintained by a repair level 2. In other words, as the program nears the end of its life, it is not worthwhile to invest in new constituent systems. Thus the decision to repair or replace depends on both the state of the system and on the time remaining.

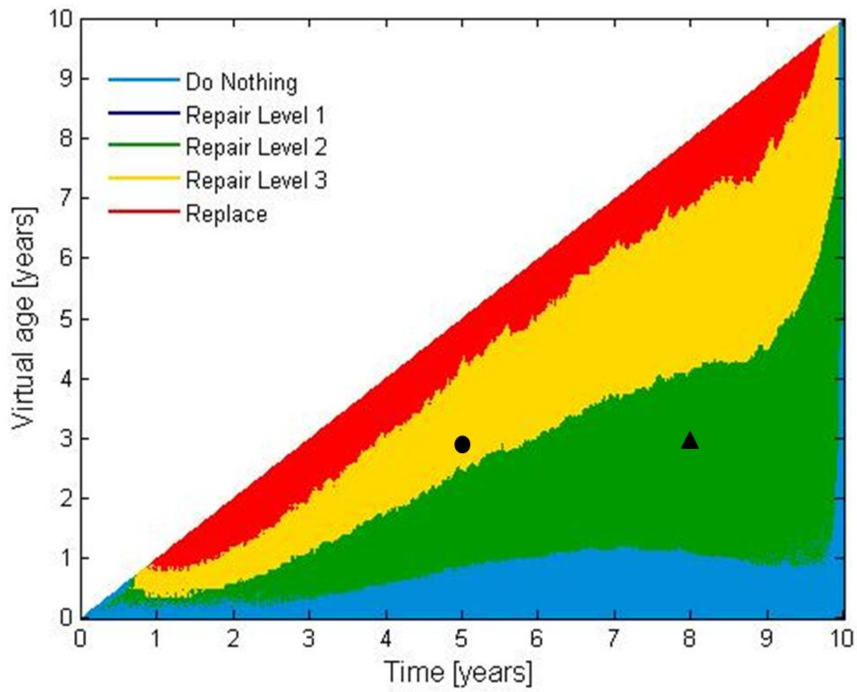

Figure 18: Optimal repair/replace decision with failure detection only

The next section demonstrates the application of this approach to studying the benefits of a CMS to a wind turbine blade. More specifically, the analysis carried out in the next section helps identify the optimal CMS that should be used by an investor in order to maximize his value.

4.2 Application: Identifying Optimal CMS

In this section, I demonstrate the use of our approach to investigate the value of turbine blade condition-monitoring systems. The cost of the CMS is applied only once at the onset of the project and I assume that the CMS itself will not require maintenance as it ages. As described previously (see Section 3.3.2), the deterioration of the turbine blade is modeled by an exponential approach. Due to the computationally intensive nature of the model, lower resolution results are provided in this section. With a higher resolution model, one would see smoother contours as shown earlier in Figure 18.

Consider first two specific cases: a CMS that can detect deterioration levels of 0.2 (higher fidelity) and one that can only detect 0.8 (lower fidelity) on rotor blades. A program lifetime of 10 years is assumed based on Hughes (2012). The results of the CMS application comprise two main parts; a graphical representation that provides maintenance strategies based on maximizing the turbine's value, and second, the VOE for each of the CMS levels.

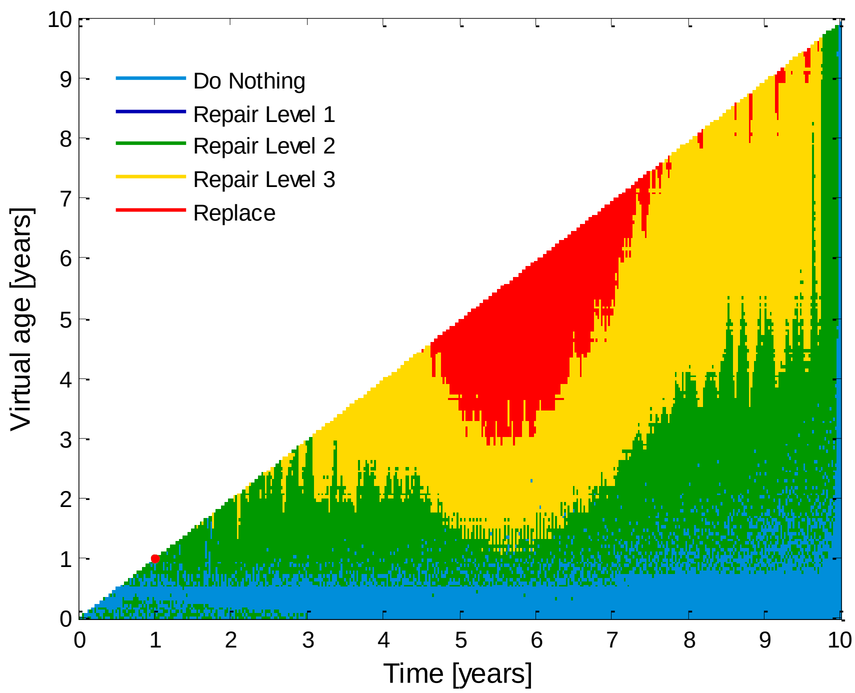

Figure 19: Optimal repair/replace decision with a CMS deterioration detection level of 0.2

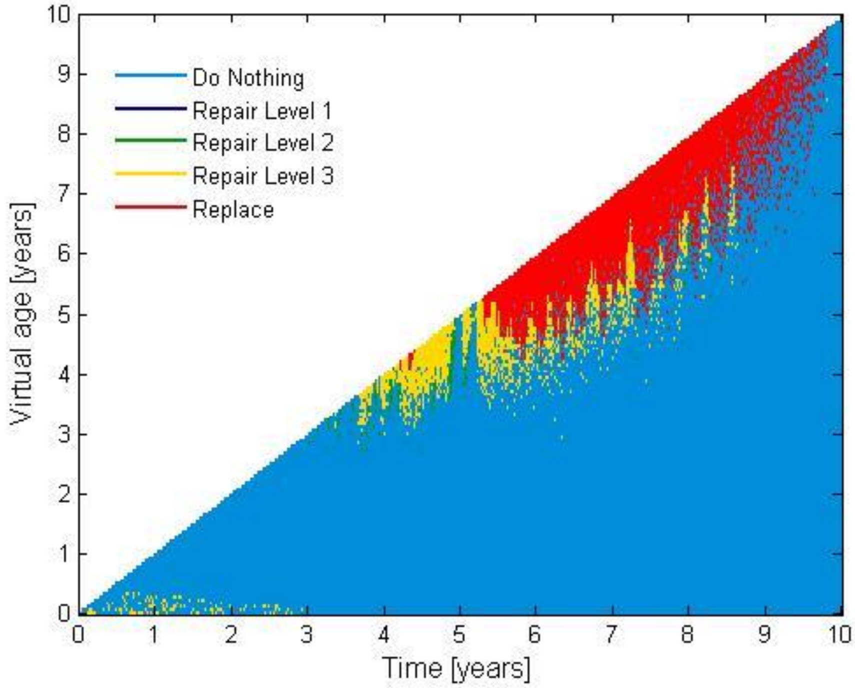

Figure 20: Optimal repair/replace decision with a CMS deterioration detection level of 0.8

I analyzed the impact different levels of CMS have on the VOE of the wind turbine blade as shown in Figure 19, and 20. Two observations are made at this stage: (1) lower repair levels are preferred at lower virtual ages, and (2) more extensive, and hence more expensive, repair options are preferred at high virtual ages. This behavior is expected: with increasing virtual age, the system experiences gradual deterioration and thus, its revenue generating capacity decreases. Now, if at any point in time the system fails, the optimal choice would be to bring it to a state that would allow for higher operating profitability, taking into consideration the repair costs as discussed in Equation 31-33. Therefore, a failure at a higher virtual age would warrant a more effective and costlier repair, provided there is sufficient time to recoup the investment. The plots also show that as the farm ages to the end of its planned life, cheaper repair actions for the turbines are preferred. This is important because an expensive repair towards the end would not allow the operator to recoup large investments in repair. Incorporation of salvage value would favor replacement instead of repair. The small green regions early in each farm's lifetime and for low virtual ages correspond to repairs done in response to "infant mortality" failures (see Figure 10).

