Operational Expenditure Optimisation Utilising Condition Monitoring for Offshore Wind Parks

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This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

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Nomenclature and Abbreviations

Abbreviations

AE	Acoustic emission
C	Cost
CAPEX	Capital expenditure
CBM	Condition based maintenance
CFD	Contract for difference
CM	Condition monitoring
CMS	Condition monitoring system
CoE	Cost of Energy
CoV	Coefficient of variance
CPT	Conditional probability table
DAG	Directed acyclic graphs
DBN	Dynamic Bayesian Network
DT	Downtime
E	Emission state matrix
f	Number of failures
FBG	Fibre Bragg Grating
FMEA	Failure mode effects analysis
G	Turbine power waiting
HMM	Hidden Markov model
IRR	Internal rate of return
LCoE	Levelised cost of energy
LP	Lost production
MC	Markov chain
NPV	Net present value
O&M	Operations and maintenance
OEM	Original Equipment Manufacturer
OPEX	Operational expenditure

P State transition matrix

PBM Period based maintenance

PBMC Performance based maintenance contracts

PM Preventative maintenance

r Discount rate

R Effectiveness of condition monitoring systems

ROC Renewable obligation certificate

ROI Return on investment

ROV Remotely operated vehicle

SCADA Supervisory control and data acquisition

SHM Structural health monitoring

SIM Structural integrity management

U Probability of failure

V Reliability of condition monitoring systems

VoI Value of information

t Time period under investigation

T Fixed period of time

Non-Roman Letters

γ CM detectability

λ Failure rate

η CM system efficacy

μ Repair rate

ω Natural frequency

Subscript

C Condition - indicates that variable involves CBM

E Vessel hire

EP Energy production

f Component failure

fa False alarm

I Installation

L Labour price

OP Operating costs

V Vessel

RP Replacement parts

Superscript

k	Number of components	y	Number of years

Abstract

There is a strong desire to increase the penetration of renewable energy sources in the UK electricity market. Offshore wind energy could be a method to achieve this. However, there are still issues, both technical and economical, that hinder the development and exploitation of this energy source.

A condition based maintenance plan that relies on fully integrating the input from condition monitoring and structural health monitoring systems could be the method to solve many of these issues. Improved maintenance scheduling has the potential to reduce maintenance costs, increase energy production and reduce the overall cost of energy. While condition monitoring systems for gearboxes, generators and main bearings have become common place over the last few years, the deployment of other monitoring systems has been slower. This could be due to the expense and complication of monitoring an entire wind farm. Wind park operators, correctly, would like to see proof that their investment will be prudent.

To assist wind park operators and owners with this decision, an offshore wind operations and maintenance model that attempts to model the impacts of using monitoring systems has been developed. The development of the model is shown in this analysis: multiple methodologies are used to capture deterioration and the abilities of monitoring systems. At each stage benchmarks are shown against other models and available data. This analysis has a breadth and scope not currently addressed in literature and attempts to give insight to industry that was previously unavailable.

Acknowledgements

While the work presented in this thesis is mine, it has only been possible thanks to the knowledge and patience of others.

Firstly, I'd like to extend my gratitude to my supervisor, Dr. David McMillan, who helped me pull apart my ideas and if they were worthwhile put them back together. Your efforts kept me focussed on the right things.

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Finally, my thanks to my friends and family. Your support has been invaluable and my English was assessed by a professional.

"The fishermen know that the sea is dangerous and the storm terrible, but they have never found these dangers sufficient reason for remaining ashore."

- Vincent Van Gogh

"If you want to build a ship, don't drum up people to collect wood and don't assign them tasks and work, but rather teach them to long for the endless immensity of the sea."

- Antoine de Saint-Exupery

CHAPTER 1

Introduction

The seas that surround Great Britain have a vast wind resource. This is shown clearly in Figure 1.1 from WindAtlas [1.1]. The colours in this figure indicate the mean average wind speed. Purple shows areas of greater than 10 m/s and light blue shows areas of greater than 6 m/s at heights of 100 m above sea level. However, these seas are a harsh and hostile environment to operate in. Dangerously strong winds and violent sea states are common. Ship reports off the west coast of Scotland in January 1894 showed "30 ft (significant) [9 m] waves during a storm with some reaching 43 ft [13 m]." [1.2]. Things have not changed much in the 21st Century. In December 2013, the maximum average wind speed was recorded at over 30 m/s with a maximum significant wave height of 13 m in the North Sea [1.3].

This fierce environment effects how any asset in the British seas must be designed, operated and maintained.

1.1. Designing for Offshore Wind

Designers must consider not just aerodynamic loads but hydrodynamic loads too. These often interact to produce non-linear dynamic effects. The structure must withstand constant fatigue loading and some of the extreme weather conditions outlined

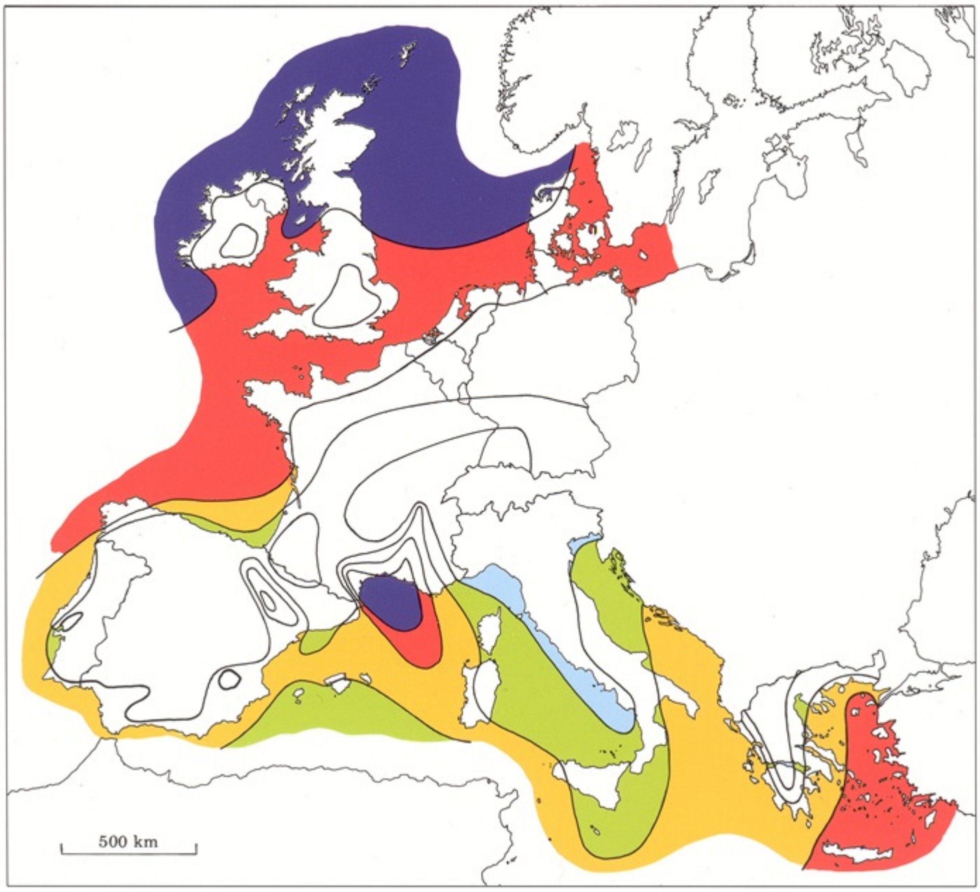


Figure 1.1.: Wind Resource in Europe Offshore [1.1]

above. The designers must not hinder the primary goal of maximising wind power production. They must protect their operational components and the people who are located on them at all costs. A disturbing conclusion from Goldman [1.2] in 1975 was that designers of offshore assets could still have been underestimating the sheer power of the sea.

However, it is no longer 1975 and there have been a wealth of improvements in design techniques and standards to assess fatigue, corrosion and wear inherited by offshore wind designers from the oil and gas industries [1.4]. New models and design techniques are being developed specifically for offshore wind structures with added criteria - one of the most important being minimising the substantial cost of an offshore foundation [1.5].

1.2. Operating and Maintaining Offshore Wind

Offshore wind turbines have particular attributes that separate them from other forms of power generation including onshore wind in terms of operations and maintenance (O&M). Tavner describes offshore wind as "unmanned, robotic power units operating 24/7, controlled from remote onshore control rooms" [1.6]. The large transient and complex loads they experience have lead to higher failure rates, and lower availability, for offshore wind turbines than their onshore equivalents. Early offshore wind farms have been affected by serial defects leading to the need for improvements with the replacement and redesign of key components [1.7].

It is here that maintenance can play a key role. The maintenance options that are available to operators are explained in Chapter 2. Onshore wind farms have most often used time based maintenance strategies to obtain high availabilities [1.8]. This works well when access is relatively straightforward. Servicing can be carried out reliably and sudden failures can be rectified with little logistics time.

This changes offshore. This is illustrated by three images from Siemens Wind Power A/S in Figure 1.2. There are inherent dangers in transferring personnel, components and equipment offshore between a moving ship and stationary turbine seen in 1.2(d). Wind turbine blades are a particularly good example of a component that is difficult to transport (1.2(a)(b)) and install (1.2(c)) - large, heavy and designed to be easily influenced by the wind. These require expensive specialist equipment that can only operate within certain weather conditions. Lead times are longer and catastrophic failures can lead to months of non-operation. The downtime can be extended further by other factors including the distance from port, water depth and port facilities.

1.3. Lowering the Cost of Energy

Offshore wind farms in the UK had a capacity of 1.3 GW in 2011 and currently have a capacity of over 4 GW [1.9]. It is estimated that this will increase with scenarios from 2011 suggesting that between 10 to 26 GW will be possible in 2020 with a potential to achieve 40 GW in 2030 [1.10]. The same source identifies that unless there "is clear evidence of cost reduction, the UK ambition for offshore wind should be limited to 13

(a) Transporting

(b) Preparing to Ship

(c) Installing

(d) Offshore Access

Figure 1.2.: Installing an Offshore Wind Turbine Blade - Photo credits: Siemens Wind Power A/S from www.siemens.com/press

GW by 2020". In 2015, it appears that these savings have yet to be made as it is now predicted that the UK will achieve around 10 GW of offshore wind for 2020 with an estimated potential investment of £16 - £21 billion until then [1.11].

The Cost of Energy (CoE) of offshore wind farms is a major concern to utilities and governments looking to increase the volume of wind in the energy generation mix. CoE is defined in Equation 1.1 and is often quoted in price per Megawatt hour (MWh). There are a range of CoE estimates for offshore wind in the UK and in the EU of between £69/MWh and £104/MWh for subsidised costs respectively [1.6]. An alternative study gives an unsubsidised range of £149/MWh to £191/MWh [1.10]. The long term goal in the UK is to achieve an offshore CoE of less than £100/MWh [1.10].

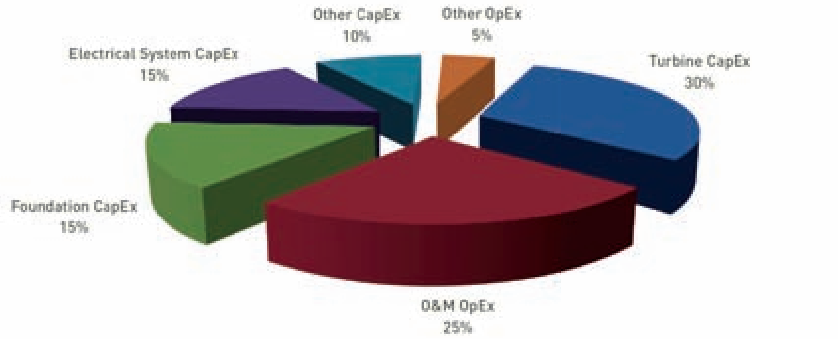
$$\text{CoE} = \frac{(\text{Captial Cost} \times \text{Fixed Rate}) + \text{O\&M Costs}}{\text{Annual Energy Production}} \tag{1.1}$$

The majority of a wind park's costs are the capital expenditure (CAPEX) costs required to buy, build and commission the wind park. However, the costs involved in completing O&M actions are not insignificant especially over a 20 year lifetime. The Scottish Government and GL Garrad Hassan estimate that the operating expenditure (OPEX) is £430,000 per annum per turbine averaged over 20 years for a 6 MW turbine or around £72,000 per MW. This appears to be an extreme value with other reports and actual data suggesting between £22,000 [1.12] and £25,000 [1.13] per MW. This represents 25% of the estimated total CoE shown in Figure 1.3 (a) [1.14].

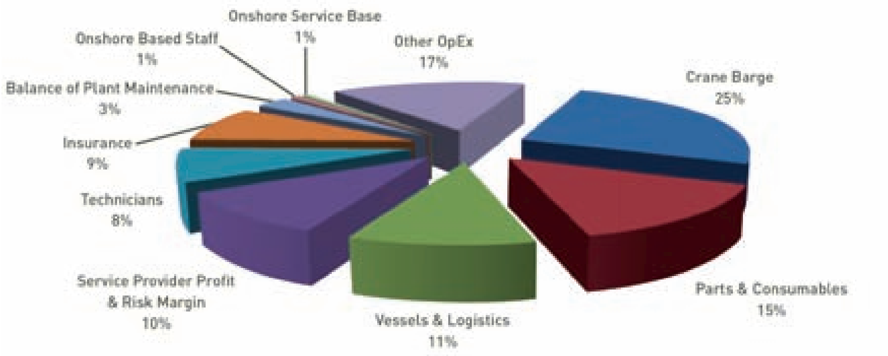
The major factors affecting offshore wind O&M costs are vessel hire costs with crane vessel hire and other logistics operations equating to around 36% of OPEX. The other factors contributing to direct OPEX costs are shown in Figure 1.3 (b). An indirect OPEX that has been identified as important but is not considered in these numbers is lost revenue - energy not produced from a wind turbine while it is not operating. These contribute more to the overall CoE than staffing or repair costs [1.15]. The availability of suitable vessels to complete maintenance work and appropriate weather windows are also major concerns.

Operators can have an impact on almost all of these variables with their O&M strategy. The CAPEX of the wind park is fixed and out of an operator's control as is the installation. If an O&M strategy improves energy production, reduces replacement costs and its implementation costs little then the CoE goes down. Improving energy production is synonymous with maximising wind turbine run time or minimising downtime.

The Fixed Rate referred to in Equation 1.1 is the cost of capital used in the project. Banks or organisations often use the internal rate of return (IRR) when deciding upon investment opportunities. The IRR is the discount rate at which the present value of the cash flow generated over the project lifetime equals the cost of initial capital investment [1.16]. The discount rate represents interest rates and the effects of inflation on the capital. Typically the higher the value of IRR the more promising a project seems to investors. It represents a higher chance of making a profit and that the project has less risk involved. Projects with higher IRR will have access to lower interest rates and have lower fixed rates as a result.



(a) Breakdown of cost of energy for representative offshore wind farm



(b) Estimated breakdown of total OPEX

Figure 1.3.: CAPEX and OPEX Breakdowns [1.14]

Generally, the fixed rate value is out of the control of an operator but there is an argument to be made that showing a high standard of operator experience - achieving high levels of reliability and availability - will increase IRR and lower fixed rates.

1.4. Goal of Thesis

There are many O&M strategies available to an operator. The goal of this thesis is to investigate the optimum maintenance strategy - that is one that maximises yield while minimising operating costs. This is explored in Figure 1.4. In this simple example, increasing the availability, or the time available for operation, reduces the cost of lost production but requires increased maintenance actions at an increased cost. There is an optimal point, which is marked by the dotted line in the Figure, where the combined costs of the lost production and the maintenance policy are minimised.

This thesis strives to analyse the effects of condition monitoring (CM) and struc-

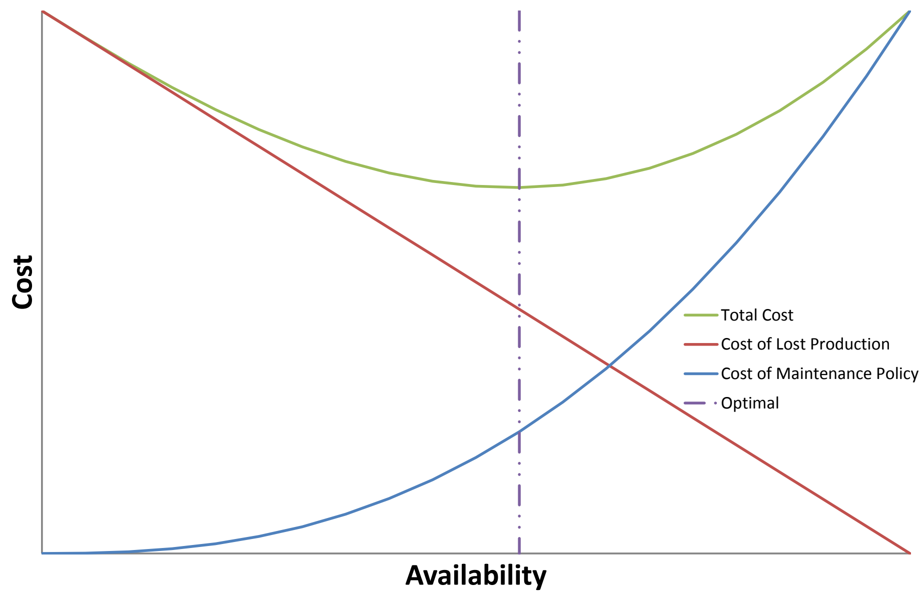


Figure 1.4.: Balancing Maintenance Policy and Lost Production

tural health monitoring (SHM) systems on the shape of the "Cost of Maintenance Policy" line. The line could be adjusted by encompassing additional monitoring benefits, or utilising more monitoring systems than are currently being exploited or considered by operators.

There is published work from both academia [1.17] and industry that CM systems can save operators money when integrated into the O&M strategy. The return on investment report from Gram & Juhl [1.18], a Danish condition monitoring system manufacturer, states that a CM system can reduce operating costs by:

- Reducing downtime.
- Reducing repair costs.
- Reducing insurance costs.
- Reducing insurance maintenance costs - Gram & Juhl state that most insurers request those without CM systems to change all bearings every 5 years.

These benefits have also been suggested by other CM system manufacturers [1.19], insurers [1.20] and CM certification bodies [1.21].

1.5. Summary of Thesis

An introduction to reliability of wind turbines and overview of maintenance strategies is detailed in Chapter 2. In Chapter 3 the techniques used to model deterioration for rotating and structural assemblies are explored. The other focus of the chapter is to establish a method of capturing the deterioration process like a CM system.

Chapter 4 begins with an analysis of existing cost model literature for both wind turbine O&M strategies involving condition monitoring and O&M strategies used in other industries. It then details what data is required in order to quantify the economic benefit of using a CM system in the maintenance strategy.

The output and results of the model are investigated, benchmarked and compared to alternative O&M models in Chapter 5. Finally, conclusions are presented in Chapter 6.

1.6. Novelty of Thesis

A novel methodology has been developed that allows for the assessment of the cost benefit of utilising CM and SHM equipment for offshore wind farms. The methodology has been built on a strong foundation after analysis of existing literature and consideration of the strengths and weaknesses of this research. Its main areas of novelty are outlined below.

Adaptable Independent application of CM and SHM systems with different properties and profiles to individual assemblies.

Flexible Application of multiple CM systems to individual assemblies - each CM system can have its own profile and abilities used to show its benefits.

Comprehensive Production of comprehensive annual costs for period based maintenance (PBM) and condition based maintenance (CBM) strategies for offshore wind - risk, vessel hire, labour, components, lost production and Structural Integrity Management (SIM) strategy.

Smaller but also key areas of novelty include:

- The completion of a survey of existing and near production CM technologies with estimations of their CAPEX and OPEX.
- Several techniques were used to allow CM systems to observe developing faults several months in advance and as a result reduce vessel costs.
- The formulation and integration of a SIM plan with mechanical component annual inspections to reduce overall operating costs.

1.6.1. Benefits for Interested Parties in Offshore Wind

The possible benefits for different interested parties in offshore wind are outlined below:

Operators and Owners This flexible and comprehensive overview of OPEX costs offers a means to aid both wind park operators and owners with their decisions as to whether to deploy additional CM/SHM hardware or not. They can view the implications of their actions in achieving their goals of minimising risk and operating costs. Various situations can be explored, including when to deploy CM systems and to what extent, at the planning phase of the wind farm. It may be useful to do so immediately, in tandem with a manufacturer monitoring program, or several years after the commissioning of the wind park.

Regulators Regulators are also aiming to decrease the CoE to increase the amount of wind in the energy mix, either by improving knowledge or informing policy. This work could be used to examine how the implementation of CM and SHM systems effects CoE and how changes in policy at a national or possibly international level can be utilised best. Regulators are also concerned with the safety of systems and workers. This tool can be used to monitor the effects of different safety levels on the operating costs.

OEMs and OEM Suppliers In a similar way to how operators and owners can get an overview of expected OPEX costs, original equipment manufacturers (OEM) can possibly use the work in this thesis to assess risk when offering extended warranties. They could choose to deploy further CM equipment to minimise this risk. If an OEM or OEM supplier complete a retrofit, upgrade or install new components then additional CM might be essential to monitor these changes. This work can be used to assess the results and implications on future OPEX.

1.7. Research Dissemination

1.7.1. Journal Publication

The author has contributed to the following published article:

A. May, D. McMillan, and S. Thöns. "Economic analysis of condition monitoring systems for offshore wind turbine sub-systems". English. In: *IET Renewable Power Generation* 9 (8 Nov. 2015), 900–907(7). ISSN: 1752-1416

1.7.2. Conference Publication

The author was the main contributor for the following conference paper publications and gave an invited talk about the work:

A. May and D. McMillan. "Condition Based Maintenance for Offshore Wind Turbines: The Effects of False Alarms from Condition Monitoring Systems". In: *ESREL 2013*. Amsterdam, 2013

A. May, D. McMillan, and S. Thöns. "Integrating Structural Health and Condition Monitoring: A Cost Benefit for Offshore Wind Energy". In: *34th International Conference on Ocean, Offshore and Arctic Engineering*. St John's, Canada, 2015

The author was the main contributor for the following conference paper publication:

A. May, D. McMillan, and S. Thöns. "Economic analysis of condition monitoring systems for offshore wind turbine sub-systems". In: *European Wind Energy Association Annual Conference*. Barcelona, Spain, 2014

The author has contributed to the following conference paper publications

D. McMillan et al. "Asset Modelling Challenges in the Wind Energy Sector". In: *Cigre Session 45*. Paris, France, 2014

J. Carroll et al. "Availability Improvements from Condition Monitoring Systems and Performance Based Maintenance Contracts". In: *European Wind Energy Association*

Offshore Annual Conference. Copenhagen, Denmark, 2015

1.7.3. Other Dissemination Work

The author presented work using a poster at the following events:

Durham Risk Day 2014, hosted by Durham Energy Institute, at Durham University, Durham, UK, 12th November 2014. `https://www.dur.ac.uk/dei/events/risk2014/`

EPSRC Supergen Wind Hub General Assembly 2015, hosted at Burleigh Court Hotel and Conference Centre, Loughborough University, Loughborough, UK, 14th April 2015.

1.8. Chapter 1 References

[1.1] I. Troen and E. Petersen. *European Wind Atlas*. Roskilde, Denmark: Risø National Laboratory, 1989. ISBN: 87-550-1482-8.

[1.2] J. Goldman. "The hostility of offshore environments–How much more?" In: *OCEAN 75 Conference*. San Diego, California, USA, 1975, pp. 204–207.

[1.3] Met Office. *Marine - Weather analysis*. Tech. rep. 13/0678. 2014.

[1.4] W. Dong, T. Moan, and Z. Gao. "Fatigue reliability analysis of the jacket support structure for offshore wind turbine considering the effect of corrosion and inspection". In: *Reliability Engineering & System Safety* 106 (Oct. 2012), pp. 11–27. ISSN: 09518320.

[1.5] S. Márquez-Domínguez and J. D. Sørensen. "Fatigue Reliability and Calibration of Fatigue Design Factors for Offshore Wind Turbines". In: *Energies* 5.6 (June 2012), pp. 1816–1834. ISSN: 1996-1073.

[1.6] P. J. Tavner. *Offshore Wind Turbines - Reliability, availability and maintenance*. 1st. The Institute of Engineering and Technology, 2012. ISBN: 978-1-84919-229-3.

[1.7] F. Besnard. "On maintenance optimization for offshore wind farms". PhD thesis. Chalmers University of Technology, 2013. ISBN: 9789173858229.

[1.8] R. Neate, P. Matthews, C. J. Crabtree, B. Kazemtabrizi, and E. Golysheva. "Optimisation of Far Offshore Wind Farm Operation and Maintenance (O&M) Strategies". In: *European Wind Energy Association Annual Conference*. Barcelona, 2014.

[1.9] C. J. Crabtree, D. Zappala, and S. I. Hogg. "Wind energy: UK experiences and offshore operational challenges". In: *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy* (Aug. 2015), pp. 1–20. ISSN: 0957-6509.

[1.10] Department of Energy and Climate Change. *UK Renewable Energy Roadmap*. Tech. rep. URN 11D/698. 2011.

[1.11] UK Trade & Investment. *UK Offshore Wind: Opportunities for trade and investment*. Tech. rep. The UK Government, 2015.

[1.12] Offshore Design Engineering (ODE) Ltd. *Study of the costs of offshore wind generation*. Tech. rep. URN 07/779. Department of Trade and Investment, 2007.

[1.13] Vattenfall Wind Power. *Kentish Flats Offshore Wind Farm 3rd Annual Report*. Tech. rep. URN 09D/P46B. 2007.

[1.14] GL Garrad Hassan. *Offshore Wind Operations and Maintenance Opportinities*. Tech. rep. Scottish Enterprise, 2013.

[1.15] I. Dinwoodie and D. McMillan. "Sensitivity of Offshore Wind Turbine Operation & Maintenance Costs to Operational Parameters". In: *42nd ESReDA Seminar*. Glasgow, 2012.

[1.16] F. P. García Márquez, R. W. Lewis, A. M. Tobias, and C. Roberts. "Life cycle costs for railway condition monitoring". In: *Transportation Research Part E: Logistics and Transportation Review* 44.6 (Nov. 2008), pp. 1175–1187. ISSN: 13665545.

[1.17] D. McMillan and G. W. Ault. "Quantification of condition monitoring benefit for offshore wind turbines". In: *Wind Engineering* 31.4 (2007), pp. 267–285.

[1.18] A. Juhl. *TCM ROI - Return On Investment*. Manufacturer's Study. 2010.

[1.19] Igus ITS. *BLADEcontrol: Condition Monitoring System*. Tech. rep. 2008.

[1.20] T. Gellermann. "Extension of the scope of Condition Monitoring Systems". In: *Proceeding from VDI-Conference "Schwingungen von Windenergieanlagen"*. Bremen, Germany: Allianz Centre for Technology, 2012, pp. 1–14.

[1.21] M. LeBlanc and A. Graves. "Condition Monitoring Systems: Trends and Cost Benefits". In: *Wind Turbine Condition Monitoring Workshop*. Broomfield, CO, USA: National Renewable Energy Laboratory, 2011.

[1.22] A. May, D. McMillan, and S. Thöns. "Economic analysis of condition monitoring systems for offshore wind turbine sub-systems". English. In: *IET Renewable Power Generation* 9 (8 Nov. 2015), 900–907(7). ISSN: 1752-1416.

[1.23] A. May and D. McMillan. "Condition Based Maintenance for Offshore Wind Turbines: The Effects of False Alarms from Condition Monitoring Systems". In: *ESREL 2013*. Amsterdam, 2013.

[1.24] A. May, D. McMillan, and S. Thöns. "Integrating Structural Health and Condition Monitoring: A Cost Benefit for Offshore Wind Energy". In: *34th International Conference on Ocean, Offshore and Arctic Engineering*. St John's, Canada, 2015.

[1.25] A. May, D. McMillan, and S. Thöns. "Economic analysis of condition monitoring systems for offshore wind turbine sub-systems". In: *European Wind Energy Association Annual Conference*. Barcelona, Spain, 2014.

[1.26] D. McMillan, I. Dinwoodie, G. Wilson, A. May, and G. Hawker. "Asset Modelling Challenges in the Wind Energy Sector". In: *Cigre Session 45*. Paris, France, 2014.

[1.27] J. Carroll, A. May, A. McDonald, and D. McMillan. "Availability Improvements from Condition Monitoring Systems and Performance Based Maintenance Contracts". In: *European Wind Energy Association Offshore Annual Conference*. Copenhagen, Denmark, 2015.

CHAPTER 2

Offshore Wind Park Reliability and Operation

The aim of this chapter is to give an overview of the theory and prerequisite background information for any discussion on the reliability and operating strategies of an offshore wind farm. It begins with the introduction of the essential reliability terminology used, how faults are classified and an overview of existing failure databases for both onshore and offshore wind farms. It ends with a discussion of the various operating strategies and what is required to conduct them efficiently.

It should be noted that the terms "Wind park" and "Wind farm" are used interchangeably in this document. Wind park is typically used by continental European organisations and wind farm by UK and USA organisations.

2.1. Wind Turbine Component Taxonomy

The first action to investigate the reliability of offshore wind farms is to analyse the functions of an individual wind turbine and the purpose of its various components. This allows an engineer to understand the effects of any component failures on both the component itself and on other components. One of the most efficient means of capturing this information is to develop a classification system or taxonomy. There are also additional benefits of using a taxonomy which are explored later in this document [2.1].

This process involves dividing the turbine into coherent system blocks sharing a common mechanical function or multiple components affected by similar failure modes. Reliability block diagrams or fault tree analyses are useful analytical techniques to use in this work. NASA has produced a working document to guide users through the process of creating these diagrams and analyses [2.2]. Fault trees are deductive processes that begin with a fault condition and work backwards to establish the reasons for failure. Reliability block diagrams are built using an inductive process where system success pathways are developed - that is series of parts that must operate to allow the system to complete its actions. This process highlights groups of components that are essential for success and for ascertaining where redundancy is useful. A template for a possible hierarchy to place the components in is shown below from Arabian-Hoseynabadi, Oraee, and Tavner [2.3].

⇒ Turbine

  ⇒ Assembly

    ⇒ Sub-assembly

      ⇒ Part

2.1.1. Failure Methods and Effect Analysis

Once a taxonomy has been developed there are further benefits as follows [2.1]:

- The major failure modes, that is those causing the largest asset downtimes due to a single event, can be identified.
- The critical failure modes, that is those causing the largest accruing asset downtime with multiple events, can be identified.
- Operational data can easily be captured and quickly analysed.

These first two points can be observed with a reliability study known as a Failure Mode and Effect Analysis (FMEA). The process of how to complete an FMEA is shown in Kahrobaee and Asgarpoor [2.4]. The weaknesses and strengths of these processes are explored in Kmenta and Ishii [2.5].

FMEA is a proven process to identify major and critical failure modes in systems. It is a qualitative approach which involves the calculation of a risk priority number using factors that are determined by experts and operators of the system or equipment. The risk priority number makes clear those components and assemblies that are most at risk of failure and allows engineers to focus on solutions to minimise their impact. As the factors used to calculate the risk priority number are different for each system, a single number is not informative by itself - it is only in comparison to other numbers that it has meaning. Typically the main calculation consists of three steps [2.4]:

1. Determination and categorisation of the probabilities of failure modes occurring.
2. A severity rating for failure modes is assigned.
3. A detection rating indicating the likelihood of detection is assigned.

Each of these ratings and categorisations is a number which is scaled according to expert opinion. A higher number indicates an increased probability of failure, a higher failure consequence or a lower chance of detection. It is these three numbers when multiplied together that forms the risk priority number.

FMEAs can be completed for individual components and then assembled to create a system wide FMEA or a scenario based FMEA can be used that begins with system failures and highlights root causes before assigning a priority number.

2.1.2. Wind Turbine Configuration and Taxonomy

At its most basic, the primary function of a wind power system can be described as transforming kinetic energy from wind into electrical energy. The rotor uses aerodynamics to translate the wind energy into mechanical rotational energy. This mechanical energy is fed into a generator to produce electrical energy. The styles, designs and sizes of wind turbines have evolved over the last 25 years. 60% of newly installed onshore turbines in 1990 were of the “Danish Concept” style or based on this design. This increased to nearly 100% of those newly installed in 2004 [2.6]. The “Danish Concept” that has become so dominant is a 3 bladed upwind turbine with a horizontal rotor axis. This typically has an extra stage in the electrical energy generation process, using a gearbox to increase the rotational speed from the rotor into the generator.

The possible configurations of the turbine are explained in the work of Pinar Pérez et al. [2.7]. Older style turbines that have the rotor rotating at a fixed speed use an asynchronous squirrel cage generator. Early semi-variable speed wind turbines used asynchronous squirrel cage generators with pole-changing capability (and so could operate at two different fixed speeds) or wound rotors with variable rotor resistance.

Modern variable rotor speed turbines use doubly fed induction generators or else use squirrel cage induction or synchronous generators with a fully rated power converter. These synchronous machines are either wound rotor machines (as used by Enercon) or permanent magnet generators. Although these synchronous machines can be used with a gearbox and operate at medium or high rotational speeds, they are often used in direct drive wind turbines. To avoid the inclusion of a gearbox, the low rotational speed necessarily means a high torque rating and so the generators often have a large diameter with multiple poles.

A useful taxonomy that is still widely used was originally developed for the WMEP, part of the "250 MW Wind" project, a German survey of operating wind turbines collecting data between 1989 and 2006. The incident report template was shown as an appendix including the full taxonomy breakdown of assemblies and sub-assemblies in a work by Faulstich, Hahn and Tavner [2.8] and the descriptions based on Bharatbhai [2.9]. This is shown below with a corresponding numbered figure in Figure 2.1.2.1 excluding items number 5 and 6. The WMEP programme incident reports were filed for intervention actions on turbines: the reason for repair, cost of spares, hours of downtime and components causing fault. These 64,000 reports from 1,500 onshore turbines were compiled and analysed in annual reports by the ISET [2.10].

There are other taxonomies that are in use or that have been used for classifying failures. Many of these are specific to individual operators or survey schemes. A good overview of these taxonomies is given in the work of Richardon [2.11]. These include the taxonomy developed for use by maintenance engineers for Clipper Wind Turbines, the taxonomy used in IEC 61400 standards and the RDS-PP. The Reference Designation System for Power Plants (RDS-PP) is a widely used taxonomy due to its flexibility and it can be used across a range of power plants which appeals to operators with different electrical generating plant. Sandia National Laboratory developed its own taxonomy for its "Wind Plant Reliability Database" [2.12].

The WMEP taxonomy was selected as it is well documented, widely used and freely available. This is not the same for all the other taxonomies mentioned above. In particular, the RDS-PP is a commercial offering and expensive to obtain. An overview of the taxonomy is given below.

2.1.2.1. WMEP Taxonomy

1. Hub

   The hub is where the rotor blades join the nacelle and contains the pitch mechanism to allow the blades to rotate. It is designed to allow access from within the nacelle.

   - Hub Body
   - Pitch Mechanism
   - Pitch Bearings

2. Rotor Blades

   The rotor consists of 3 blades normally formed from glass reinforced plastic around structural spars. They contain lightning protection systems.

   - Blade Bolts
   - Blade Shell
   - Aerodynamic Brakes

3. Generator

   The generator can be any of the types listed above. It is fed from a shaft from the gearbox and connects to the electrical converter system.

   - Windings
   - Brushes
   - Bearings

4. Electric

   The electrical assembly has multiple roles. It is used to start the turbine with an external power source before the turbine is operating. The converter and transformers condition the output of the generator ready for transmission into the electrical grid. Fuses and switches protect the entire system and iso-late it when necessary.

- Converter
- Fuses
- Switches
- Cables and Connectors

5. Sensors

   There are a number of sensors that are employed to monitor performance, condition and operation of a turbine. A simple set of the major sensors incorporated into the SCADA data feed are shown below. If a CM or SHM system is included on a turbine then these will be added here.

   - Anemometer or Wind Vane
   - Vibration Switch
   - Temperature
   - Oil Pressure Switch
   - Power Sensor
   - Revolution Counter

6. Control System

   The controller electronically oversees the operation of the turbine, ensuring that the turbine remains within safe operating parameters regardless of the conditions.

   - Electronic Control Unit
   - Relay
   - Measurement Cables and Connections

7. Gearbox

   The gearbox connects the hub to the generator. The type of turbine dictates the type of gearbox. Commonly, gearboxes have 3 stages, transforming from low rotational speed through an intermediate speed stage to a high speed shaft.

   - Bearings
   - Wheels
   - Gear Shaft
   - Sealings

8. Mechanical Brake

   Braking a wind turbine is normally achieved by pitching the rotor blades. A mechanical brake is attached to the gearbox to assist for emergency and for parking. The brake is a disk and is acted upon by a hydraulic shoe. An additional rotor lock using a "peg in hole" arrangement is used to keep the rotor stationary in an emergency.

- Disc
- Pads
- Shoe

9. Drive Train

   The drive train supports the weight of the rotor. It takes the energy from the rotor and hub assembly and, using a large shaft retained by bearings, transfers it through a coupling to the gearbox.

   - Rotor Bearings
   - Drive Shafts
   - Couplings

10. Hydraulic System

    Hydraulics are used in many of the other assemblies. They require dedicated equipment to provide pressure and fluid.

    - Hydraulic Pump
    - Pump Motor
    - Valves
    - Pipes or Hoses

11. Yaw System

    The yaw drive rotates the nacelle into the wind. The nacelle is located on a large bearing. The system can use a gliding yaw bearing with a hydraulic oil to create a low friction surface to rotate on or a roller bearing. It can be rotated with either hydraulic or electric motors.

    - Bearings
    - Motor
    - Wheels and Pinions

12. Structural Parts or Housing

    All the structural components, including the foundation, that are responsible for supporting the turbine. Another important role includes giving access to the nacelle for maintenance.

    - Foundation
    - Tower or Tower Bolts
    - Nacelle Frame
    - Nacelle Cover
    - Ladder

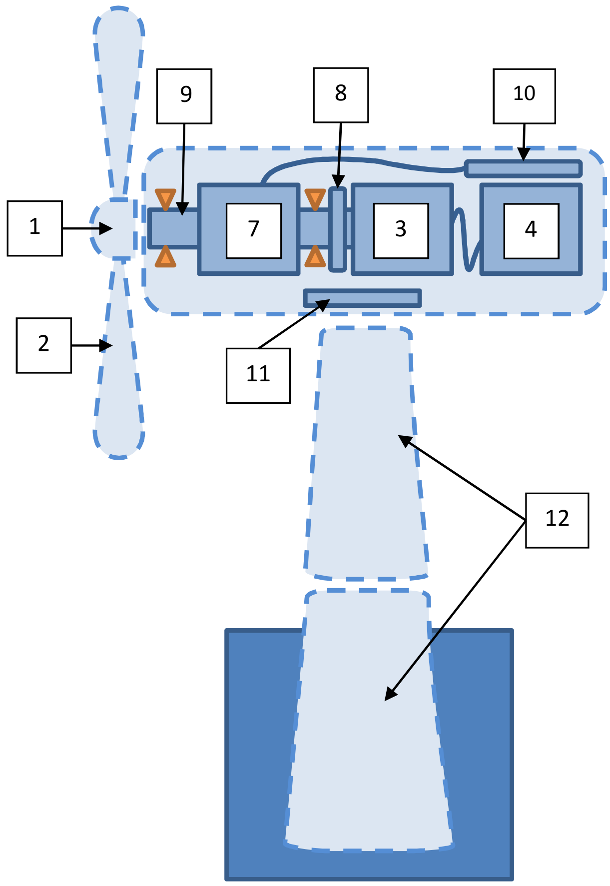


Figure 2.1.: Numbered Schematic Diagram of an Offshore Wind Turbine

2.2. Reliability Terminology and Metrics

The major key performance indicator used in operational contracts is availability. Technical availability is the time that the turbine is available for operation compared to the theoretical maximum available - the time period often used is a year. Commercial availability has a reduced theoretical maximum time by excluding some downtime for pre-agreed reasons for aspects out with the control of the wind farm owners or operators [2.13]. These include annual servicing, loss of grid connection or waiting on weather. The majority of the work in this document will use availability, A, to refer to technical availability. These are far from the only types of availability used for contracting service agreements. Hawker and McMillan [2.14] gives an overview of many types of availability including those used here and the impact of maintenance contract on the yield.

Time is a useful metric to base turbine reliability terms on:

MTTF Mean time to failure - the average time from a system going online until it fails - referred to as 'uptime'.

MTTR Mean time to repair - the average time taken to repair a failure event - referred to as 'downtime'.

MTBF Mean time between failure - the time between each system failure event. A combination of MTTF and MTTR.

Availability can now also be described using these definitions from the WMEP programme [2.8], shown in Equation 2.1.

$$A = \frac{MTBF - MTTR}{MTBF} \text{ or } \frac{MTTF}{MTBF} \tag{2.1}$$

Capacity factor, CF, is an alternative means of establishing the utilisation of a wind turbine or wind park. It looks at the amount of the energy produced annually, Operating Hours, in MWh compared to the annual total possible yield. This is shown below in Equation 2.2 with the power of the turbine, P. The 8760 refers to the number of hours in a year. This allows both the weather (wind speed) and reliability to be examined in one figure.

$$CF = \frac{P \times \text{Operating Hours}}{P \times 8760} \tag{2.2}$$

2.2.1. Failure Rates

The inverse of MTBF is the useful and commonly used failure rate, λ. This is shown in Equation 2.3. The failure rate can also be determined by examining the number of failures of identical components over a set time period, where N_f is the number of failures for a set time period and N_o is the number of components monitored.

The inverse of the MTTR is the repair rate, μ. This is shown in Equation 2.4.

$$\lambda = \frac{1}{MTBF} = \frac{N_f}{N_o} \tag{2.3}$$

$$\mu = \frac{1}{MTTR} \tag{2.4}$$

The failure rate is useful as it allows quick comparison and is easy to understand. If the annual failure rate is used then a value of 1 represents on average one failure per year.

2.2.2. Hazard Function

The metrics discussed above do not deviate with respect to time. The failure rates of components will vary depending on a large amount of variables including manufacturing defects, wear rates and usage. The stationary metrics are updated to show this change over time.

The survivor function, $S(t)$, is the number of surviving components at time t, N_s, compared to the total number of identical components. Likewise, the unreliability function, $Q(t)$, examines the number of failed components at time t compared to N_o. These are displayed in Equations 2.5 and 2.6. The relationship between survivor and unreliability is shown in Equation 2.7.

$$S(t) = \frac{N_s(t)}{N_o} \tag{2.5}$$

$$Q(t) = \frac{N_f(t)}{N_o} \tag{2.6}$$

$$S(t) = 1 - Q(t) \tag{2.7}$$

$$f(t) = \frac{dQ(t)}{dt} \tag{2.8}$$

$$h(t) = \frac{f(t)}{S(t)} \tag{2.9}$$

One particularly useful metric is the hazard function, $h(t)$, which is built from the failure density function, $f(t)$, (probability density function) and the survivor function, see Equation 2.9.

Again, NASA have produced guidance as to the 6 most likely forms the hazard functions will take and the types of components they will represent [2.15]. One of the most famous hazard function profiles is the "Bathtub Curve". This shows increased failure rates at the beginning and end of components' lives, referred to respectively as infant mortality and wear out. A diagram from NASA [2.15] showing these different types is shown in Figure 2.2 with the Bathtub Curve highlighted as Type A.

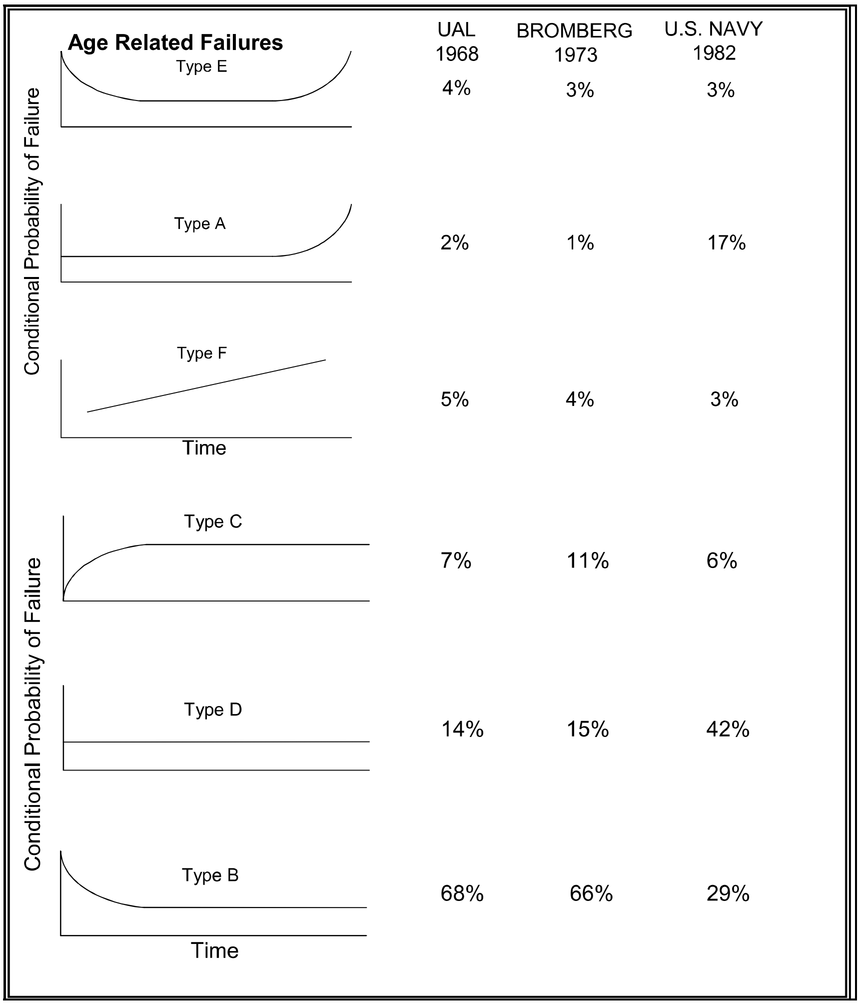


Figure 2.2.: Hazard Rate Profiles [2.15]

However, work by Smith [2.16] shows that when analysing aircraft fleets the majority of components follow different hazard rate profiles: showing only infant mortality with very limited or non-existent burn out (Profiles B, D & C). This was especially applicable to electronic components. Smith states that, in all, nearly 90% of all components show no significant burn out characteristics. NASA suggest that non-complex single use items such as brake pads or compressor blades show significant burn out while other more complex items do not.

Remaining useful life (RUL) is the expected life remaining of the component given existing knowledge of the failure profile of the component [2.17]. RUL is a function of the current age, t, and the likely failure time, T, which is based on both survivor function and the past operation profile, $Z(t)$.

$$RUL = T - t, Z(t) \tag{2.10}$$

2.3. Wind Park Reliability

2.3.1. Overall Reliability

Harman [2.18] gave the mean system availability in 2008 for the Garrad Hassan database of over 1,000 onshore turbines as 96.4% and stated that the industry was heading to beat a standard of 97.0%. The system availability allows for exceptions for annual services and shutdowns caused by normal operating events - cable unwind or high winds - and is the same as commercial availability. As mentioned in Section 1, availabilities now regularly exceed 98% [2.19]. The American database CREW showed an improvement in operational availability from 94.8% in 2011 to 97% in 2012 [2.20].

Tavner [2.21] gave an overview of some early offshore wind turbines in their first years of deployment. These all showed much lower technical availability levels across all wind speeds. Two British wind farms were at the extremes of this data. Barrow wind farm was one of the worst affected with an availability of less than 40% at wind speeds over 12 m/s and North Hoyle averaged between 80 and 90% across a range of 6 to 14 m/s. In the same document, a general increase in capacity factor is observed as the operational experience of the farm increases.

2.3.2. Reliability Databases

Various institutions have been working to collect and analyse the operation of onshore wind turbines in numerous studies with vastly different scales and scopes. These databases have been widely studied and analysed in academic fields and a short overview is given below. An interesting point highlighted by Lange, Wilkinson, and van Delft [2.22] is that the majority of these studies are European even though there are mature wind industries around the world:

LWK A German database concerning wind farms installed in the Schleswig-Holstein region between 1993 and 2006. A maximum of 643 turbines were observed. These were mostly small wind turbines of under 400 kW.

WindStats Germany A German database updated quarterly between 1996 and 2008. 4924 turbines were tracked at its peak.

WindStats Denmark A Danish database updated monthly between 1994 and 2003.

WMEP A long running German study that has been the framework for other studies. 1500 turbines were tracked between 1989 and 2006 with an average rating of 167 kW.

Vinstat A Swedish database running between 1997 and 2004. The maximum number of turbines recorded was 1050. The turbines tracked tended to be small in size and were 430 kW on average.

VTT A smaller Finnish study recording at most 118 turbines. Running between 1999 and 2009 turbines ranged from between 0.5 MW and 1.0 MW.

ReliaWind A European wind study that built on some of the previous studies and expanded further. 283 medium turbines of 1.2 MW were tracked in this study.

CREW A recent American study attempting to benchmark the onshore fleet. The study covers between 800 and 900 turbines of on average 1.3 MW.

The way of reporting downtime, failures, repairs and the taxonomy of the wind turbine varied significantly between these studies. However, once collated the data shows some notable assemblies and sub-assemblies that fail frequently and cause considerable downtime and these are explored below.

Study	Assemblies with Highest Failures		
	Assembly	Sub-Assembly	Contribution to Failure Rate [%]
ReliaWind	Hub	Pitch System	21.29
	Electric	Frequency Converter	12.96
	Yaw	-	11.28
Vinstat, VTT & WMEP	Electric	-	17.5
	Sensors	Sensors & Comms	14.1
	Rotor	Blades & Pitch System	13.4
WMEP	Electric	-	23[1]
	Control	Controllers	18[1]
	Sensors	-	10[1]
CREW	Rotor	-	12.9[2]
	Generator	-	7.2[2]
	Control	-	4.9[2]

[1] Contribution to repair rate. [2] Contribution to unavailability.

Table 2.1.: Unreliable Assemblies

2.3.3. Assembly Reliability

The top 3 assemblies (and sub-assemblies where appropriate) with the largest contribution of failure from 4 studies are shown in Table 2.1. This includes the ReliaWind study as presented by Wilkinson and Hendriks [2.23], work from Ribrant and Bertling [2.24] analysing the Vinstat, VTT & WMEP, the WMEP data alone from Durstewitz et al. [2.10] and the CREW database from Bond, Peters, and Ogilvie [2.20]. The CREW database excludes a generic fault class containing unknown SCADA alarms contributing 63.7% of all alarms.

Some of the most consistent component failures of the assemblies are broken down further by Tavner [2.21]. These are shown in Table 2.2. As the pitch system is a major contributor to downtime and consists of both electrical and hydraulic systems then these faults are displayed in different categories.

Failure rates and number of failures alone are not significant by themselves. Downtime is a metric that can show the severity of a failure. For example, as mentioned above, the largest source of failures in the CREW study was unattributed system alarms that were quickly solved.

Figure 2.3 shows the failure rates of wind turbine systems and the resulting down-

Assembly	Sub-assembly	Failure Mode 1	Failure Mode 2	Failure Mode 3
Hub	Pitch System (Electrical)	Battery Failure	Pitch Motor Failure	Motor converter failure
Hub	Pitch System (Hydraulic)	Hydraulic	Internal leakage of proportional valve	Internal leakage of solenoid valve
Electric	Frequency Converter	Inverter failure	Loss of generator signal speed	Crowbar failure
Yaw System	Yaw System	Yaw gearbox and pinion lubrication out of specification	Degraded wind direction signal	Degraded guiding element function
Control	Control Systems	Temperature sensor module malfunction	PLC analogue input malfunction	PLC analogue output malfunction

Table 2.2.: Failing Components

time caused based on WMEP data taken from Faulstich, Hahn, and Tavner [2.8]. In this diagram, the failures have been classified into "Major" and "Minor" failures - with the distinguishing feature of a major failure being that the downtime exceeded 24 hours. The summary of the work is that minor failures account for 75% of the faults but only 5% of the downtime while major failures account for 25% causing 95% of the downtime.

The mean annual downtime - the annual failure rate multiplied by the downtime per failure - is also shown. The mean annual downtime highlights that the major faults of the electrical system, control, hub, gearbox and generator are large contributors to downtime. There is another simple division that can be made: control, electrics and hub assemblies have higher annual failure rates (>0.06) and lower downtimes while the gearbox and generator have lower failure rates and higher downtimes.

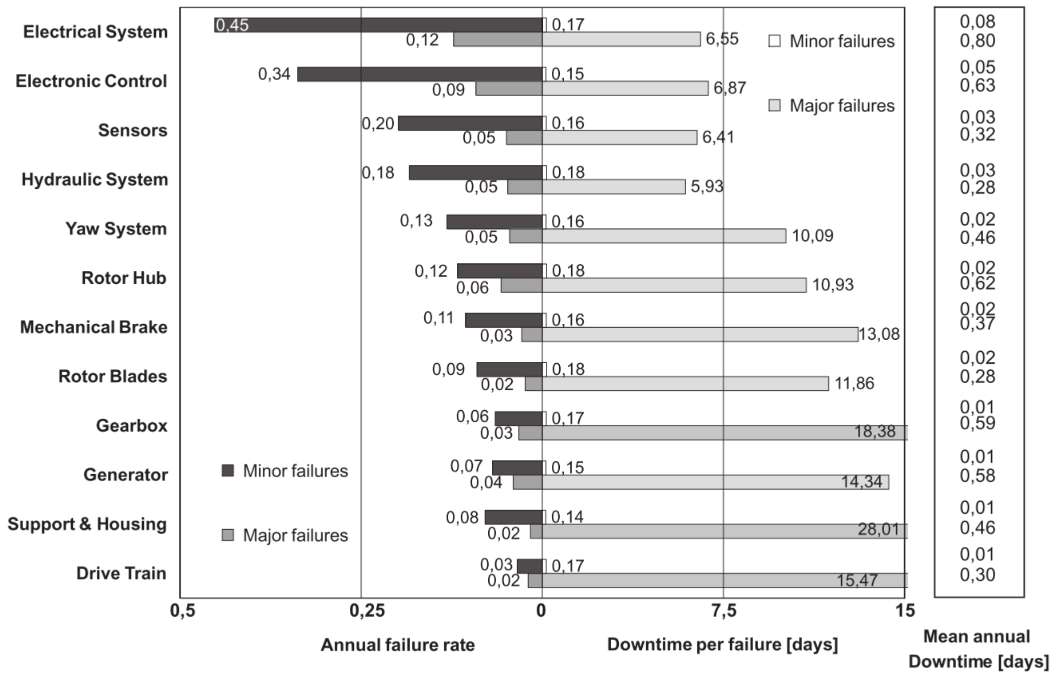


Figure 2.3.: Wind Turbine Failure Rate and Caused Downtime [2.21]

The average annual downtime for a turbine is 6.01 days. This downtime equates to in excess of €13,000 in lost revenue for a 2.3 MW turbine at €0.04 per kW h.

An alternative examination of this data was completed by Pinar Pérez et al. [2.7] and is shown in 2.4. In the Figure, "SWE" refers to Vinstat values, "FIN" is the VTT study, "DEU" is the German WindStats and "DEU_LKW" is data from LWK. The top line is the boundary of an envelope indicating assemblies that cause mean downtime per turbine per year in excess of 25 hours. The gearbox, generator, blades and electric assemblies all feature from multiple different studies.

2.3.4. Offshore Reliability Data

The amount of reliability data available for offshore wind parks is limited. However, availability data is available for the first few operating years of several British wind farms that received a UK Government grant - including Kentish Flats operated by Vattenfall and Scroby Sands operated by E.ON. This can be used as a non-exact estimation or proxy for reliability.

The DOWEC consortium estimated offshore turbine failure rates in 2003 using expert knowledge based on existing onshore data [2.25]. They predicted a reduction in

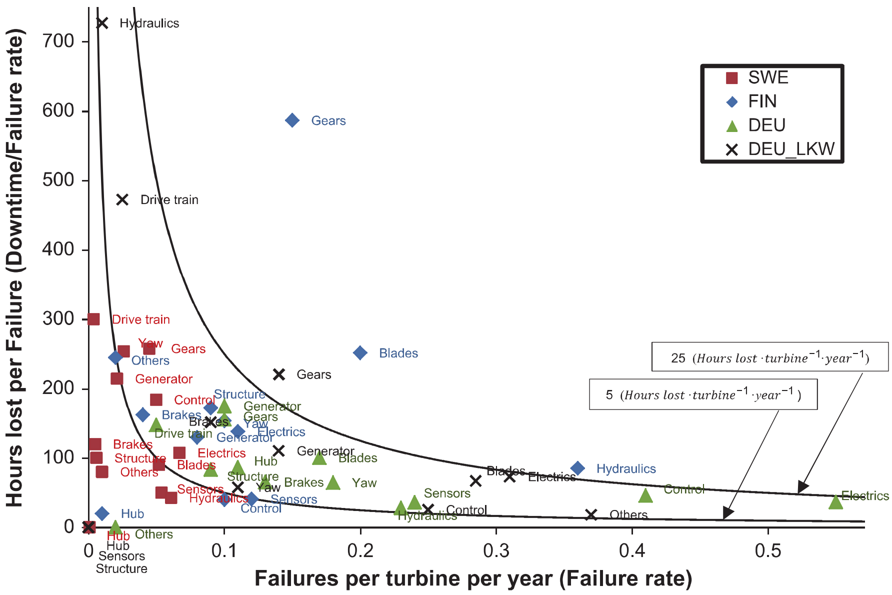


Figure 2.4.: Rate of Failure vs Hours Lost per Failure [2.7]

overall failure rate for offshore turbines to 1.55 from an onshore value of 2.31.

One of the most complete sources of offshore data is operation reports from Egmond aan Zee. The farm consists of 36 Vestas V90 3 MW turbines which have the number of turbine stops (regardless of whether on site intervention was required or not) and downtime per subsystem reported. The farm is located between 10 and 18 km from the coast of the Netherlands in the North Sea. Failure rates can be derived from this data in multiple ways and this is discussed in Chapter 3 and Appendix A.

2.4. Detecting Developing Faults

Many faults can be detected as they develop and before they cause the loss of operating function. The simplest way of searching for developing faults is during servicing and while conducting other repairs. For more advanced monitoring, SCADA (Supervisory Control and Data Acquisition) data and CM systems can be used. The following section introduces the most common methods for collecting this data for both the rotating machinery and the structure as well as some more experimental techniques.

2.4.1. SCADA

A SCADA record is sent from the turbine every 10 minutes. It is time stamped and can consist of up to 200 channels. Additionally, fault alarms are instantly recorded and reported to the administrator. The control room can comment on how these alarms are attributed or cleared and store this information in the report log. The amount and type of data recorded in SCADA data is dependent on the turbine manufacturer. However, some channels are key and always reported:

Wind Speed Average for 10 minutes and the 10 minute minimum and maximum.

Wind Direction Absolute wind direction, average yaw direction and relative direction averaged over 10 minutes.

Generator Power Power output (both actual and reactive) averaged over 10 minutes, maximum, minimum and standard deviation values.

Rotor Rotational Speed Average revolutions per minute (RPM), maximum, minimum and standard deviation.

Generator Rotation Speed Average RPM, maximum, minimum and standard deviation.

Temperature information Including average bearing, cooling water and phase temperatures for the generator and drive train.

The actual recorded power output allows the wind turbine's performance to be plotted against the manufacturer's power curve. Anecdotally, monitoring deviations from the power curve is still one of the most important forms of turbine diagnostic.

The other channels of SCADA, depending on the manufacturer, may contain additional data. The below are example channels from a Siemens SCADA system:

Grid Information Average frequency, power factors and production voltages averaged for each phase.

Temperature Information Average, maximum and minimum temperatures for the controllers, nacelle, gear oil and inverters.

Power Quality In depth power information from the electronics, such as reactive and actual power.

2.4.2. Structural Health Monitoring Technology

A great amount of technology for SHM of wind parks has been adopted from the oil and gas offshore industry. Many of these technologies are presented in a report from the Health and Safety Executive [2.26] and compare well to those in a review of wind turbine SHM technologies [2.27].

Offshore wind turbine foundation structures can consist of tubular members that are nominally internally dry for normal operation even though they are located underwater. Flooded member detection involves placing a sensor inside or outside the component that is activated when the member cracks and floods. After the sensor is activated there are techniques that can be used to assess the time left until a critical crack size on the member is achieved [2.28]. A flooded member detection system can have water activated batteries and use the structure itself to transmit an alarm to a dedicated receiver [2.29]. Various sensors can use different frequencies so that the location of the flooded member can also be obtained.

Strain measurement is one of the most widely deployed methods for measuring damage to structural components with strain sensors and fibre optics [2.30]. Forces applied to structures cause small changes in length. These deformations in length can be measured by a variety of sensors – electrical resistance, capacitance and inductance – which are well established and relatively inexpensive [2.31]. Studies have followed the development of a strain measurement system for smaller wind turbine systems [2.32].

Another technique for monitoring strain and displacement is with fibre optic sensors. Fibre Bragg Gratings (FBG) are etched optical fibres that can be retrofitted into blades and structures or embedded during manufacture. These etched gratings change shape when strain is applied, changing the properties of the reflected light. Instead of gratings, fibres can also be corrugated to affect the properties of light in a process known as microbending. Impregnating blades with optical fibres during their construction is expensive but offers further advantages. The fibres can be used while blades are curing and observe when the cure process is complete [2.31]. Rotor monitoring systems in general are particularly useful for ice detection and improving safe operation.

Vibration data obtained using accelerometers can be used to measure changes in the responses of structural components. Once the modal parameters of a structure have been obtained, such as resonant frequencies or damping values, observing changes in these values can indicate damage [2.27]. Strain data can also be used to calculate and monitor these parameters.

In wind turbines, the major structural excitation frequencies to be avoided are ω and 3ω. These refer to the rotational frequency of the rotor and the rotational frequency of the blades, respectively. Foundation and support structures are categorised depending on how these are avoided. Stiff-stiff foundations have a natural frequency higher than 3ω, soft-stiff between ω and 3ω and soft-soft lower than ω. DNV GL stipulate that the frequencies must be separated by at least 5% [2.33].

Acoustic Emission (AE) is mentioned in several of the above studies as a possible alternative or addition to vibration. Piezoelectric transducers capture high frequency stress waves ($>$ 50 kHz) released by deformations that have altered the internal structure of materials such as cracks. The sensors record sound directly. AE systems can achieve higher signal to noise ratios than vibration systems but have a relatively narrow detection band [2.34] and can be useful in determining fault locations in structural systems such as blades [2.27].

In normal static loading tests, an object has a load applied in excess of the highest expected service load for a period of around 10 minutes. When the load is first applied, AE cracks will be observed but unless the structure is fundamentally damaged the AE crack hits will cease. Constant observation of hits is a sign of damage.

The descriptions of other technologies used in SHM systems have been developed from the work of Ciang, Lee, and Bang [2.27].

Ultrasound scanning has been commonly used in aerospace and other infrastructure applications to detect cracks and structural weaknesses. However, ultrasound does not have the resolution to observe individual fibre damage in fibre reinforced plastics. Only when multiple fibres are damaged in the same location of a blade will ultrasound show a defect. Ultrasound for SHM can now be installed and used remotely where the transmitter and receiver are located in the same device.

Thermography can be used to produce an image that can be completed quickly with little expertise required to read the output. Thermography is often used for condition monitoring of mechanical and electrical equipment. Heat produced from poorly meshing or misaligned rotating equipment can be captured by a viewing device. It can also be used for the structural assessment of blades. This method of SHM can capture a lot of information quickly and is non-intrusive. Systems have been deployed for boats and helicopters for the evaluation of blades. Rumsey and Paquette [2.35] use thermography cameras to obtain pictures of stress hot spots and the resulting damage. A range of other studies using thermography for SHM are highlighted in the work of Bagavathiappan et al. [2.36].

A Laser Doppler machine measures the vibration of a surface without making physical contact. It collects an image of a wind turbine structure, similar to that of an ultrasound for diagnosis. A laser is reflected onto the surface and the change in phase of the beam is calculated. Different machines have different options - most can be set to examine single points and some can be set to a scan an area.

The electrical output of the generator is a useful parameter to monitor. It will need to be compared to other concurrent parameters as the operating state will effect the output. As the drive train ages and accrues damage, the electrical output of the WTG will exhibit different trends over time.

X-rays can be used to penetrate many materials and detect damage. Images are obtained in parallel and the spatial resolution exceeds that of ultrasound. X-ray machines for damage detection are small and can be placed and used remotely to limit exposure to technicians.

The focus of all the technologies mentioned so far has been to monitor damage and fatigue occurring on structural components. However, there have been several products developed to understand corrosion or scour. The level of the seabed around the piles of a tripod or the base of a monopile can be observed with acoustic echo systems. Probes are available that can be suspended from a wind turbine deck into the monopile to monitor corrosion. Further information about these systems including

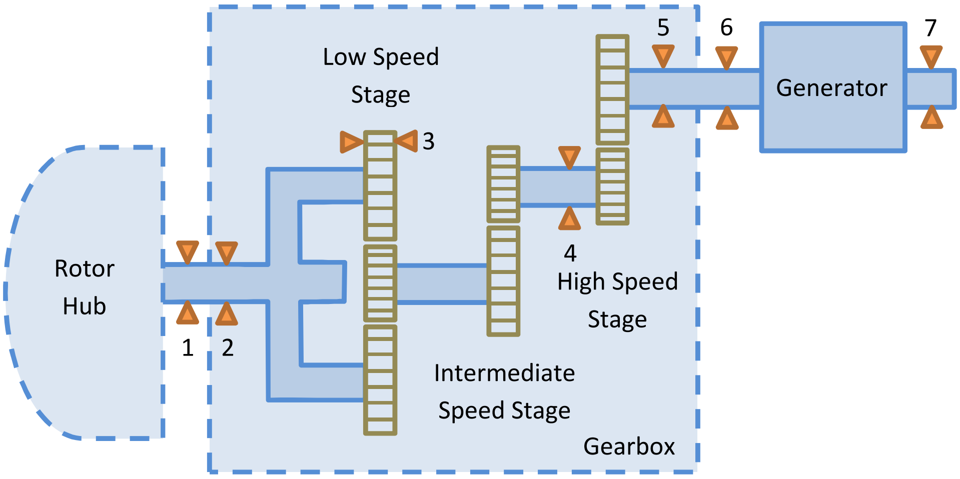


Figure 2.5.: Wind Turbine CM Sensor Schematic

some commercial suppliers can be found in the work of Carroll et al. [2.37].

2.4.3. Condition Monitoring Technology

A vibrational measurement system for CM normally consists of 5 to 8 accelerometers on the drive train and 1 rotational speed sensor located on the high speed shaft. Optionally, a current meter for power output may be installed if it cannot be obtained from the turbine controller.

These accelerometers send signals representing shock peak readings which are measured in 'g'. From this a large amount of information can be created including frequency spectrum for individual parts of the drive train. Common points for mounting vibration sensors are noted below and in Figure 2.5. This summary is based on a review of technical documents from certification bodies [2.38] and insurers [2.39] for a Danish concept wind turbine with a 3 stage gearbox.

1 Upwind main bearing

2 Downwind main bearing

3 Planetary stage of the gearbox

4 Intermediate stage of the gearbox

5 High speed stage of the gearbox

6 Inboard side of the generator

7 Outboard side of the generator

Using the techniques described below, information on the state of the system can be observed. Vibration analysis is a widely deployed form of condition monitoring with most large turbines being fitted with it and turbine manufacturers including it as standard on many models. It has the largest number of commercially available systems compared to other CM systems. In the study by Crabtree [2.40], there are 14 systems mentioned based primarily on drive train vibration most of which use frequency domain analysis to ascertain the condition of components.

Vibration systems have a high frequency sampling rate and create a large amount of data when used for diagnosis. Normally, they operate at a lower frequency until an alarm activates a diagnostic mode. The different system types have different sampling frequencies as follows:

- Vibration systems for diagnosis: > 10 kHz.
- Vibration systems for continuous monitoring: < 50 Hz.
- Rotor health monitoring: > 100 Hz.
- Structural health monitoring: < 5 Hz.
- SCADA: < 0.002 Hz.

There have been many examples of AE monitoring systems being implemented for conventional rotating machinery [2.41]. One manufacturer integrates an AE sensor with a more conventional vibration system for wind turbine drive trains and uses the two systems to complement one another [2.42].

Both the condition and particle content of oil are useful for establishing the condition of components such as gearboxes and bearings [2.43]. Often, the majority of oil testing is still done off-line in a laboratory from collected samples and basic oil information is provided from SCADA. Sample collection frequencies were not found in documentation. In-line oil particle sensors can send updates on a large array of oil parameters including [2.44]:

- Ferrous and non-ferrous particles
- Acid content

- Viscosity
- Water content
- Oxidation level
- Temperature

Particle sensors are the most common type of in-line sensors. These sensors use either a magnetic induction counter or an optical sensor to analyse the contents of the oil. An induction sensor observes the change in magnetic field as particles pass through it. Using this method, both non-ferrous and ferrous particles can be sized and counted. Optical counters can identify the size and shape of particles from electrical pulses produced as they pass a photo-diode.

Radioactive tagging is another method under investigation. The internal surfaces of the drive trains would be irradiated. When wear occurs radioactive particles will be liberated and detected on a radiation detector. Oil monitoring techniques are examined in detail in Hamilton and Quail [2.44]. Particle monitoring is typically significantly less expensive than wear debris analysis sensors [2.45].

The Shock Pulse Method (SPM) is used by the manufacturer SPM Technologies and has been endorsed by insurer Allianz for monitoring the drive train [2.46]. Mechanical shock pulses - ultrasonic frequency pulses - in these components are generated and propagate through the component, for example, when a bearing roller strikes debris or a pit on the raceway. It is this shock amplitude level and the frequency of high amplitude shocks that is used as an indicator of condition. As the impacts develop it becomes a lower frequency vibration.

Displacement sensors are useful for measuring the relative movements of rotating components such as bearings and shafts. This can aid in the determination of loads, degradation and misalignment. Sensors typically use eddy currents or induction to determine distance [2.47].

Electrical monitoring of generator and other electrical components can be monitored using machine current analysis and other electrical effects to detect issues [2.48, 2.49, 2.50]. Other techniques are available for power electronic equipment such as transformers or switchgear. These include discharge measurements [2.51].

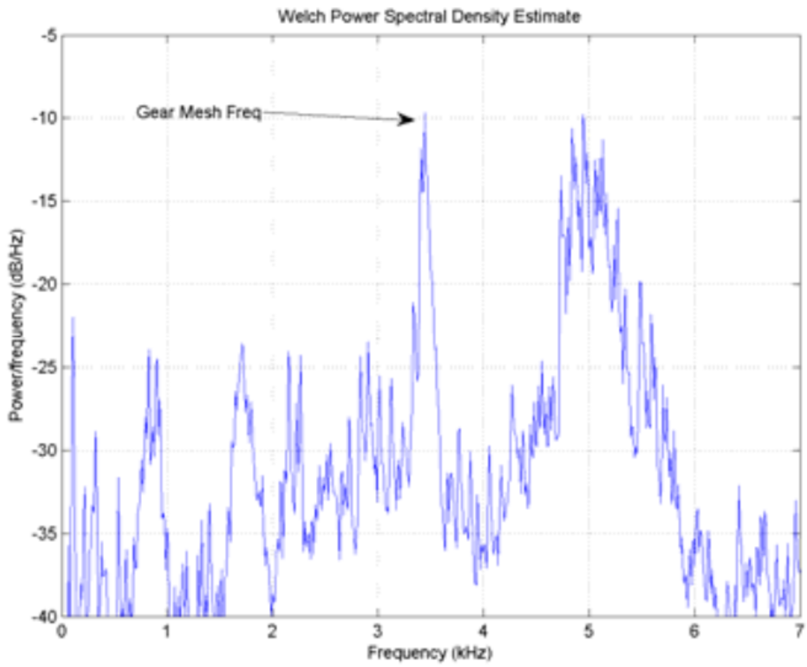


Figure 2.6.: Frequency Plot Example [2.52]

One of the data points commonly recorded is temperature. Temperature can be used to monitor the condition of bearings, oil and generator [2.51]. In rotating equipment, an increase in temperature can be an indication of increased wear or misalignment. Poor electrical contacts can also increase the temperature of components [2.30].

2.4.4. Signal Processing

Time domain analysis uses information about the operating state of the turbine, such as load, rotational speed and vibration, to generate condition indicators (CI). The signals can be unfiltered, filtered or indexed against the rotation of the shaft. A frequency plot is shown in Figure 2.6 from Bechhoefer and Kingsley [2.52].

Further signal processing techniques in the frequency domain, especially Fast Fourier Transforms (FFT), have allowed for the development of further efficient CIs. Analysis techniques using FFTs include spectral Kurtosis and envelope analysis. If healthy operating frequency characteristics of components are known in advance then deviation from these can be interpreted as deterioration [2.53]. However, due to the complex and varied nature of operating conditions for wind turbines it is not always easy to ascertain if the turbine is producing healthy frequency characteristics from the SCADA data [2.54].

More advanced signal processing techniques used for wind turbines are explored in reviews by Nie and Wang [2.43] and Antoniadou et al. [2.55]. Time-frequency, time-scale techniques or empirical mode decomposition are some of the techniques mentioned. Wavelet transforms are an example of time-scale methods that have now been used to detect faults in various wind turbine components [2.56].

2.4.5. Condition Indicator Development

The majority of CIs for wind turbines are based on observing changes in signal processing trends. CIs have advanced by automating this process and developing new CIs that combine multiple sources of information.

A recent approach has used a frequency domain algorithm to process accelerometer data before automating the selection of modal parameters and deviation from these values [2.57]. Strain measurement data has also been used to develop a CI for residual fatigue life estimation [2.58].

Artificial intelligence has been used to search for relationships and patterns of failure between multiple data sources. Genetic algorithms, artificial neural networks and fuzzy logic have all been applied to wind turbine CM [2.59, 2.60]. SCADA data is a good candidate for these techniques [2.61]. Other studies have focused on using multiple sources of data to increase the reliability of results [2.54] or using some of these techniques to reduce sensor numbers [2.62].

The majority of systems use non-volatile memory buffer to store signal information and CIs temporarily. This aids data transfer and protects from data loss during a power outage to the CM system.

2.4.6. Overview

Table 2.3 provides an overview of what assemblies CM systems can be used on.

Table 2.3.: Types of CM system and their applicable subsystems

	Vibration Analysis	Acoustic Emission	Oil Analysis	Strain	SPM	Displacement	Optical Fibre	Electrical Effects	Temperature
Gearbox	X	X	X		X				X
Generator	X				X			X	X
Bearings and Shafts	X				X	X			X
Blades		X		X			X		
Tower		X		X		X	X		
Foundation		X		X		X	X		

2.5. Detection System Certification Standards

As documented in the previous section, certification for CM systems comes from two major bodies in the industry - Germanischer Lloyd Renewables (or GL Renewables now a part of DNV GL) and Allianz Verischerungs-AG. Additionally, TÜV Nord and several other organisations offer turbine certification services (some of these providers have been certified by DNV GL).

The qualifications for Allianz certification could not be ascertained and compiled for this document.

2.5.1. IEC Standard 61400

The majority of the certification standards offered by these companies, including DNV GL, reference the International Electrotechnical Commission standard IEC 61400 [2.63]. This document contains, among other things, the standards for:

- Design basis evaluation
- Design evaluation
- Manufacturing evaluation
- Type testing
- Foundation design and testing
- Type characteristics measurement

• Final evaluation

Summaries of this document can be found in documents by GL Group [2.64] and TÜV Nord [2.65] that explain the certification process.

The part of the standard dealing with requirements for real time communication devices (i.e. CM and SCADA) is 61400-25 - 'Communications for monitoring and control of wind power plants'. The document is broken down in to sub-sections regarding data management, information exchange and wind turbine modelling. This is displayed in Figure 2.7 from the British Standards Institute [2.63].

The standard is split into operational and management functions and all of these relate to client-server based data exchange. These different functions are shown in Table 2.4 from the British Standards Institute [2.66].

Table 2.4.: Communication Functions

Operational	Management
Monitoring	User management
Control	Time synchronisation
Data retrieval	Diagnostics
Logging	System setup
Reporting	

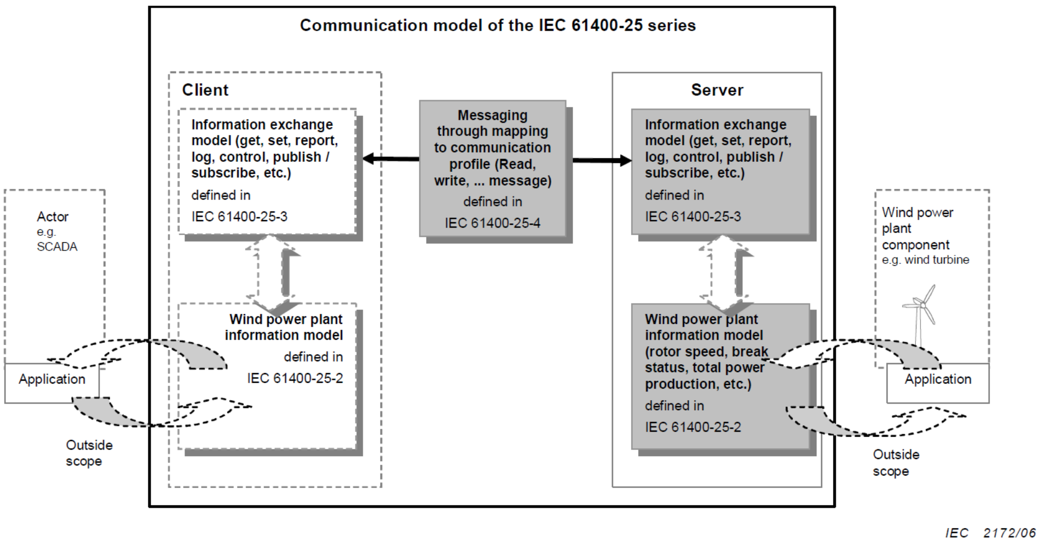


Figure 2.7.: Conceptual communication model of the IEC 61400-25 series [2.63]

A technical committee was established in 1964 by the International Organization for Standardization to investigate the "fields of mechanical vibration and shock and ... the condition monitoring of machines and structures, using multidisciplinary approaches". ISO/TC 108 now has 5 sub-committees investigating and standardizing, among others, the measurement and evaluation of vibration [2.67]. However, until recently, most of their standards had ignored or specifically excluded wind turbines. "Evaluation of machine vibration by measurements on non-rotating parts", the title of ISO 10816, specifically excluded wind in ISO 10816-3. 2015 saw the introduction of ISO 10816-21 for horizontal axis wind turbines with a gearbox and ISO 10816-22 is under development for wind turbines without gearboxes [2.68]. ISO/CD 16079 are guidelines also now under development for "Condition monitoring and diagnostics of wind turbines" (where CD indicates a Committee Draft version).