From Figure 19, we observe that the "better" CMS with a deterioration detection level of 0.2 allows the operator to use the range of repair actions, which results in a relatively high lower levels of repair are not useful. The result is a lower VOE of 30.63 $/MWh. Note that with the less sensitive CMS, replacement is more often the optimal choice, because the system has deteriorated to such an extent that lower repair options would not prove beneficial and because repair costs increase significantly as the deterioration level increases (see Figure 12). Therefore, the optimal choice would be to replace the blade, which would improve the state considerably, rather than resorting to repair.

These results suggest that there is an optimal level of CMS that maximizes VOE by balancing improved deterioration level with the cost of CMS. Figure 21 illustrates the VOE for a range of CMS deterioration detection levels. From this graph, we conclude that the optimal CMS, that is, the one which provides the maximum VOE (48.9 $/MWh), is at the 0.4 level (as indicated by the dashed line). Thus a better CMS is not always better from a value point of view. This model allows decision makers to identify quantitatively the optimal CMS.

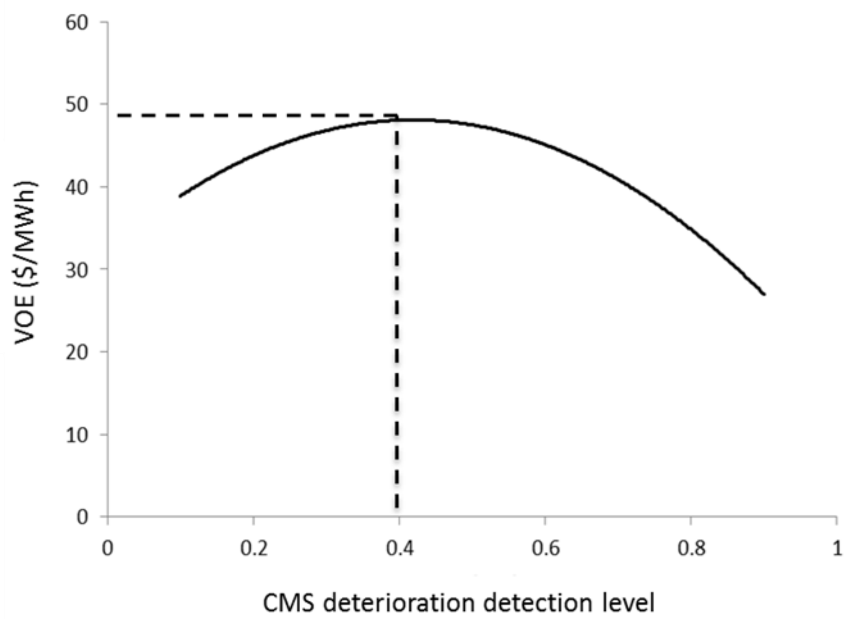

Figure 21: Total VOE ($/MWh) generated with CMS deterioration detection level

Next, I define the value of a CMS as the difference between a blade maintained in a value-optimal sense with a CMS, and without the benefit of a CMS. For the system without a CMS, deterioration is only detected when actual failure occurs. Figure 22 shows the estimated value provided by CMS of varying sensitivity. As expected from Figure 22, the maximum benefit is observed for a CMS level of 0.4, where the CMS provides a net present value over 10 years of US$M 2.2 (as indicated by the dashed line).

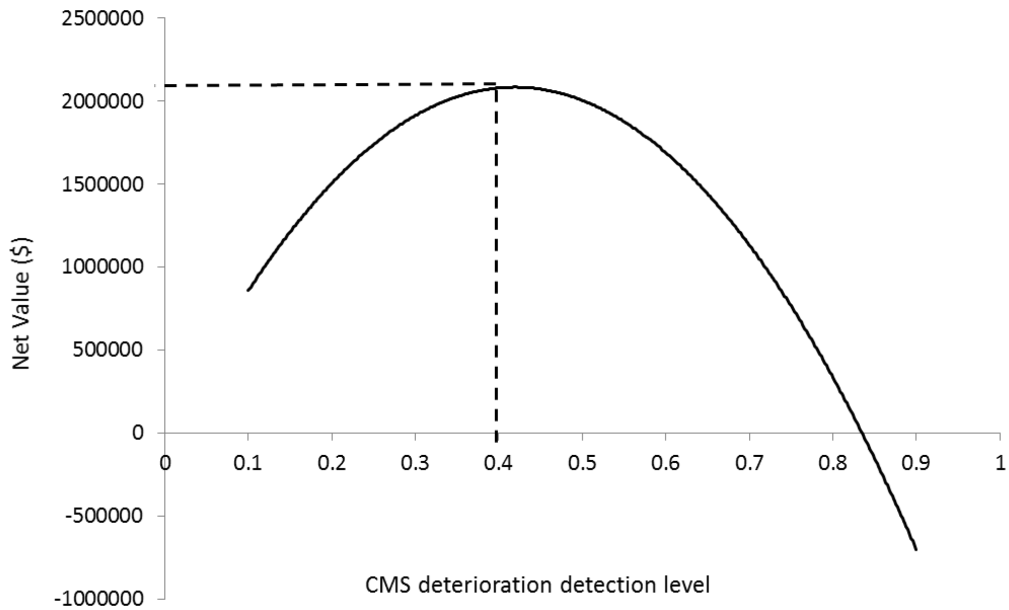

Figure 22: Net value ($) with CMS deterioration detection level

4.2.1 Optimal CMS Sensitivity Study to study VOE

Now, considering this optimal level of CMS, I carried out a sensitivity study to understand the effects of repair costs, wind speed and turbine type on the Value of Energy. Table 6 provides a summary of the values of the parameters used for this study. The remaining nominal values are provided in Table 5.

Table 6: Sensitivity study table

Sensitivity study	Parameters varied	Value (USD)
Repair cost effect	1. All repair costs high	R_1= 40,000 R_2= 300,000 R_3= 650,000
	2. All repair costs low	R_1= 400 R_2= 3000 R_3= 20000
	3. Only repair level 2 cost low	R_1= 4000 R_2= 15000 R_3= 65000
Wind Speed effect	Average wind speed	6-20 m/s
	Variance (shape factor)	2-5