2.5.2. GL Renewables Certification

The GL Renewables master document - 'Rules and Guidelines - Industrial Services - 4 - Guidelines for the Certification of Condition Monitoring Systems for Wind Turbines' - was updated in 2013 [2.64]. DNV GL release a list of CM system vendors that have been approved [2.69].

There are many conditions to be met to achieve this status and some are detailed below. The document is broken down into parts for data collection, processing, reporting and diagnosis. It is fundamentally designed for vibration drive train analysis but special criteria can be applied to different CM systems, for example the Bosch Rexroth BLADEcontrol system is approved as a rotor blade sensor system.

2.5.3. Measured Components and Sensors

Components to be monitored as a minimum are detailed below and the minimum measuring points are illustrated in Table 2.5.

- For measuring planet-helical gears, vibration sensors must be installed on the ring gears, sun pinion shaft and output gear.
- The CM system needs to collect operating parameters either from the control

system, an additional SCADA or dedicated system. These parameters include: wind direction, wind speed, air temperature, temperatures of generator windings and messages about the interventions of turbine control.

- Monitoring of the difference between rotation angle between the gearbox output shaft and the generator input shaft is recommended. It allows conclusions to be drawn about the load variations in the gearbox.
- Oil particle sensors are recommend by GL Renewables but are not mandatory.

Table 2.5.: Necessary Measuring Points

Component	Minimum Sensors Per Component	Direction of Measurement	Frequency Range
Rotor Bearing	1	Radial	0.1 Hz to ≥ 10 kHz
Gearbox	3	Radial	0.1 Hz to ≥ 10 kHz
Generator Bearing	2	Radial	10 Hz to ≥ 10 kHz
Tower with Nacelle	2	Axial and Transversal	0.1 Hz to ≥ 100 Hz

2.5.4. Data Processing and Storage

The regulations specify that the signals must be processed, enhanced and correlated against operational parameters which may affect them. After the signals have been processed the system must then conduct relevant and accurate analysis on the data.

DNV GL suggest several different forms of analysis depending on the type of vibration analysis. Envelope spectra are necessary for most types of rotating components. Resultant characteristics from the envelope spectra, broadband characteristics and high-resolution amplitude spectra are also suggested. The document stresses that speed fluctuations must be accounted for and an appropriate analysis tool must be selected.

CM systems are required to be able to average, limit and apply trending to the data.

DNV GL acknowledge that large amounts of data will be generated by the systems but state that this must be stored including calculated values. Data reduction may occur but only post processing. Constraints must be stored with the data to give it meaning. To protect data, system information must be stored externally once a day.

A storage concept and plan must be shown to DNV GL and account for data transfer over limited connection speeds.

2.5.5. Reporting and Diagnosis

Alarms should be immediate, concise, stored in the database and transmitted through several different means of communication. DNV GL are concerned about how alarms are reported to users. A maximum number of alarms must be set, each with a maximum number of allowed clearances. This should stop repeated alarm messages being ignored or overlooked.

After an alarm has been set a specialist must be able to analyse the data independently and diagnose particular faults. To do this the CM system and its data must be accessible both on and off site.

2.5.6. Future Extension of Certification Standards

In a report published by the Allianz Centre for Technology [2.47] it was stated that implementing a minimum CM system specification had aided risk management. The report states that these requirements have proven results in assessing the health of the overall system.

The report recommends extending the CM system minimum requirements for offshore turbines. Some of the extensions include:

- Independent vibration monitoring of the rotor, tower and foundation;
- Rotor and direct driven generator bearings to have displacement monitoring;
- Distributed temperature measurements of the rotor bearing and, in a directly driven machine, the generator bearings and windings;
- The rotor bearing and gearbox to have oil particle counting instrumentation installed;
- The electric parameters of the generator windings should be monitored.

2.6. Wind Park Maintenance Strategies

2.6.1. Maintenance Strategy Taxonomy

Maintenance strategies can be broadly categorised in to two groups. A diagram displaying the taxonomy of maintenance types is shown in Figure 2.8 based on [2.70].

Using a **Corrective Maintenance Strategy**, the asset is run for as long as possible with minimal intervention until an event occurs that causes operation to cease. At this point, components will need to be replaced and downtime will occur until repair steps have taken place. This strategy is also known as "Run to Failure" and colloquially as "fix it when it breaks".

Corrective maintenance can be **Planned** or **Unplanned**. If a component failure does not cause immediate system shut down and maintenance actions can be scheduled then it is planned corrective maintenance. If intervention is required immediately due to safety concerns or operational losses then it is unplanned corrective maintenance.

The strategy is low cost, easy to implement and extracts maximum RUL from components. It works well in systems with high levels of redundancy, very low failure rates or difficult access. Offshore wind parks have limited redundancy, relatively high failure rates and the costs accrued in operational losses mean that this strategy is not suitable. Repair costs are generally more expensive then other strategies as damage is more severe in components run to failure [2.71].

A **Preventive Maintenance Strategy** attempts to schedule interventions before a failure event that would interrupt operation occurs. Work actions happen more frequently than with a corrective strategy but generally the amount of stoppages reduce significantly.

Preventive maintenance strategies can be divided further into **Period Based** and **Predictive**.

2.6.2. Period Based Maintenance

Period based maintenance (PBM) (also known as time based maintenance (TBM) or calendar based maintenance) relies on the scheduling of regular maintenance. It occurs at intervals short enough to statistically minimise the risk of failure. This period can be based on elapsed time or number of cycles - say rotations completed or operating hours - being achieved. An additional age related criterion can be added to defer the onset of periodic maintenance. The regular changing of components such as oil filters or lubrication allow for equipment to run at full performance, high efficiency and increase the lifetime of assemblies. The planning of maintenance actions allows for labour costs to be minimised with limited emergency responses. In summary, periodic maintenance is an effective strategy to reduce downtime and improve system reliability. Some studies place the value of periodic maintenance over a corrective strategy at 12 to 18% [2.71].

Unfortunately, periodic maintenance does not remove the possibility that catastrophic failures will occur. There are many more hours of labour that are required to perform this strategy and higher overheads in management and training. Consumables and components will be replaced with a higher RUL than in other strategies - in theory less value is extracted from them.

A lesser problem that still needs to be addressed is imperfect maintenance. As with all procedures that involve humans, there is a chance that the technician or engineer completing the maintenance accidentally causes additional damage to the system or does not fully complete the repair. The more frequently maintenance occurs, the larger the chance of this occurring.

2.6.3. Predictive Maintenance

Predictive maintenance requires the condition of components to be monitored regularly. This allows maintenance to be conducted only when it is necessary, before failure occurs and, if the condition of the assemblies is observed at appropriate intervals, the possibility of catastrophic failures is removed.

The RUL of components approaches zero as they are fully utilised. Alternative operation strategies can be used to ensure this - for example slightly reducing the performance of an asset could significantly increase the life of a component. This reduces the hours of labour needed to maintain assemblies and the scheduling of maintenance reduces costs. Spares levels can be reduced.

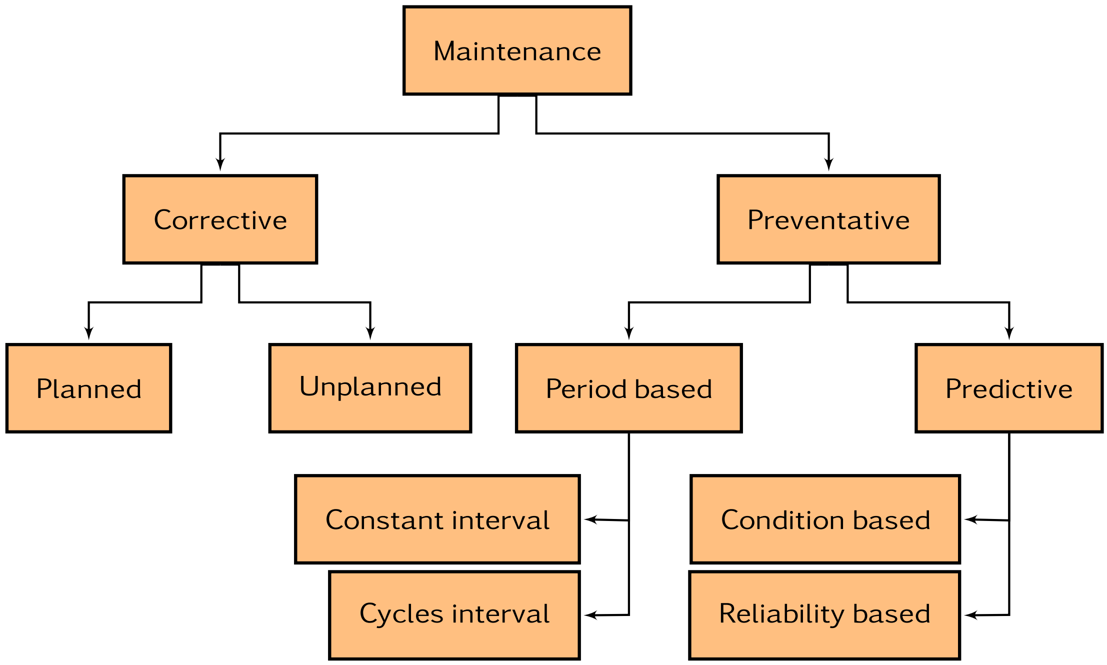


Figure 2.8.: Graphical overview of maintenance types

The effectiveness of this strategy relies entirely on the monitoring equipment being accurate and the correct monitoring intervals being selected. These two items can incur significant costs as can training staff to incorporate it into the maintenance plan. If there are failure modes not detected by the monitoring system or if it does not have a 100% detection rate then catastrophic failures may still occur but the possibility may be reduced. If the system produces an alarm that needs to be investigated when no action was required - a false alarm - then this may incur unnecessary costs in labour or downtime.

Reliability centred maintenance is a holistic maintenance strategy. CBM techniques are used in conjunction with analytical design tools to minimise downtime of the current components and to reduce this further over time [2.72]. Components can be redesigned to remove unseen issues or serial defects. The number of assembly overhauls can be reduced over the lifetime of the asset.

The Department of Energy in the US compared these strategies for pumps and assigned the O&M costs as: period based - $13/hp/year; condition based - $9/hp/year; and reliability based - $6/hp/year. [2.71]

2.6.4. Performance Based Maintenance Contracts

Turbine manufacturers - often referred to as Original Equipment Manufacturers (OEMs) - can offer Performance Based Maintenance Contracts (PBMCs) for their turbines. These are contracts offering various levels of support and guarantee for the turbines often with the manufacturers conducting maintenance for the beginning of the turbine's life.

The information below regards the offerings available from Siemens Wind Power [2.73], Vestas A/S [2.74] and General Electric Company [2.75]. This list is not exhaustive but is chosen for the amount of information publicly available about the products. Other manufacturers have indicated that they will offer similar contracts such as Alstom Power [2.76] and MHI Vestas Offshore Wind [2.77]. While this literature shows the main goals of these contracts, they are often negotiated on an individual basis.

2.6.4.1. Time or Energy Availability

Siemens Wind Power's most basic PBMC that includes an availability clause is the SWPS-200A. This includes remote diagnostic services and servicing. The most advanced PBMC also includes individual component warranties and the inclusion of offshore logistic costs where – in certain situations – Siemens will utilise their own fleet of helicopters and service vessels.

GE's EPSA (Extended Parts and Services Agreement) and FSA (Full Service Agreement) PBMC include availability guarantees and coverage for completing manual resets. The more advanced FSA further covers unplanned maintenance actions and turbine performance review with an aim for turbine life extension.

Finally, the AOM (Active Output Management) 5000 is the most advanced PBMC offered by Vestas. This offers an "energy-based availability guarantee that maximises output". This agreement and some of their lower level PMBCs include a 97% energy-based availability.

Energy-based contracts such as the AOM 5000 are becoming more common. Instead of time based availability being the sole metric used to evaluate the contract, the amount of energy lost is used as well. This encourages service providers to ensure work is done in periods of calm weather, and that the turbines are operational for high wind periods. This maximises the energy captured by the turbine. A good discussion of energy vs time based availability is given in the work of Conroy, Deane, and Gallachóir [2.78].

2.6.4.2. Options After Expiry of Warranty

GL Garrad Hassan [2.79] state that the OEMs have an effective monopoly on turbine maintenance during the warranty period for the first few years of operation. It is during the post-warranty period that operators can decide how much risk to take. The authors go on to state that due to the intellectual property issues and specialist knowledge associated with wind turbines the majority of OEMs tend to remain contracted in some role.

There is a separation in many of these plans between offshore logistics and maintenance or repair actions. Risk associated with weather interruptions is an important factor and whoever is responsible for managing this risk should be responsible for offshore logistics. Larger owners or operators that assume this risk may even purchase vessels rather than contracting them. The optimisation of purchasing vessels compared to contracting them is explored in the work of Dalgic et al. [2.80].

The contracts noted above appear to be designed to remove large amounts of perceived risk of offshore maintenance from the operator/owner at a fixed premium. Some contracts focus on the lifetime operation or extension of turbine life while others look to remove the unpredictable costs of service vehicle fleet management. The production based guarantees offered from several manufacturers stand out as particularly interesting as they are of benefit to operators by forcing maintenance actions to be moved to low-wind periods, thereby maximising energy capture.

2.7. Conclusions

In this chapter, the basics of system reliability, including the necessary terminology, and the different maintenance strategies that are deployed to improve reliability have been explored. Important aspects of this are the wind turbine taxonomy and existing reliability databases.

The technologies that are currently being deployed to monitor turbines and how this captured data is converted into condition indicators have been shown. The standards that dictate the requirements of these systems have also been listed.

Finally, one of the most important aspects addressed in this chapter are the viewpoints and goals of different parties in the wind industry. OEMs, wind park operators and owners each have different goals and view risks differently. This is highlighted in the PMBCs. OEMs are willing to offer generous service contracts at a premium to reduce their risk which may appeal to operators and owners. Operators, however, may be willing to reduce operating costs further by completing maintenance actions themselves. Owners' goals are to ensure long term profits and they may be more willing to pay higher premiums to OEMs for guaranteed results.

2.8. Chapter 2 References

[2.1] R. Hill, J. Stinebaugh, and D. Briand. *Wind Turbine Reliability: A Database and Analysis Approach*. Tech. rep. Sandia National Laboratories, 2008.

[2.2] M. Stamatelatos, W. Vesely, J. Dugan, J. Fragola, J. Minarick III, and J. Railsback. *Fault Tree Handbook with Aerospace Applications*. Tech. rep. NASA, 2002.

[2.3] H. Arabian-Hoseynabadi, H. Oraee, and P. J. Tavner. "Failure Modes and Effects Analysis (FMEA) for wind turbines". In: *International Journal of Electrical Power & Energy Systems* 32.7 (Sept. 2010), pp. 817–824. ISSN: 01420615.

[2.4] S. Kahrobaee and S. Asgarpoor. "Risk-based Failure Mode and Effect Analysis for wind turbines (RB-FMEA)". In: *2011 North American Power Symposium* (Aug. 2011), pp. 1–7.

[2.5] S. Kmenta and K. Ishii. "Scenario-Based Failure Modes and Effects Analysis Using Expected Cost". In: *Journal of Mechanical Design* 126.6 (2004), p. 1027. ISSN: 10500472.

[2.6] S. Pfaffel, V. Berkhout, S. Faulstich, P. Kühn, K. Linke, P. Lyding, and R. Rothkegel. *Wind Energy Report - Germany 2011*. Tech. rep. IWES, 2011, p. 87.

[2.7] J. M. Pinar Pérez, F. P. García Márquez, A. Tobias, and M. Papaelias. "Wind turbine reliability analysis". In: *Renewable and Sustainable Energy Reviews* 23 (2013), pp. 463–472. ISSN: 13640321.

[2.8] S. Faulstich, B. Hahn, and P. J. Tavner. "Wind Turbine Downtime and Its Importance for Offshore Deployment". In: *Wind Energy* 14.July 2010 (2011), pp. 327–337.

[2.9] M. G. Bharatbhai. "Failure Mode and Effect Analysis of Repower 5M Wind Turbine". In: *International Journal of Advance Research in Engineering, Science & Technology* 2.5 (2015), pp. 2394–2444.

[2.10] M. Durstewitz, C. Enßlin, B. Hahn, P. Kühn, B. Lange, and K. Rohrig. *Wind Energy Report Germany 2005*. Tech. rep. Kassel: Institut für Solare Energieversorgungstechnik (ISET), 2006.

[2.11] P. Richardon. "Relating onshore wind turbine reliability to offshore application". PhD thesis. Durham University, 2010.

[2.12] R. Hill, V. Peters, J. Stinebaugh, and P. Veers. "Wind Turbine Reliability Database Update". In: *sandia.gov* March (2009).

[2.13] E.ON Climate and Renewables. *Scroby Sands Offshore Wind Farm 3rd Annual Report*. Tech. rep. 08/P48. Department of Business Enterprise & Regulatory Reform, 2007, p. 15.

[2.14] G. S. Hawker and D. A. McMillan. "The impact of maintenance contract arrangements on the yield of offshore wind power plants". In: *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability* 229.5 (2015), pp. 394–402. ISSN: 1748-006X.

[2.15] NASA. *RCM Guide - Reliability Centered Maintenance Guide for Facilities and Collateral Equipment*. Tech. rep. September. 2008.

[2.16] A. M. Smith. "A Proven Approach". In: *Reliability-Centered Maintenance*. McGraw-Hill, 1993. Chap. 4.

[2.17] A. K. Jardine, D. Lin, and D. Banjevic. "A review on machinery diagnostics and prognostics implementing condition-based maintenance". In: *Mechanical Systems and Signal Processing* 20.7 (Oct. 2006), pp. 1483–1510. ISSN: 08883270.

[2.18] K. Harman. "Availability trends observed at operational wind farms". In: *European Wind Energy Conference*. April. 2008, pp. 1–8.

[2.19] R. Neate, P. Matthews, C. J. Crabtree, B. Kazemtabrizi, and E. Golysheva. "Optimisation of Far Offshore Wind Farm Operation and Maintenance (O&M) Strategies". In: *European Wind Energy Association Annual Conference*. Barcelona, 2014.

[2.20] C. Bond, V. Peters, and A. Ogilvie. *Continuous Reliability Enhancement for Wind (CREW) database: wind plant reliability benchmark*. Tech. rep. SAND2012-7328. Sandia National Laboratories, 2012.

[2.21] P. J. Tavner. *Offshore Wind Turbines - Reliability, availability and maintenance*. 1st. The Institute of Engineering and Technology, 2012. ISBN: 978-1-84919-229-3.

[2.22] M. Lange, M. Wilkinson, and T. van Delft. *Wind Turbine Reliability Analysis*. Tech. rep. GL Garrad Hassan, 2011.

[2.23] M. Wilkinson and B. Hendriks. *Report on Wind Turbine Reliability Profiles*. Tech. rep. 212966. Reliawind, 2007, p. 13.

[2.24] J. Ribrant and L. M. Bertling. "Survey of Failures in Wind Power Systems With Focus on Swedish Wind Power Plants During 1997 - 2005". In: *IEEE Transactions on Energy Conversion* 22.1 (Mar. 2007), pp. 167–173. ISSN: 0885-8969.

[2.25] DOWEC. *Estimation of Turbine Reliability figures within the DOWEC project*. Tech. rep. 10048. 2003, p. 16.

[2.26] P. Tallett, G. Mendy, J. Sharp, D. Sanderson, and P. May. *Structural Integrity Monitoring - RR685*. Tech. rep. Health and Safety Executive, 2009.

[2.27] C. C. Ciang, J.-R. Lee, and H.-J. Bang. "Structural health monitoring for a wind turbine system: a review of damage detection methods". In: *Measurement Science and Technology* 19.12 (Dec. 2008), p. 122001. ISSN: 0957-0233.

[2.28] K. P. Kou and F. M. Burdekin. "The applicability of leak-before-break on flooded member detection for offshore structures under fatigue". In: *Engineering Fracture Mechanics* 75.1 (Jan. 2008), pp. 31–40. ISSN: 00137944.

[2.29] R. Mijarez, P. Gaydecki, and M. Burdekin. "Flood member detection for real-time structural health monitoring of sub-sea structures of offshore steel oil-rigs". In: *Smart Materials and Structures* 16.5 (Oct. 2007), pp. 1857–1869. ISSN: 0964-1726.

[2.30] P. Takoutsing, R. Wamkeue, M. Ouhrouche, F. Slaoui-Hasnaoui, T. Tameghe, and G. Ekemb. "Wind Turbine Condition Monitoring: State-of-the-Art Review, New Trends, and Future Challenges". In: *Energies* 7 (2014), pp. 2595–2630. ISSN: 1996-1073.

[2.31] P. Schubel, R. Crossley, E. Boateng, and J. Hutchinson. "Review of structural health and cure monitoring techniques for large wind turbine blades". In: *Renewable Energy* 51 (2013), pp. 113–123. ISSN: 09601481.

[2.32] M. Benedetti, V. Fontanari, and D. Zonta. "Structural health monitoring of wind towers: remote damage detection using strain sensors". In: *Smart Materials and Structures* 20.5 (2011), p. 055009. ISSN: 0964-1726.

[2.33] Det Norske Veritas. *DNV-OS-J101 Design of Offshore Wind Turbine Structures*. 2011.

[2.34] W. Wang. "Condition-based maintenance modelling". In: *Complex Systems Maintenance Handbook*. 2008. Chap. 5, pp. 111–131. ISBN: 978-1-84800-010-0.

[2.35] M. Rumsey and J. A. Paquette. "Structural Health Monitoring of Wind Turbine Blades". In: *Proceedings of SPIE 6913, Smart Sensor Phenomena, Technology, Networks, and Systems 2008*. Ed. by W. Ecke, K. J. Peters, and N. G. Meyendorf. San Diego, California, USA, 2008.

[2.36] S. Bagavathiappan, B. Lahiri, T. Saravanan, J. Philip, and T. Jayakumar. “Infrared thermography for condition monitoring â€“ A review”. In: *Infrared Physics & Technology* 60 (Sept. 2013), pp. 35–55. ISSN: 13504495.

[2.37] J. Carroll, A. May, A. McDonald, and D. McMillan. “Availability Improvements from Condition Monitoring Systems and Performance Based Maintenance Contracts”. In: *European Wind Energy Association Offshore Annual Conference*. Copenhagen, Denmark, 2015.

[2.38] GL Group. *Guideline for the Certification of Condition Monitoring Systems for Wind Turbines*. 2007.

[2.39] T. Gellermann. “Extension of the scope of Condition Monitoring Systems”. In: *Proceeding from VDI-Conference "Schwingungen von Windenergieanlagen"*. Bremen, Germany: Allianz Centre for Technology, 2012, pp. 1–14.

[2.40] C. J. Crabtree. *Survey of Commercially Available Condition Monitoring Systems for Wind Turbines*. Tech. rep. November. Durham: SUPERGEN, 2010, p. 14.

[2.41] D. Mba and B. Rao. “Development of Acoustic Emission Technology for Condition Monitoring and Diagnosis of Rotating Machines; Bearings, Pumps, Gearboxes, Engines and Rotating”. In: *The Shock and Vibration Digest* 38.1 (2006), pp. 3–16.

[2.42] Mistras Group. *One Source for Wind*. 410B-14102-01. 2014.

[2.43] M. Nie and L. Wang. “Review of Condition Monitoring and Fault Diagnosis Technologies for Wind Turbine Gearbox”. In: *Procedia CIRP* 11.Cm (Jan. 2013), pp. 287–290. ISSN: 22128271.

[2.44] A. Hamilton and F. Quail. “Detailed State of the Art Review for the Different Online/Inline Oil Analysis Techniques in Context of Wind Turbine Gearboxes”. In: *Journal of Tribology* 133.4 (2011), pp. 1–8. ISSN: 07424787.

[2.45] C. Walford and D. Roberts. *Condition Monitoring of Wind Turbines: Technology Overview, Seeded-Fault Testing, and Cost- Benefit Analysis*. Tech. rep. 3. Palo Alto, CA, USA: Electric Power Research Institute, 2006, pp. 1–110.

[2.46] SPM Instruments AB. *Allianz approves shock pulse technology for condition monitoring of wind turbines*. 2014. URL: https://www.spminstrument.com/de-AT/News/2014/Allianz-approves-shock-pulse-technology-for-condition-monitoring-of-wind-turbines-/ (visited on 03/04/2014).

[2.47] T. Gellermann. *Extension of the scope of Condition Monitoring Systems for multi-MW and offshore wind turbines*. Tech. rep. May. Allianz Risk Consulting GmbH, 2012, p. 2.

[2.48] Z. Daneshi-Far, G. A. Capolino, and H. Henao. "Review of failures and condition monitoring in wind turbine generators". In: *The XIX International Conference on Electrical Machines - ICEM 2010* (Sept. 2010), pp. 1–6.

[2.49] W. Yang, M. Wilkinson, and P. J. Tavner. "Condition monitoring and fault diagnosis of a wind turbine synchronous generator drive train". In: *IET Renewable Power Generation* 3.April (2008), pp. 1–11.

[2.50] W. Yang. "Condition Monitoring the Drive Train of a Direct Drive Permanent Magnet Wind Turbine Using Generator Electrical Signals". In: *Journal of Solar Energy Engineering* 136.2 (2013), p. 021008. ISSN: 0199-6231.

[2.51] Sinclair Knight Merz. *Condition Monitoring of Wind Turbines*. Tech. rep. UP00-195/R/0001. Sinclair Knight Merz, 2006.

[2.52] E. Bechhoefer and M. Kingsley. "A review of time synchronous average algorithms". In: *Annual Conference of the Prognostics and Health Management Society*. 2009, pp. 1–10.

[2.53] W. Yang, P. J. Tavner, C. J. Crabtree, Y. Feng, and Y. Qiu. "Wind turbine condition monitoring: technical and commercial challenges". In: *Wind Energy* (2012).

[2.54] L. Gelman, R. Zimroz, J. Birkel, H. Leigh-Firbank, D. Simms, B. Waterland, and G. Whitehurst. "Adaptive vibration condition monitoring technology for local tooth damage in gearboxes". In: *Non-Destructive Testing and Condition Monitoring* 47 (2005), pp. 461–464.

[2.55] I. Antoniadou, N. Dervilis, E. Papatheou, A. E. Maguire, and K. Worden. "Aspects of structural health and condition monitoring of offshore wind turbines". In: *Philiosophical Transactions A Royal Society* 373 (2015).

[2.56] B. Lu, Y. Li, X. Wu, and Z. Yang. "A review of recent advances in wind turbine condition monitoring and fault diagnosis". In: *IEEE Power Electronics and Machines in Wind Applications* 1.1 (2009), pp. 1–7.

[2.57] C. Devriendt, W. Weijtjens, M. El-Kafafy, and G. De Sitter. "Monitoring of resonant frequencies and damping values of an offshore wind turbine in parked conditions". In: *IET Renewable Power Generation* 8.4 (2014), pp. 433–441. issn: 1752-1416.

[2.58] M. Benedetti, V. Fontanari, and L. Battisti. "Structural health monitoring of wind towers: residual fatigue life estimation". In: *Smart Materials and Structures* 22.4 (Apr. 2013), p. 045017. issn: 0964-1726.

[2.59] S. Sharma and D. Mahto. "Condition Monitoring of Wind Turbines: A Review". In: *International Journal of Scientific and Engineering Research* 4.8 (2013), pp. 35–50.

[2.60] P. Cross and X. Ma. "Model-based and fuzzy logic approaches to condition monitoring of operational wind turbines". In: *International Journal of Automation and Computing* 12.1 (2015), pp. 25–34. issn: 1476-8186.

[2.61] S. Gill, B. Stephen, and S. Galloway. "Wind turbine condition assessment through power curve copula modeling". In: *IEEE Transactions on Sustainable Energy* 3.1 (2012), pp. 94–101. issn: 19493029.

[2.62] K. Elbhbah and J. K. Sinha. "Vibration-based condition monitoring of rotating machines using a machine composite spectrum". In: *Journal of Sound and Vibration* 332.11 (May 2013), pp. 2831–2845. issn: 0022460X.

[2.63] British Standards Institute. *BS EN 61400 Part 25-3: Communications for monitoring and control of wind power plants. Information exchange models*. Tech. rep. 2007, p. 36.

[2.64] GL Group. *Guideline for the Certification of Condition Monitoring Systems for Wind Turbines*. Tech. rep. 2013, pp. 4–7.

[2.65] TUV Nord. *Type and Project Certification - Wind Energy*. Tech. rep. 2012, p. 4.

[2.66] British Standards Institute. *BS EN 61400 Part 25-6: Wind Turbines. Communications for monitoring and control of wind power plants. Logical node classes and data classes for condition monitoring*. Tech. rep. 2011, p. 36.

[2.67] Technical Committee 108. *ISO/TC 108 Business Plan*. Tech. rep. Geneva: International Organisation for Standardization, 2012, p. 18.

[2.68] ISO. *Mechanical vibration — Evaluation of machine vibration by measurements on non-rotating parts - Part 21: Horizontal axis wind turbines with gearbox*. ISO ISO 10816-21. Geneva, Switzerland: International Organization for Standardization, 2015.

[2.69] DNV GL. *List of Certifications - Condition Monitoring Systems (CMS) / Monitoring Bodies for CMS*. 2015.

[2.70] M. Ben-Daya. *Handbook of Maintenance Management and Engineering*. Ed. by M. Ben-Daya, S. O. Duffuaa, D. Ait-Kad, A. Raouf, and J. Knezevic. 2009. ISBN: 9781848824713.

[2.71] G. P. Sullivan, R. Pugh, A. P. Melendez, and W. D. Hunt. "Types of Maintenance Programs". In: *Operations & Maintenance Best Practices*. US Department of Energy, 2010. Chap. 5, pp. 1–9.

[2.72] J. Moubray. *Reliability-centred Maintenance*. Butterworth Heinemann, 1993. ISBN: 9780750633581.

[2.73] Siemens Wind Power. *Siemens Offshore Service Program : SWPS-430O*. E50001-E530-A118-X-7600. 2012.

[2.74] Vestas A/S. *AOM - Active Output Management*. 10/2011-EN. 2011.

[2.75] General Electric Company. *Flexible Wind Services*. GEA17817D. 2014.

[2.76] Alstom Power. *Wind Power Solutions*. RPWR/BRCH/WINDPWS. 2014.

[2.77] MHI Vestas Offshore Wind. *Service Packages*. 2014. URL: www.mhivestasoffshore.com/operations-maintenance/ (visited on 03/03/2015).

[2.78] N. Conroy, J. Deane, and B. P. Ó. Gallachóir. "Wind turbine availability: Should it be time or energy based? – A case study in Ireland". In: *Renewable Energy* 36.11 (2011), pp. 2967–2971. ISSN: 0960-1481.

[2.79] GL Garrad Hassan. *A Guide to UK Offshore Wind Operations and Maintenance*. Tech. rep. Scottish Enterprise and The Crown Estate, 2013.

[2.80] Y. Dalgic, I. Lazakis, I. Dinwoodie, D. McMillan, and M. Revie. "Advanced logistics planning for offshore wind farm operation and maintenance activities". In: *Ocean Engineering* 101 (June 2015), pp. 211–226. ISSN: 00298018.

CHAPTER 3

Modelling Wind Turbine Deterioration

This chapter contains information about the different methods used to model component deterioration and about how to model the capturing of this deterioration using condition monitoring systems. Due to the differences in the design and operation of structural and rotating components the modelling of each is handled in different sections.

3.1. Rotating Machinery Components

Deterioration modelling often requires stochastic processes that accrue over time. The wind itself is a stochastic process, leading to turbines having complex loading and failure patterns [3.1]. The modelling of the failure and deterioration process is helpful for producing effective maintenance plans. Markov chains are one of the commonly used methods to represent such processes accurately [3.2].

3.1.1. Markov Processes

The Markov process allows random variables to be modelled. If a random variable has a finite number of mutually exclusive discrete states, exists in discrete time and has a conditional probability distribution for each of these states then it is known as a

Markov chain (MC). The state of the variable can evolve over time and each state can have a different probability distribution for the remaining states. This evolution process is memoryless - the result of the next time step depends only on the current state and not on any previous information. The probability distributions can be combined into a transition probability matrix. A complete set of the mathematical definitions for Markov chains are provided by Janssen and Manca [3.3].

If the variable X is the discrete range of states $x_1,...,x_n$ then the marginal probability of the state of X, $P(X)$, can be calculated from the probability distribution of $P(x_1,...,x_n)$. Conversely, the probability of a particular state of X can also be defined, $P(x_n)$. The probability distribution can be different for each existing state. These distributions are contained within an array, P_T, and are shown in Equation 3.1. The probability across each row must total 1.

$$P_T = \begin{bmatrix} x_{11} & ... & ... & x_{1n} \\ x_{21} & ... & ... & x_{2n} \\ ... & ... & ... & ... \\ x_{n1} & ... & ... & x_{nn} \end{bmatrix} \tag{3.1}$$

This variable can easily be made to represent a non-repairing component with two states and its transition matrix is shown below in Equation 3.2 and in Figure 3.1. The two states are ′operating′ and ′failed′ which are denoted by ′1′ and ′2′ respectively. The arrows indicate dependence. The probability of transition, U, is obtained from knowledge of the failure rate and the survivor function of the failure.

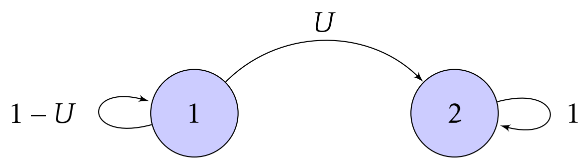


Figure 3.1.: Simple Two State Markov Chain for variable X

$$P_T = \begin{bmatrix} 1-U & U \\ 0 & 1 \end{bmatrix} \tag{3.2}$$

As it is impossible using this matrix to leave the failed state, it is known as an ab-

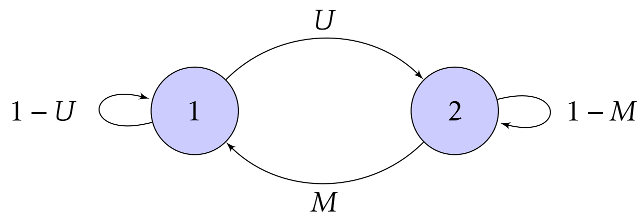


Figure 3.2.: Simple Two State Markov Chain for Variable X with Repair

sorbing Markov chain. Physical systems generally cannot move back to an operating state without external intervention. By adding the repair rate, μ, to the model, the probability of transitioning to the original state, M, can be obtained with the probability distribution of repair. This is shown in Figure 3.2.

The Markov chain is said to be ergodic if an independent probability distribution can be estimated for a particular time, t. If the transition matrix probabilities are constant over time then this can be calculated based on the equation shown in Equation 3.3.

$$P_T = \begin{bmatrix} 1-U & U \\ M & 1-M \end{bmatrix}^t \tag{3.3}$$

Deterioration processes are normally not directly observable but produce some events and criteria that are. Graubner, Schmidt, and Proske [3.4] states that with inspections and CM systems it is the additional discrete random variable X' that is directly observed instead of the direct degradation process occurring in variable X.

Hidden Markov Models (HMM) are an extension of MCs and a good definition is given by Eddy [3.5]. These additional variables, X', are used with their own states and probability distributions that are observable. This information can also be represented in a matrix form, known as the emissions matrix, P_E, with each row being a probability distribution depending on the state of X. A simple emissions matrix is shown in Equation 3.4 for the repairable example above when the emission itself only has two states. These are again operating and failed and for clarity are denoted as O and F. The updated HMM is shown graphically in Figure 3.3 with emission probabilities shown in

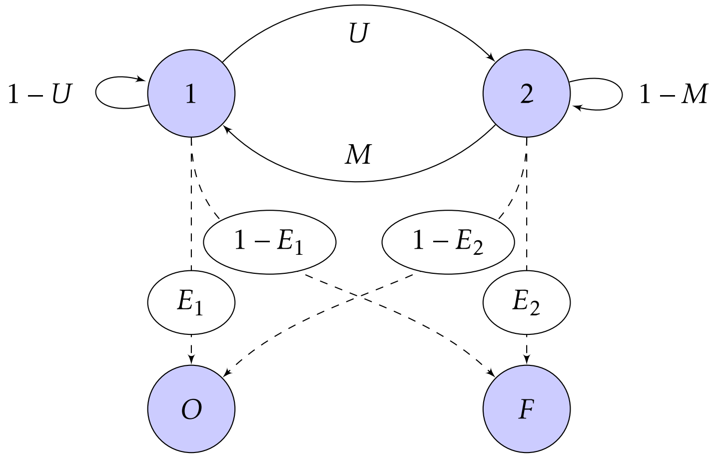


Figure 3.3.: Hidden Markov Model with Emission States

the ellipses.

$$P_E = \begin{bmatrix} E_1 & 1-E_1 \\ 1-E_2 & E_2 \end{bmatrix} \tag{3.4}$$

3.1.2. Survivor Functions

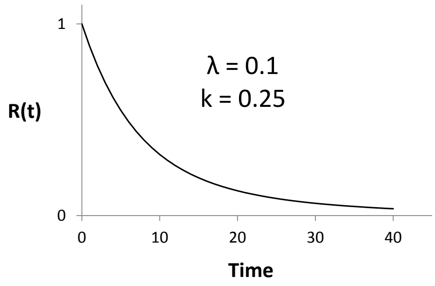
It is appropriate now to revisit survivor or reliability functions, $S(t)$, as described in Chapter 2. The probabilities that are used in the transition matrices are converted from the failure and repair rates. These probability values depend on the probability density function used of the survivor function. Four major survivor functions are outlined below in Equations 3.5, 3.6, 3.7 and 3.8 based on those contained within the work of Jardine [3.6]. These are shown in Figure 3.4 with the same illustrative constants as the source material with additional variables used to show the different possibilities with the Weibull distribution.

$$\text{Hyper-exponential:} \quad S(t) = k\exp(-2k\lambda\, t) + (1-k)\exp(-2(1-k)\lambda\, t) \tag{3.5}$$

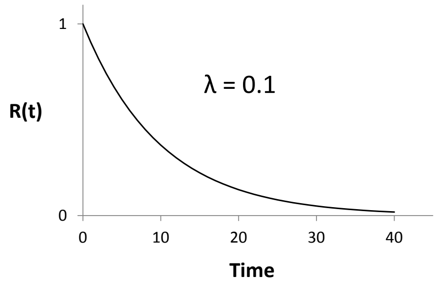
$$\text{Exponential:} \quad S(t) = \exp(-\lambda\, t) \tag{3.6}$$

$$\text{Normal:} \quad S(t) = \frac{1}{\sigma\sqrt{2\pi}}\int_t^{\infty}\exp\left(\frac{-(t-\mu)^2}{2\sigma^2}\right) \tag{3.7}$$

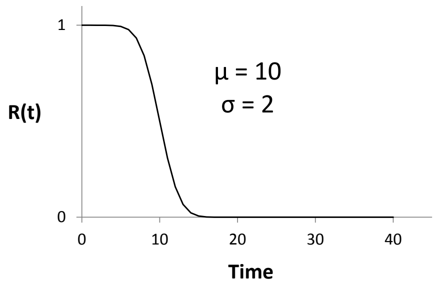
$$\text{Weibull:} \quad S(t) = \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \tag{3.8}$$



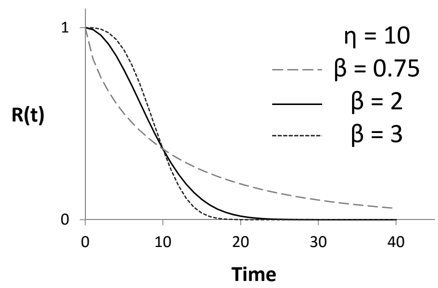
(a) Hyper-exponential



(b) Exponential



(c) Normal



(d) Weibull

Figure 3.4.: Survivor Functions

Billinton and Allan [3.7] states that exponential decay is one of the most commonly used survivor functions. However, for this survivor function to be applicable the hazard rate should remain constant throughout the life of the component. The equivalent hazard functions for the survivor functions given in Figure 3.4 are shown in Figure 3.5.

The hazard function profiles shown in Figure 2.2 can be recreated with combinations of these four functions. The hyper-exponential function is used when equipment has very long or very short failure times. The Weibull distribution can be made to represent different components, along with Gamma and Rayleigh distributions, using various parameters [3.7]. If the β value of the Weibull distribution is less than 1 then it will produce a decaying hazard function and if it is greater than 2 then it will show non-linear growth.

Jardine [3.6] also gives examples of components that follow these functions. Much electrical equipment is subject to constant random failures throughout its life. Some electrical equipment has a period of "burn-in" with a reduction in the hazard rate over the first few years of life. This means that electrical equipment can be represented by hyper-exponential, exponential and Weibull functions (where the β value is less than 1). Exponential functions can be used to represent pieces of industrial equipment with the possibility of sudden excess loading. Incandescent light bulbs are often cited as an example where the hazard rate can be described by a normal function.

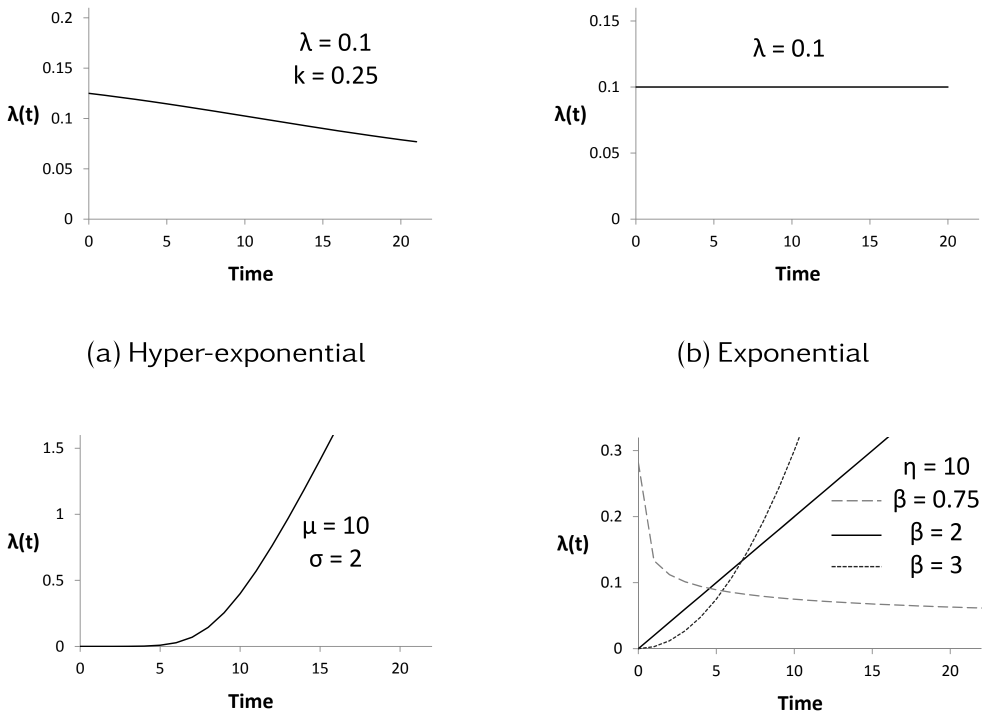
Examples of fitting hazard functions to real data can be seen in the work of Wang, Hsu, and Liu [3.8]. In several case studies, the authors take different component populations and model the hazard rate function. Automotive components are shown to have an increasing hazard function over their lifetimes and modelled as a normal or Weibull function (where the β value is greater than 1). Electrical modules in an airborne system follow the hazard functions described above for electrical equipment. The last case studies in the paper deal with simple mechanical components that exhibit the bathtub curve. A work from Wong and Lindstrom [3.9] also shows a much more complex hazard function for some electrical equipment that it refers to as a "roller coaster".

These varying hazard rates require that the Markov chain become time-inhomogeneous. The transition matrix must now be updated depending on the age of the component. This can be achieved by using a Markov - Switching model. These were originally developed for modelling in economics. They have the capability to analyse the effects of large structural changes in financial institutions [3.10, 3.11].

Mixed Markov methods are an alternative explored by Singh et al. [3.12]. This paper updates the transition matrix with a Weibull distribution to represent the bathtub curve. The mixed Markov process is defined in the work of Murphy [3.13] where a switching variable, referred to as the "guard condition", is updated from a previous time step and this selects the transition matrix parameters.

These processes have been applied to model components in wind turbines. One of the most notable examples is from the work of Neate et al. [3.14]. The authors use a 6 state Markov chain to represent the possible states of components within a wind turbine. A diagram of the states and transitions are shown in Figure 3.6.

State 'UP' is a healthy state while state 'MiF' indicates that a maintenance or repair action will seed the next failure. The states 'PO' and 'POds' indicate that a CM system



(a) Hyper-exponential

(b) Exponential

(c) Normal

(d) Weibull

Figure 3.5.: Hazard Functions

has an alarm and there is an increased likelihood of failure but in 'POds' the turbine has been de-rated to minimise damage. The turbine is required to stop in the state 'FO' with the following letter indicating the severity of the failure. The final state is 'Maint' where the component is undergoing maintenance.

3.1.3. Dynamic Bayesian Networks

Bayesian Networks (BN) and their time based equivalents, Dynamic Bayesian Networks (DBN), also handle the requirements for modelling reliability [3.15] and deterioration [3.16].

These include [3.17]:

- Robust probabilistic model describing random variables
- Parameters specified from statistical data or expert judgement
- Reasoning with uncertainty and inference

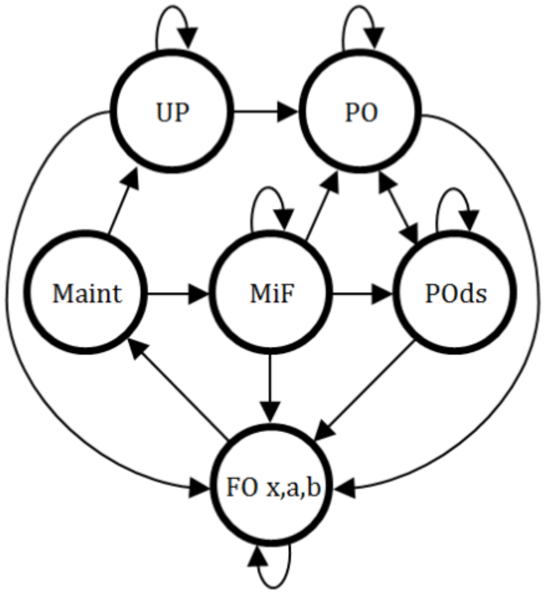


Figure 3.6.: Six State Markov Chain Representing a Wind Turbine [3.14]

- Updating of uncertainty by incorporating observations
- Mathematically sound and efficient

3.1.3.1. Bayesian Networks

Bayesian Networks are defined in Nielsen and Jensen [3.18] as follows:

- A collection of variables with directed causal links between variables.
- Each of the variables defined in the network has a finite set of exclusive states (either discrete or continuous).
- The causal links between variables must not be acyclic.
- Each variable with parents has conditional probability.
- BNs can therefore be referred to as directed acyclic graphs (DAGs).

BNs have been applied to different aspects of reliability. Mahadevan, Zhang, and Smith [3.19] and Langseth and Portinale [3.20] use BNs to assess system reliability using BN fault tree equivalents. The work completed by Langseth and Portinale gives an overview of how to build and analyse BNs of systems. It also explains how to understand the output of, and conduct the mathematics involved in, solving BN models. Similarly, Torres-Toledano and Sucar Succar [3.15] uses BNs to solve reliability block diagrams.

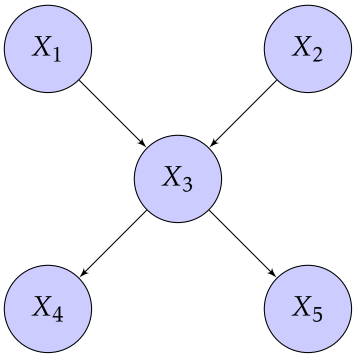


Figure 3.7.: An Example Bayesian Network with 5 Nodes

U is a universe of random variables where $U = \{X_1, X_2, ..., X_n\}$. The probability distribution for each variable can be discrete or continuous.

An example BN is taken from Langseth and Portinale [3.20] and shown in Figure 3.7 with 5 nodes. The arrows in the diagram indicate causal links. The links represent $P(U)$, the joint probability mass function of the nodes in U. If the variables exist in discrete time and space then the joint probability mass function can be expressed as a conditional probability table (CPT).

The node X_3 is said to be a descendant of X_1 and X_2 and likewise X_4 is a descendant of X_3. The nodes X_1 and X_2 can be referred to as the parents of X_3. This is written as $pa(X_3) = \{X_1, X_2\}$.

The conditional probability of a specific outcome of node X_3, occurring given a particular state of X_1, can be shown as $P(X_3|X_1)$. This can then be defined in Equation 3.9.

$$P(X_3 \mid X_1) = \frac{P(X_3, X_1)}{P(X_1)} \tag{3.9}$$

In a more general sense X_n can be thought of as a descendant of variable Y_n. This can now be extended into Baye's Theorem:

$$P(X_n|Y_n) = \frac{P(Y_n|X_n)P(X_n)}{P(Y_n)} \tag{3.10}$$

The variable Y_n could be set with evidence, e, and then $P(X_n|e)$ would represent the probability of X_n occurring based on e. The joint probability distribution for a BN with a universe of variables, U, can then be calculated by using the chain rule on the rearranged Equation 3.10.

$$P(U) = P(X_n|X_1,...,X_{n-1})P(X_1,...,X_{n-1}) \tag{3.11}$$

The chain rule can be extended for BN and the joint probability given by the product of all conditional probability tables to show the probability of X given its parents, $pa(X)$ [3.21, 3.22].

$$P(U) = \prod_{i=1}^{n} P(X_i|pa(X_i)) \tag{3.12}$$

3.1.3.2. Dynamic Bayesian Networks

The following definitions are based on the work of Murphy [3.13].

Dynamic Bayesian Networks are a special class of BN that incorporate a temporal dimension. A BN is produced to represent the system at each time step or 'time slice'. DBNs are typically defined as a two slice network for time t and time $t+1$. This is shown in Figure 3.8 where dashed lines represent connections through time slices for 3 times slices: $t, t+1$ and $t+2$.

The chain rule can be extended to DBNs for all $t > 1$. The variables in the first time slice, t, have no real direct temporal arcs as inputs but those in the second slice, $t+1$, may. The nodes at time t may require initialising. Separate initialising nodes can exist either in the current time slice or in $t-1$ for this purpose. If the model requires more non-real time slices then these can be defined. This allows initialising parent nodes to exist in other time slices such as $t-2$.

Figure 3.8 with variable S as the parent of X could represent a HMM [3.23]. Variable S would be the actual system state with the deterioration handled by the CPT link to

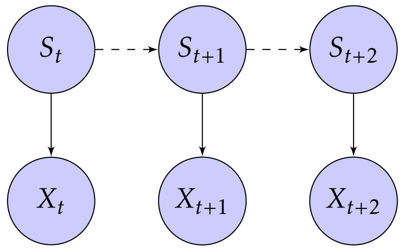


Figure 3.8.: Dynamic Bayesian Network Over 3 Time Steps

S_{t+1} and the equivalent of the two states 1 and 2 in Figure 3.3. The observable nodes, X, would be updated based on the hidden nodes and the distribution within the nodes would take the form of the emissions matrix of a HMM to determine the conditional probability of its output.

Finding the exact solution to a DBN is a nonlinear computational problem [3.24]. It can be solved using stochastic simulation. The process involves computing probability distributions for nodes without evidence and taking a random sample from that distribution.

3.1.3.3. DBNs in Literature Used to Model Deterioration

DBNs are flexible and adaptable. Different types of HMM - mixed mode, coupled and abstract HMMs - as well as Kalman filters can all be represented in a DBN format [3.13]. Nielsen and Sørensen [3.25] state that for risk based planning Bayesian methods are ideal as evidence from inspections or CM systems can be used to update the state of knowledge of deterioration. Nielsen and Sørensen in the same work extend a DBN deterioration framework to create an influence diagram representing a decision tree. This allows for decision analysis for inspection and repair actions.

Straub [3.26] uses a DBN to model stochastic deterioration and to include observations to update the probabilities of failure. This is used in two example applications: modelling crack growth using time invariant random variables and using crack growth as a truly stochastic process. Both examples show that the use of DBNs is accurate, reliable and efficient. The author claims that their DBN framework has 'a huge potential for applications in monitoring, inspection, maintenance and repair planning'.

Wang et al. [3.27, 3.28] use common DBN software tools such as GeNie and Hugin to model the deterioration of bridge elements. The authors use DBNs to simultaneously monitor several different failure modes and update the possible condition of elements based on inspection over 100 years.

Further examples of work focussing on deterioration processes utilising DBNs include [3.29, 3.30, 3.16].

3.1.3.4. Modelling Technique Selection

Both HMMs and DBNs are useful for and applicable to modelling deterioration in components. Initially, due to their simplicity, functionality and ease of use, HMMs were selected for use in the O&M models. However, as the models became more complex and interdependent DBNs became a more efficient means to solve the simulations. The greater flexibility of DBNs, as mentioned in Murphy [3.13], allows for possible future integration with other models and can be updated with observations from inspections.

3.1.4. Capturing Deterioration of Non-Structural Assemblies

A full overview of work completed in modelling the quantification of CBM is undertaken in Chapter 4. An overview of the techniques used in these studies to model the capture of deterioration by CM systems is given in this section. These techniques do not need to be used exclusively and can be combined.

In this work, it is assumed that there are four states that a CM system can operate in for non-structural assemblies. The first two would be regarded as operating normally: (1) when the system is healthy, the CM system indicates that it is healthy, and (2) when the system is deteriorating towards failure, the CM system indicates an issue. The other two possibilities are that (1) the CM system fails to observe an unhealthy system, and (2) the CM system indicates an unhealthy system when there are no issues with the assembly. For example, if a CM system is advertised as being able to observe bearing failures and the bearing in a wind turbine gearbox fails without warning then this is known as a false negative. Another example would be when the CM system indicates an issue with the gearbox and upon investigation no issue is found, known as a false positive. Together these two states are known as false alarms.

There is an important distinction to be drawn between a false negative and a non-detectable failure. In the example given above, the CM system was believed to detect bearing failures in a gearbox and it did not. If, however, it was a gear tooth that failed and the CM system offered no detection capability for that failure mode then this is a non-detectable failure.

Finally, the difference between when the CM system alerts the user of a deteriorating assembly and when the system fails is important for maintenance. The larger the time between the two the more options are available to the operator. Damage to the assembly and downtime can possibly be minimised.

3.1.4.1. Effectiveness

One of the most common methods of modelling CM systems is to use an effectiveness metric. This value is applied to appropriate assemblies and shows the percentage of failures that are observed in advance of failure of the total number of failures occurring.

This metric has been given many names: McMillan [3.31] refers to it as a failure capture probability and Wiggelinkhuizen et al. [3.32] refers to the inverse as non-detected failures.

This value is useful as it allows multiple non-perfections of the CM system to be captured simultaneously. These are failure modes that cannot be detected using the CM system installed. The effectiveness value could also include the likelihood of random incredibly quickly developing failures or those from attached auxiliary systems without CM. However, by utilising an FMEA fully and an integrated, appropriate CM system then the number of undetected failures can be very small.

A case study undertaken for a NASA space launch vehicle, Ares I, by Maul et al. [3.33] showed only 28 undetectable failure modes from a total of 567 active failure modes meaning 95% of failures were detectable for equipment in the operational phase. This was achieved using a multitude of monitoring sensors, technologies and inspections. Another interesting result of this case study was that "124 of the 189 ambiguity groups are isolatable [sic]". This suggests that the vast majority of assemblies had only one major failure mode.

Due to the high levels of funding, complexity and safety concerns of space travel, other industries are unlikely to achieve the same high level of CM effectiveness.

Once a value of this metric has been decided upon it can be inserted into the emissions matrix of a HMM in place of the E_2 value in Figure 3.3 and Equation 3.4. This would mean that when the underlying system has transitioned to state 2, it is the effectiveness metric that defines whether or not the CM system observes the failure.

Very few CM manufacturers state what they believe to be the effectiveness of their systems. In a presentation on behalf of GE Bentley Nevada, Weiss [3.34] gives possible effectiveness values - recorded as "Detection Rate" - for their ADAPT wind platform. These are shown in Table 3.1. The author also gives some of the failure modes that are detectable and states that these faults can usually be located.

Table 3.1.: CM System Effectiveness

Assembly	**Effectiveness**
Gearbox	50%
Generator	80%
Drive Train (incl. Main Bearing and Coupling)	40%

The effectiveness is also a rather blunt metric: it does not give an indication of how much damage has occurred or how much time is available before an assembly fails. The CM system might be better at detecting some failures than others - multiple failure modes may be required to be modelled with their own CM effectiveness value.

3.1.4.2. Multiple CM Systems

Multiple CM systems that observe different properties can be added to the same assembly. A common example is the combination of an oil particle sensor and vibration CM system on the gearbox assembly. This should increase the number of failure modes that can be detected or improve the probability of fault detection and hence increase the CM effectiveness value.

To model the effect of using multiple CM systems reliability theory is used. In a reliability block diagram, systems with redundancy can be expressed with subsystem

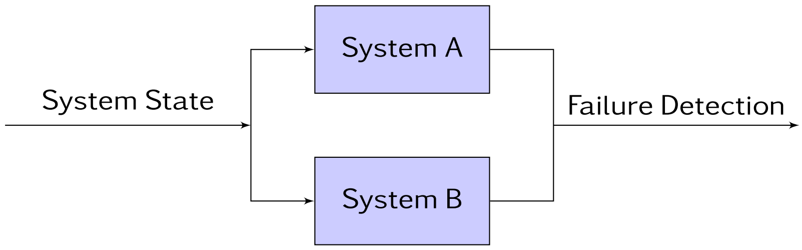


Figure 3.9.: Diagram of Parallel CM Systems

blocks in parallel like those in Figure 3.9. This implies that both subsystem A and B would need to fail in order for the overall system to fail and increases the reliability of the system [3.35].

When applying this analogy to CM systems it is not the risk of failure being calculated but the risk of non-detection. This is shown in Equation 3.13. In this equation, R_p is the overall chance of detection and R_i is the individual system detection rate.

$$R_p = 1 - \Pi R_i \tag{3.13}$$

3.1.4.3. P-F Curves

The work of Moubray [3.36] introduces deterioration in the form of P-F curves for use with Reliability Centred Maintenance. An example curve is shown in Figure 3.10 from Van Horenbeek et al. [3.37]. This figure shows a failure mode initiating at time t'. The component's condition, on the y axis, deteriorates to point P which is the first point at which the impending failure can be detected. The deterioration continues until the component fails at point F.

The definitions of both P and F are important. These terms can have different meanings to different people in different situations. The point P could refer to the point in time where it is theoretically possible to detect a fault or is mechanically possible with current CM technology. In this work it will refer to the latter. Detection is when a CM system triggers an alarm. Failure for an engineer could mean that a component has failed but that component has no effect on the operation of the asset. Likewise, a failure for an asset manager could only be when the turbine has an unscheduled stop that affects energy production. In this work, a failure is when a component has failed that requires an intervention.

Moubray states that the P-F curve can take many forms including being linear and gives examples for bearings, gearboxes and generator windings among others.

Terms to measure the effectiveness of the CM systems using the P-F curve are introduced by Van Horenbeek et al. [3.37]. The difference between the time from detection until failure, t_D, and the time until failure at point P, t_P, indicates the efficiency of the CM system, η, explained mathematically in Equation 3.14. Therefore if the failure is detected immediately at point P then η is 100% and if it is not detected before failure then η equals 0%.

$$\eta = \frac{t_D}{t_P} \tag{3.14}$$

A related detection metric is detectability, γ. This shows the probability of detection at a particular point on the P-F curve. An example with a linear detectability profile is shown in Figure 3.11. Point P in this example is 6 months before failure. Efficiency would be 100% if detected at 6 months until failure but the probability of detection is very small. Conversely, η would be 0% at 0 months to failure but the probability of detection is 100%.

The detectability at F does not need to equal 100%, nor does γ at P need to start at 0% and the detection profile does not need to be linear. Some random failures will never be detectable before failure. Some failure modes will have a large possibility of detection as soon as a defect becomes seeded and may remain fairly constant. An alternative profile is shown in Nielsen and Sørensen [3.38]. Expert opinion on detectability and effectiveness profiles has been obtained for several components and some of this information is shown in Table 3.2. Different deterioration processes are captured using CM systems in Wiggelinkhuizen et al. [3.32]. This information of deterioration and relating CM signals could be converted into further detectability profiles.

Finally, there are three zones highlighted in Figure 3.10 - A, B, and C - which are delineated by efficiency values - Threshold 1 (TH1) and Threshold 2 (TH2). These three zones represent the different stages of deterioration. An example given in Moubray [3.36] refers to a bearing which will eventually fail due to seizing through wear and

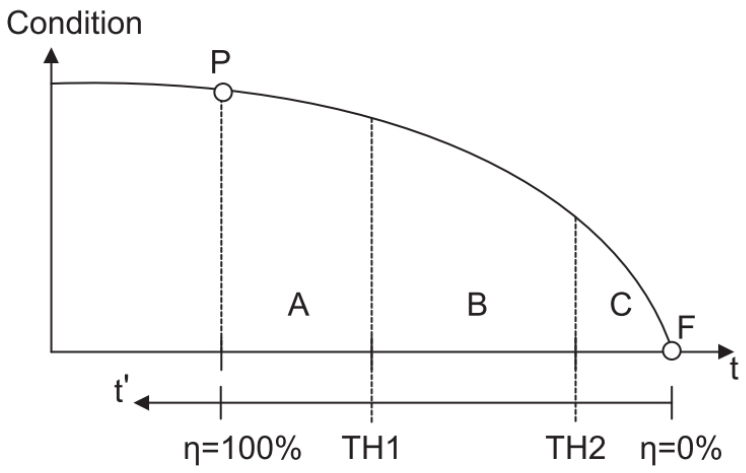


Figure 3.10.: Example of a P-F Curve [3.37]

Table 3.2.: Sample Expert Component Detection Rates

Assembly	Sub-Assembly	Months Until Failure $\gamma = 0\%$	Months Until Failure $\gamma = 100\%$
Blades	Blades	12	6
Drive train	Main Shaft	9	1
Gearbox	Lubrication	12	6
Gearbox	Lower Stage Planet Bearings	1	0

tear. For this component, the earliest stages of wear change the vibration characteristics which is observable with vibration analysis. This is shortly followed by particles of a size which is detectable by oil analysis. These two modes are in zone A where the component damage is limited and small adjustments can stop further deterioration. This will allow the component to have a full life. The damage is significant in zone B but still most likely confined to only the single component. The bearing is now producing audible signs of failure. In zone C the bearing is now producing heat. Damage to the component is severe and likely to affect others in the assembly. Failure will occur soon.

3.1.4.4. False Alarms

False alarms from CM systems have been a problem within the wind industry with Takoutsing et al. [3.39] stating that erroneous warnings and alarms occur on a regular basis. The same authors state that the number is reducing with improved smart al-

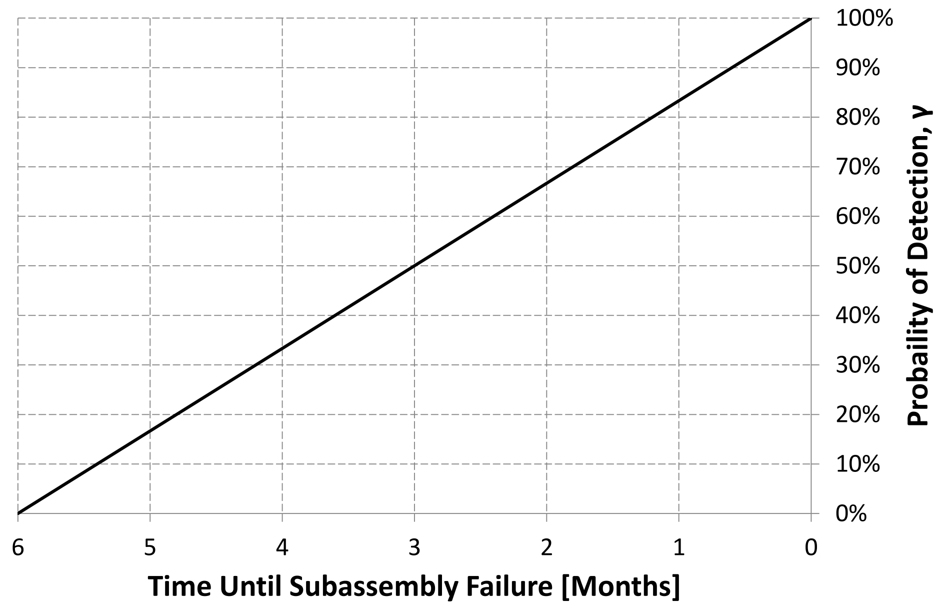


Figure 3.11.: Example of a Linear Detectability Profile

gorithm management of CM data. The exact number of false alarms has proved hard to obtain. Anecdotally, the number of false alarms is around 10% of total alarms.

The majority of false alarms are of minimal inconvenience to operators. Investigation of the alarm, such as further manual analysis of the operational data, takes place in the control room. They are quickly understood to be false and dismissed. If the alarm is for a slowly developing failure, an additional work order is added to the next serviced inspection.

There are a minority of false alarms that cannot be dismissed easily and show significant imminent faults. These require an immediate intervention from the operator. The turbine could need to be shut down. An expensive investigation may be required - such as a boroscope of the main bearing - to allow the turbine to be reinstated. In LEANWIND [3.40], the challenges with false alarms are described and it is stated that "the margin between false alarms and late detections is narrow". The implications of false alarms on the operation of turbines is investigated in Chapter 4.

Rademakers et al. [3.41], as part of the CONMOW project, model false alarms by adding additional false alarms. The total number of simulated failures was taken and 10%, 30% and 50% of this number were added as false alarms. Van Horenbeek et al.

[3.37] added up to 10 false alarms per year for the gearbox.

In the work of May and McMillan [3.42] a reliability metric was used to model false alarms. This value was used to estimate the percentage of time that the CM system spent observing the system as operational while it is operating normally. This work used HMMs where the CM reliability value was E_1 in Equation 3.4. The implications of the value of CM reliability is explored in Chapter 5.

3.1.4.5. Conclusions

If CM systems are to be modelled as accurately as possible then a large number of parameters need to be captured. Unfortunately, many of the techniques mentioned above fail to capture all of this information or require multiple uses per component to be accurate. For example, 6 failure modes are modelled by Van Horenbeek et al. [3.37] for the generator alone with 4 requiring P-F curve variables. To achieve the goal of modelling a wide array of CM operating situations as efficiently as possible, many of the techniques above will be required to be used together.

3.2. Structural Components

3.2.1. Fatigue

The Leonardo da Vinci Pilot Project [3.43] in the 2nd Handbook for the "Implementations of Eurocodes" provides insight into the difficulties of designing structural components to minimise the probability of failure. The handbook gives 6 different definitions of uncertainty that must be accounted for.

The structure has to deal with these uncertainties and sustain an appropriate degree of reliability throughout its design life. When designing for reliability it must include a definition of failure, a required service life, a probability of failure and limiting operation windows. There may be other requirements for design including for fire safety and access.

There are many different ways in which a structure can fail. These are outlined in the work of Collins and Daniewicz [3.44] and wind tower and foundation specific failure modes are given by Luengo and Kolios [3.45]. Failure modes such as yielding, buckling, fatigue crack propagation and corrosion can all contribute to an increase in the probability of failure and are explored in Dasgupta and Pecht [3.46].

Of all the failure modes mentioned above it is fatigue that is often cited as a major design concern for offshore wind turbine structures [3.47, 3.48]. This is based on a background of fatigue based failures for offshore structures, including notably the collapse of the Alexander L Kielland offshore platform in 1980 [3.49, 3.50].

Yielding is an overstress failure and can normally be discounted as it does not often have significant probabilities of failure for wind support structures [3.51]. However, if the actual operational loadings differ significantly from those predicted then this failure mode must be considered.

It is for these reasons that in this thesis the focus of structural failure is fatigue.

3.2.1.1. S-N Curves

S-N curves are often used to estimate the damage that has been accrued on structural parts. This process is a combination of S-N curves and partial safety factors that are the basis for fatigue design in the IEC standards [3.52]. Samples of material are tested to high cycle fatigue to produce the S-N curves. The number of cycles until failure at a particular stress level are recorded.

The damage estimation equation that is based on S-N curves and Miner-Palmgren's hypothesis is shown in Equation 3.15. In this equation, D is the accrued damage, n_i is the number of cycles and N_i is the number of cycles until failure for an expected nominal stress level.

$$D = \sum_i \frac{n_i}{N_i} \tag{3.15}$$

3.2.1.2. Limit State Function

The limit state function, $g(X)$, is used to define the probability of failure, where X is a set of basic variables defining the properties of the structure. The limit state function is defined so that the component is still in a favourable state when it is positive and in a failed state when it is negative. The definition of failure is an important factor in the limit state [3.50]. If the ultimate limit state of a structure is exceeded then it is likely that the structure will become unsafe and lead to collapse. If the serviceability limit state is exceeded then the structure is unsafe to continue operation but will not be at risk of collapse. Situations that may lead to unsafe operation may include excessive vibration, heat or deformation that may impact on critical non-structural components or human comfort.

$$P_f = P\{g(X) < 0\} \tag{3.16}$$

If the variables stored within X can be described by a time independent joint probability density then the probability of failure can be shown in an alternative form described below:

$$P_f = \int_{g(X)<0} \varphi(x)dx \tag{3.17}$$

This can be transformed into the reliability index, β, by taking the negative value of a standardized normal distribution of the probability of failure. The reliability index is an alternative form that is used commonly for bridge safety and other civil assets that can be updated from several variables [3.53].

$$\beta = -\Phi^{-1}(P_f) \tag{3.18}$$

These two variables, β and P_f, allow for the deterioration of a structure to be simulated over time.

3.2.2. Offshore Structure Design

There are well defined procedures to design an offshore structure to minimise the chance of fatigue failures. Offshore wind turbine structure design is covered by DNV-OS-J101 [3.54]. These combine both limit state and damage modelling.

The fatigue limit state shows a resistance of the structure, Δ, and a damage accumulation term, D. The damage is accumulated according to the stress ranges applied and the number of cycles to failure obtained from S-N curves where X is a set of random variables and the model uncertainties are given by M. The damage accumulation term is approximated in Thöns and Faber [3.55] where v is the number of stress cycles per year of service, t is the number of years in service, K represents a material property from the S-N curve from DNV-OS-J101, and $E[\Delta\sigma^m]$ is the expected fatigue stress range. The terms in this equation take account of the operating conditions of the structure - sea, humidity, weld and plate thickness among others.

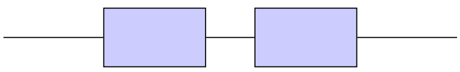
$$g(X,M) = \Delta - D \tag{3.19}$$

$$g(X,M) = \Delta - vt\frac{E[\Delta\sigma^m]}{K} \tag{3.20}$$

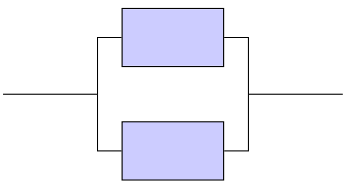
3.2.2.1. Structural System Modelling

Fatigue failure is expected to occur in locations where stress concentrations are high. These locations are often referred to as "hot spots" [3.56]. A hot spot could be where structural braces join or along welds. The limit state equation is used to calculate the probability of failure for a component. These component probabilities must be combined to give an overall probability of failure for the structure.

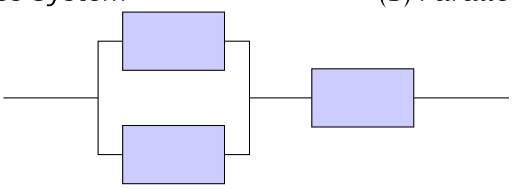
The theory of structural systems reliability is used to calculate the system or overall probability of failure for a structure. The structural system can be modelled as a logical system. This allows for a block diagram to be built of the structure's components. The different ways that a structure can be represented are (a) series, (b) parallel, or (c) mixed. Possible examples of these layouts are shown in Figure 3.12.



(a) Series System



(b) Parallel System



(c) Mixed System

Figure 3.12.: Structural System Logical Representations

The probability of failure for a series system is expressed using Equation 3.21. The probability of failure for a parallel system is expressed using Equation 3.22 [3.7].

$$P_f = 1 - \prod_{i=1}^{n}\left(1 - P_f(i)\right) \tag{3.21}$$

(a) Series System

$$P_f = \prod_{i=1}^{n} P_f(i) \tag{3.22}$$

(b) Parallel System

It is the dependencies between components that define how the system is represented. Thöns, Faber, and Rücker [3.51] define both the tower and the foundation as non-redundant structures and are therefore modelled as a series system.

The equations presented above assume no correlation between failures. However, there is likely to be some correlation for component failures - similar material properties and loading across the structure. The actual probability of failure for the system will fall between uncorrelated failure events and fully correlated failure events. These two values form the simple bounds of system reliability. If the system is fully correlated then the system probability of failure becomes the component with the maximum probability of failure for a series system [3.57]. The simple bounds of probability of failure for a series system are shown in Equation 3.23.

$$\underbrace{\max_{i=1}^{n}\left\{P_f(i)\right\}}_{\text{Full correlation}} \leq P_f \leq \underbrace{1 - \prod_{i=1}^{n}\left(1 - P_f(i)\right)}_{\text{Uncorrelated}} \tag{3.23}$$

3.2.2.2. Constant Threshold Approach

In Straub [3.50] it is the annual probability of failure that is used to determine when inspections will occur. The annual probability of failure for the year t_i, $\Delta p_F(t_i)$, is defined in Equation 3.24 where there is no repair in the period.

$$\Delta\, p_F(t_i) = \frac{P_f(t_i) - P_f(t_{i-1})}{1 - P_f(t_{i-1})} \tag{3.24}$$

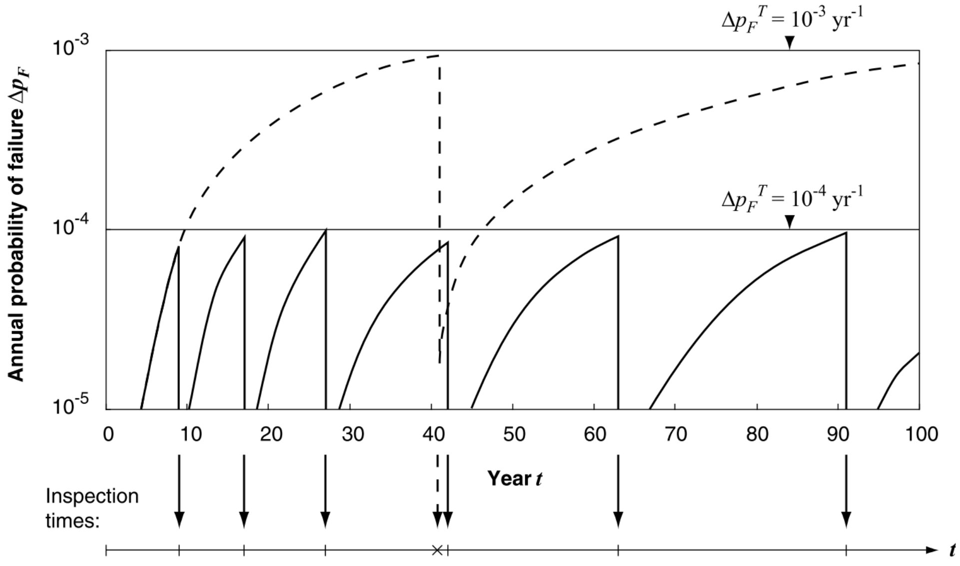


Figure 3.13.: Annual Probability of Failure for a Structure Over Time Undergoing Inspections for Two Different Safety Thresholds [3.50]

A constant threshold approach is shown in Figure 3.13 for two different thresholds, Δp_F^T, of 10^{-4} and 10^{-3}. Inspection times are chosen so that they occur before the threshold is exceeded.

The failure probabilities for the component or structure can be updated depending on the outcome of the inspection. In Moan [3.49] the fatigue failure probability of a structural joint, j, is updated based on the outcome events of an inspection, IE, shown in Equation 3.25. The inspection events could be crack depth or thickness measurements. An example is given in Moan using the results from multiple inspections - each with their own probability of detection. The results show increased reliability index values over time when the inspections indicated no crack was detected and that the coating protection had not failed.

$$P_{f,UPj} = P[(X(t) \leq\ 0)|IE_j] \tag{3.25}$$

In the figure, the lower annual probability of failure threshold results in much more frequent inspections. The information from the inspection updates the probability of failure and the resulting annual probability of failure.

3.2.3. Modelling the Impacts of SHM Systems

The use of a SHM system reduces the probability of failure as it allows for lower model uncertainties. However, it introduces its own additional measurement uncertainty. This is based on the method shown in Thöns and Faber [3.55].

The expected value of the fatigue stress, $E[\Delta\sigma^m]$, is shown in Equation 3.26. This equation is valid when using a single slope S-N curve with constant m and assumes that the long term stress ranges are Weibull distributed with scale parameter λ and location parameter k. B_σ refers to the model uncertainties which can contain information on the stress calculations, material and weld quality uncertainties.

$$E[\Delta\sigma^m] = (B_\sigma\ k)^m\,\Gamma\left(1 + \frac{m}{\lambda}; \left(\frac{s_0}{k}\right)^\lambda\right) \tag{3.26}$$

Adding a SHM system to the structure allows for the actual loading to be measured. Other parameters can also be observed: modal analysis could confirm the resistance of the structure. The expected value of the fatigue stress is updated based on the realised model parameters, $\hat{B}$, and this is shown in Equation 3.27. There is still uncertainty in the measurement values and the model uncertainty regarding the relationship between hot spot stress ranges and the strain measurements recorded by the SHM system. These are incorporated in the model with U_{HS} and $M_{U,HS}$ respectively.

$$E[\Delta\sigma^m|\hat{\boldsymbol{B}}] = \left(\hat{B}_\sigma\ M_{U,HS}U_{HS}k\right)^m\,\Gamma\left(1 + \frac{m}{\lambda}; \left(\frac{s_0}{k}\right)^\lambda\right) \tag{3.27}$$

3.3. Offshore Support Structure

3.3.1. Foundation Types

There are multiple types of foundation that are used for the deployment of offshore wind turbines and these are explored in the design codes from Det Norske Veritas [3.54]. The support structures and the methods used for attaching them to the seabed are shown below.

Fixing Method

- Piled
- Gravity-based
- Skirt & Bucket
- Moored floating

Structure Configuration

- Monopile
- Tripod
- Lattice
- Gravity
- Floating

The majority of offshore wind farms have used monopiles while those in shallower water have used concrete gravity bases. It is at water depths of 30m or greater that jackets begin to outperform monopiles and in even deeper waters floating tension leg structures will be required [3.58].