4.2.1.1 Repair Cost Effects:

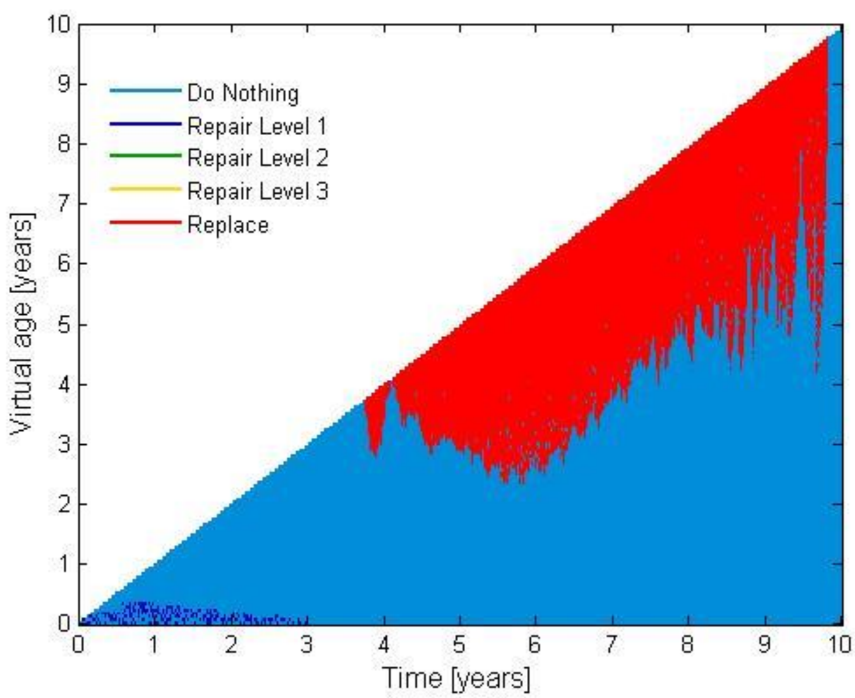

Figure 23: Optimal maintenance decisions for high repair costs

Figure 23 shows that when the repair costs are high (see Table 6), the dominant maintenance strategy is replacement. This option is exercised in most cases as the replacement action brings the system to a new state while costing the operator almost the same as any of the other repair options. The VOE obtained here is 4.7 $/MWh. The VOE is low because the replacement action is considered for almost all failure instances.

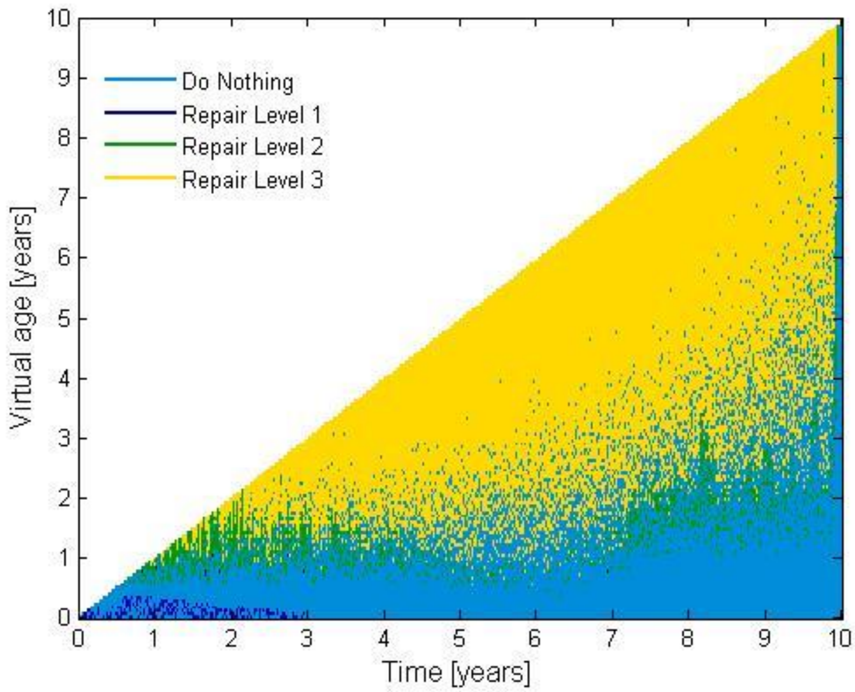

Figure 24: Optimal maintenance decisions for low repair costs

Figure 24 shows that when all three repair costs are made low (see Table 6), the optimized maintenance strategy is to apply repair level 3 for most failure instances. This is because repair 3 costs are low and the benefit in virtual age is much more than repair level 1 and repair level 2. The VOE obtained in such a situation is 87.9 $/MWh.

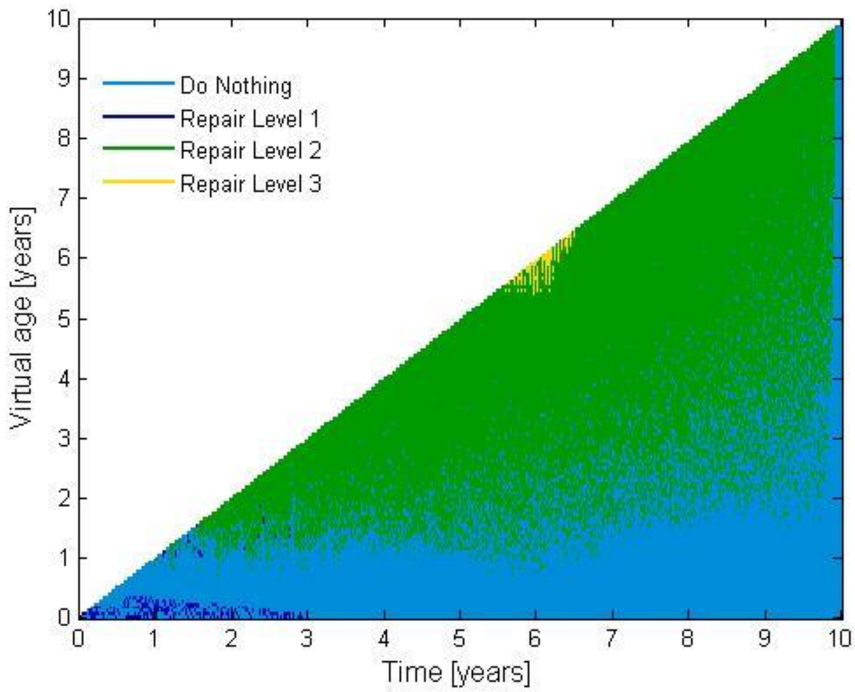

Figure 25: Optimal maintenance decisions for low repair level 2 costs

Figure 25 shows that when repair level 2 cost is made low in comparison to its nominal value, we can see that repair level 2 is selected as the optimal maintenance strategy for majority of the cases. The VOE in this case is found to be high but still lower than when all three repair costs are made low. The VOE obtained is 56.4 $/MWh. Table 7 summarizes the VOE for the different cases of repair costs.

Table 7: VOE ($/MWh) for different cost cases

Condition	**VOE ($/MWh)**
High repair costs	4.7
Low repair costs	87.9
Repair 2 cost low	56.4

4.2.1.2 Wind Speed Effects

The effects of wind speed on the VOE was also studied. First I considered the impact of varying the average wind speed while keeping the shape factor constant (*k* = 2). A shape factor of 2 was used here as this accurately replicates the average wind speed variance of the United States for a range of average wind speeds (Zhou et al, 2013). This analysis proves particularly useful to decision makers as it allows them to understand favorable locations for their wind farms. The effect of shape factor on the average wind speeds of 10, 14 and 18 m/s as an example is shown in Figure 26. Table 8 shows the wind speeds which were studied and the corresponding VOE obtained.

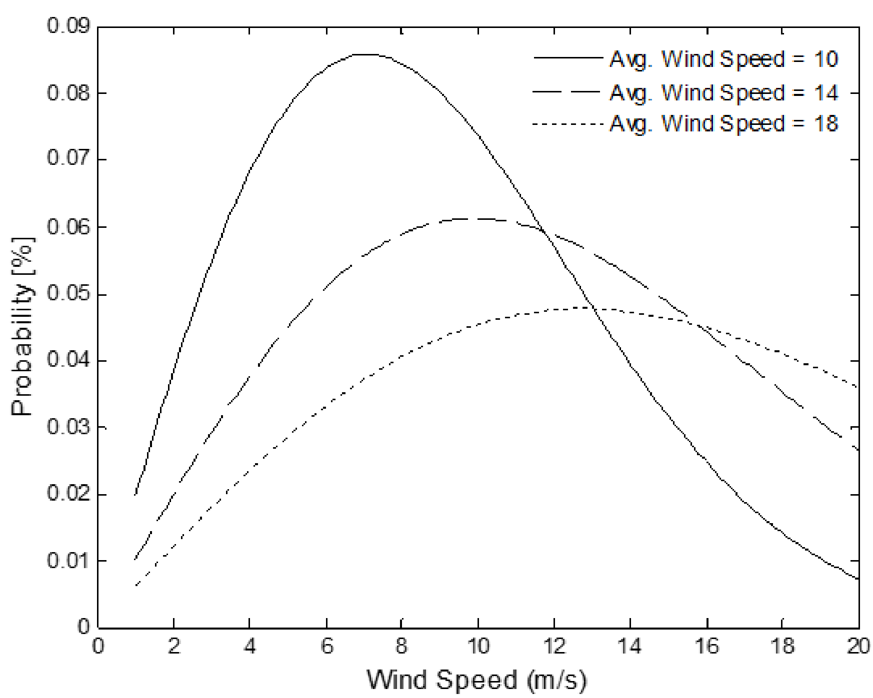

Figure 26: Wind speed distribution for shape factor=2

Table 8: VOE for different Wind Speeds

Average Wind Speed (m/s)	Value of Energy ($/MWh)
8	36.5
10	44.1
12	49.5
14	52.3
16	51.3
18	48
20	40.2

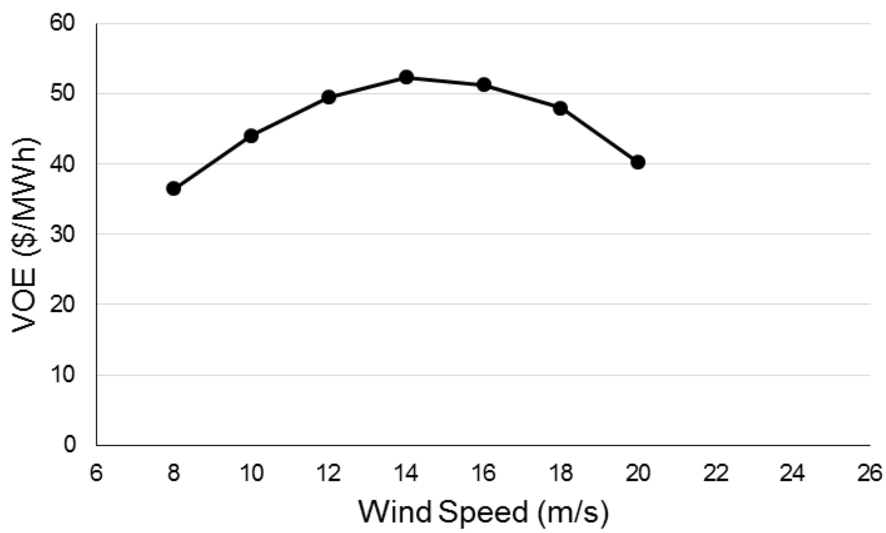

Figure 27 : VOE ($/MWh) with average wind speed (m/s)

Figure 27 indicates an increasing trend for the VOE as the average wind speed at a location increases. By establishing accurate meteorological data, such as average wind speed, an investor can accurately estimate the return on his investments at different locations. It should also be noted that as the average wind speed at a location increases, there are days when the turbine fails to function as the wind speed exceeds the cut-off wind speed.

As a result, it can be inferred that a higher average wind speed does not necessarily result in better returns.

Once I identified the optimal average wind speed, which was 14 m/s for maximum VOE, I carried out a variance analysis on this wind speed. The variance analysis was done by varying the value of the shape parameter $'k'$ from 2 to 5. The effect of the shape parameter on the wind speed distribution is shown in Figure 28.

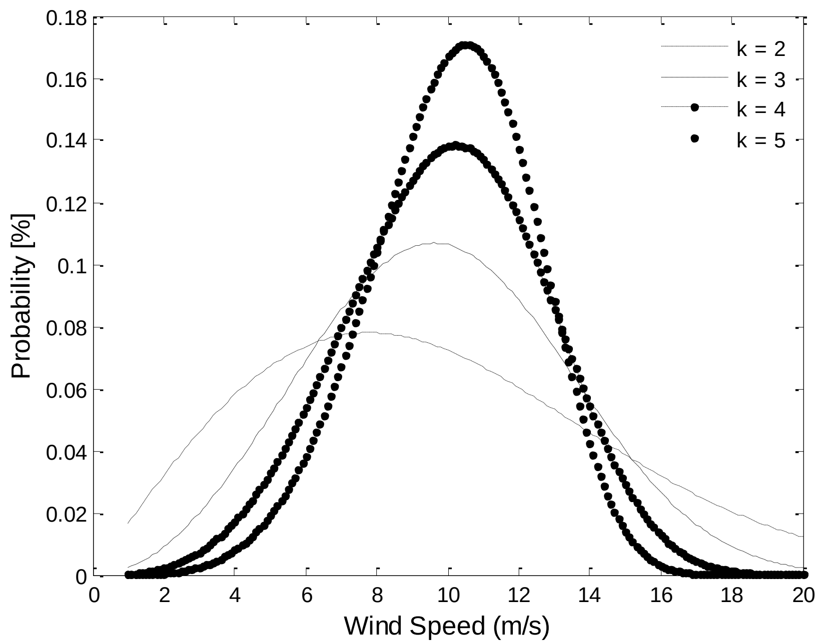

Figure 28: Average wind speed (14 m/s) distribution with shape factor

It is seen that the VOE decreases as the shape factor decreases (see Figure 29). This is because as the shape factor decreases, the variance increases and thus there is a higher probability of lower and higher wind speeds being generated than the optimal wind speed of 14 m/s. As we know from our analysis earlier (Figure 27) the VOE is greatest for a wind speed of 14 m/s. Thus anything above or below this will contribute to generating a lower VOE. It can also be seen that when the variation in wind speed is reduced (shape factor is 5), we observe the highest VOE. This trend was observed to be true for all average wind speeds within the designed speeds of the turbine.

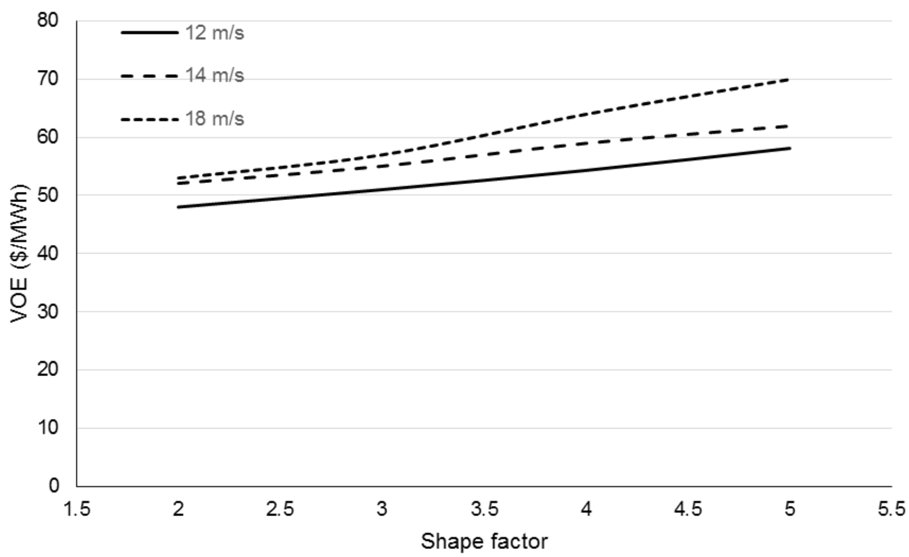

Figure 29: VOE ($/MWh) trend with shape factor for average wind speed of 12, 14 and 18 m/s

4.3 Application: Identifying Optimal Manual inspection.

This section discusses the application of manual inspection techniques in the detection of fatigue damage on wind turbine blades. Further, a comparison is done to understand the optimal manual inspection technique. The deterioration is modelled using the fatigue growth model as described in section 3.3.3. This is because lower fidelities of manual inspection techniques such as visual inspection are restricted in the sense that they can detect only exterior cracks.