3.3.2. AREVA Wind M5000 Tripod Structure

The AREVA Wind M5000 was one of the first 5MW wind turbines deployed offshore. The M5000 is now known as the AD 5-135 and is produced by Adwen - a 50:50 joint venture between AREVA and Gamesa.

The support structure that the turbine uses is site specific. Alpha Ventus, a German offshore wind park, deployed 6 M5000 turbines using "three-legged foundation structures or tripods, fastened to the bed of the North Sea using piles" [3.59]. These were recommended because of the water depth at the site of around 30 metres. Figure 3.14 shows a diagram of the tripod foundation taken from Thöns, Faber, and Rücker.

3.3.2.1. Probabilities of Failure

A selection of the components with the highest probability of failure in the fatigue limit state for a 20 year life are shown in Table 3.3 taken from Thöns, Faber, and Rücker [3.51] and use the same segment designations in Figure 3.14. The same source gives the system failure probability 5.38×10^{-7} for uncorrelated failure events and 1.46×10^{-6} for correlated failure events with tower segment III contributing the most to the

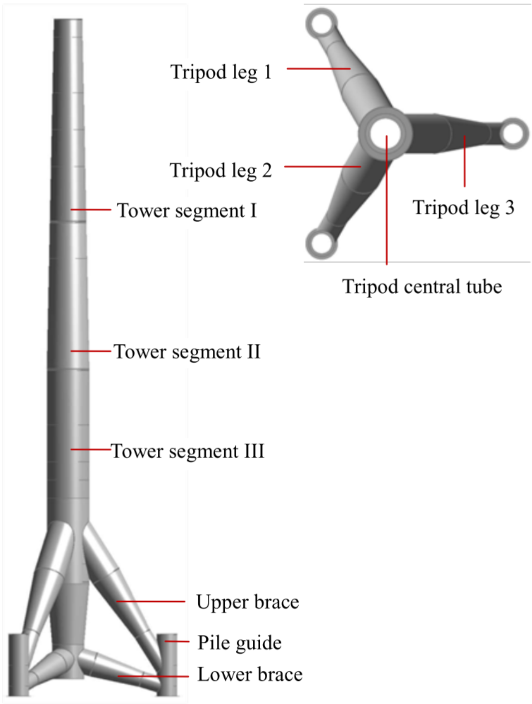


Figure 3.14.: Diagram of the Foundation of the M5000 [3.51]

probability of failure.

The change in probability of failure over time can be reconstructed from this data and using the information in the previous section. The different parameters required for Equations 3.26 and 3.19 are shown in Table 3.4. The k value is adjusted for each hotspot to produce the probability of failure value shown above for fatigue after 20 years. The k values are then kept constant and Equations 3.27 and 3.19 are used to produce the probabilities of failure for a system using SHM.

Table 3.3.: Major Component Probabilities of Failure, P_f, in the Fatigue Limit State

Segment	Component	Location	P_f
Tower I	2	Top weld, inside	1.66E-03
Tower III	8	Top weld, outside	2.47E-04
	9	Top weld, outside	1.33E-04
	10	Bottom weld, inside	1.25E-03
	11	Top weld, outside	2.40E-04
Tripod	Leg 1	Upper brace, upper kink	3.05E-04
	Leg 2	Upper brace, pile guide	3.15E-04
	Leg 3	Upper brace, pile guide	3.15E-04

Table 3.4.: Probabilistic Model of Parameters

Variable	Dim.	Distribution	Expected Value	Standard Deviation
Δ	-	LogNormal	1.0	0.3
$\ln K$	-	Normal	28.995	0.572
m	-	Deterministic	3.0	
k	MPa	LogNormal	variable	$0.2\times \mu_k$
$1/\lambda$	-	Deterministic	1.2	
s_0	MPa	Deterministic	0.0	
v	yr^{-1}	Deterministic	6.0×10^{-6}	
B_σ		LogNormal	1.01	0.12
U_{HS}		Normal	1.00	0.10
$M_{U,HS}$		LogNormal	1.00	0.05

3.4. Conclusions

In this chapter, methods for modelling the deterioration of wind turbine components and offshore structures have been investigated. Markov chains and Dynamic Bayesian Networks when used with information from reliability modelling have been used frequently to model mechanical components. It has been shown that structural components can be modelled using limit state equations to approximate the resistance and loading which can then be used to estimate the probability of failure.

How this deterioration can be captured by CM and SHM systems has also been investigated. There are an array of options that can be used to model CM systems to ensure that all the various operating states are captured. Modelling methods such as CM effectiveness or P-F curves can be used to model different information such as the time between failure and detection. SHM systems can be used to decrease the uncertainty in structural modelling.

3.5. Chapter 3 References

[3.1] E. Byon, L. Ntaimo, C. Singh, and Y. Ding. "Wind energy facility reliability and maintenance". In: *Handbook of Wind Power Systems*. Ed. by P. Pardalos, S. Rebennack, M. V. F. Pereira, N. A. Iliadis, and V. Pappu. 2011, pp. 639–672.

[3.2] Z. Ghahramani. "An Introduction to Hidden Markov Models and Bayesian Networks". In: *International Journal of Pattern Recognition and Artifical Intelligence* 15.1 (2001), pp. 9–42.

[3.3] J. Janssen and R. Manca. "Numerical Solution of non-Homogeneous Semi-Markov Processes in Transient Case". In: *Methodology and Computing in Applied Probability* 3 (2001), pp. 271–293.

[3.4] C.-A. Graubner, H. Schmidt, and D. Proske. *6th International Probabilistic Workshop*. Tech. rep. 2008, p. 582.

[3.5] S. R. Eddy. "Hidden Markov models." In: *Current opinion in structural biology* 6.3 (June 1996), pp. 361–5. ISSN: 0959-440X.

[3.6] A. K. Jardine. *Maintenance, Replacement and Reliability*. First. Pitman Publishing, 1973. ISBN: 0 273 316540.

[3.7] R. Billinton and R. Allan. *Reliability Evaluation of Engineering Systems: Concepts and Techniques*. 1st ed. Plenum, 1987. ISBN: 0-306-41296-9.

[3.8] K. Wang, F. Hsu, and P. Liu. "Modeling the bathtub shape hazard rate function in terms of reliability". In: *Reliability Engineering & System Safety* 75.3 (Mar. 2002), pp. 397–406. ISSN: 09518320.

[3.9] K. Wong and D. Lindstrom. "Off the bathtub onto the roller-coaster curve (electronic equipment failure)". In: *Annual Reliability and Maintainability Symposium*. Vol. 1. Los Angeles, CA, USA: IEEE, 1988, pp. 356–363. ISBN: 9788578110796. arXiv: `arXiv:1011.1669v3`.

[3.10] P. Ailliot and V. Monbet. "Markov-switching autoregressive models for wind time series". In: *Environmental Modelling & Software* 30 (Apr. 2012), pp. 92–101. ISSN: 13648152.

[3.11] J. D. Hamilton. *Regime-switching models*. Tech. rep. San Diego, California, USA: University of California, 2005.

[3.12] S. Singh, S. Abdullah, N. A. Nik Mohamed, and M. S. Mohd Noorani. "Markov chain modelling of reliability analysis and prediction under mixed mode loading". In: *Chinese Journal of Mechanical Engineering* 28.2 (2015), pp. 307–314. ISSN: 1000-9345.

[3.13] K. P. Murphy. "Dynamic Bayesian Networks: Representation, Inference and Learning". PhD thesis. University of California, Berkely, 2002, p. 225.

[3.14] R. Neate, P. Matthews, C. J. Crabtree, B. Kazemtabrizi, and E. Golysheva. "Optimisation of Far Offshore Wind Farm Operation and Maintenance (O&M) Strategies". In: *European Wind Energy Association Annual Conference*. Barcelona, 2014.

[3.15] J. Torres-Toledano and L. Sucar Succar. "Bayesian Networks for Reliability Analysis of Complex Systems". In: *Progress in Artificial Intelligence â€" IBERAMIA 98*. Vol. 1484. Springer, 1998, pp. 195–206. ISBN: 978-3-540-64992-2.

[3.16] H. Langseth and B. H. Lindqvist. "A maintenance model for components exposed to several failure mechanisms and imperfect repair". In: *Mathematical and Statistical Methods in Reliability* (2003), pp. 415–430.

[3.17] A. Bobbio, L. Portinale, M. Minichino, and E. Ciancamerla. "Improving the analysis of dependable systems by mapping fault trees into Bayesian networks". In: *Reliability Engineering & System Safety* 71.3 (Mar. 2001), pp. 249–260. ISSN: 09518320.

[3.18] T. D. Nielsen and F. V. Jensen. *Bayesian networks and decision graphs*. Springer, 2009. ISBN: 9780387682815.

[3.19] S. Mahadevan, R. Zhang, and N. Smith. "Bayesian networks for system reliability reassessment". In: *Structural Safety* 23.3 (Jan. 2001), pp. 231–251. ISSN: 01674730.

[3.20] H. Langseth and L. Portinale. "Bayesian networks in reliability". In: *Reliability Engineering & System Safety* 92.1 (Jan. 2007), pp. 92–108. ISSN: 09518320.

[3.21] A. Grêt-Regamey and D. Straub. "Spatially explicit avalanche risk assessment linking Bayesian networks to a GIS". In: *Natural Hazards and Earth System Sciences* 6 (2006), pp. 911–926.

[3.22] K. Nishijima, M. A. Maes, J. Goyet, and M. H. Faber. "Constrained optimization of component reliabilities in complex systems". In: *Structural Safety* 31.2 (Mar. 2009), pp. 168–178. ISSN: 01674730.

[3.23] Z. Ghahramani. "Learning dynamic Bayesian networks". In: *Adaptive processing of sequences and data structures* (1998).

[3.24] T. Hrycej. "Gibbs sampling in Bayesian networks". In: *Artificial Intelligence* 46.3 (Dec. 1990), pp. 351–363. ISSN: 00043702.

[3.25] J. J. Nielsen and J. D. Sørensen. "Bayesian networks as a decision tool for O&M of offshore wind turbines". In: *ASRANet: Integrating Structural Analysis, Risk & Reliability*. 1. Edinburgh, 2010, pp. 1–8.

[3.26] D. Straub. "Stochastic modeling of deterioration processes through dynamic Bayesian networks". In: *Journal of Engineering Mechanics* 135.10 (2009), pp. 1089–1099.

[3.27] R. Wang, L. Ma, C. Yan, and J. Mathew. "Structural reliability prediction of a steel bridge element using Dynamic Object Oriented Bayesian Network (DOOBN)". In: *Proceedings of International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering*. IEEE, 2011, pp. 7–12.

[3.28] R. Wang, L. Ma, C. Yan, and J. Mathew. "Condition deterioration prediction of bridge elements using Dynamic Bayesian Networks (DBNs)". In: *2012 International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering*. Ieee, June 2012, pp. 566–571. ISBN: 978-1-4673-0788-8.

[3.29] H. Boudali and J. Dugan. "A discrete-time Bayesian network reliability modeling and analysis framework". In: *Reliability Engineering & System Safety* 87.3 (Mar. 2005), pp. 337–349. ISSN: 09518320.

[3.30] P. Weber and L. Jouffe. "Reliability modelling with dynamic bayesian networks". In: *5th Symposium on Fault Detection, Supervision and Safety of Technical Processes*. Washington, D.C., USA, 2003.

[3.31] D. McMillan. "Techno-Economic Evaluation of Condition Monitoring and its Utilisation for Operation and Maintenance of Wind Turbines using Probabilistic Simulation Modelling". PhD thesis. University of Strathclyde, 2008, p. 262.

[3.32] E. Wiggelinkhuizen, T. Verbruggen, H. Braam, L. Rademakers, J. Xiang, and S. Watson. "Assessment of Condition Monitoring Techniques for Offshore Wind Farms". In: *Journal of Solar Energy Engineering* 130.3 (2008). ISSN: 01996231.

[3.33] W. Maul, K. Melcher, A. Chicatelli, and S. Johnson. "Application of diagnostic analysis tools to the ares I thrust vector control system". In: *AIAA Infotech at Aerospace 2010*. April. Atlanta, Georgia, US, 2010. ISBN: 9781600867439.

[3.34] A. Weiss. "Condition Monitoring - Case Histories". In: *AWEA Windpower 2012*. 2012.

[3.35] P. J. Tavner. *Offshore Wind Turbines - Reliability, availability and maintenance*. 1st. The Institute of Engineering and Technology, 2012. ISBN: 978-1-84919-229-3.

[3.36] J. Moubray. *Reliability-centred Maintenance*. Butterworth Heinemann, 1993. ISBN: 9780750633581.

[3.37] A. Van Horenbeek, J. Van Ostaeyen, J. R. Duflou, and L. Pintelon. "Quantifying the added value of an imperfectly performing condition monitoring system: Application to a wind turbine gearbox". In: *Reliability Engineering & System Safety* 111 (Mar. 2013), pp. 45–57. ISSN: 09518320.

[3.38] J. J. Nielsen and J. D. Sørensen. "On risk-based operation and maintenance of offshore wind turbine components". In: *Reliability Engineering & System Safety* 96.1 (Jan. 2011), pp. 218–229. ISSN: 09518320.

[3.39] P. Takoutsing, R. Wamkeue, M. Ouhrouche, F. Slaoui-Hasnaoui, T. Tameghe, and G. Ekemb. "Wind Turbine Condition Monitoring: State-of-the-Art Review, New Trends, and Future Challenges". In: *Energies* 7 (2014), pp. 2595–2630. ISSN: 1996-1073.

[3.40] A. Valland and V. G. B. Pedersen. *Industry Challenges Report – O&M*. Tech. rep. D4.1. LEANWIND, 2014.

[3.41] L. Rademakers, E. Wiggelinkhuizen, G. Giebel, T. Verbruggen, S. Watson, J. Xiang, E. Norton, M. Tipluica, A. Christensen, and E. Becker. *CONMOW Final Report*. Tech. rep. Energy Research Centre of the Netherlands, 2007, p. 72.

[3.42] A. May and D. McMillan. "Condition Based Maintenance for Offshore Wind Turbines: The Effects of False Alarms from Condition Monitoring Systems". In: *ESREL 2013*. Amsterdam, 2013.

[3.43] Leonardo da Vinci Pilot Project. *Implementation of Eurocodes - Handbook 2*. Tech. rep. Prague, 2005.

[3.44] J. Collins and S. Daniewicz. "Failure Considerations". In: *Mechanical Engineers' Handbook*. 1998. Chap. 18, pp. 377–396. ISBN: 0471130079.

[3.45] M. Luengo and A. Kolios. "Failure Mode Identification and End of Life Scenarios of Offshore Wind Turbines: A Review". In: *Energies* 8.8 (2015), pp. 8339–8354. ISSN: 1996-1073.

[3.46] A. Dasgupta and M. Pecht. "Material failure mechanisms and damage models". In: *IEEE Transactions on Reliability* 40.5 (1991), pp. 531–536. ISSN: 00189529.

[3.47] A. Muhammad and M. Ristow. "Fatigue Life of Wind Turbine Structural Components". In: *NAFEMS Seminar: "Simulation-based Fatigue and Lifetime Predictions"*. 2010, pp. 1–7.

[3.48] W. Dong, T. Moan, and Z. Gao. "Fatigue reliability analysis of the jacket support structure for offshore wind turbine considering the effect of corrosion and inspection". In: *Reliability Engineering & System Safety* 106 (Oct. 2012), pp. 11–27. ISSN: 09518320.

[3.49] T. Moan. "Reliability-based management of inspection, maintenance and repair of offshore structures". In: *Structure and Infrastructure Engineering* 1.1 (Mar. 2005), pp. 33–62. ISSN: 1573-2479.

[3.50] D. Straub. "Generic Approaches to Risk Based Inspection Planning for Steel Structures". PhD thesis. ETH Zurich, 2004, p. 247.

[3.51] S. Thöns, M. H. Faber, and W. Rücker. "Support Structure Reliability Of Offshore Wind Turbines Utilizing an Adaptive Response Surface Method". In: *29th International Conference on Ocean, Offshore and Arctic Engineering*. Shanghai, China: ASME, 2010.

[3.52] International Electrotechnical Commission. *IEC 61400-1 Wind Turbines*. 3rd ed. Geneva, Switzerland, 2005. ISBN: 2-8318-8161-7.

[3.53] D. Frangopol, J. S. Kong, and E. S. Gharaibeh. "Reliability-based life-cycle management of highway bridges". In: *Journal of Computing in Civil Engineering* January (2001), pp. 27–34.

[3.54] Det Norske Veritas. *DNV-OS-J101 Design of Offshore Wind Turbine Structures*. 2011.

[3.55] S. Thöns and M. H. Faber. "Assessing the value of structural health monitoring". In: *Safety, Reliability, Risk and Life-Cycle Performance of Structures and Infrastructures*. Ed. by G. Deodatis, D. Frangopol, and B. R. Ellingwood. Taylor & Francis, 2013, pp. 2543–2550. ISBN: 9781138000865.

[3.56] C. Sundararajan, ed. *Probabilistic Structural Mechanics Handbook*. Springer, 1995. ISBN: 978-1-4613-5713-1.

[3.57] S. Thöns. "Monitoring Based Condition Assessment Of Offshore Wind Turbine Support Structures". PhD thesis. ETH Zurich, 2011, p. 150.

[3.58] The Crown Estate. *A Guide to an Offshore Wind Farm*. Tech. rep. 2010.

[3.59] AREVA. *Offshore Windpower - M5000*. 2011.

CHAPTER 4

Modelling Wind Park Costs

In this chapter an examination of existing work on quantifying the cost benefit of condition monitoring equipment is conducted. This is initially analysed generally followed by a closer focus on the wind industry. The analysis of these works is used as a basis to then define a cost model that is presented in the second part of this chapter and used in this thesis.

4.1. Overview of Existing Cost Benefit Analysis on Condition Monitoring

In this document, the terms "wind farm operator" and "wind farm owner" have been used interchangeably. This is because often they are both and are known as "owner-operators". A wind farm operator is the organisation responsible for the management of the wind farm - they are responsible for the energy yield, O&M and administration. They may outsource the O&M to a third party. An owner owns the assets and is focussed on the long term yield, asset safety and ensuring a return on investment. A service provider is a third party organisation that may provide a range of services to either the owner or operator such as O&M services.

The ultimate aim of wind farm operators is to maximise profits. Profit is derived from the obtained revenue after OPEX has been deducted. Therefore the operator seeks to maximise revenue and to minimise the operation costs. The initial capital costs that are incurred when using condition monitoring equipment threaten these two goals unless they can be proven to offer lifetime reductions in operation costs.

A wind farm owner may wish to use an offshore turbine where a CM system is included as standard by an OEM or make the purchasing decision to add additional CM/SHM systems. However, it is how the operator integrates these systems into their maintenance plan that will determine how OPEX can be minimised. For example, if a service provider has no liability for poor weather days - days where turbines cannot be accessed due to high sea states or winds - then there is no incentive to use the output from the CM system to take maintenance actions in periods of calm weather other than annual services. This can be addressed with appropriate contractual obligations such as energy based PBMCs discussed in Chapter 2.

The following section examines the existing literature associated with quantifying benefits for condition based maintenance plans. It is displayed graphically in Appendix B.

4.1.1. Generic Condition Based Maintenance Plan

Grall et al. authored two papers [4.1, 4.2] examining maintenance plans using gamma processes for a large range of mechanical equipment and civil structures. Gamma processes are stochastic deterioration accumulating processes where events occur randomly, independently of each other and are non-negative - examples could be emails arriving in an inbox or in this case damage accruing on a component. The time or distance interval between events (sometimes referred to as arrival time) is a continuous random variable defined by a gamma distribution. Gamma processes themselves and their applications to deterioration are surveyed by van Noortwijk [4.3]. This work states that gamma processes are suitable for a wide range of deterioration processes with gradual increments - "wear, fatigue, corrosion, crack growth, erosion, consumption, creep, swell, degrading health index" among others.

In Grall et al. [4.1] inspections are used to determine the current state of a 1-

dimensional system. The paper offers a methodology to establish appropriate inspection windows and warning thresholds for taking corrective action. A lifetime cycle costs (LCC) model is used to obtain the total maintenance costs using the possible physical deterioration parameters of the system, the relative costs of maintenance and inspection costs. In the paper, repair, inspection and preventative actions are all assumed to take negligible time to complete. This makes it unsuitable for the high periods of downtime associated with offshore wind turbines.

This is addressed in Grall et al. [4.2] which investigates a generic continuously monitored system. A term for delay time until a maintenance action occurs is introduced. An additional gamma process is used to represent the stochastic delay and the new failure rate is calculated. The study shows that increasing the alarm threshold increases the overall failure rate for the components.

Van der Weide, Pandey, and van Noortwijk [4.4] simulate components in a safety critical situation for the nuclear industry. Both homogeneous and non-homogeneous Poisson processes are used to simulate shock or transient loading which, similar to gamma processes, are accumulating stochastic processes where the arrival time is often described using an exponential distribution. Homogeneous Poisson processes have a constant mean value of damage over time. Non-homogeneous Poisson processes have a variable mean value over time [4.5]. The shocks produce a random amount of damage and these are summed until a damage threshold is exceeded that triggers preventative maintenance.

The authors examined the effects of varying an alarm threshold for an inspection plan and a maximum allowable age. The plans were then optimised to minimise maintenance costs. The results showed that the maintenance costs can be reduced with the use of CBM. The maximum savings occur when removing the upper age limit on the component. Components in a nuclear environment are replaced when reaching a maximum allowable age, regardless of condition. As wind turbines are not regarded as safety critical as nuclear systems so upper age limits are not normally considered for components. However, parts such as bearings and valves may be changed during services.

Gamma processes and Poisson processes are well used by both civil and mechanical engineers. Straub describes the Poisson process as "arguably the most important process in risk analysis" [4.5]. Poisson processes have been used to model failure occurrences in many fields including wind in the work of Byon et al. [4.6] and Tavner, Xiang, and Spinato [4.7]. This relates to the survivor functions as discussed in Chapter 2. Poisson processes have been used to represent loadings, shocks, and transients on systems - van Noortwijk et al. [4.8] uses Poisson process to simulate loading only when the loads are larger than a threshold value as the "Poisson assumption is ... better justified". The loading is used as an input to a gamma process to represent the deterioration of a structural system. The work of Pandey, Yuan, and Noortwijk [4.9] compares a gamma process to a random variable process for the replacement and ageing of structural components. The authors find that the gamma process is more versatile and more conservative over a long term horizon.

Bouvard et al. [4.10] uses a gamma process to deteriorate components in a heavy commercial vehicle. A maintenance profile is developed with the aim of obtaining an availability goal. Individual components are scheduled for replacement and these actions are grouped into sets to ensure that vehicle services are a minimum time apart. The condition of other major components are inspected during other services.

A penalty cost function was introduced to account for servicing costs and to assess the value lost in removing components before their remaining useful life has been reached. An updating algorithm shuffles maintenance groups to minimise the cost. The results of the study showed a decreasing penalty cost with increasing service interval until an optimal inspection window is reached. After this point a rapid increase in costs is seen. The framework presented in this paper is of great use in setting up servicing plans for a fleet of assets. However, downtime costs are accounted for in the model not in time but are associated with the value of components. Importantly in a wind turbine context, the monitoring/inspection cost is not included in the model.

Van Horenbeek, Pintelon, and Muchiri [4.11] perform a wide study of the literature on maintenance optimisation models. The authors found that most focused on a small number of optimisation factors - such as availability, costs or spares levels. The authors consider all of those factors and highlight what they believe to be the most important ones for business maintenance optimisation for those developing further models.

Van Horenbeek and Pintelon [4.12] build on this knowledge to develop a dynamic predictive maintenance policy for complex systems. A gamma process is used to simulate the degradation of components. A long term static maintenance plan is updated based on the different goals including: grouped maintenance actions, calendar, inspection and continuous condition based plans. The study found that group and age based maintenance policies outperformed condition based maintenance when there were high dependencies between components - that is the health of one component is related to the health of others. However, the inverse was true for systems with low interdependencies between components. If possible it would be helpful to integrate this knowledge into the modelling of wind assets. The paper states that knowledge about dependencies will be gained throughout the life of the system and suggests future work might investigate system dependencies.

These generic maintenance plans show methods for: component deterioration; how to model system failures; detection or inspection thresholds; repair actions; and how these can be combined together with costs. There are many parts of these models that are applicable to the wind industry. However, in the majority of these other cases access for maintenance is not as limited as it is for wind. Nuclear industries have dedicated on site maintenance teams and commercial vehicles can attend a service depot whenever necessary. This hindrance to the maintenance of wind turbines will need to be modelled with specific plans.

4.1.2. Wind Specific Condition Based Maintenance Plans

One of the initial studies into the benefits of switching from either a failure based maintenance plan or a service interval plan to a reliability centred plan using CM systems is the work by Andrawus et al. [4.13]. An FMEA is performed on the turbine to ascertain the major failure modes and its effects. Failure data is obtained from analysing failure logs and work orders from 26 onshore turbines that are 600 kW in size. Two lifetime cycle cost analyses are performed - for PBM and for CBM. Mechanical failures with observable long term trends indicating the onset of failure are assumed to be captured by applicable CM hardware. Monte Carlo simulations are used to assess variables and risks. The results showed that levelised CBM offers savings of £180,152 compared to TBM over 18 years, comprised of savings in labour, access and materials. CM systems rarely capture all failure events in advance with enough confidence in order for decisive maintenance actions to be modelled in accordance with this study. Additionally, the systems produce false alarms that are not accounted for in this work.

A similar approach is taken by Besnard, Nilsson, and Bertling [4.14]. A life cycle cost model determined that by integrating a CM system into a maintenance plan produced a levelised saving of € 190,000 for one 3 MW turbine. The savings were observed for lost production, maintenance costs, and repair costs. Failure rates in the model are determined from using Weibull distributions and vary over the lifetime of the turbine. Discrete values are chosen during a Monte Carlo simulation. The ability of the CM system to identify faults is given as an 'efficiency' which reduces the amount of corrective action by increasing the preventative maintenance actions. Consequential (secondary) damage is also reduced. This methodology uses many efficiency parameter assumptions, does not include false alarms and assumes that the CM system detects all faults equally.

The work in [4.14] is built upon previous work from Nilsson and Bertling [4.15] and case studies in the thesis of Ribrant [4.16]. Ribrant builds a failure database from surveying available statistics and work orders for wind farms in northern Europe. The author also highlights the importance of the wind turbine gearbox and the capabilities of condition monitoring systems for wind turbines of detecting faults (this final point is explored more thoroughly in Walford and Roberts [4.17]).

Nilsson and Bertling uses a LCC model to compare several maintenance strategies to assess the level of reduction in repair actions or increases in availability necessary to obtain return on investment from adding CM systems. A 4.5% reduction in unnecessary scheduled maintenance would be required to cover the cost of CMS for a wind farm. If corrective maintenance actions are included then this number drops to 3.5%. In one strategy, major components from turbines are replaced simultaneously due to predictions from CMS. This leads to a reduction in logistics costs of €230,000 over the 20 year lifetime of a 30 turbine wind farm.

McMillan and Ault [4.18] use a Monte Carlo simulation to generate a wind time series, a related turbine energy yield and simulate component failures. The downtime of a turbine due to failure or maintenance will cause a reduction in yield. The turbine's systems are represented by either a two or three state Markov chain.

Risk is used to create a condition based maintenance strategy. A priority list for components is constructed giving wait times, in days, which are set based on impact and probability. This was used to create a LCC compared to a periodic maintenance strategy.

The condition of the components was taken from the simulated Markov state. An LCC was produced to compare between the CBM and periodic maintenance for one 5 MW offshore turbine. An effectiveness coefficient was added to the state condition output so that the number of faults detected by CM systems were reduced. The results of the paper showed an increase in availability and revenue and a decrease in failure rates. The costs of operations and maintenance actions were estimated as £30,000 per year which equates to an annual benefit of £75,000 for using a CBM plan when the CM system is 100% effective. The benefit ceases to exist when the system effectiveness reduces to 60% - therefore the more expensive a CM system is, the more effective it must be.

Wiggelinkhuizen et al. [4.19] at the ECN in the Netherlands produced the CONMOW study investigating whether integral condition monitoring could be cost effective. Several monitoring systems were added to five N80 wind turbines and high frequency and SCADA data was taken and analysed. They showed that this data and oil particle monitoring can be used for prognostic purposes for major failure classes found during an FMEA.

This information is used in ECN's simulation tools produced by Braam et al. [4.20]. The tool generates Monte Carlo years for three types of failure - random, calendar and condition. When a failure occurs a repair is scheduled and the turbine remains non-operational until the full repair is completed. A suitable weather window is searched for and selected then an appropriate vessel chosen to conduct the repair and the availability of the resources checked.

In the Wiggelinkhuizen et al. study, the failure modes that can be detected using CM systems are given percentages of non-detected failures that are classed as 'random' and detected failures that are classed as 'condition'. The quality of the system is also quantified with the addition of false alarms as a percentage of overall failures. The results showed a reduction in revenue losses for 20% non-detected failures with 10% false alarms of 14.5%. This decreased to around 0.5% with 60% non-detected failures and 50% false alarms.

Sørensen [4.21] shows a framework for developing O&M plans for the maintenance of offshore wind turbines using a range of inspection techniques including CM systems. Bayesian decision analysis is used to complete optimisation of the plans that utilise a risk and probability of failure method to obtain costs. The large uncertainties in the probability of failure for fatigue, corrosion, wear and erosion are reduced with the use of inspections.

Two examples are given showing the possible applications of the model. In the first, a gearbox has several damage modes with different deterioration methods and various inspection techniques - each of which give the condition of the gearbox to a certain reliability. Examples of how the decision model could be set to optimise the maintenance plan depending on the level of information available about the system are given. In the second example, limit states are used in a fatigue critical structural system to determine the optimum inspection model. The design criteria of offshore structures are used and the uncertainties reduced with inspections over time to give the probability of failure in the structure. A crack model is introduced for the inspection plan.

Van Horenbeek et al. [4.22] examine the value of a CMS for a wind turbine gearbox that is imperfectly performing in an influential work for this thesis. A P-F curve, based on the work of Moubray, is used as a method to quantify the effectiveness of CM systems. The efficiency of a CMS is defined as the difference in time between a fault being observable and it being observed. It is assumed that as a fault progresses towards failure, it becomes easier to detect. Expert opinions are used to estimate these values.

An FMEA is performed that identifies key failure modes for the gearbox and the ease with which they are detected as they develop. This allows consequential damage to be accounted for. From this an LCC was conducted to ascertain any value added. One of the interesting components of this LCC is that it includes the value of the metal used in the turbine at the end of the turbine's life. False alarms for different failure modes are added to the LCC as a set number per year. The simulations consist of Monte Carlo sampling of failure rates and access costs.

The results of the study shows a mean added value of €46,114 per turbine over the lifetime of 20 years and added value in approximately 60% of cases. The CMS adds value at 19.5% detectability and until more than 5 false alarms are triggered each year.

More recently this field has been investigated in the work of Netland et al. [4.23] and Williams, Crabtree, and Hogg [4.24].

The work of Netland et al. uses not only a standard vibration CM system but also a robotic remote inspection system consisting of a camera and microphone to work alongside.

The wind farm is modelled to the turbine level and there are four failure categories for the turbine - minor, medium, major (repair) and major (replacement). All failures that fall within the category of medium or greater require inspections beforehand lasting three hours.

Three different maintenance strategies are investigated - corrective, condition based and condition based with remote inspection capabilities. Adding the CM system was assumed to reduce work duration and the equipment needed for each failure category. There is a 70% chance that the CM system will provide a 10 day warning for the lower failure classes and 20 days for the major. False alarms and sensor failures are included.

The model is solved by simulation. The results show an improvement of around 6% in the CM case over a corrective maintenance plan and an 8% improvement using remote inspection as well. The authors conclude that there are economic benefits of using remote inspection as well as CM systems.

The modelling of the CM system is quite simple in this case but appropriate and effective for the authors' goal.

Williams, Crabtree, and Hogg is one of the few deterministic solutions examined.

Onshore failure data is used for assemblies in the WMEP taxonomy and there are 3 failure modes specified - minor, major and catastrophic. CM systems are used to decrease the severity of the failures. 75% of catastrophic faults are assumed to be reduced to major and 25% of the major faults are reduced to minor when a CM system is used. Additionally, there are variables to account for access and incorrect detection. False alarms are assumed to occur at 10% of the minor fault rate for the assembly.

The results of the study show the cost of energy to be £95 per MWh using a corrective based maintenance strategy and £91 per MWh with a condition based maintenance strategy. However, the authors highlight that the model predicts an O&M contribution to CoE of 11% but the authors would expect it to be a minimum of 15%. The model incorporates many important factors in ascertaining the cost of a maintenance strategy but the CM system has again been modelled with simple variables and uniformity across all assemblies. The cost model used in this paper is quite similar to the one described below.

Applicable studies have been combined below in Table 4.1 for comparison - showing the stated CBM savings and a lifetime savings per installed MW. Most of the costs displayed are levelised costs and this makes it difficult to produce an average annual saving. The study with the first author Wiggelinkhuizen only includes lost production values and the Van Horenbeek study only examines a gear box.

4.1.3. Structural Integrity Maintenance Plans

There is much work dedicated to structural integrity maintenance plans and some of these plans are included in the generic condition based maintenance plans. However, often these plans use manual inspections and do not include data from condition monitoring or structural health monitoring systems. The previous wind specific condition based plans did include information from CM systems but these were exclusively used on the mechanical or energy generating components. This section examines the works available for structural integrity plans involving SHM systems.

Inaudi [4.25] uses commercial experience to identify several situations where structural health monitoring (SHM) systems can offer ′immediate, near-term and long-

Table 4.1.: Overview of Cost Benefit Literature

First Author	Offshore	No of Turbines	Turbine Size [MW]	Lifetime [Years]	Stated CBM Savings	Lifetime Savings per MW
Andrawus [4.13]	N	26	0.6	18	£180,152	£11,548
Besnard [4.14]	N	1	3	25	£148,181	£49,393
McMillan [4.18]	Y	1	5	1	£76,784	£15,356
Wiggelinkhuizen [4.19]	Y	100	2.5	1	£791,598	£3,166
Van Horenbeek [4.22]	N	1	3	20	£35,987	£11,996
Williams [4.24]	Y	100	3	20	£2,750,000	£9,167

Y = Offshore, N = Onshore

term′ cost benefits. The author neatly describes the different benefits that can be created by integrating SHM into a structure and gives a potential qualitative procedure for developing a cost benefit optimisation. The examples given are mostly from building construction or bridge management but the procedures discussed are generic.

The same principles are used in Smarsly, Law, and Hartmann [4.26] to examine the benefits of integrating SHM into ′life-cycle maintenance′ (LCM). These are found to be mostly positive - including increased knowledge of operation and reduced uncertainties of loads and resistance - for a 500 kW turbine but no exact costs are given.

One of the few articles explicitly dealing with the quantification of cost benefit with the use of SHM is provided by Thöns and Faber [4.27]. In the authors′ simulations, SHM systems are placed on key hot spots with the highest probability of failure on an offshore wind structure. The knowledge of the stress values that are gained through the SHM is used to update the design equations and recalculate the probability of failure for the hot spot. This value is used to determine an appropriate inspection and maintenance plan.

Different SHM strategies were implemented with strain gauges placed in various amounts on and around the 3 hot spots. The results showed that SHM can deliver return on investment when the hot spots are measured directly. This value is maximised when the allowable probability of failure threshold was increased compared to the original design value. Limited benefit was seen when the structure had properties that allowed it to perform exactly as designed. A poorly designed SHM strategy which saw sensors placed far from the active hotspots incurred increased costs.

This work relies on utility and decision theory to derive the 'value of information' (VoI) that SHM has. The VoI is obtained from comparing the life cycle costs for different strategies - often described as in Equation 4.1 where B_0 is the lifetime cost *benefits* when deciding not to implement SHM and B_1 is the lifetime cost *benefits* expected when deciding to implement SHM. Interestingly, B_1 varies depending on the choice of SHM strategy and each strategy has uncertainty associated with it. This allows for the expected lifetime benefits to be realised and the optimal solution for Equation 4.1 is one where B_1 is maximised.

$$VoI = B_1 - B_0 \tag{4.1}$$

The work of Thöns in quantifying the value of SHM has continued using this integration of deterioration modelling and the value of information. In the work of Thöns, Schneider, and Faber [4.28], the authors present an approach for assessing the VoI for steel structures experiencing fatigue deterioration. A case study for a Daniels system is completed and shows that the approach allows for the optimisation of SHM strategies and the majority of the benefits come from reduction in system risk. A Daniels system is a theoretical system where a member is suspended from independent, identical fibres. Faber, Val, and Thöns are currently expanding and developing a theoretical framework that allows for the VoI to be determined for a wide range of structural systems [4.29].

4.1.4. Conclusions

Much work has been conducted into condition based maintenance and optimising operation and maintenance plans. Different processes - gamma [4.10], Poisson [4.4] and Markov chains [4.18] - have been used to simulate deterioration in components and structures. These are combined with lifetime cost models that investigate different aspects of assigning value to actions and assets - including such techniques as risk, expected benefit and remaining useful life.

The frequency of updating condition indicators varies widely across the work. In some studies - notably for structures - inspections are carried out on a greater than biennial schedule with the intention that corrective actions be carried out even less frequently. In other work, the condition indicators are constantly monitored thereby significantly reducing the physical inspection activities.

The methods for evaluating how much maintenance can be saved with real time condition monitoring systems also varies across the works. Many use an 'effectiveness' value [4.18, 4.30], in effect a percentage of the total faults that were captured by the condition monitoring system. Others use reduction in probability of failure [4.21, 4.31] to achieve this. One of the most complex solutions is the P-F curve [4.22]. This method of modelling can be used to show an increasing likelihood of detection as a fault progresses, similar to real systems. However, the information required to accurately use this technique is based on expert judgement which is hard to obtain. The different values used to represent the capabilities of the CM systems are shown in Table 4.2.

Structural components are modelled in a different way to that of rotating or energy generating components due to the different natures of the components. The major work in this area [4.27] uses a risk based method to generate the possible cost benefits and a limit state approach to assess the accruing damage.

Likewise little work has been done to quantify the benefit of using or developing a holistic wind turbine monitoring system. While work has shown that individual systems for components offer reductions in and of themselves - this is documented well in Thöns and McMillan [4.31] - there has been little work exploring the benefits of a combined system. This could offer the possibility of reducing O&M costs further and increasing revenue with complete management of spare parts, grouping of maintenance actions or inspections. A model documenting any of these possible benefits would be complex but demonstrate any advantages or disadvantages to wind park operators.

Table 4.2.: CM Parameters Used in Literature

First Author	CM Type	Detection	False Alarms	Notes
McMillan [4.18]	E	40% to 100%	-	False alarms may be analysed de facto in varying operating costs.
Wiggelinkhuizen [4.30]	E	40% to 80%	10% to 30%	False alarms added as a percentage of total alarms.
Sørensen [4.21]	I	-	-	A deterioration model is coupled with an inspection model to reduce probability and the uncertainty in that value.
Van Horenbeek [4.22]	P-F	100%, 70% and 0%	0 to 10	6 failure modes analysed for gearbox only with P-F curve. 100% detection for 3 failure modes and 70% for 1. False alarms added per year.
Netland [4.23]	E	70%	50%	70% refers to probability of detection 10 days before a minor or medium failure and 20 days before a major. 50% of all alarms are false.
Williams [4.24]	E	0 to 100%	10%	A range of values representing the reduction of fault classification. Two different independent percentages for Catastrophic to Major and Major to Minor. 10% of minor fault alarms.
Thöns [4.27]	I	-	-	SHM reduces uncertainty and different aspects are modelled - SHM strategies, uncertainty, and decision rules.