Consider first two specific cases: a manual inspection technique that can detect deterioration levels of 0.2 (higher fidelity), and one that detects levels of 0.8 (lower fidelity). The results of the manual inspection technique comprise of two main parts; a graphical representation that provides maintenance strategies based on maximizing the turbine's value, and second, the VOE for each of the manual inspection techniques.

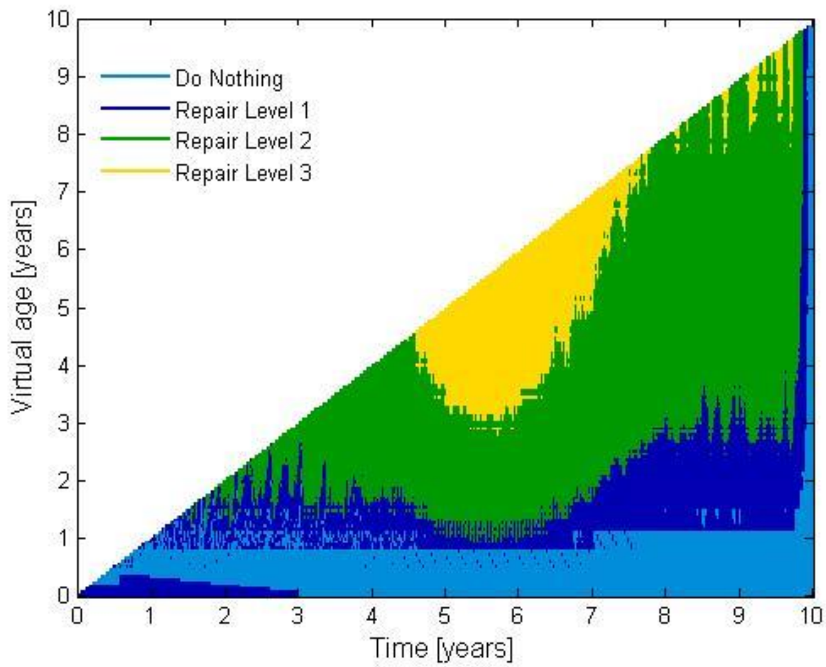

Figure 30: Optimal repair/replace decision with a Manual Inspection detection level of 0.2 (λ)

Figure 30 shows the results for a 0.2 (higher fidelity) manual inspection detection level. A better inspection procedure has a higher probability of detection for lower levels of deterioration and also yields a higher VOE. The VOE obtained in this case was 34.3 $/MWh. The advantage of using a better inspection procedure is that it detects lower deterioration and also provides the operator more number of repair options for lower deterioration levels.

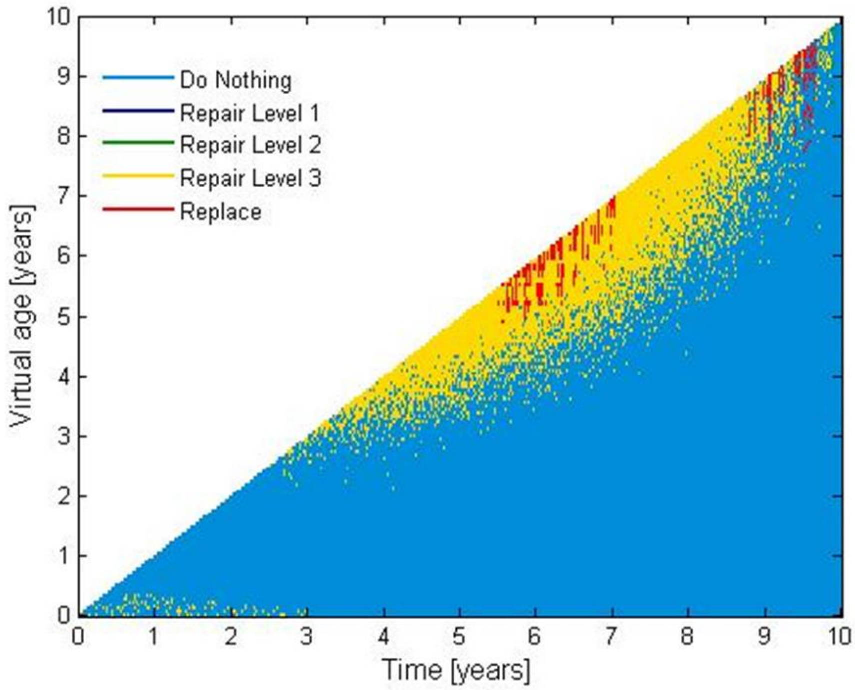

Figure 31: Optimal repair/replace decision with a Manual Inspection detection level of 0.8 (λ)

Next, I simulated a lower fidelity inspection technique, i.e. one that can detect only higher levels of deterioration (see Figure 31). The VOE obtained by using this technique is 18.6 \$/MWh, which is much lower than the higher fidelity technique (34.3 \$/MWh). This dramatic drop in VOE can be ascribed to two main causes. First, at these higher levels of deterioration, the action that is taken is to carry out more expensive levels of repair, or replacement as this can improve the turbine state considerably. Second at these unchecked higher deterioration levels, the turbine cannot generate as much energy and thus revenue.

With the lower fidelity inspection technique, we get fewer repair options. Note that lower fidelity inspection, repair level 3, and replacement are more often the optimal choice. This can be attributed to the fact that the system has deteriorated to such an extent that lower repair options would not prove beneficial. This is due to the fact that repair costs increase significantly as the deterioration level increases (see Figure 12). Therefore, the optimal choice would be to replace the blade, which would improve the state considerably, rather than resorting to repair.

These results suggest that there is an optimal manual inspection method that results in maximum VOE. Figure 32 illustrates the VOE for a range of manual inspection detection levels. From this graph, we conclude that the optimal manual inspection procedure, that is the one that provides the maximum VOE (34.3 $/MWh), is at the 0.3 manual inspection detection level (as indicated by the dashed line). A better manual inspection procedure is associated with higher costs and thus does not necessary yield a higher VOE.

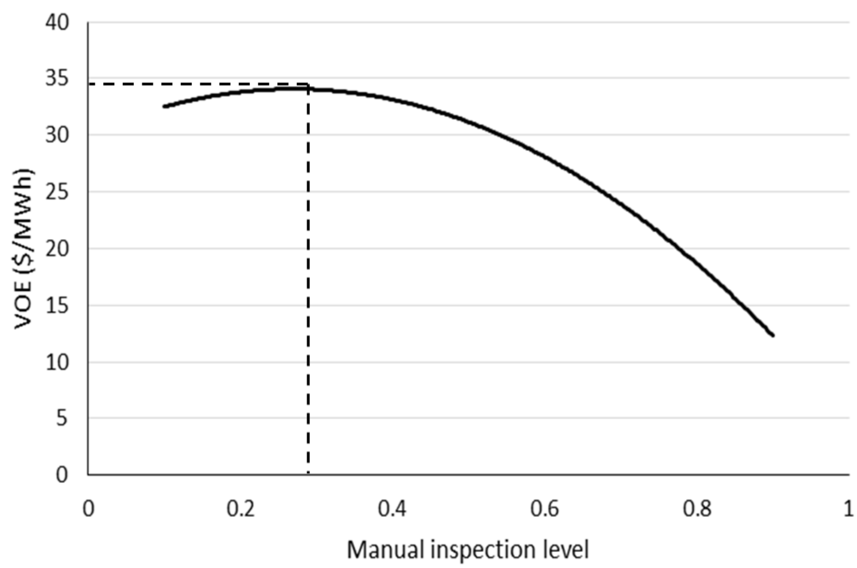

Figure 32: VOE ($/MWh) with Manual Inspection Detection Level

Further, Figure 33 shows the estimated value provided by Manual Inspection for the various detection levels. As expected from Figure 33, the maximum benefit is observed for a manual inspection detection level of 0.3, where a value of US$M 1.08 is seen over 10 years (as indicated by the dashed line).