E = CM Effectiveness, P-F = P-F Curve, I = Improvements in Modelling

4.2. O&M Model Requirements

The previous sections have examined the components necessary to develop cost models for assessing different maintenance models. The following section shows and explains the cost models that have been selected for use in this work.

4.2.1. Component Replacement

When a failure occurs in an assembly there will be a cost to replace the damaged and failed components. This cost depends on the magnitude of the failure and consequential damage caused by the failure on surrounding components and sub-assemblies, C_f. The cost of replacement parts, C_{RP}, are summed for each subsystem, k, as seen in Equation 4.2.

If the failure is detected in advance by the CM system then in some cases the replacement costs, C_{fC}, can be lowered if the damage is less severe. This alternate cost, C_{RPC}, is shown in Equation 4.3.

$$C_{RP} = \sum_{i=1}^{k} C(i)_f \tag{4.2}$$

$$C_{RPC} = \sum_{i=1}^{k} (C(i)_f + C(i)_{fC}) \tag{4.3}$$

4.2.1.1. Secondary Damage

If a component is allowed to reach the final zones of failure with a P-F curve as described in Chapter 3 without intervention from the operator then there is a chance that the surrounding components, sub-assemblies and assemblies will get damaged. This phenomenon is often referred to as consequential or secondary damage [4.22, 4.32]. A good explanation of secondary damage is given below.

> *"A new gearbox may cost upwards of £60,000 whilst reconditioning the same gearbox, should a defect be found in time, may cost just £15,000. Aside from the generator, all other major components have significantly smaller cost implications, typically at least*

an order of magnitude less."

- Sinclair Knight Merz [4.33]

Table 4.3.: Risk Based Reduction in Component Costs from CM System

Replacement Action	**CM Savings**	**Failure Rate**	**CM Effectiveness**	**Total Savings**
Gearbox	$80,000	3%	50%	$1,200
Gearbox Refurbishment	$80,000	38%	50%	$15,200
Generator	$30,000	5%	80%	$1,200
Main Bearing	$20,000	18%	40%	$1,440
Generator Refurbishment	$30,000	10%	80%	$2,400
Gearbox Stage Replacement	$10,000	35%	50%	$1,750
Total				$23,190

It is the commercial literature rather than the academic that contains more examples of secondary damage. Weiss [4.34] uses the information contained in Table 4.3 to arrive at an average risk based figure of $23,190 for a 2.3 MW GE turbine from using a CM system. The savings from the CM system are multiplied by the failure rate and effectiveness value to give a total saving. These savings are added together. It is not stated in the source but it is believed that this a lifetime risk figure per turbine.

Morton [4.35] gives two scenarios where CM systems lead to reduced secondary damage in an onshore 1.5 MW turbine. These are displayed in Table 4.4 and show that stopping secondary damage can have significant financial implications. Finally, LeBlanc and Graves [4.36] states that a full gearbox replacement for an onshore 2.3 MW machine costs between $250,000 and $350,000. If the secondary damage can be reduced using CM systems then the gearbox can be refurbished instead of replaced for a cost of between $150,000 to $200,000. The lowest repair costs come from reducing the damage to a single stage of the gearbox which costs between $50,000 to $90,000.

4.2.1.2. Deriving Costs

To understand the components affected by different levels of damage an FMEA of the wind turbine must be examined. This will highlight the key failure modes and those that can be detected by CM systems. Usefully in this situation it can be used to estimate what damage will occur if some components are allowed to be operated at the different degraded states. The commercial sensitivity of this data has ensured that there are not many widely available FMEAs for wind turbines. One of the most complete FMEAs available was completed by General Electric Company [4.37] in 1979 for NASA's MOD-1 wind turbine - the first wind turbine to produce 2 MW. A much more recent study was completed by Bharatbhai [4.38] for the REpower 5M 5MW turbine (REpower Systems SE has since become Senvion SE).

The costs for turbine spare parts are compiled from Poore and Walford [4.39] as part of a NREL study. This study obtained new onshore component costs in 2004 for different turbine power ratings based on book costs, receipts and metal prices. A rebuild cost factor is used to create a component cost per event depending on how much of the component can be recovered and rebuilt. Finally a relationship between costs and size is developed. This can be used to estimate component costs for much larger turbines of 5 MW size.

Martin-Tretton et al. working for DNV and NREL released a review of manufacturer component costs in 2012 [4.40] based on book costs alone for 2010 prices grouped in two power bands - 1.5 to 2 MW and 2.1 to 3 MW.

The two different sources are compared. The component costs from 2004 were adjusted to account for inflation to 2010. There were significant differences between the 2010 study costs and the 2004 adjusted costs.

The gearbox, generator and rotor components were slightly smaller using the 2004 data and an inflation rate of 2.2% - the EU and UK average inflation rate since 2000

Table 4.4.: Examples of Possible Secondary Damage

	Corrective Maintenance	**Condition Based Maintenance**
Fault Type	Gearbox: High Speed Bearing Failure	
Details	Damage to other stages. Refurbishment required.	Bearing replaced in-situ.
Costs	\$154,000	\$44,000
Fault Type	Generator: Rotor Bearing Failure	
Details	Rotor contacts stator. Windings and bearings replaced	Bearing replaced in-situ
Costs	\$53,000	\$3,500

taken from CIA [4.41] and Triami Media BV [4.42] - compared to the 2010 data. Brake, yaw system and hydraulic costs were significantly under-predicted by the 2004 data. However, control system and electrical component costs were significantly over-predicted.

The combined FMEAs of General Electric Company and Bharatbhai and how this is mapped to the replacement component costs in Poore and Walford are shown in Appendix C.

Almost all of these costs are based on their use in land based turbines. The assemblies require special preparation - undergoing a process known as marinisation - before they can be used offshore. This can involve adding further coatings and improved seals to items such as the gearbox and electrical components. Fingersh, Hand, and Laxson [4.43] suggests that an additional factor be added to all component prices to account for this. The authors suggest a factor of between 10% and 15%. This value is from 2006 - a year before a report to the DTI from Offshore Design Engineering (ODE) Ltd. [4.44] highlighted issues with the use of marinised components. Failures due to poor marinisation resulted in the development of offshore specific components and increased quality assurance.

In 2012, it was suggested that the average of the previous factors be doubled to account for this [4.45]. A factor of 1.27 was selected to account for marinisation and has been used by other authors [4.46].

A grouting issue, described in more detail in Appendix A, that affected the foundations of certain offshore turbines with monopile foundations has been discussed at length in print but not in academic work. Retrofitting work to repair the turbines' foundations would cost as much as € 120,000 per turbine (for 2 MW Vestas V80s) [4.47]. Scottish & Southern Energy were quoted as suggesting that repairing all the turbines at Greater Gabbard offshore wind park would cost £ 4-5 million or £ 35,000 per turbine (for 3.6 MW Siemens SWT-3.6-10) [4.48]. However, it is not expected that all turbines' foundations would need to be retrofitted and the majority of wind parks that use a monopile design have installed monitoring systems to ensure the ongoing safety of their systems.

4.2.2. Lost Production

A turbine cannot produce energy while it is not operational or offline during maintenance. The longer the downtime (DT) associated with a failure then the greater the lost production (LP). In a cost benefit analysis this number is used to represent income that could have otherwise been earned.

The cost of lost production, C_{LP}, is the sum of the DT from all subsystem failures,T_f, multiplied by the energy production cost, C_P, shown in Equation 4.4. This is the cost of energy in the market, C_{EP}, and obligation tariffs prices per unit, C_{ROC}, multiplied by the capacity factor, CF, and the power output rating of the turbine's generator, G. This is shown in Equation 4.5.

If a CM system can detect a failure in advance then the DT will be reduced. Logistic operations can be started before the failure occurs, T_{fC}. However, when using a CM system the possibility of a false alarm occurs. A critical subsystem alarm will result in a turbine shut down until a trained technician can inspect the component. This time for false alarms, T_{fa}, is added to the DT in Equation 4.6. No average downtime associated with false alarms was available so therefore 24 hours is used to represent the DT in the model as an approximation.

$$C_P = CF \times G \times (C_{ROC} + C_{EP}) \tag{4.4}$$

$$C_{LP} = C_P \times \sum_{i=1}^{k} T(i)_f \tag{4.5}$$

$$C_{LPC} = C_P \times \sum_{i=1}^{k} (T(i)_f + T(i)_{fC} + T(i)_{fa}) \tag{4.6}$$

4.2.2.1. Lost Production Values

Capacity factors have been discussed in Chapter 2 and the capacity factors of offshore farms are also discussed in Appendix A. The capacity factor can represent the utilisation of the wind turbines if they were operational. A capacity factor can represent both average wind conditions at the site and the overall health of the wind turbines at the wind park.

More modern offshore wind farms are achieving capacity factors in excess of 40%. The majority of the older wind parks have not reached this level. The models in this thesis use the capacity factor from Egmond aan Zee [4.49] in its early years of operation of 33.3% unless otherwise stated.

The other important components for modelling from Equation 4.4 are the market cost of energy, C_{EP}, and the additional subsidies added used to make the generation of renewable energy more attractive for investors, C_{ROC}.

The spot market price of energy is taken from trading on the UK market. In the UK, electricity can be traded for a long period of time up to an hour before that energy is due to be delivered (known as the gate closure). The majority of these deals are conducted as over-the-counter deals - direct transactions between two parties buying and selling energy. More details about trading energy in the UK can be found in the work of Elexon [4.50]. However, energy exchanges exist to allow more short term trading such as day ahead auctions. Examples of these include the Nordpool Spot N2EX and the APX Auction. The shortest term trading is referred to as the spot market and is final hours trading up until gate closure. APX have an additional spot market exchange.

The UK's electricity regulatory body, the Office of Gas and Electricity Markets, OFGEM, provides data and pricing for the day ahead contracts including over the counter deals and exchange trading [4.51]. APX provide daily average data and pricing for their spot market [4.52].

The Renewable Obligation Certificates, ROCs, is the program used to encourage the production of renewable energy in the UK market. For every Megawatt-hour of renewable energy generated a ROC is earned by the energy generator. The energy is then sold to an energy supplier. ROCs can be sold with the energy from the generators to the suppliers or traded separately.

At the end of a tax year, an energy supplier is required to present the ROCs owned by the company to OFGEM. The energy supplier must present certificates to account for a proportion of its total generation or pay the difference to OFGEM at a fixed buy out price. In the tax year 2014/2015, the buy out price was £43.30 per ROC with suppliers having to show 0.244 ROCs/MWh [4.53].

Table 4.5.: Example of Energy Costs

Cost Type [pMwh]	**Cost**
Spot Price	£41.15
ROC Price	£43.30
ROC Multiplier	2
LEC Price (pre-2015)	£5.54
Total	£133.29

The ROC market traders such as e-Power publish the average ROC trade price from their monthly auctions. The average trade price in September 2015 was £42.94 per ROC compared to £47.12 in October 2002 with highs of £53.27 and lows of £38.42 [4.54].

The UK government can alter the rate that generators accrue ROCs to give more or less aid to particular technologies. To increase the attractiveness of offshore wind for investors they generate 2 ROCs per MWh. This is for new parks or those gaining additional capacity up until the end of the financial year 2014/2015. The level of support will reduce for following financial years to 1.8 ROCs per MWh in 2016/2017 [4.55].

The UK government has also used a Climate Change Levy that has been applied to electricity generated for non-domestic users. Originally, energy generated from renewable sources gained a levy exception certificate equating to about £5.54 per MWh in 2015. The exemption was recently removed with immediate effect in July 2015 [4.56].

All these above prices are summarised using an example in Table 4.5.

4.2.2.2. Downtime

The hours of downtime for each failure situation are derived from the failure data from Egmond aan Zee and the calculated downtimes for major and minor failures are shown in Table A.3. This information is shown below after it has been transcribed into the standard taxonomy used for this thesis in Table 4.6 from Appendix A.

The detected faults have various reductions applied to them from the non-detected faults. When using only a CM effectiveness value when modelling operations the fol-

Table 4.6.: Major and Minor Downtimes for Egmond aan Zee

Assembly	Major Downtime [h]	Minor Downtime [h]
Gearbox	5416	24
Generator	3465	24
Drivetrain	370	24
Rotor Hub	264	24
Rotor Blades	2977	24
Yaw	37	6
Mechanical Brake	1130	24
Electrical System	1692	24
Electrical Control	292	24
Sensors	37	6
Hydraulics	334	24
Support & Housing	725	24
Foundation	725	24

lowing occurs:

- Faults that cause in excess of 1,000 hours of downtime have their downtime reduced by a 30 day month.
- Faults causing more than 240 hours have been reduced by a 7 day week.
- Reductions only apply where a CM system exists that can detect faults with these particular assemblies.
- There are no downtime reductions for minor failures so only one number is presented.

There are special cases modelled where the downtime can be reduced further - for example when detection occurs very early in the development of a defect or a vessel has been kept on standby. The conditions and amount of downtime reduction will be stated explicitly in Chapter 5. In the above situation where very early detection allows for good planning and execution of maintenance actions the 30 days reduction in downtime is extended to 45 days.

When a P-F curve is used, for major failures, variable detection periods are capable of being modelled. The downtime for failures is reduced by the time period between detection and failure.

One of the major benefits of using the downtimes from Egmond aan Zee is that these values incorporate many different factors associated with the logistics issues noted below. These include the effects of weather windows, vessel mobilisation and vessel availability.

4.2.3. Logistics Costs

To complete resets and to replace spare parts, technicians and appropriate vessels need to be used. Each failure mode including false alarms is assigned a failure category. This category relates to the severity of the failure.

A high category failure indicates that large parts will need to be replaced requiring a crew access vessel and a crane vessel. It also requires a large logistics time and a crew in excess of 7. Conversely, an alarm that is uncertain and cannot be discounted due to further data observation and analysis will have to be investigated by inspection before being classed as a false alarm. Therefore a false alarm is classed as low category failure. This inspection can be organised quickly by utilising only a crew access vessel and a small crew.

The installation costs, C_I, are given in Equation 4.7 where the costs of vessel hire, C_E and the costs of labour, C_L, are included.

$$C_I = \sum_{i=1}^{k} (C(i)_E + C(i)_L) \tag{4.7}$$

4.2.3.1. Fault Classification and Vessel Requirements

Each failure mode of the turbine will require certain assets to complete a maintenance action.

A crew transfer vessel (CTV) is, in general, a small, fast vessel used for accessing the wind park. The main goals of a CTV is to transfer personnel, small tools and parts to the wind park. These vessels are used for inspections and small repairs but will require support from additional vessels if larger components (or a large number of small components) need to be repaired. Those used at Egmond aan Zee are typically catamarans that hold up to 15 personnel and travel at a speed of up to 30 knots (~55 kph). They can operate in a wide range of sea states but can only transfer personnel to turbines in seas with less than 1.5m significant wave height [4.49]. This allows them to respond quickly to incidents with minimal mobilisation times.

A field support vessel (FSV) is used for transporting large components to and from the wind farm. They typically have large flat bed areas for transporting a large variety of goods. They also generally have their own internal cranes capable of moving items both on and off the vessel. These are used to transfer larger components to the wind turbine which are too large to carry but small enough to fit in the turbine's internal lift and can be fitted without further external help. These vessels are in demand due to their flexibility and they often compete for work with the oil industry. They require moderate mobilisation times.

A jacking crane vessel, often referred to as just a jack-up, is a larger support vessel and is similar to the FSV in that it can transport larger components to and from the wind park. It also is capable of lowering legs into the sea and raising itself to create a stable platform from which to conduct external operations on a wind turbine. It normally has a high rated crane and is used for major repairs where external work is required - for example blade replacement or to hold the rotor while a main bearing or main shaft is replaced. These are specialist vessels and in high demand requiring high mobilisation times.

Finally, another specialist vehicle is required to conduct underwater surveys of the foundation. In private conversations with industry, remote operated vehicles (ROVs) are preferable to deep sea divers to conduct these due to safety concerns and longer operating times. These remote inspection vehicles are commonly used for offshore cable laying and examining offshore oil production elements such as Christmas trees and valves. While there is a high demand for these vessels there is also a large regular supply. One of the larger companies providing this service is Oceaneering International Inc. which providse information on the capabilities of its fleets and prices [4.57].

The vessels required for different failure classifications are shown in Table 4.7.

Table 4.7.: Failure Classification and Vessel Requirements

Class	Type	Vessel			
		CTV	FSV	Crane	ROV
1	Inspection	X			
2	Inspection Outdoor	X			X
3	Small Repair	X			
4	Small Parts Replacement	X			
5	Large Internal Parts Replacement	X	X		
6	Large External Parks Replacement	X		X	

4.2.3.2. Logistics and Labour Costs

Each time an intervention action is required the vessel or vessels must be mobilised before they can be dispatched. For small vessels such as CTVs this will include small logistics work such as preparing the crew and vessel. The necessary permits and work orders must also be completed. Larger vessels will require longer mobilisation times due to availability and preparing the vessel for sea - typically these vessels are at sea for a much longer time than CTVs.

Each class of failure has a different requirement for crew and time to complete work. Labour costs are charged per hour, per crew member. Crew are paid from the time they leave dock so travel to and from the site is included. This is calculated by taking the average distance from shore of the wind park and dividing it by the speed of the vessel.

A commercial report has been made available containing estimates of many of these values including:

- The total number of work hours per job.
- The total number of hours required to mobilise.
- The crew required to complete the maintenance action.

There are multiple sources for estimating the costs of vessel hire and day rates, as well as labour. These include some of the work noted in the previous section such as the work of Williams, Crabtree, and Hogg [4.24], McMillan [4.58], Bjerkseter and Ågotnes [4.59], Dalgic, Lazakis, and Turan [4.60] and private communications with those in industry.

The mobilisation time for each failure classification is included in the downtime figures above in Table 4.6. However, the costs in mobilising are not. The mobilisation time is multiplied by a lower rate of labour. This accounts for the costs of making ready the vessel, diesel and onshore staff completing permits and work orders.

4.2.4. Monitoring Systems

The majority of condition monitoring systems incur costs for the procurement and installation of the CM system and annual costs associated with maintenance, analysis and software.

4.2.4.1. Monitoring System Costs

Generic costs have been anonymised from an array of vendors and academic sources have been averaged to produce the values shown in Tables 4.8 and 4.9. 15 systems have been used to produce this table. Some of this information was collected in the knowledge that individual costs of each system will not be published. The majority of the capital costs include prices for the system, sensors and cabling. Installation costs have not been considered. In this work the CM or SHM systems are present in each turbine from being commissioned and not retrofitted during the turbine life.

The data for the foundation is taken from the work of Thöns and McMillan [4.31] where it is the size of the turbine that determines the cost of the SHM system. In this case the turbine is 5 MW. The work of Sørensen et al. [4.61] gives a predicted cost for each blade monitoring system technology.

Table 4.8.: Generic Costs of Commercially Available CM Systems

Subsystem	Drive Train		
CM Type	Vibration	Oil	Acoustic
Capital Costs [£]	6,550	9,210	8,146
Annual Costs [£]	570	0	0

There are several limitations to this table including that not all of the vendors contacted were willing to provide any or full details of their costs such as the omission

Table 4.9.: Generic Costs of Commercially Available SHM Systems

Subsystem	Blades			Tower	Foundation
CM Type	Vibration	Acoustic	Optical	Vibration	Vibration
Capital Costs [£]	10,880	28,390	12,280	4,346	14,040
Annual Costs [£]	770	0	0	80	4,070

of installation or cabling costs and annual running costs. However, several manufacturers stated that their systems had no annual costs at all.

The sample sizes of some of the technology types are very limited and in the survey there was sometimes limited distinction placed on whether the prices were for optimistic bulk purchases or single systems. In discussion with industry, they appear to favour the use of significantly cheaper oil quality sensors that offer fewer features than the ones quoted in the table. This appears to be backed by research that is attempting to build ultra low cost oil sensors (using components costing < £4) [4.62].

4.2.4.2. Data Costs

Data processing is an important factor in obtaining the information from CM systems. The data that is captured from CM systems must then be processed, transmitted, possibly subjected to further processing and analysed. The importance of data management and fault reporting is shown in the standards regarding CM systems. This is recorded in Chapter 2.

This data management requires its own dedicated equipment and personnel. Data can be transmitted using modems, stored on servers and processed and reported by engineers. One source that examines the cost of this data management is a work completed by Juhl [4.63] for the CM system manufacturer Gram & Juhl. This document uses the output of an online ROI calculator from the same authors [4.64]. Analysis of this source showed that these data services for an onshore windfarm could be estimated at approximately £15,000 per year per farm.

In the tables above some costs for communication software are included. The annual running costs are mostly estimates from manufacturers and in some cases include annual system services, data collection and data processing.

A final point to note is that the lifetime of these systems are not considered. It is assumed that once deployed, the system will last for the lifetime of the turbine with minimal intervention. This seems improbable especially for some of the SHM systems which will be exposed to harsh environments. Higher operating costs could be attributed to the systems to cover the expense of replacing CM and SHM components.

This information can be used when examining the cost benefit of these systems by varying their prices and annual costs.

4.2.5. Annual Servicing

The procedures and actions that are completed during an annual service or scheduled service are not widely known. The literature made available from OEMs is limited. This is partially because, as noted by Broehl [4.65], there is no standard wind turbine. The requirements for gearbox oil changes or re-greasing or re-lubing bearings and gears are different. Many modern turbines now have auto-greasing systems and these require topping up. Siemens Wind Power [4.66], when describing annual servicing, suggest the majority of the service is spent investigating the different assemblies' conditions and addressing minor issues such as bolt torquing. The other major part of the service is replacing and changing consumables such as oil and hydraulic fluids. The following list showing the actions taken in an annual service are based on those from Broehl [4.65].

Transformer No regular service but visually inspected or scanned with a thermograph.

Gearbox Oil filters are often replaced annually and the oil is replaced every few years. If observed in advance, smaller gears and bearings can be replaced during the annual service.

Generator Bearings and brushes can wear out or move out of alignment. These are often easily replaced up tower and done as part of the annual service.

Brake The service life of brake pads varies massively depending on the operating conditions. They are often replaced annually.

Table 4.10.: Annual Generic Consumable Costs for Onshore Wind

Turbine Size	2.0 MW [£]	2.5 MW [£]
Gear oil filter	185	230
Hydraulic filter	70	70
Offline filter	70	70
Hydraulic oil	15	15
Gear oil	260	320
Yaw gear grease	110	140
Bearing grease	85	105
Oil testing	85	85
Electricity	1215	1520
Total	**2095**	**2555**

Main Bearing Small repairs can be completed during the service depending on the design of the bearing.

Pitch and Yaw Motors If an auto-greaser is not installed, gears should be inspected, cleaned and re-greased.

Blades Annual visual inspection with binoculars. Inspected more frequently if struck by lightning or severe icing. Actual repairs can not be completed during the service.

Poore and Walford [4.39] gave some annual generic costs of consumables for onshore turbines with different power ratings. Some of these are shown in Table 4.10 accounting for inflation and converted into Pound Sterling. Electricity costs are the largest of these costs and used for turbine ancillary equipment such as heaters, internal lift and lights. A figure of £5,000 could be used to represent the annual offshore service cost for components and consumables for a 2.5 or possible 3.0 MW machine. This includes the marinisation factor of 1.27 and the small additional component replacements that are completed during a service - such as brushes.

There are additional logistics costs that are incurred in an annual service. This would be a Class 3 logistics operation.

4.3. Levelised Costs

The operating cost for the year is shown by C_{OP} which is a combination of the above defined parameters from Section 4.2.2 and this is defined in Equation 4.8 and the comparative operating costs using a condition based maintenance policy is C_{OPC}. The costs of the condition monitoring system are added to C_{OPC} in the first year and the annual running costs of the CM systems are added each year.

$$C_{OP} = C_{RP} + C_{LP} + C_I \tag{4.8}$$

The costs for each year are discounted - or levelised - to represent the Net Present Value (NPV) of each future operating cost. That is the amount of money that should be deposited into a bank account today to cover the lifetime operating costs [4.14]. NPV is shown in Equation 4.9 where a discount rate, r, is used and cost of the year i.

$$NPV = \sum_{i=1}^{y} \frac{C(i)_{OP}}{(1+r)^i} \tag{4.9}$$

The discount rate - or alternatively, the rate of return - shows the value of risk aversion and represents the cost of capital. The value most commonly used in this thesis is 4% as suggested in van Noortwijk and Frangopol [4.67]. However, higher rates are commonly used to cover uncertainty, such as 5% [4.68], 8.2% [4.59] or 10% [4.22, 4.69].

4.4. Conclusions

In this chapter a cost model has been presented that can be used to assess the different costs involved in operating and maintaining a wind park. Literature sources have been explored that have attempted to quantify the lifetime operating costs of plant and the effects of using condition based maintenance. This was completed both for generic systems and specifically for wind parks.

Although the framework of the cost model is not novel in its own right, when it is combined with novel CM operation modelling techniques and allows modelling to a higher resolution that previously seen (i.e. individual assemblies have individual

CM specifications and capabilities) a novel and valuable quantification model can be presented.

A large array of possible cost inputs and sources have also been introduced and discussed that could be integrated into the model. One of the most important aspects explored in this chapter are the costs of the CM and SHM systems where limited data is available publicly.

4.5. Chapter 4 References

[4.1] A. Grall, L. Dieulle, C. Bérenguer, and M. Roussignol. "Continuous-time predictive-maintenance scheduling for a deteriorating system". In: *IEEE Transactions on Reliability* 51.2 (2002), pp. 141–150.

[4.2] A. Grall, L. Dieulle, C. Bérenguer, and M. Roussignol. "Asymptotic failure rate of a continuously monitored system". In: *Reliability Engineering & System Safety* 91.2 (Feb. 2006), pp. 126–130. ISSN: 09518320.

[4.3] J. van Noortwijk. "A survey of the application of gamma processes in maintenance". In: *Reliability Engineering & System Safety* 94.1 (Jan. 2009), pp. 2–21. ISSN: 09518320.

[4.4] J. van der Weide, M. Pandey, and J. van Noortwijk. "Discounted cost model for condition-based maintenance optimization". In: *Reliability Engineering & System Safety* 95.3 (Mar. 2010), pp. 236–246. ISSN: 09518320.

[4.5] D. Straub. *Lecture Notes in Engineering Risk Analysis*. October. Munich, 2012, pp. 1–226.

[4.6] E. Byon, L. Ntaimo, C. Singh, and Y. Ding. "Wind energy facility reliability and maintenance". In: *Handbook of Wind Power Systems*. Ed. by P. Pardalos, S. Rebennack, M. V. F. Pereira, N. A. Iliadis, and V. Pappu. 2011, pp. 639–672.

[4.7] P. J. Tavner, J. Xiang, and F. Spinato. "Reliability analysis for wind turbines". In: *Wind Energy* 10.1 (2007), pp. 1–18. ISSN: 10954244.

[4.8] J. M. van Noortwijk, J. A. M. van der Weide, M. J. Kallen, and M. D. Pandey. "Gamma processes and peaks-over-threshold distributions for time-dependent reliability". In: *Reliability Engineering and System Safety* 92.12 (2007), pp. 1651–1658. ISSN: 09518320.

[4.9] M. Pandey, X. Yuan, and J. van Noortwijk. "Gamma process model for reliability analysis and replacement of aging structural components". In: *9th International Conference on Structural Safety and Reliability (ICOSSAR)*. Rome, Italy, 2005, pp. 2439–2444.

[4.10] K. Bouvard, S. Artus, C. Bérenguer, and V. Cocquempot. "Condition-based dynamic maintenance operations planning & grouping. Application to commercial heavy vehicles". In: *Reliability Engineering & System Safety* 96.6 (June 2011), pp. 601–610. ISSN: 09518320.

[4.11] A. Van Horenbeek, L. Pintelon, and P. Muchiri. "Maintenance optimization models and criteria". In: *International Journal of System Assurance Engineering and Management* 1.3 (Apr. 2011), pp. 189–200. ISSN: 0975-6809.

[4.12] A. Van Horenbeek and L. Pintelon. "A dynamic predictive maintenance policy for complex multi-component systems". In: *Reliability Engineering & System Safety* 120 (Dec. 2013), pp. 39–50. ISSN: 09518320.

[4.13] J. Andrawus, J. Watson, M. Kishk, and A. Adam. "The selection of a suitable maintenance strategy for wind turbines". In: *Wind Engineering* 30.6 (2006), pp. 471–486.

[4.14] F. Besnard, J. Nilsson, and L. M. Bertling. "On the economic benefits of using Condition Monitoring Systems for maintenance management of wind power systems". In: *IEEE 11^{th} International Conference on Probabilistic Methods Applied to Power Systems*. Istanbul: Ieee, June 2010, pp. 160–165. ISBN: 978-1-4244-5720-5.

[4.15] J. Nilsson and L. M. Bertling. "Maintenance management of wind power systems using condition monitoring systems - Life cycle cost analysis for two case studies". In: *IEEE Transactions on Energy Conversion* 22.1 (2007), pp. 223–229.

[4.16] J. Ribrant. "Reliability performance and maintenance - A survey of failures in wind power systems". PhD thesis. KTH Royal Institute of Technology, 2006, p. 81.

[4.17] C. Walford and D. Roberts. *Condition Monitoring of Wind Turbines: Technology Overview, Seeded-Fault Testing, and Cost- Benefit Analysis*. Tech. rep. 3. Palo Alto, CA, USA: Electric Power Research Institute, 2006, pp. 1–110.

[4.18] D. McMillan and G. W. Ault. "Quantification of condition monitoring benefit for offshore wind turbines". In: *Wind Engineering* 31.4 (2007), pp. 267–285.

[4.19] E. Wiggelinkhuizen, T. Verbruggen, H. Braam, L. Rademakers, J. Xiang, and S. Watson. "Assessment of Condition Monitoring Techniques for Offshore Wind Farms". In: *Journal of Solar Energy Engineering* 130.3 (2008). ISSN: 01996231.

[4.20] H. Braam, T. Obdam, R. van de Pieterman, and L. Rademakers. "Properties of the O&M Cost Estimator (OMCE)". 2011.

[4.21] J. D. Sørensen. "Framework for Risk-based Planning of Operation and Maintenance for Offshore Wind Turbines". In: *Wind Energy* 12 (2009), pp. 493–506.

[4.22] A. Van Horenbeek, J. Van Ostaeyen, J. R. Duflou, and L. Pintelon. "Quantifying the added value of an imperfectly performing condition monitoring system: Application to a wind turbine gearbox". In: *Reliability Engineering & System Safety* 111 (Mar. 2013), pp. 45–57. ISSN: 09518320.

[4.23] Ø. Netland, I. Bakken, M. Hofmann, and A. Skavhaug. "Cost-benefit evaluation of remote inspection of off shore wind farms by simulating the operation and maintenance phase". In: *Energy Procedia* 53.1876 (2014), pp. 239–247. ISSN: 1876-6102.

[4.24] R. Williams, C. Crabtree, and S. Hogg. "Quantifying the economic benefits of wind turbine condition monitoring". In: *Proceedings of ASME Turbo Expo 2014: Turbine Technical Conference and Exposition*. Dusseldorf, Germany, 2014.

[4.25] D. Inaudi. "Cost-Benefits Analysis in SHM Projects". In: *5th Iternational Conference on Structural Health Monitoring of Intelligent Infrastructure*. Cancun, Mexico, 2011.

[4.26] K. Smarsly, K. Law, and D. Hartmann. "Towards life-cycle management of wind turbines based on structural health monitoring". In: *Proceedings of the First International Conference on Performance-based Life-cycle Structural Engineering*. Hong Kong, 2012.

[4.27] S. Thöns and M. H. Faber. "Assessing the value of structural health monitoring". In: *Safety, Reliability, Risk and Life-Cycle Performance of Structures and Infrastructures*. Ed. by G. Deodatis, D. Frangopol, and B. R. Ellingwood. Taylor & Francis, 2013, pp. 2543–2550. ISBN: 9781138000865.

[4.28] S. Thöns, R. Schneider, and M. H. Faber. "Quantification of the Value of Structural Health Monitoring Information for Fatigue Deteriorating Structural Systems". In: *12th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP12*. Vancouver, Canada, 2015, pp. 1–8.

[4.29] M. H. Faber, D. Val, and S. Thöns. "Value of Information in SHM - Considerations on the Theoretical Framework". In: *COST TU1402: Proceedings of the 1st Workshop*. Ed. by S. Thöns. May. 2015, pp. 5–16. ISBN: 9781138001237.

[4.30] E. Wiggelinkhuizen, T. Verbruggen, H. Braam, J. Xiang, D. Scheffler, E. Becker, A. Christensen, M. Tipluica, E. Norton, and G. Giebel. *CONMOW: Condition Monitoring for Offshore Wind Farms*. Tech. rep. D. Energy Research Centre of the Netherlands, 2007, pp. 7–10.

[4.31] S. Thöns and D. McMillan. "Condition monitoring benefit for offshore wind turbines". In: *12th International Conference on Probabilistic Methods Applied to Power Systems*. Istanbul, 2012.

[4.32] W. Yang, P. J. Tavner, C. J. Crabtree, Y. Feng, and Y. Qiu. "Wind turbine condition monitoring: technical and commercial challenges". In: *Wind Energy* (2012).

[4.33] Sinclair Knight Merz. *Condition Monitoring of Wind Turbines*. Tech. rep. UP00-195/R/0001. Sinclair Knight Merz, 2006.

[4.34] A. Weiss. "Condition Monitoring - Case Histories". In: *AWEA Windpower 2012*. 2012.

[4.35] B. Morton. "The Value of Early Detection". In: *Wind Tech International* (2013), pp. 27–29.

[4.36] M. LeBlanc and A. Graves. "Condition Monitoring Systems: Trends and Cost Benefits". In: *Wind Turbine Condition Monitoring Workshop*. Broomfield, CO, USA: National Renewable Energy Laboratory, 2011.

[4.37] General Electric Company. *Mod 1 Wind Turbine Generator Failure Modes and Effects Analysis*. Tech. rep. DOE/NASA/0058-79/1. NASA, 1979, p. 95.

[4.38] M. G. Bharatbhai. "Failure Mode and Effect Analysis of Repower 5M Wind Turbine". In: *International Journal of Advance Research in Engineering, Science & Technology* 2.5 (2015), pp. 2394–2444.

[4.39] R. Poore and C. Walford. *Development of an Operations and Maintenance Cost Model to Identify Cost of Energy Savings for Low Wind Speed Turbines*. Tech. rep. NREL/SR-500-40581. NREL, 2008.

[4.40] M. Martin-Tretton, M. Reha, M. Drunsic, and M. Keim. *Data Collection for Current U.S. Wind Energy Projects : Component Costs, Financing, Operations, and Maintenance*. Tech. rep. NREL/SR-5000-52707. 2012.

[4.41] CIA. *Field Listing: Inflation Rate (Consumer Prices)*. 2012.

[4.42] Triami Media BV. *Historic harmonised inflation Europe – HICP inflation*. 2015. URL: http://www.inflation.eu/inflation-rates/europe/historic-inflation/hicp-inflation-europe.aspx.

[4.43] L. Fingersh, M. Hand, and A. Laxson. *Wind Turbine Design Cost and Scaling Model Wind Turbine Design Cost and Scaling Model*. Tech. rep. NREL/TP-500-40566. NREL, 2006, pp. 1–43.

[4.44] Offshore Design Engineering (ODE) Ltd. *Study of the costs of offshore wind generation*. Tech. rep. URN 07/779. Department of Trade and Investment, 2007.

[4.45] G. Hagerman. "The Economics of Making Offshore Wind a Reality in Virginia". In: *ODU ECOnference*. Norfolk, VA, USA., 2012.

[4.46] I. Dinwoodie, D. McMillan, and F. Quail. "Analysis of offshore wind turbine operation & maintenance using a novel time domain meteo-ocean modeling approach". In: *ASME Turbo Expo 2012*. Copenhagen, 2012, pp. 1–11.

[4.47] J. Deign. *Monopile failures put grout in doubt*. 2011. URL: http://social.windenergyupdate.com/offshore/monopile-failures-put-grout-doubt.

[4.48] Society of Operations Engineers. *Offshore wind farm grout failure may cost 25 million*. 2010. URL: http://www.soe.org.uk/news/iplante-news/item/offshore-wind-farm-grout-failure-may-cost-25-million/.

[4.49] Noordzee Wind CV. *Operations Report 2007*. Tech. rep. OWEZ_R_000_20081023. NoordzeeWind, 2008.

[4.50] Elexon. *The Electricity Trading Arrangements - A Beginner's Guide*. Tech. rep. 2013.

[4.51] The Office of Gas and Electricity Markets. *Monitoring the market*. 2015. URL: https://www.ofgem.gov.uk/monitoring-market/wholesale-market-indicators (visited on 10/21/2015).

[4.52] APX Group. *Market Results APX Power UK*. 2015. URL: https://www.apxgroup.com/market-results/apx-power-uk/dashboard/ (visited on 10/21/2015).

[4.53] The Office of Gas and Electricity Markets. *The Renewables Obligation buy-out price and mutualisation ceiling 2014-15*. 2014. URL: https://www.ofgem.gov.uk/publications-and-updates/renewables-obligation-buy-out-price-and-mutualisation-ceiling-2014-15 (visited on 10/21/2015).

[4.54] e-Power Limited. *e-ROC track record*. 2015. URL: http://www.epowerauctions.co.uk/erocrecord.htm (visited on 10/21/2015).

[4.55] Department of Energy and Climate Change. *Government response to the consultation on proposals for the levels of banded support under the Renewables Obligation for the period 2013-17 and the Renewables Obligation Order 2012*. Tech. rep. URD 12D/274. 2012.

[4.56] S.-J. McArthur. *No more LECs for Renewables*. Brodies LLP. 2015. URL: http://www.brodies.com/blog/renewables/no-more-lecs-for-renewables/ (visited on 10/21/2015).

[4.57] Oceaneering International Inc. *ROV Services Rate Schedule UK & Europe*. Tech. rep. Aberdeen, UK, 2010.

[4.58] D. McMillan. "Techno-Economic Evaluation of Condition Monitoring and its Utilisation for Operation and Maintenance of Wind Turbines using Probabilistic Simulation Modelling". PhD thesis. University of Strathclyde, 2008, p. 262.

[4.59] C. Bjerkseter and A. Ågotnes. "Levelised cost of energy for offshore floating wind turbine concepts". MA thesis. NTNU, 2013.

[4.60] Y. Dalgic, I. Lazakis, and O. Turan. "Vessel charter rate estimation for offshore wind O&M activities". In: *Developments in Maritime Transportation and Exploitation of Sea Resources - IMAM 2013*. Ed. by C. . G. Soare and F. . L. Peña. 2013, pp. 899–908.

[4.61] B. Sørensen, L. Lading, P. Sendrup, M. McGugan, C. P. Debel, O. Kristensen, G. Larsen, A. Hansen, J. Rheinländer, J. Rusborg, and J. Vestergaard. *Fundamentals for remote structural health monitoring of wind turbine blades - a preproject*. Vol. 1336. May. 2002, p. 40. ISBN: 8755030440.

[4.62] A. Hamilton, A. Cleary, and F. Quail. "Development of a Novel Wear Detection System for Wind Turbine Gearboxes". In: *IEEE Sensors* 14.2 (2014), pp. 1–8.

[4.63] A. Juhl. *TCM ROI - Return On Investment*. Manufacturer's Study. 2010.

[4.64] Gram & Juhl A/S. *TCM ROI Form*. 2010. URL: http://www.gramjuhl.dk/index.php?page=roi (visited on 10/10/2012).