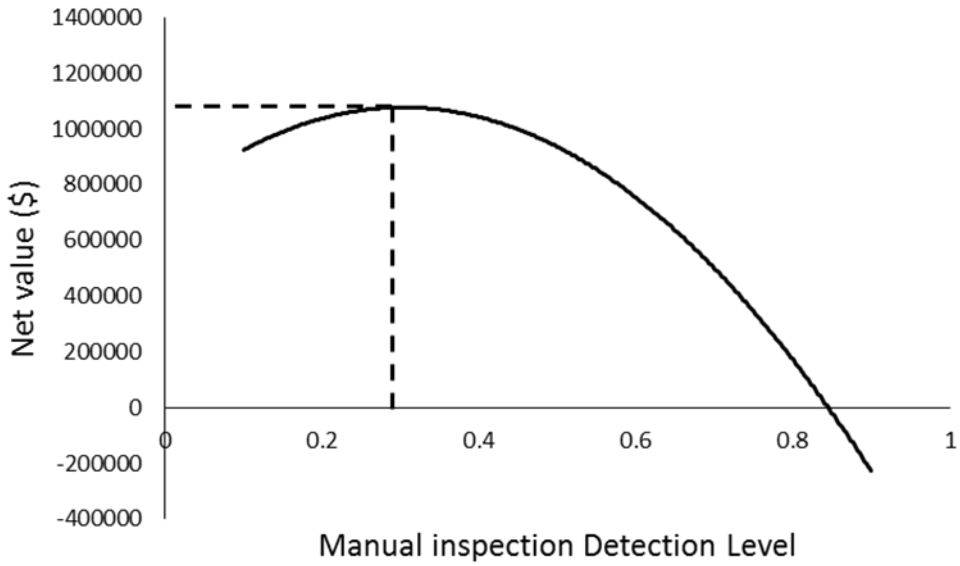

Figure 33: Net value ($) of Manual Inspection Detection Level

The sensitivity study of the manual inspection also showed similar results to that of the CMS (see Section 4.2.1). When all the repair costs were made high (Table 6) the optimal choice of maintenance action was replacement and when the repair costs were made low (Table 6) the optimal choice was repair level 3. Further, wind speed effects showed that the VOE increased till 14 m/s and then went on to decrease with wind speed. This confirmed the earlier explanation that when the wind speed is higher, there are some days when the wind exceeds the cut-off and hence there is no revenue generation leading to a lower VOE. Also, the effect of increase in parameters such as radius and turbine height confirmed an increase in the VOE of the turbine.

4.4 Comparison of CMS and Manual Inspection technique

Here I compare results from both CMS and manual inspection techniques. In order to carry out this comparison, I use the same deterioration model that was used for the manual inspection procedure for the CMS (recall that for CMS in section 3.3.2 I had used an exponential deterioration model). It must be noted that using this deterioration model for CMS will underestimate the value of a CMS.

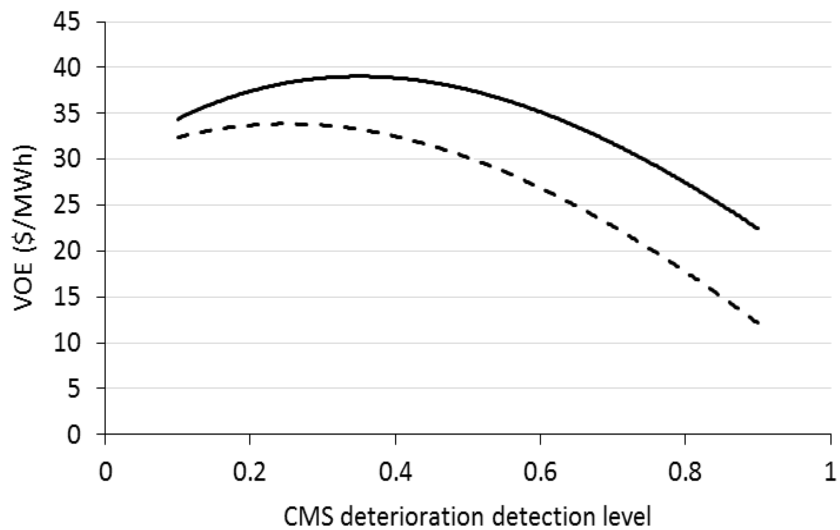

Figure 34: Comparison of VOE of CMS and manual inspection for a fatigue driven deterioration model

The results indicate a maximum VOE of 39.3 $/MWh with an optimal CMS deterioration detection level of 0.3. This is higher than the maximum VOE obtained by a manual inspection detection level (see Figure 34), because I assumed that CMS has a one-time installation cost and negligible operating costs, whereas the manual inspection technique costs every time an inspection is carried out. Future work should consider the effect of incorporating operating costs for the CMS, and also model deterioration in the CMS detection ability over time. Also, note that the VOE associated with lower fidelities of CMS is also higher than the lower fidelity manual inspection techniques. This is again because I apply a one-time cost for CMS, and the fact that the probability of detection for manual inspection techniques is very low for lower fidelities.

4.5 Summary

This chapter discussed results obtained with the application of a condition monitoring system and a manual inspection technique to the Value a wind turbine. It showed how the benefit of these maintenance techniques can be captured by the VOE model. A sensitivity study confirmed the robustness of the model to various input parameters such as repair costs, wind speed, variance and turbine radius. Further, it also illustrated that there will be an optimal level of inspection detection level that will result in the maximum VOE and that the benefit is not observed for all fidelities of these inspection techniques.

CHAPTER 5. DECISION FRAMEWORK FOR CHOOSING AN OPTIMAL CMS

This section provides an analysis that can help in the decision making process for a wind energy investor. In Section 4.2 I showed that input parameters such as wind speed, variance and repair costs have a significant effect on the VOE. Here, I show that these parameters also influence the selection of an optimal CMS/Manual inspection method.

Some of the parameters that an investor is confronted with at the onset are the wind speed, wind speed variance, repair costs in the region and the turbine type. Figure 35 shows the framework for selecting inspection techniques. The first stage involves the selection of input parameters based on the available data. The second stage involves using the VOE model to establish the VOE and an optimal maintenance plan for the selected input parameters. Finally, the third stage involves the development of a database by going through stages 1 and 2 with different input values. The rest of the chapter goes into detail as to how this framework works.