[4.65] J. Broehl. *So what is involved in servicing a wind turbine?* 2010. URL: http://www.windpowermonthly.com/article/989447/so-involved-servicing-wind-turbine (visited on 11/05/2015).

[4.66] Siemens Wind Power. *Daniel Walker Job Profile*. 2015. URL: http://www.siemens.co.uk/en/wind/daniel-walker-job-profile.htm (visited on 11/05/2015).

[4.67] J. van Noortwijk and D. Frangopol. "Two probabilistic life-cycle maintenance models for deteriorating civil infrastructures". In: *Probabilistic Engineering Mechanics* 19.4 (2004), pp. 345–359.

[4.68] A. R. Henderson, C. Morgan, B. Smith, H. C. Sørensen, R. J. Barthelmie, and B. Boesmans. "Offshore wind energy in europe - A review of the state-of-the-art". In: *Wind Energy* 6.1 (2003), pp. 35–52. ISSN: 10954244.

[4.69] P. J. Tavner, H. Long, and Y. Feng. "Early experiences with UK round 1 offshore wind farms". In: *Proceedings of the ICE - Energy* 163.4 (Nov. 2010), pp. 167–181. ISSN: 1751-4223.

CHAPTER 5

Advanced Operation & Maintenance Models

An operation and maintenance simulation model has been developed during the course of this PhD, with emphasis placed on different goals during different periods of this project. This chapter contains the development of the model, benchmarking of the output against similar models and results of the model at these stages. This process is presented in this chapter as shown in Figure 5.1.

The first part of each section begins with a description of the model in its current form. The output from the model is then evaluated. This is done using a reference case and available industrial data. This reference case is a simulated offshore wind farm that has been used to assess several other O&M models.

Next, an offshore wind farm is simulated which is designed to be similar to Egmond aan Zee. Other wind farms may be simulated if required to investigate particular criteria. For each wind farm two maintenance cases are simulated - one using period based maintenance and the other using condition based maintenance. The difference between these two situations is presented. The model's state is then reviewed and its current strengths are highlighted as are its weaknesses. Where possible these weaknesses are addressed in the next iteration of the model.

The different components that are available at each model stage are shown in Ta-

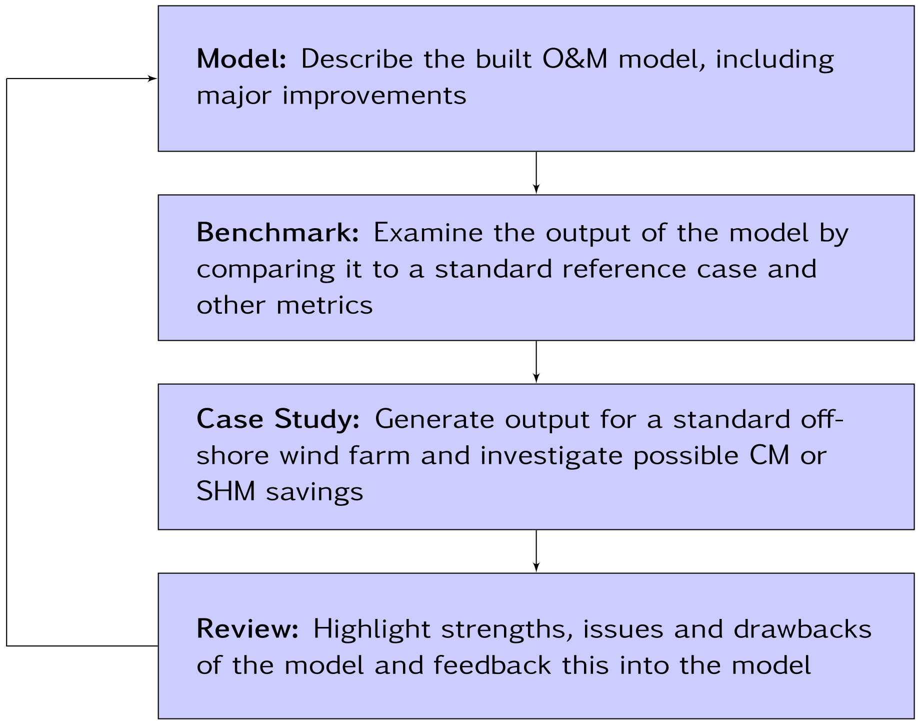


Figure 5.1.: Diagram of the modelling process used in this chapter

ble 5.1. All of the components mentioned in the table have been described in the previous two chapters. In the table, the term 'partially' identifies components that have been modelled with basic techniques or are not fully considered.

5.1. Prototype Markov Model

The focus of this work was to create a simple probabilistic operations model and validate this model against other literature and real operational figures. This would allow for further development. The other goals of this model were to create a suitable framework for exploring different modes of modelling CM systems and investigate CM effectiveness and false alarms. The majority of the work presented in this section was presented in a peer reviewed paper for a conference in 2013 [5.1].

The turbine was modelled as 12 separate assemblies as per the WMEP taxonomy. Taxonomies are discussed at length in Chapter 2. Each assembly was represented by 2 hidden Markov chains - for major and minor failures - each with 2 states - operating and failed. The hidden output is the actual unknown condition of the assembly with the CM output being the observed state related to the hidden state by the CM effec-

Table 5.1.: Components Considered in Each Model

Model	Component Repair	Lost Production	Logistics	CM Effectiveness	False Alarms	Time Until Failure	Realistic SIM
Prototype MC	✓	✓	∘	✓	✓	∘	∘
Improved MC	✓	✓	✓	✓	✓	•	∘
Initial DBN	✓	✓	✓	∘	∘	✓	•
Final DBN	✓	✓	✓	✓	✓	✓	✓

Yes = ✓, Partially = •, No = ∘

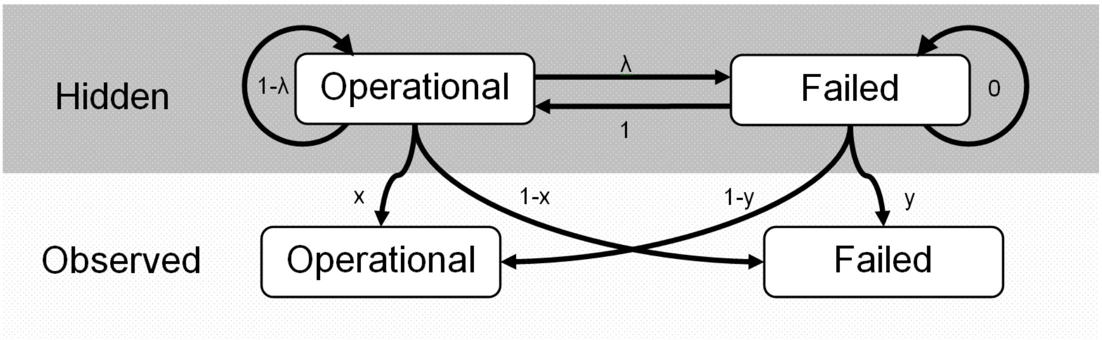


Figure 5.2.: Example assembly hidden Markov chain used in the model

tiveness and CM reliability. The diagram used to represent the system in this thesis is shown in Figure 5.2.

The deterioration model used the unmodified failure data as shown in Appendix A in Table A.3 for major and minor failures and a time resolution of one year per time step. The distinction between the failure modes are that minor failures take 24 hours or less to repair or clear. The failure rates are converted into failure percentages for Markov chains using exponential decay - the inverse of the survivor function in Equation 3.6 from Chapter 3. Labour and logistic costs are not included in this simulation but repair costs with secondary damage and lost production costs are included.

5.1.1. Monte Carlo Simulation and Convergence

When working with Monte Carlo models convergence is an important aspect to consider. Both Markov chain and Bayesian models can be solved by Monte Carlo simulations. This involves drawing random samples of the variables - for example, condition level at failure or structural resistance.

A simple example is used to explain how the output of Monte Carlo simulations improves when the sample size is increased. This is taken from Lapeyre [5.2] where a function, $f(x)$, utilises a uniformly distributed random variable, U, shown in Equation 5.1. The average of the output, $\bar{x}$, then converges towards the expected value of $f(U)$, $E[f(U)]$, as the number of samples, N, tends towards infinity as shown in Equation 5.2. This is based on the strong law of large numbers.

$$\int_{[0,1]} f(U)dU \tag{5.1}$$

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} f(U_i) \tag{5.2}$$

Obviously infinite numbers of samples are not available so the user must specify when the value of $\bar{x}$ is acceptably close to $E[f(U)]$ - often without knowing the value of $E[f(U)]$. When the number of samples is large enough so that the output values are close enough to the expected value then the simulation is said to have converged. To optimise simulations the value of N should be kept as low as possible while still allowing convergence to occur.

Gelman and Rubin suggested a technique to monitor convergence of a simulation [5.3, 5.4]. This is done by examining some basic statistical information for individual parameters and across developing multiple parameters. If, for example, there are M parameters of length N (where $M \geq 2$) then these values could be represented by a single variable s. Any value could then be defined in θ by its parameter value, j, and sample position, i.

The variance within a parameter, σ^2, is averaged across all parameters to produce a value of W as shown in Equation 5.3. In Equation 5.4 the variance of the parameters$'$ means are multiplied by N to produce B.

$$
\begin{aligned}
W &= \frac{1}{M}\sum_{j=1}^{M}\sigma_j^2 && (5.3)\\
B &= \frac{N}{M-1}\sum_{i=1}^{M}(\bar{\theta}_j-\bar{\bar{\theta}}) && (5.4)\\
\hat{Var}(\theta) &= (1-\frac{1}{N})W+\frac{1}{N}B && (5.5)\\
\hat{R} &= \sqrt{\frac{\hat{Var}(\theta)}{W}} && (5.6)
\end{aligned}
$$

Once W and B have been calculated then a weighted average of the two is used to estimate the total variance, shown in Equation 5.5, and then a potential scale reduction factor, $\hat{R}$, is produced as seen in Equation 5.6. If $\hat{R}$ is large then further simulations should be conducted to improve the results. If $\hat{R}$ is close to 1 then the observations from the simulation are said to have converged.

This information is used to analyse an example turbine simulation. The output streams contain repair costs with CM, repair costs without CM, lost production with CM and lost production without CM for one 2 MW turbine. The results have been normalised against the mean for that stream and are shown in Figure 5.3. The Gelman - Rubin criteria has also been produced for these streams and is shown in Figure 5.4 for the first 2,000 simulation years.

The simulation may converge rather quickly but there is still some uncertainty associated with the output. The coefficient of variation (CoV) can be used to examine the relative standard deviation by comparing the mean and standard deviation - assuming a normal distribution of results. The relationship between the two is shown in Equation 5.7. Faber [5.5] contains a good explanation of the relationship between the number of samples and the uncertainty in the output including CoV.

$$CoV = \frac{\sigma}{\bar{x}} \tag{5.7}$$

The CoV of the repair costs with CM is 1.8% across the 1,000 to 1,500 simulated years with a mean of £78,851 and standard deviation of £1,415. This variable reduces to 1.5% across the 1,500 to 2,000 simulation years. If this extended to examine

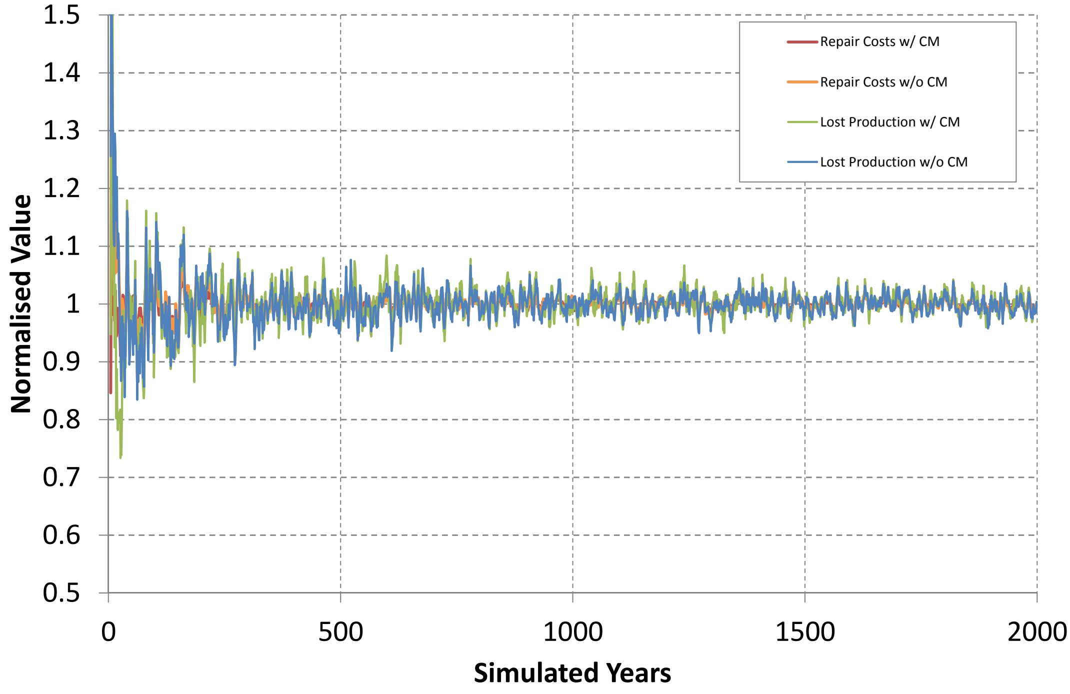


Figure 5.3.: Following the Convergence of Various Streams

the output across 90,000 to 100,000 simulation years then the percentage becomes 0.3%. This pattern is repeated across all streams.

This information has led to the selection of 2,000 simulation years per turbine for this model. As it is the entire wind farm being simulated and turbines are duplicates of each other then the effective number of Monte Carlo simulation years is multiplied by the number of turbines in the wind farm. A 20 turbine wind farm would therefore have 40,000 simulation years per operational year giving CoV values well below 1%.

5.1.2. Benchmarking

5.1.2.1. Metrics and Sources

There are several metrics available that can be examined to assess the model's output. These are both O&M costs obtained from offshore wind farms and other similar O&M logistic models.

Two metrics that can be used to compare actual wind farm costs to each other and simulations are the annual O&M cost per installed Megawatt and the annual O&M cost per produced Megawatt Hour.

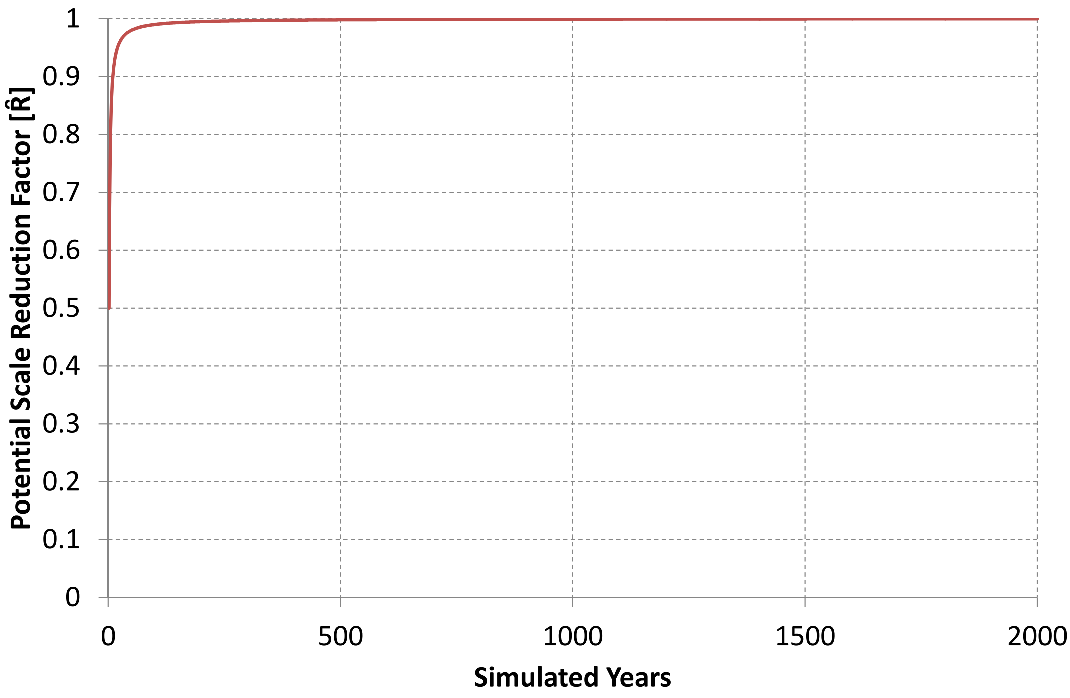


Figure 5.4.: Example of Simulation Convergence Using the Gelman-Rubin Criteria

Table 5.2.: Annual O&M Costs for Offshore Wind Farms

Year	Scroby Sands	Kentish Flats	North Hoyle	Barrow
1	£1,484,135	£1,300,000	-	£1,558,000
2	£1,649,728	£1,375,000	£2,500,000	£2,656,000
3	£1,642,736	£1,100,000	£2,800,000	-
Per MW	£26,536	£13,981	£44,167	£23,411
Per MWh	£10.23	£5.59	£14.56	£8.70

The Capital Grants annual reports for early years of UK Round 1 are an incomplete source of this information. The O&M costs for Scroby Sands, Kentish Flats, North Hoyle and Barrow are shown in Table 5.2. Unfortunately, confidentiality issues obscure the true value of these figures - some operators are not allowed to disclose the true value of their O&M contracts or the full breakdown of costs.

Where possible the values in the table show the direct O&M costs, which generally arise from the O&M service contract with the original equipment manufacturer. These contracts do not specify the cover levels. Some of the details about the differences in the levels of PBMCs coverage are discussed in Chapter 2. Some of the Capital Grants reports break the O&M costs down further to include insurance, surveys and environmental management amongst others.

Tavner, Long, and Feng [5.6] states that offshore O&M costs account for around 18% of the total LCoE for UK and EU sites. This is compared to 12% for onshore O&M costs. The authors discuss discrepancies in reported offshore O&M costs and the inclusion of lost production figures in some but not all of the numbers. The paper gives an offshore LCoE value of £105 per MWh. This compares to a range of €135 - €175 per MWh in 2013 given by Bjerkseter and Ågotnes [5.7] which is approximately £113 - £146 per MWh at 2013 exchange rates [5.8]. This gives an O&M cost of around £18.90 - £26.28 per MWh.

5.1.2.2. Model Output and Comparison

The output of the model was adjusted to produce costs for 2012 and results in dollars using historical conversion rates [5.8]. For ease, the results will be presented in this document in Pounds Sterling.

The wind farm that was first simulated had 30 turbines of 2 MW in order to be similar to Scroby Sands or North Hoyle. The simulation produced an average base case scenario with a component replacement cost of £2,290,000: £150,000 for annual servicing (assuming an average of £5,000 of components are used during the service) and lost production cost of £3,139,000 which total £5,579,000 per annum for the farm. These numbers are shown in Table 5.3 with the commercial availability. Each turbine was down for an average of 1,443 hours per year giving a technical availability value of 83.5%. This equates to £40,666 per MW installed or between £13.26 and £16.82 per MWh assuming that the wind farm would produce 145,000 MWh at 27.6% capacity factor or 184,000 MWh at 35% capacity factor. These are the capacity factor values of Scroby Sands and North Hoyle respectively in their 3rd year of operation.

For the same time period, North Hoyle had a commercial availability of 88% (or 87.4% including subsea cabling and grid faults). Unfortunately, the technical availability is not presented. Scroby Sands had a technical availability of 83.8% and a commercial availability of 87.0%. In Williams, Crabtree, and Hogg [5.9] a figure of 40% is used to represent the percentage of the time that the wind park is inacces-

Table 5.3.: Simulation Output Breakdown

Simulation Output	Model Output
Component Costs	£2,290,000
Annual Service	£150,000
Lost Production	£3,139,000
Total	£5,579,000

Table 5.4.: Simulation Outputs of Early Model and Comparison

Simulation Output	Model Output	Scroby Sands	North Hoyle
Component & Service	£2,440,000	£1,591,000	£2,650,000
Per MW	£40,666	£26,536	£44,167
Commercial Availability	88.5%	87.0%	88.0%

sible due to weather. At 40% the turbine is inaccessible for 146 days. Using values of 30% and 40% to adjust the simulation's technical availability to commercial availability gives 88.5% and 90.1%. These numbers are presented for comparison in Table 5.4.

Since this work was published a reference case for O&M simulation has been developed by Dinwoodie et al. [5.10]. This base case uses 80 Vestas V90 3 MW machines located 50km from a support base (although distance from shore is not included) and a price of £90 per MWh. In the work, five separate O&M models all simulate the base case and present their outputs. The outputs for all models are averaged and shown in Table 5.5 under 'Reference Case Average'. The repair costs include consumables used in annual servicing and replacement components.

A comparative simulation was completed on the current model and this is also shown in Table 5.5. The large distance to the maintenance base suggests that the wind farm is further from shore than the 10 - 16 km of Egmond aan Zee. The Danish wind farms that are further from shore have higher capacity factors. Horns Rev II and Anholt have some of the highest capacity factors of Danish offshore wind farms and are some of the furthest from shore at approximately 33km and 22km from shore [5.11] so a capacity factor of 45% is used. The German wind farm Alpha Ventus is located some 45 km from shore and it has regularly achieved capacity factors of around 50% [5.12].

Table 5.5.: Comparison of Output with Published Reference Model

Simulation Output	Reference Case Average	Early Presented Model
Availability - time	83.16%	83.52%
Annual Lost Production	£17.01m	£13.99m
Annual Repair Cost	£3.76m	£10.72m

The average output for the reference simulation gives £15,600 per MW installed compared to £44,700 per MW from this simulation.

5.1.3. CM System Efficacy

To examine the effect of CM systems on the O&M costs, simulations were completed with CM systems installed on certain assemblies. The assemblies and the effectiveness values of the CM systems are those given in Table 3.1 with gearbox (50%), generator (80%) and drive train (40%).

Now the model is able to produce both a base simulation - where a period based maintenance (PBM) strategy is utilised - and a simulation using a condition based maintenance (CBM) strategy relying on condition monitoring systems. The failure rates and downtimes used in the PBM that come from Egmond aan Zee include scheduled service and the use of SCADA data for maintenance actions. It is the difference in cost between implementing these two strategies that will show the benefit of one strategy over the other.

In the CBM strategy there is an additional cost associated with installing and operating the CM systems. Operating the CM system in this situation refers to the data processing and alarm management. Estimations of the costs of CM systems in this model are taken from investment data from CM manufacturer data [5.13]. The costs of CM systems are added for every year of operation. These equate to around £3,150 per turbine with an additional £15,000 for data services.

A wind farm scenario similar to Scroby Sands or North Hoyle is simulated with CBM where the wind park consists of 20 3 MW turbines. The output of the model gave average costs of £1,913,000 with an additional £150,000 in annual servicing and £2,132,000 in lost production totalling £4,195,000. Availability increased to 88.8%

from 83.5%. This represents a reduction in average turbine downtime per year from 1443 to 980 hours.

When using a discount rate of 4% this gives a levelised total operating cost including both lost production and component costs over 20 years as £58.44 million. This compares to a levelised cost of £77.81 million for only the PBM strategy. This is a reduction of around 25%.

The CM costs stated above were originally used because more detailed information about CM systems was not available at that time. From the costs above, for 20 turbines, the capital cost for the CM equipment is £63,000 and £15,000 per year which over 20 years give a levelised total of approximately £265,000. When the alternative CM numbers are used from Table 4.8 this becomes £131,000 in CAPEX and a levelised total of approximately £280,000. This is a lifetime difference of £15,000 between the two sets of costs in this situation.

5.1.3.1. Extending CM Systems to Other Assemblies

A theoretical CM system is then added to every turbine so that all assemblies can have their condition monitored and their failure modes give warning before failure. This theoretical CM system does not incur any further costs.

The CM effectiveness rate for the drivetrain, gearbox and generator are still as detailed above. The CM systems of all other assemblies has a CM effectiveness set to 20%. The CM reliability rate to estimate the simulation of false alarms is set at 99.99%.

Component costs are reduced further to £1.85 million per year excluding annual services and lost production costs become £2.08 million. The average downtime per turbine becomes 913 hours and the wind farm availability becomes 89.56%.

5.1.3.2. Variations in CM Effectiveness

To investigate the implications of CM effectiveness on the overall operating costs, the CM effectiveness rate is varied from 20% to 90% for all of the other assemblies not noted above. This range of effectiveness values is within those used in other literature and shown in Table 4.2. The difference between the PBM and the CBM strategies are shown as a percentage of the PBM strategy for different CM effectiveness rates. These rates are shown in Figure 5.5.

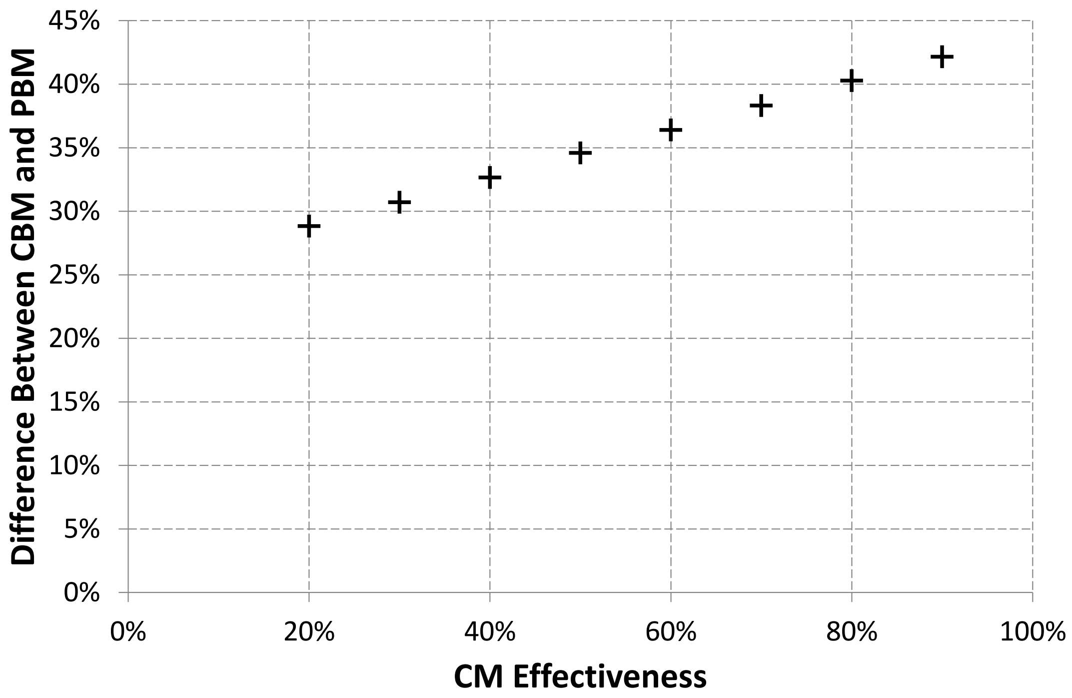


Figure 5.5.: Percentage Saving between PBM and CBM Strategies Varying CM Effectiveness

The values ranged from a 29% reduction in lifetime strategy costs at 20% CM effectiveness to a 42% reduction at 90%. In real terms this is a change in lifetime operating costs of £55.5 million at 20% effectiveness with a CBM strategy to £45.0 million at £90.0 million.

5.1.3.3. Examination of False Alarms

CM reliability is the metric used to examine the implications of false alarms which is discussed in Chapter 3. The CM reliability rate was varied from 70% to 100% in 10% increments with additional points to ascertain what happens as the reliability approaches 100%. This is done both for a turbine with only the 3 drive train assemblies monitored, the results presented in Figure 5.6, and also with all assemblies monitored at 20% effectiveness and the results shown in Figure 5.7.

In Figure 5.6 at 70% reliability there is a 23.4% difference between the PBM and

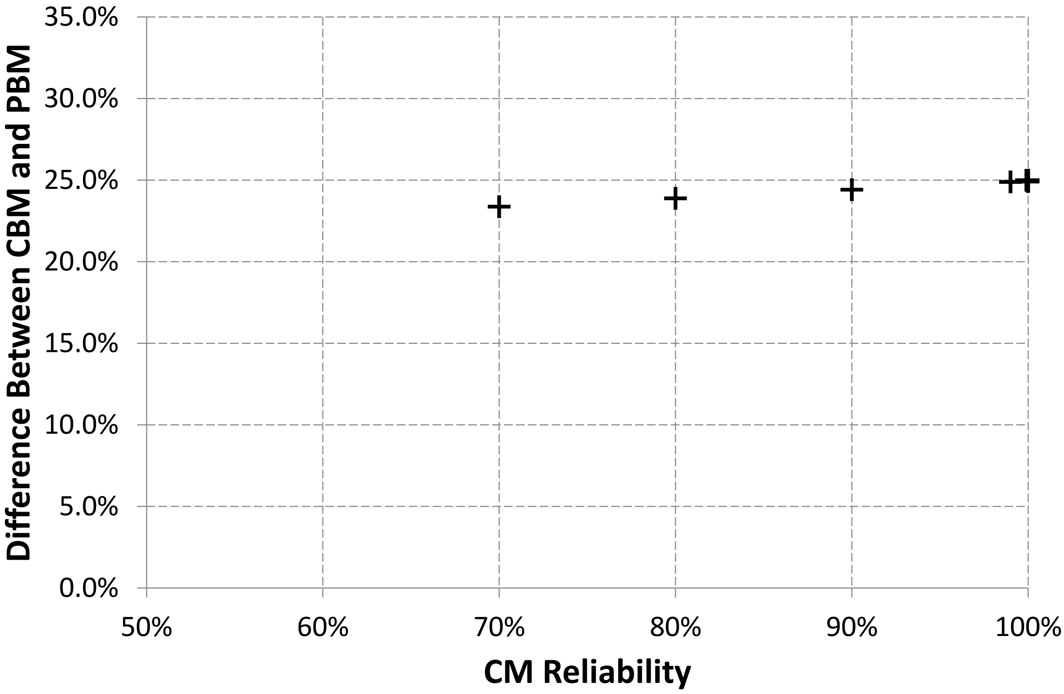


Figure 5.6.: Percentage Saving between PBM and CBM Strategies Varying CM Reliability for Gearbox, Generator and Drivetrain CM Systems

CBM strategies. This is a saving of around £18.2 million. This increases to a 25% difference and a saving of £19.5 million at 100% reliability. The savings increase linearly as CM reliability increases.

The same pattern is visible but more pronounced in Figure 5.7 where CM systems have been installed over the whole turbine at 20% effectiveness. The difference between the CBM and PBM strategies increases from 23.2% to 28.8% when the reliability increases from 70% to 100%.

Originally, it had been expected the CM reliability would have a greater cost difference at the higher percentage reliability numbers (>90%). This was investigated by borrowing techniques from the telecommunications and computing industries regarding high availability. Common availability levels are set according to the theory of "nines" [5.14]. Three nines refers to an availability of 99.9% and six nines refers to an availability of 99.9999%.

The models were simulated with reliability values of one through five nines - i.e. 90%, 99%, 99.9%, 99.99%, and 99.999%. However, the results with reliability values

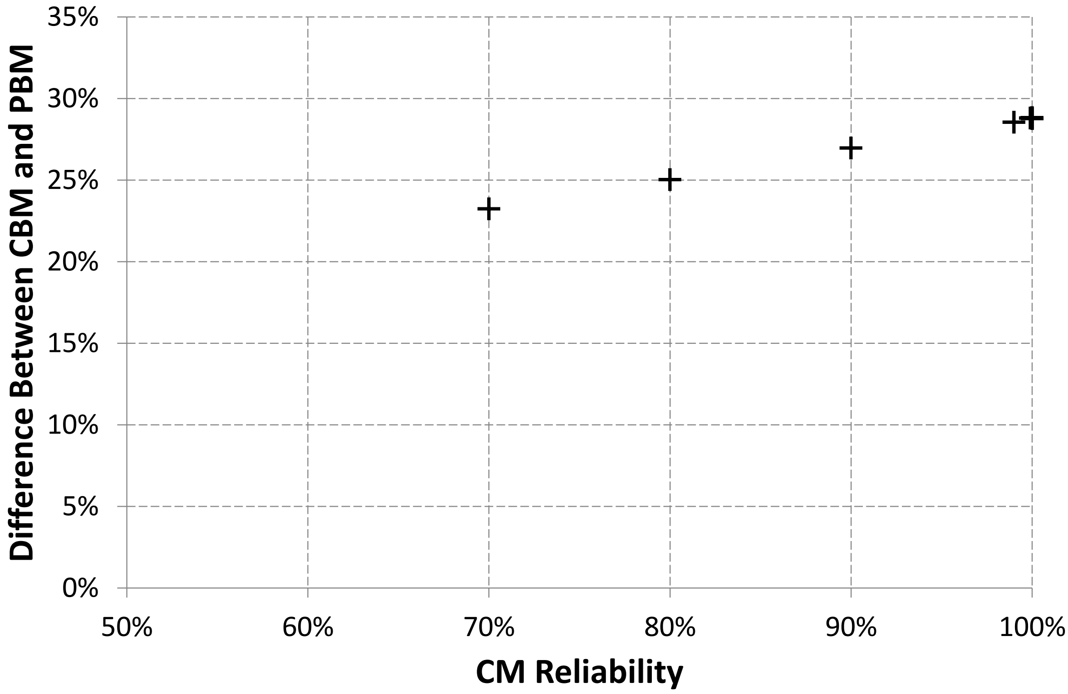


Figure 5.7.: Percentage Saving between PBM and CBM Strategies Varying CM Reliability for All CM Systems

greater than three nines are all within the margin of error of the simulation. These numbers are presented in Figure 5.8. The three-sigma value of the values shown, that is three standard deviations from the mean values and accounting for 99.7% of simulation output, is approximately 0.1%. At 99.9% CM reliability, the mean difference between maintenance strategies is 24.98% giving a range between 24.88% and 25.08%. No value of CM reliability greater than 99.9% falls outside that range.

5.1.4. Discussion of Prototype Model

The benchmarking that the model has completed shows that the output far exceeds those of a developed reference case for replacement costs and probably also slightly exceeds component costs of early offshore wind parks. Unfortunately due to confidentiality restrictions the true cost outputs for the real wind farms cannot be known. The early wind farms are important for the model - the data from Egmond aan Zee has similar features to these farms - and would be useful in assessing the success of the model.

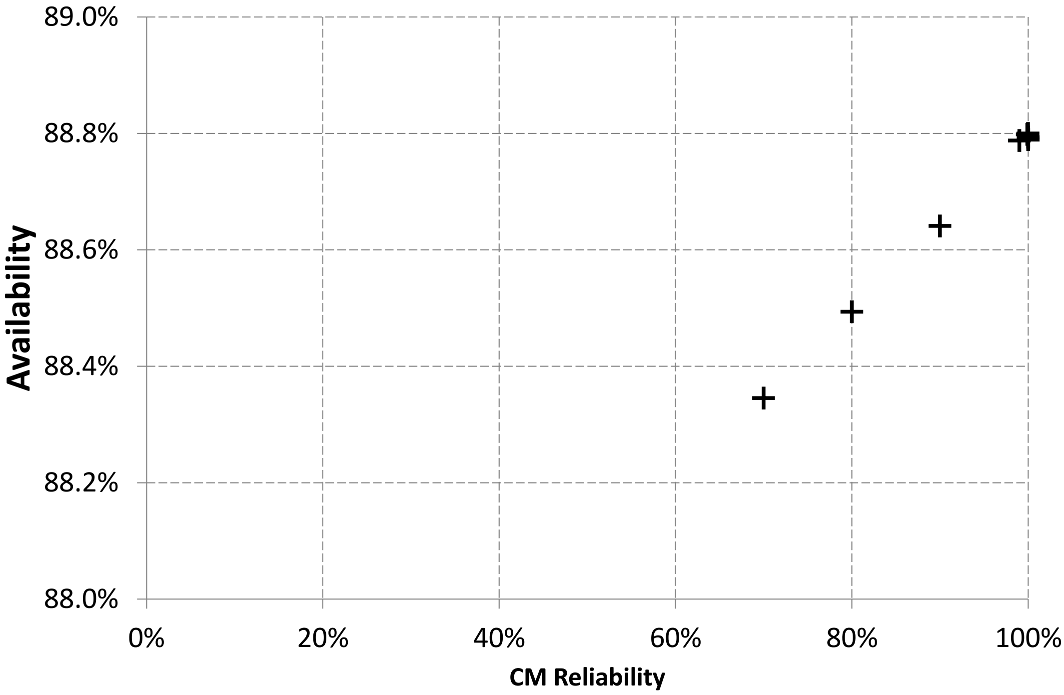


Figure 5.8.: Availability Varying CM Reliability for All CM Systems

However, the model does predict similar levels of availability both for the reference cases and for early offshore wind farms which suggests similar levels of wind farm downtime. It also predicts smaller amounts of lost production costs due to a simpler cost and yield deriving mechanism.

Due to how the simulation operates, the hidden Markov chains are generated for each assembly independently for each turbine and for a whole wind farm. To give an example, it is possible for the gearbox to fail and, while the turbine is being repaired, the generator simultaneously fails even though the turbine is not operating.

This deviation in costs could be because the predicted costs of repairs are too high or the failure rates are too high. As noted in Appendix A, the major failure rates are already quite high compared to a regular modern offshore wind farm and modifying these rates heavily will change the availability figures.

To investigate the contributions from major and minor failures to component costs, further simulations were completed. The minor costs were reduced by a factor of 4 for the reference case chosen to ensure all minor repairs now cost less then £10,000 and on average cost just over £1,000. This factor was selected as it is assumed that repair costs that are significantly less than an annual service of £2,555 could easily be actioned by a maintenance manager. Repairs costing more than this would likely need to be approved by more senior management.

These new annual repair costs became £7.8 million, a reduction of £2.92 million. When this factor for minor failures was kept and the same factor was used to reduce the major costs of 4 assemblies with high annual major failure rates then the annual repair cost became £5.9 million, a further reduction of £1.9 million.

This shows that while improving the reliability of major unreliable assemblies - an often quoted goal of OEMs and operators - is important for reducing operating costs, there are substantial benefits in decreasing the costs of all subsystems including minor, short term faults. This may be useful for operators and owners in driving down lost production costs.

This model has shown that it can used to produce credible outputs in multiple situations. These simulations can be repeated and produce similar results. It is the difference between the maintenance strategies that is important to see if a cost benefit of condition monitoring systems can be achieved. The information in the model such as failure rates and component costs can be adapted and changed quickly (such as the component cost tweaks as shown above) as more information about the operating conditions of offshore wind farms and component costs become known.

The lack of modelling for logistic operations is a major restriction in this model. This does not allow for a complete picture of maintenance activities and costs to be made for comparison. The structural components of the tower and foundation have been modelled simply. These have been treated as mechanical components in this model rather than structural. There is no assessment of the risk of collapse of these assemblies. Additional and specialist equipment required for completing structural operations is not included.

Finally, the model also uses generic, theoretical CM systems that are either applied to all systems equally whether they exist or not. The time between detection and failure is also important - the further in advance a failure is observed the more planning can be done to mitigate this failure. This model does not take this fact into account. All failures are detected equally - with one value of effectiveness. A better model would allow for different detection times for the same fault and with varying repercussions.

5.2. Improved Detection Modelling

The conclusions from the previous section are used to build on and improve the model.

The simulations in this section use a wind farm consisting of 20 turbines of 3 MW size for an operational life of 20 years. The model changes from an annual time step to a monthly time step and the failure rates are adjusted accordingly using exponential deterioration. The capacity factor used is still 33.3% and is based on the value from Egmond aan Zee as is the average distance to shore – 13 km [5.15].