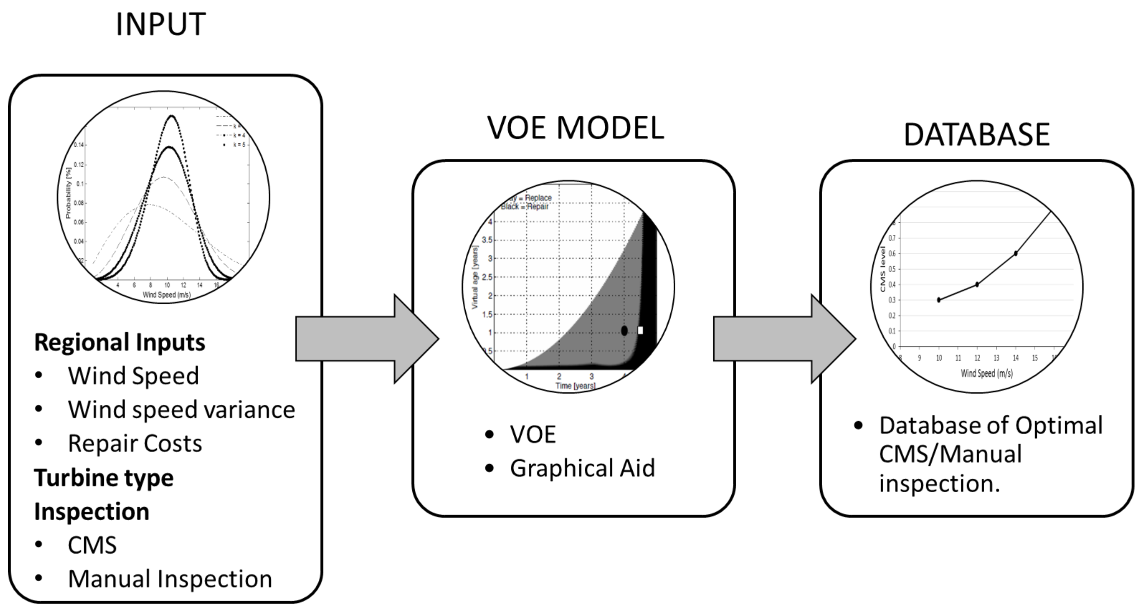

Figure 35: Process flowchart for an Investor

5.1 Optimal CMS with wind speed

Consider first the effect of average wind speed on the optimal selection of a CMS. Here the average wind speed varies from 10 m/s to 16 m/s, and the variance is constant (shape factor k = 2). Figure 36 shows the optimal CMS level for different average wind speeds. These results indicate that at higher average wind speeds a lower fidelity CMS is the better choice. This can be understood as follows: at higher average wind speeds a turbine can generate more revenue than at lower wind speeds, even when it is somewhat deteriorated. As a result, it is better to run the wind turbine through these deteriorated states than to invest in a higher fidelity CMS which would only provide a ‘do nothing’ solution in this situation.

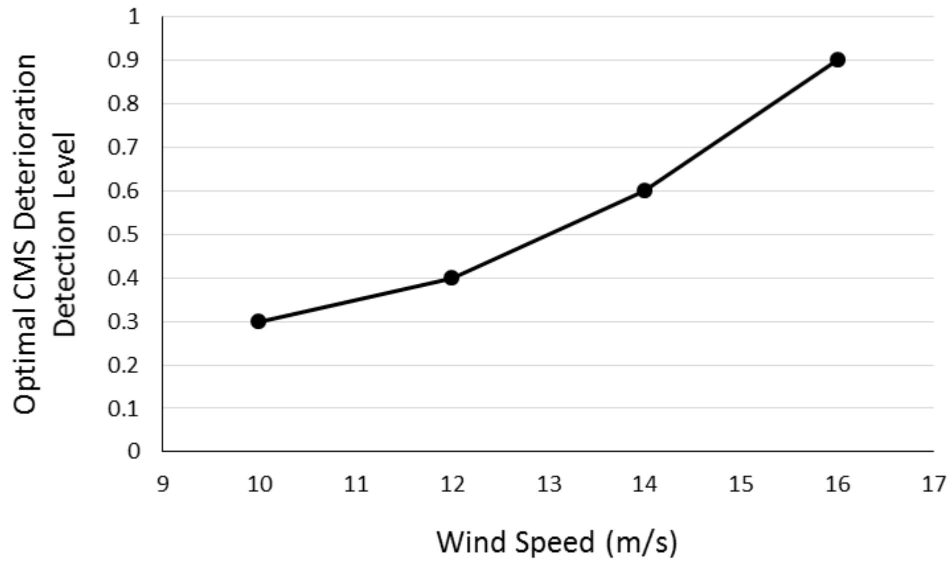

Figure 36: Optimal CMS deterioration detection level with average wind speed (m/s).

5.2 Optimal CMS taking into account both wind speed and variance

From the previous section, we saw that the optimal CMS changes with the wind speed. Here we consider the combined effect of varying wind speed and shape factor. This is particularly important if the investor wants to consider different regions for his investment. Figure 37 compiles a selection of the results for the combinations of wind speed and shape factor. The figure illustrates how a particular region can influence the selection of a CMS in order to achieve the maximum VOE. The x-axis in the figure corresponds to the shape factor, while the y-axis relates to the wind speed. Each entry in the figure then corresponds to the optimal CMS level that should be availed for that particular combination of wind speed and shape factor in order to achieve the maximum VOE. For example, as an investor, you would first go get the wind statistics for the different regions that you are considering. Then with these parameters, you would use the VOE model to arrive at optimal CMS for the different regions that would give the maximum VOE. Finally, after establishing this, you can draw a comparison between the different regions based on the resulting VOE.

Note that a region with higher average wind speeds may not necessarily give a higher VOE. This is particularly seen for the case where a lower shape factor (higher variance) is associated with higher average wind speeds (indicated by red (17.4 $/MWh) in Figure 37). A higher variability in wind speed means that there may be some days when the wind speed has exceeded the cut-off wind speed, which would then result in zero revenue for the day. On the other hand, a region where the average wind speed is high and the variance is low (shape factor is equal to 4) would yield the highest VOE (74 $/MWh) out of all the combinations of wind speed and shape factors (indicated by green in Figure 37). All the other regions indicated by blue yield a moderate VOE (30-60 $/MWh) in comparison.

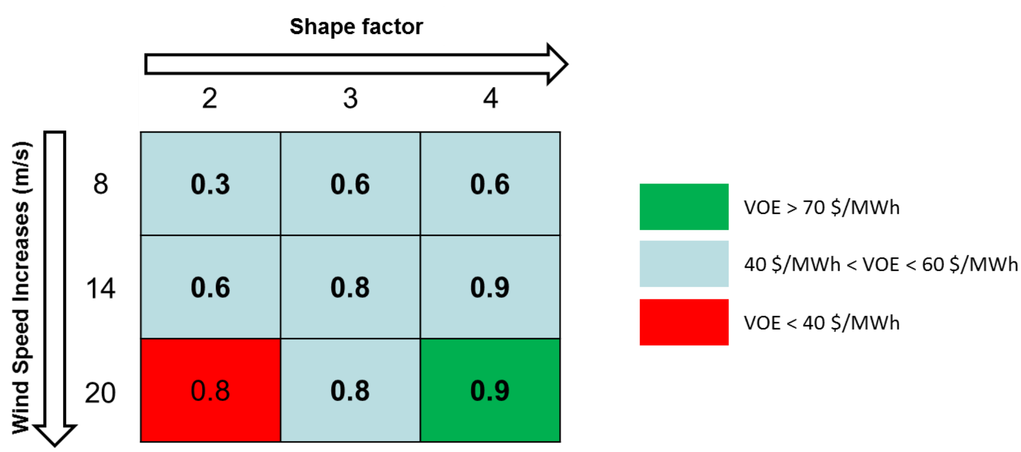

Figure 37: Optimal CMS detection level with average wind speed and shape factor

5.3 Optimal CMS with repair costs

Consider now the impact of repair costs on the selection of an optimal CMS. I consider here three cases: 1) High repair cost, 2) Nominal repair costs, and 3) Low repair costs (Refer to Table 6). The repair costs could vary with time due to numerous reasons. For e.g., the factors that may influence these costs could be: 1) proximity of maintenance personnel, 2) lower wages of maintenance technicians, 3) better availability of equipment and spares, and 4) Improved logistics. Figure 38 shows how the CMS level varies with repair costs.

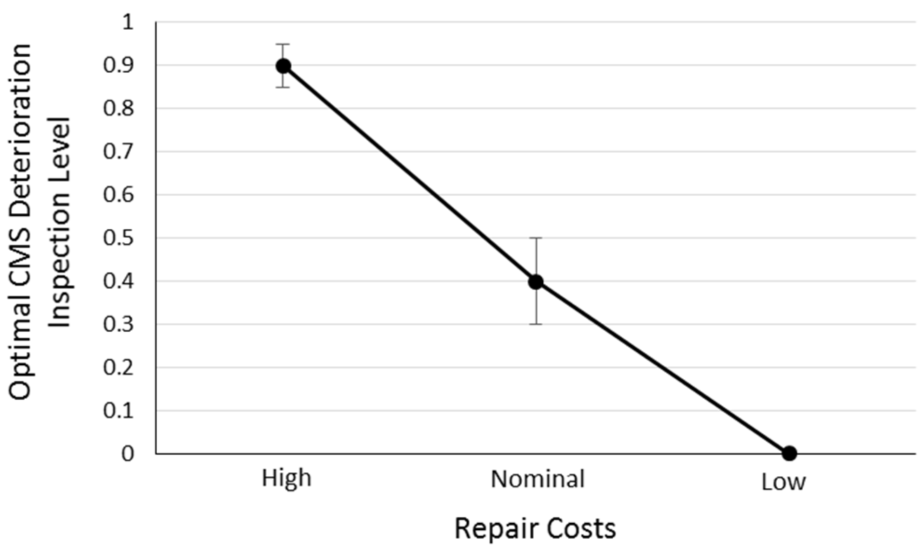

Figure 38: Optimal CMS with varying repair costs

From Figure 38 it can be seen that when repair costs are low, the operator should invest in the highest fidelity CMS. This makes sense as the operator would want make use of the lower repair costs to maintain or improve the state of the turbine. While the added accuracy of a CMS may come at a price, the low repair costs here compensate this loss in value. On the other hand, when the repair costs are high, the model recommends the use of a lower fidelity CMS.

5.4 Graphical User Interface

The Graphical User Interface (see Figure 39) provides the decision maker an understanding of the value of his investment by varying parameters such as average wind speed, CMS level and the radius of the turbine blade. The investor can then identify the location based on wind speed data and CMS fidelity that he should use in order to maximize his return. The GUI also provides a maintenance map which can guide the operator on the optimal maintenance strategies that should be adopted based on the real age and the state of the turbine.

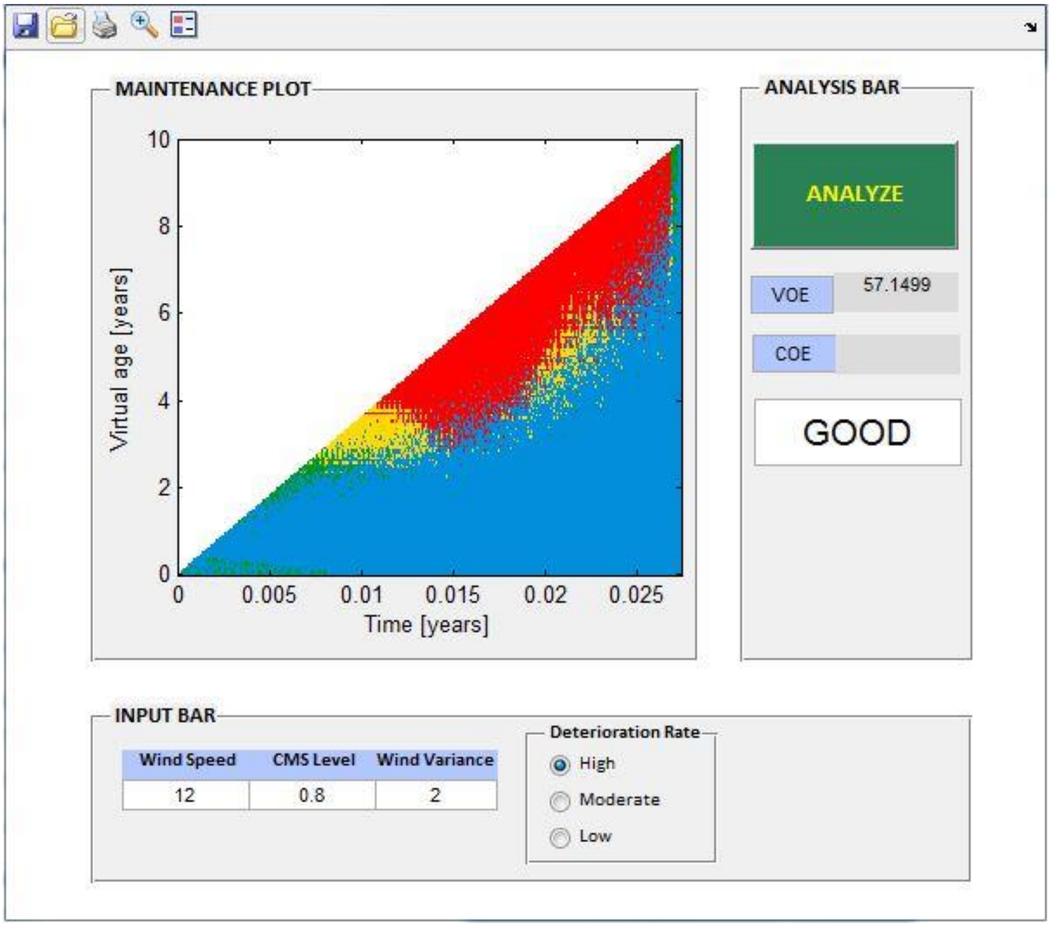

Figure 39: GUI showing the results after analysis

5.5 Summary

This chapter developed a decision framework for an investor using CMS as an example. It expands on the sensitivity study done earlier in Section 4.2 to discuss how regional parameters of wind speed, wind speed variance and repair cost can also affect the optimal selection of a CMS. A graphical user interface that has been developed to study the same has also been described in this chapter.

CHAPTER 6. CONCLUSIONS AND FUTURE WORK

The main objectives of this work were: 1) Apply the VOE model to capture the benefits of various maintenance techniques, 2) Study if there is an added value that a CMS or a manual inspection technique brings, and 3) Show how one can select the best CMS/manual inspection technique. First, I introduced the VOE concept and illustrated how it differs from the COE metric. I then applied this metric to capture a two-dimensional aspect to the cash flow for a wind turbine. Second, I expanded the VOE model to to include damage detection techniques in the form of 1) Condition Monitoring Systems and 2) Manual Inspection methods. Next, I applied real world financial modeling to develop a dynamic simulation that determines the optimal maintenance strategy for each deteriorated state of the turbine. Finally, I developed a decision framework to aid an investor to make better informed decisions on the inspection type and the region he should consider.

The results show how the value perspective can be used to determine an optimal maintenance strategy for the maintenance policy consisting of different levels of repair and replacement. Further, the results indicate that there is an added value observed only for certain fidelities of CMS or manual inspection techniques, and not for all. The results also aim to inform the investor of the impact of regional parameters such as wind speed, variance and maintenance costs to his investment.

The analysis makes use of a trends and relationships that are observed for a 1.8 MW turbine, and thus it would need more refinement if needed to be applicable to other turbines. I recommend here that more work be done to understand the different deterioration mechanisms of turbines in order to apply this model more accurately. For this I suggest using experimental data in order to properly establish a relation between the performance and deterioration of the wind turbine.

Additionally, I recommend that more refinement be done in properly quantifying the performance of CMS and manual inspection techniques. Good data on CMS and manual inspection techniques for the wind industry is hard to come by, especially since most of it is proprietary information, and hence I suggest further work be done to include more accurate data.

Another area for future work will be to develop this model for a wind farm, and to incorporate turbine wake effect into the modeling. Turbine wake affects the power generation capabilities of a wind turbine, which in turn can have significant impacts on the choice of optimal strategy

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