The FMEA has undergone minor revisions to the component cost model and some of the most extreme major downtimes have been reduced after better understanding of the data is achieved. This was partially based on industrial insight. The model itself operates in the same manner as the previous section. The model has additional features added to it to deal with some of the issues raised in the previous section: a logistics cost model, with the ability to observe failures 6 months in advance; modelling of the foundation and tower as separate systems; and additional CM system modelling capabilities including price and ability [5.16].

All of the required data for the model and the flow of information is now presented in Figure 5.9.

5.2.1. Modifications

5.2.1.1. CM Ability and Cost

In the previous model, the modelling of the cost and operation of CM systems was limited. Theoretical CM systems were added to wind turbine assemblies regardless of the feasibility of technology. This is addressed by completing a survey of existing monitoring equipment and collecting generic costs. This is done for technologies with a high technology readiness or that have functioning experimental systems.

Costs are produced for the 'Drive Train' which is a term that is used to represent the

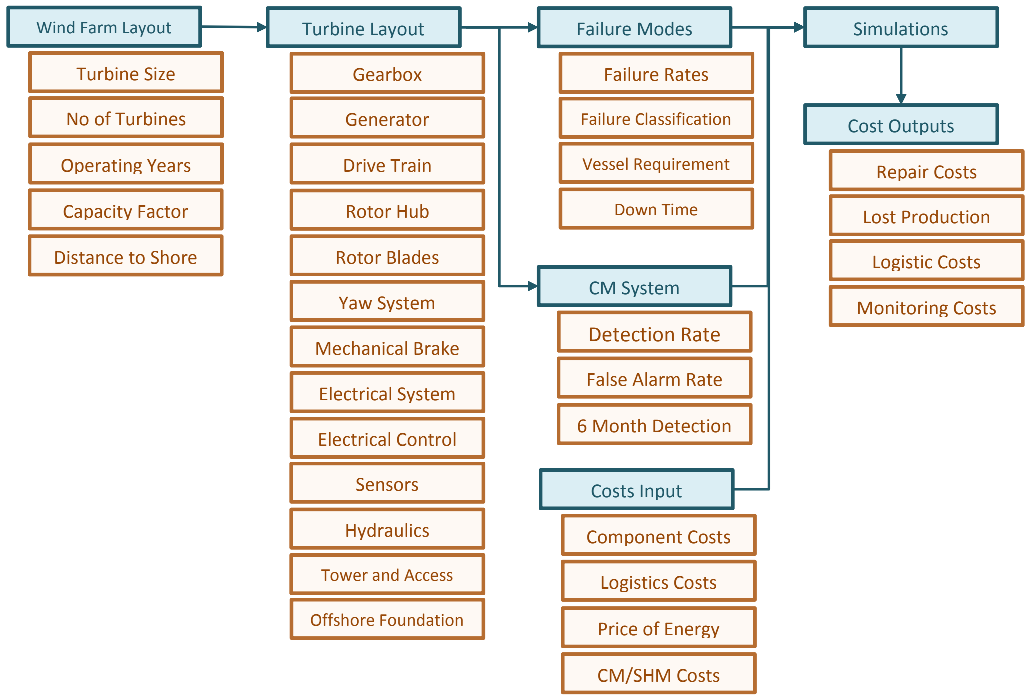


Figure 5.9.: Required Data and Information for O&M Model

the gearbox, generator and drivetrain assemblies and 'SHM' which is a term used to represent the blades, tower and foundation assemblies. Different technologies incur different costs for the same assembly.

Tables 5.6 and 5.7 show the generic costs used which are reproductions of Tables 4.8 and 4.9. These are both initial capital costs and annual operating costs. The full description of how these costs were arrived at is in Chapter 4.

Subsystem	Drive Train		
CM Type	Vibration	Oil	Acoustic
Capital Costs [£]	6,550	9,210	8,146
Annual Costs [£]	570	0	0

Table 5.6.: Generic Costs of Commercially Available CM Systems

Multiple condition monitoring systems can be incorporated onto the same assembly or assemblies. This will improve the detection rate or the CM effectiveness value and this is modelled as a parallel system. This is explained further in Chapter 3. Some systems are offered incorporating multiple CM technologies - Mistras Group [5.17]

Subsystem	Blades			Tower	Foundation
CM Type	Vibration	Acoustic	Optical	Vibration	Vibration
Capital Costs [£]	10,880	28,390	12,280	4,346	14,040
Annual Costs [£]	770	0	0	80	4,070

Table 5.7.: Generic Costs of Commercially Available SHM Systems

use "dual-function technology" of both vibration and acoustic emission. If oil sensors are added to a vibration CM system then further failure modes can be detected and the CM effectiveness will increase. However, this method relies on the accuracy of the effectiveness values of the CM systems. Assuming high values of effectiveness in a parallel system it is easy to achieve very high effectiveness levels - two systems each with a CM effectiveness level of 70% give an overall level of 91%. This may not be realistic.

5.2.1.2. Logistics Modelling

The logistics failure classification system developed in Chapter 4 and shown in Table 4.7 is used as the basis to ascertain the logistics costs.

Major and minor faults are assigned a classification. The classification of major and minor faults can be different when detected by a CM system in advance. To continue an example from Morton [5.18] given in Chapter 4, when a major fault of a generator bearing that would cause significant secondary damage is detected far enough in advance only the bearing itself needs to be replaced. In certain types of gearbox this can be done in-situ. This means that a crane vessel is no longer required to complete the repair - reducing it from a logistics failure Class 6 operation to a Class 4 or 5 depending on the size of the bearing.

As discussed above, some failures are capable of being detected several months in advance. Procuring large vessels significantly in advance or for long periods of time can reduce effective day rate costs [5.19]. A percentage of the failures detected by the CM system are assigned to have been detected over 6 months in advance for applicable subsystems where it is probable that this may occur and that would require crane or large service vessels. These use a lower vessel cost, C_{EC}, to give an alternative operations costs, C_{IC}, shown in Equation 5.8. The lower vessel cost is taken from the spread of values shown in Bjerkseter and Ågotnes [5.7].

$$C_{IC} = \sum_{i=1}^{k} (C(i)_E + C(i)_{EC} + C(i)_L) \tag{5.8}$$

5.2.1.3. Age-related Failures

Poisson processes have been mentioned previously in Chapter 4 as way to model deterioration over time. The Power Law process is an example of a Non-Homogeneous Poisson process often used in reliability modelling [5.20]. It is used to produce a hazard rate and can represent multiple stages of a Bath-tub curve. The equation for the Power Law process is shown in Equation 5.9. In this equation it is the value of β, often referred to as the shape function, that defines the type of hazard rate. If $\beta < 1$ the hazard rate is decreasing over time and represents infant mortality. If $\beta = 1$ the hazard rate is constant and represents working useful life. Finally, if $\beta > 1$ the hazard rate is increasing and represents the wear out phase of a mechanical component. ρ is a scale parameter.

$$u(t) = \rho\beta\, t^{(\beta-1)} \tag{5.9}$$

The failure rates are adapted in this work to represent the learning, infant mortality and the alleviated serial defects (or inappropriately designed assemblies) that will occur over the years of operation. As the failure rates are derived from 3 years with issues occurring over them it would not be appropriate to adapt these average failure rate figures. A value of 0.8 was selected for β. This value was chosen based on the work of Guo et al. [5.21] after their analysis of the reliability of German and Danish onshore turbines from the WindStats database. A Power Law process and a further Power Law process with three variables were fitted to the data. The estimated β values given for the German and Danish farms were 0.7984 and 0.8468, respectively.

A graph showing the failure rate over time for selected components is shown in Figure 5.10. Learning is shown in this figure for 10 years. However, in the work, it is limited to 5 years before becoming constant. This value is based on observing capacity factors of operational offshore wind farms shown in Figure A.5. Wear out failures with an increasing hazard function are not used for reasons given in Chapter 3 and Appendix A.

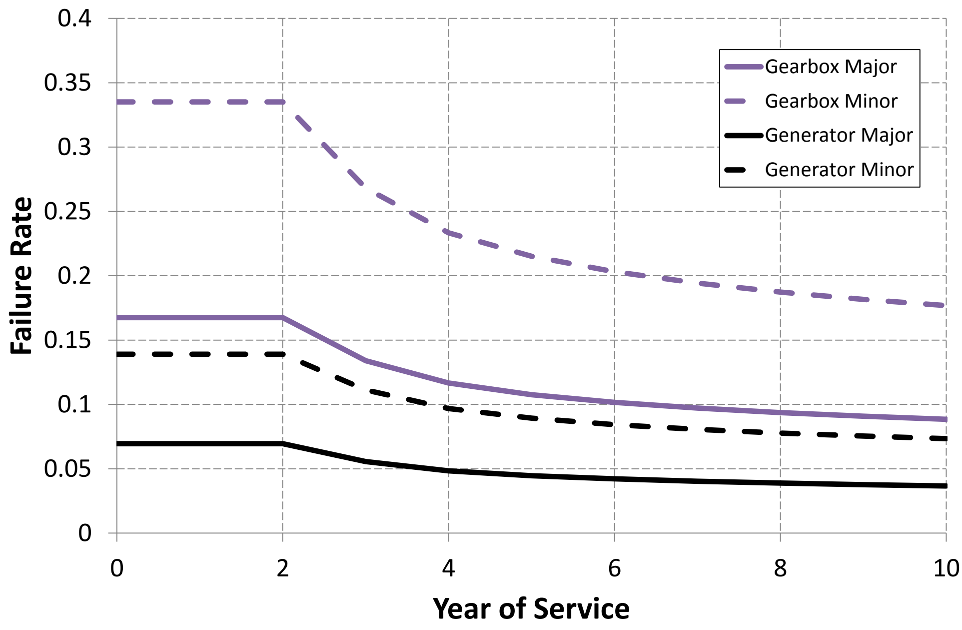


Figure 5.10.: Changing Failure Rate of Two Components with Learning

5.2.2. Outputs

5.2.2.1. Benchmarking

This updated model was again benchmarked according to the reference case in Dinwoodie et al. [5.10]. The component costs of the annual service are still £5,000 per turbine. The labour and logistics costs sum to a further amount of approximately £3,300.

The model produced annual component costs of £9.66 million with a further servicing cost of £400,000, lost production of £11.17 million, logistics costs of £11.93 million and £264,000 for servicing logistics. These values are presented against the maximum, minimum and average output from the reference case models are presented in Table 5.8.

The minor alterations of the FMEA and downtimes have led to increases in predicted availability and reductions in lost production. The inclusion of logistics costs allow for

Table 5.8.: Comparison of Output with Published Reference Model

Simulation Output	Reference Case			Improved HMM Model
	Min	Average	Max	
Availability - time	80.82%	83.16%	84.40%	86.92%
Annual Lost Production	£15.48m	£17.01m	£18.64m	£11.17m
Annual Repair Cost	£3.00m	£3.76m	£4.39m	£10.06m
Logistics Cost	£10.9m	£16.24m	£20.78m	£12.19m
Total	£29.38m	£37.01m	£43.81m	£33.42m

a full comparison with the reference case. The model still appears to over-predict repair costs and under predict lost production. The logistics costs are within the range of the reference case and, when combined, the model output is well within the spread of the reference case outputs.

The base case with PBM strategy shows the annual outputs for one 3 MW turbine are approximately £120,000, £146,000 and £146,000 for component, lost production and logistics costs respectively. When this is scaled to represent a 20 turbine wind farm, and annual servicing costs are included, the operating and maintenance costs become £7.75m. A breakdown of costs per turbine is shown in Figure 5.11. The component costs attribute to 30% in this model while in the average reference case component costs are around 10%. The lost production and logistics costs contribute around 45% each in the average reference case while in this model each contribute 35%.

Unless otherwise stated, every CM system has a detection rate of 80%, excluding the systems for the vibration drive train which are as noted in Table 3.1. Likewise, the percentage of faults that are detected more than 6 months in advance to access lower vessel costs is set at 10% of all detected faults unless otherwise noted. In Tavner [5.20] the ability to diagnose gearbox faults using SCADA temperature data is discussed. This shows that there is a significant chance of capturing some faults at least 6 months in advance. Other techniques are also discussed for long term detection. The base value of 10% was chosen to be a conservative value as this is applied only to effective diagnosis by a CM system.

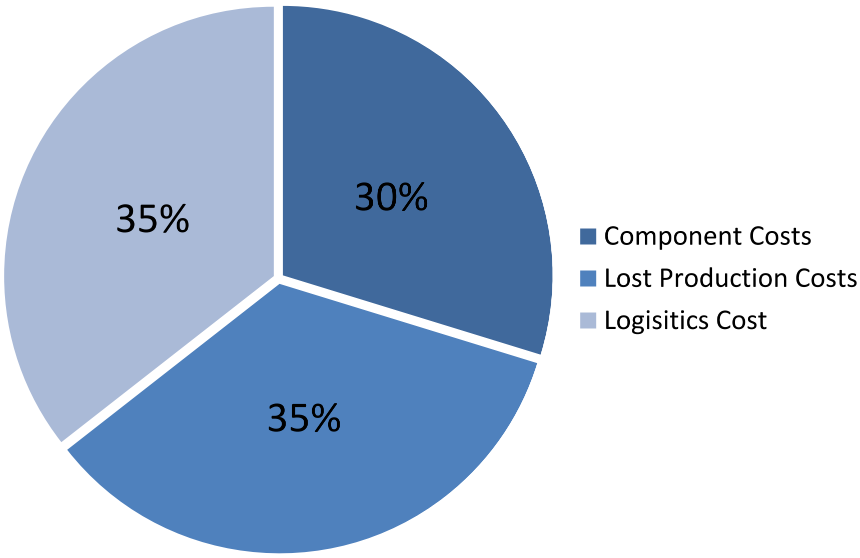


Figure 5.11.: Breakdown of Annual Operating Costs per Turbine inc Annual Service

Table 5.9.: Lifetime Savings Over PBM with Various CM Systems

Drive Train CMS	Lifetime Saving Over PBM	Percentage Saving
Vibration	£12,000,000	17.7%
Vibration & Oil Sensor	£19,100,000	28.8%
Vibration & AE	£18,900,000	28.7%
Vibration, Oil & AE	£20,300,000	30.6%

5.2.2.2. Drivetrain CM Systems

As discussed in the previous chapter, most studies find that vibration based CM systems for the drive train offer return on investment (ROI) - if CM effectiveness values are too low and access is reliable then the CM system might not be viable. A 'Drive Train CMS' is defined as one that detects failures on the gearbox, generator, main bearing and output shafts. Other CM methods that can be used in the same way as a Drive Train CMS include oil sensors and Acoustic Emission (AE) systems. The effects of these systems on the operating costs are examined in Table 5.9.

An example simulation year from the improved HMM model for the first 3 years of O&M costs for the CBM strategy for the entire farm is £6.6 million, consisting of £1.97m in spare parts (30%), £2.47m in lost production (37%) and £2.19m for logistics costs (33%) including CM annual operating fees. The simulation was for an

Table 5.10.: Lifetime Savings Over PBM with Various SHM Systems

SHM System & Drive Train Vib CM	Lifetime Saving Over PBM	Percentage Saving
Blades (Optical)	£13,000,000	19.5%
Blades (Vib)	£12,900,000	19.4%
Blades (AE)	£12,600,000	18.9%
Tower	£11,800,000	17.9%
Tower & Foundation	£11,700,000	17.6%
Tower, Foundation & Blades (Vib)	£12,500,000	18.6%
Foundation	£11,800,000	17.6%

Egmond aan Zee type wind farm as described at the start of this section. This compares to £8.3 million for the PBM strategy for the same year where all components of the model show higher costs.

In the model, a vibration CM system offers potential lifetime savings of approximately £6m over a PBM strategy. If either an oil sensor system or an AE system is used in addition to the vibration CM system the lifetime savings increase. This indicates that the additional O&M costs reduction found from adding CM systems are larger than the costs of the CM systems themselves.

However, this statement is dependent on the AE or oil sensor increasing the failure modes that can be detected by a large amount. The probability of detection increases from 50% for the gearbox system with only a vibration CM system to 98% for one with all three drive train systems. This results in an increase of capital costs for a 20 turbine wind farm from £131,000 to £478,000. However, the improved detection rates allow for an approximate reduction in replacement part costs of 17% per annum. While overall lost production values remained similar, the smaller repairs also allowed for significantly smaller logistics costs. More information is required before the levels of effectiveness can be assessed.

5.2.2.3. Structural Monitoring

Blade, tower and foundation SHM systems were added to a standard vibration based drive train CM system. The effects of these systems on operating costs are shown in Table 5.10.

Blade SHM systems offer further savings over a Drive Train CMS alone. The largest saving over a PBM strategy was seen when using an optical blade SHM system. The optical SHM system that is envisioned for the blades is similar to that described by Rademakers [5.22]. Those fiber Bragg grating strain and temperature sensors get installed in the root of each blade with a communications unit in the hub. Processing and further communications are done in a secondary unit in the tower. This gave savings of £13 million, which is an increase of 7% over the drive train CMS. If a SHM system to monitor the tower is added this increases lifetime costs over using only a Drive Train CM by 1.6%. In a scenario where a CM system is utilised on the tower, foundation, blade and Drive Train an increase of 4% in savings is observed compared to PBM.

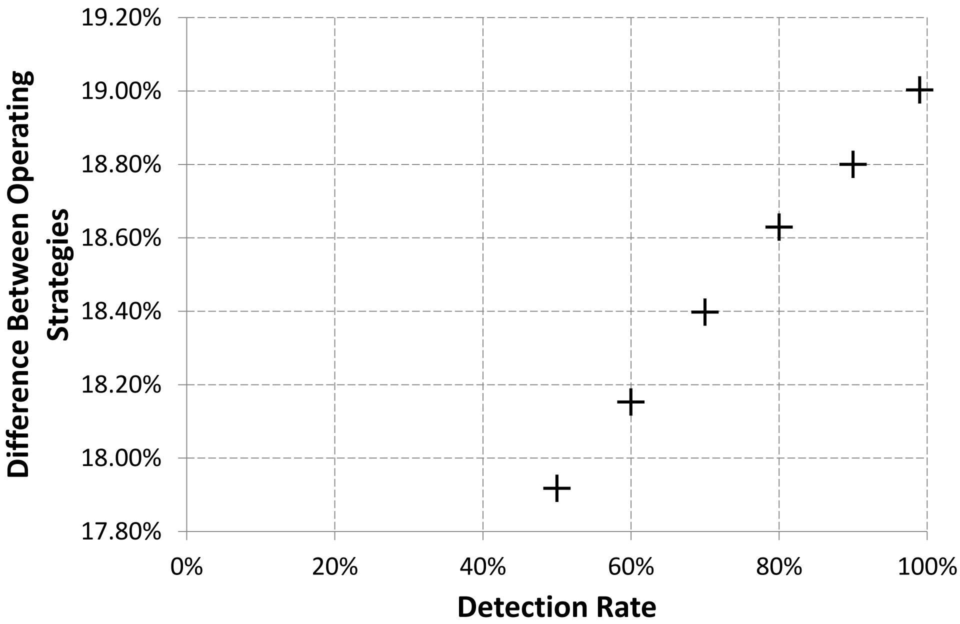


Figure 5.12.: Difference in Lifetime Costs Between PBM and CBM Strategies Against CM Effectiveness

The ability of the CM and SHM systems to detect failures has a direct influence on the ROI of the monitoring system. This is investigated in Figure 5.12. A vibration based monitoring system is placed on the drive train, blades, tower and foundation. The detection rates for all the SHM systems is set at 60% and increased in increments to 99% and the resulting levelised lifetime savings recorded. The drive train effectiveness values remain unchanged.

At 60% the lifetime O&M saving was £12,300,000. This increased to £12,800,000, an increase of 4%, when the fault detection rate was set at 99% and followed a linear pattern for detection rates in between. The higher the effectiveness of a CM or SHM system, that is one with a high detection rate, the more likely it is to reduce the O&M costs of a wind farm.

5.2.2.4. Advanced Failure Warning

All of the previous simulations assume that 10% of the total detected faults by CM and SHM systems were detected with greater than 6 months warning. The assemblies that have the possibility of greater than 6 month detection are those that require a jack up vessel to repair a major failure. These include the drivetrain and rotor blades.

This assumption is examined in Figure 5.13. The number of faults detected in advance is increased from 10% to 50%. This gives an increase in savings of £250,000 from £11.91m to £12.16m over the lifetime of the wind park - an increase of 2% for a scenario where only a Drive Train CMS is used.

It is difficult to estimate the number of failures that can be detected more than 6 months in advance. If the ability for a CM system to detect these faults improves then it is more likely that it will require a smaller intervention and it could possibly even be categorised as minor fault. However, if it is possible to charter a vessel substantially in advance then these simulations show the benefits.

5.2.2.5. Failure Data Modification

A report from GL Garrad Hassan, The Crown Estate and Scottish Enterprise gives more recent offshore availability figures as between 90% and 95% [5.23]. The definition of availability used in this work is given as a "measure of how little electricity is lost due to equipment downtime" but it is not clear if servicing and out of environmental specification time are excluded. Carroll et al. [5.24] also shows real offshore availabilities of between 92% to 96%. This is much higher than the average figures reported from Egmond aan Zee of 80% for the 3 years up to 2009. The simulation with the modified Egmond aan Zee data with assumed learning rates gives a figure of 87%. This suggests that the failure rates used are too high for wider conclusions to

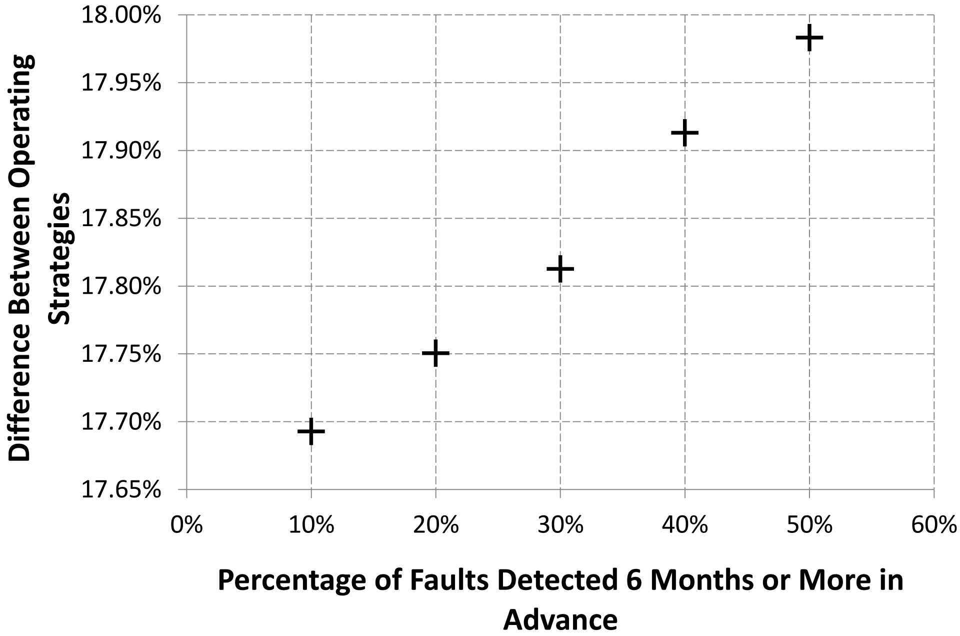


Figure 5.13.: Difference in Lifetime Costs Between PBM and CBM Strategies Against 6 Month Fault Detection Rate

be drawn.

In this simulation, a new wind park uses the reduced failure rates, after learning, as its initial failure rate. These new failure rates also suffer from infant mortality rates for 5 years in the same pattern as used previously. The annual availability figures for each year of learning are shown in Table 5.11. For the first 3 years (learning year 3 in the table) the availability is 91% with a PBM strategy and 92% with a CBM strategy. This increases to approximately 92% and 93% respectively for the CBM strategies with a reduced failure rate profile with a further two years of learning (learning years 4 and 5 in the table). In this last scenario, savings when a vibration drive train CM system is used become £8.6 million.

As the costs for both the PBM and CBM strategies have changed in this scenario the savings between strategies are compared to the total levelised cost of each PBM strategy. The reduced failure rate case gives savings of 16%. In the similar scenario listed in Table 5.9, £12.0 million of savings is 18% of the PBM strategy cost.

Increasing the capacity factor of the wind farm to 50% increases the cost of LP. This increases savings to £13.7 million (17.5% of the PBM strategy cost) for a vibration only drive train CM system. Conversely, by reducing all the vessel hire costs to 80%

Table 5.11.: Offshore Availability vs Learning and Infant Mortality

Learning Year	Gearbox Major Failure Rate	Annual Availability	
		CBM	PBM
1	0.155	88.95%	86.95%
2	0.124	91.77%	90.33%
3	0.108	92.32%	90.99%
4	0.099	92.66%	91.39%
5	0.094	92.94%	91.72%

of the standard day charter prices the savings reduce to £10.7 million (17%).

5.2.3. Discussion

This model has solved many issues raised with its predecessor. Although logistics costs are included the model appears to under-evaluate their contribution to O&M costs. The modelling of CM and its effects has been greatly enhanced and allowed for different types of CM systems to be deployed independently on all assemblies. Detection modelling is identified as an area for improvement of the model. The CM failures are no longer modelled as binary choices - there are options for long term detection but this only offers limited improvement. A more continuous detection technique rather than the discrete methods employed so far would offer further improvements.

A more effective energy yield model would improve the figures for lost production. Failures are more likely to occur at higher wind speeds and this is when wind turbines are able to generate the most energy [5.20]. This issue could be solved by revising the capacity factor upwards but how this revised figure would relate to the annual capacity factors of operating wind parks is unknown.

Two other important issues are simultaneous failures and a better understanding of the costs incurred while operating an offshore structure are yet to be fully addressed.

5.3. Developed DBN Model

The use of Dynamic Bayesian Networks was identified as having potential benefits over HMMs. DBNs had been shown to model reliability in mechanical and civil structures. These flexible modelling tools allow for updating the probability of failure for assemblies based on inspections and are efficient in reducing the amount of states that need to be generated [5.25]. This Bayesian approach could then further be used with Bayesian decision analysis to formally solve for the VoI as discussed in Chapter 4.

5.3.1. Modifications

The model has been redesigned using DBNs for deterioration modelling. The wind park is modelled with monthly time steps. The structure of the DBN is shown in Figure 5.14 which is a reproduction of Figure 3.8. In this figure, S refers to the state of an assembly that deteriorates from t, to $t+1$ and $t+2$, while X is the CM output at that particular value of t.

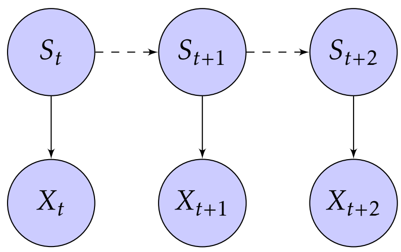


Figure 5.14.: Dynamic Bayesian Network over 3 time steps

A random number is generated from a uniform distribution to represent the condition level of the component at failure. The component condition level is set at 1 and deteriorates over time. When the component condition is lower than the random number a failure is triggered. A partial output from the model is shown in Figure 5.15. The component in this figure deteriorates without failure for 3.5 simulated years. The repaired component survives for a further 2 years without the need for intervention. After this, the component is able to survive for 35 simulated years. Over the sample period shown the component fails 5 times over 650 simulated months.

The way the simulation operates has also been adapted. Each time step is eval-

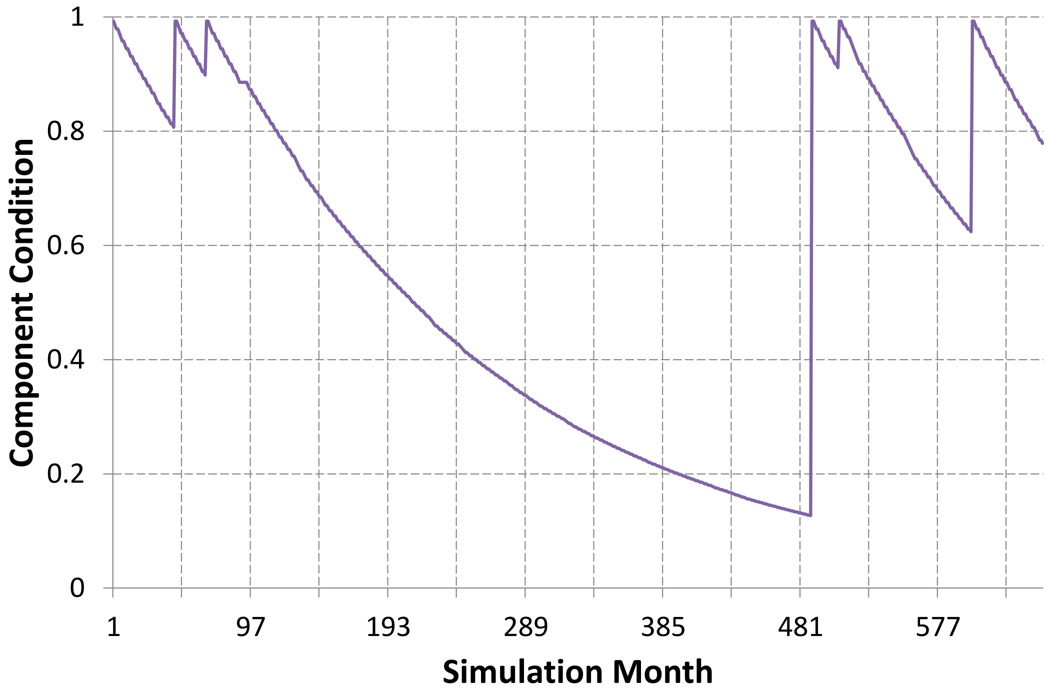


Figure 5.15.: Simulating Component Deterioration in DBN Model

uated across all turbines and assemblies in the wind farm. This is instead of simulations occurring for each assembly separately. When a failure has occurred that causes the turbine to shut down, the other assemblies will not continue to deteriorate. Structural assemblies are excluded from this as the wind and waves continue to load and deteriorate these parts.

5.3.1.1. CM Modelling

Once a failure has occurred the simulation stops and uses a P-F curve as introduced in Chapter 3. The performance of the CM system is based on the 'detectability window' as used in Van Horenbeek et al. [5.26].

A CM system is assumed to have a period of time where it is possible to detect the fault before it fails. The probability of detection increases as the failure grows nearer. A linear relationship is used as demonstrated in Van Horenbeek et al. as shown in Figure 3.11 and is reproduced in Figure 5.16. There is a 100% chance of detection when it fails. A secondary random number is generated and when the probability of detection exceeds this value the failure has been detected. The month that this

Table 5.12.: Generic Costs of Monitoring Systems Used

Type	Capital Cost	Annual Operating Cost
CM System	£ 6,700	£ 590
SHM System	£ 10,080	£ 4,200

occurs before failure gives a reduction in downtime for that failure instance.

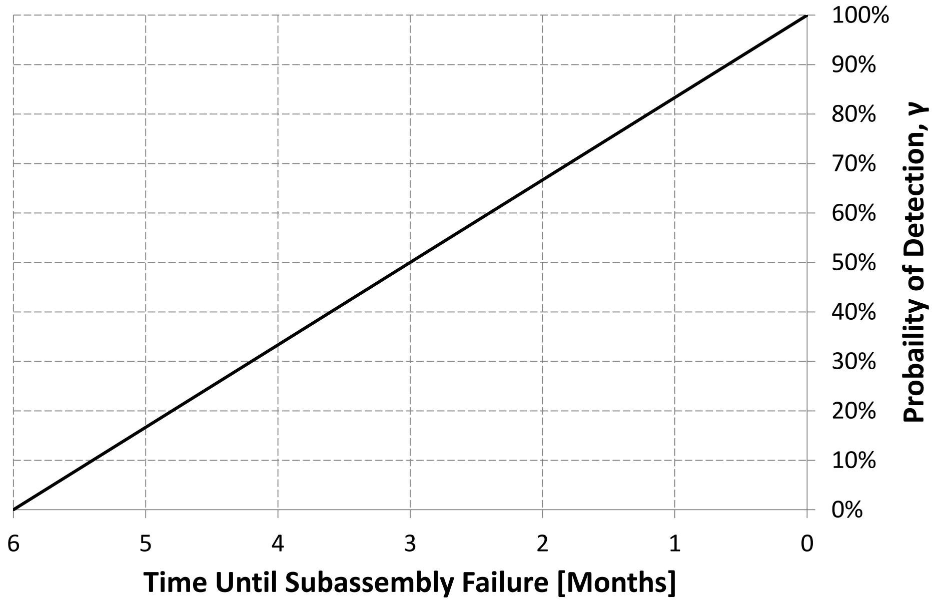


Figure 5.16.: Example of a Linear Detectability Profile

Due to the increased complexity of the CM modelling a reduced set of CM systems was used. They covered only structural health monitoring (SHM) systems and a Drive Train CM system as defined for the previous model. The costs of the SHM system is for a combined tower and foundation SHM.

5.3.1.2. Structural Integrity Management Plan

A basic Structural Integrity Management (SIM) plan was developed following the methodology outlined in Chapter 3.

In this model, 5 hotspots in the tower and 3 stress hotspots on the foundation are examined for a tripod foundation as used with the M5000 turbines in Alpha Ventus. The final probability of failure values for fatigue after a 20 year period for these hotspots were taken from Thöns, Faber, and Rücker [5.27] and variables (notably the k

parameter) were adjusted in the limit state equation until these values were achieved. This was repeated with a SHM system using measurement realisations to produce an alternative probability of failure curve.

The annual probability of failure was taken from these curves and multiplied by the costs of failure to produce an expected benefit. In this situation the cost of the failure is £3.78 million based on the generic costs of £1.26 million per MW as suggested by European Wind Energy Association [5.28] (converted from Euros). This risk based cost is presented separately from other costs as it is different from an incurred operating cost in the same way that an inspection visit is. However, when the annual probability of failure exceeds a threshold value of 1×10^{-4} an inspection and a repair is triggered that does incur a cost.

An example repair may be cleaning, painting, or replacement of cathodic protection. The cost for an inspection is added to the logistics cost. The costs for completing this repair are added to component repair costs.

5.3.2. Outputs

5.3.2.1. Benchmarking

The annual outputs when the model is benchmarked against the reference case are £1.94 million for the component costs including annual services, £12.99 million for lost production and £7.87 million in logistics costs which total £21.86 million. The technical availability is 84.74%.

Table 5.13.: Comparison of Output with Published Reference Model

Simulation Output	Reference Case			Initial DBN
	Min	Average	Max	Model
Availability - time	80.82%	83.16%	84.40%	84.74%
Annual Lost Production	£15.48m	£17.01m	£18.64m	£12.99m
Annual Repair Cost	£3.00m	£3.76m	£4.39m	£3.02m
Logistics Cost	£10.9m	£16.24m	£20.78m	£7.87m
Total	£29.38m	£37.01m	£43.81m	£23.88m

The most striking change using this model is a significant reduction in component costs which are now below the range of the reference case. However, if the cost of an annual service is increased to that used in the reference case, from £5,000 to £18,500 per turbine, the component costs become £3.02 million - well within the range. It is these values that are presented in Table 5.13.

The lost production values are still below the reference case while the availability is slightly higher than predicted. The reasons for the lower lost production costs have been explained in a previous section. If the capacity factor is increased to 54% then the lost production values reach the lower indicated value of the reference case.

The cost of completing logistics is £3.0 million lower than the lowest predicted values.

5.3.2.2. Results

A simulation has been performed to represent a 20 turbine offshore wind farm with turbines of size 3 MW for 20 years. The results of the simulation showed that for an average year of operation there was a reduction in all costs associated with component replacement, logistics work and lost production.

The largest percentage reduction of approximately 18% was in component costs - reducing from around £363,000 per annum to £295,000.

There was also a reduction of around 11% in logistics costs - dropping from approximately £1.87 million to £1.67 million. Lost production saw the smallest reduction in cost of £82,000 and 3%. This can be seen in Figure 5.17.

An average annual breakdown of costs for the wind farm is presented both with and without the utilisation of CM systems and SHM in Figures 5.18 and 5.19 respectively. The amount proportionally spent on component replacement reduces from 7% to 6% as does the logistics costs from 35% to 33% when CM systems are used. This gives a 3% change in the value attributed to lost production.

The total levelised costs for all actions during the 20 years of operation saw a reduction of 6.3% from £73.00 million to £68.50 million. An analysis across multiple simulations produced a three-sigma value of approximately £150,000. This puts the saving between maintenance strategies in a range of £4.35 million and £4.65 million.

The expected benefit from the reduction in risk from using an SHM system, $E[B]$,

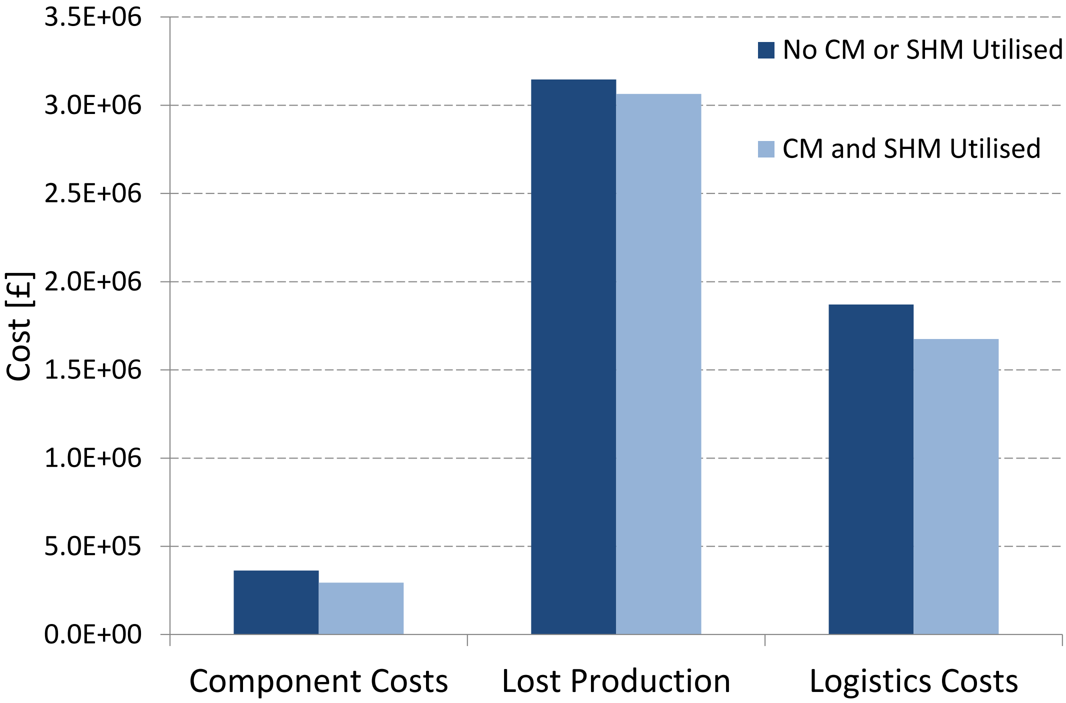


Figure 5.17.: Comparison of Average Annual Costs with and without CM and SHM Utilisation

was found to be around 50% from £187,000 to £92,000 for both the uncorrelated tower and foundation failure events. For the correlated failure events, the values change to a 46% reduction with the expected benefit reducing from £78,000 to around £42,000.

The annual O&M costs per MW can be calculated by taking the logistics costs and component replacement costs for the wind farm and dividing by the size of the farm in MW. For the simulated wind farm without CM or SHM systems the O&M price per MW is approximately £40,000. When utilising CM and SHM this drops to £33,000, a reduction of 18%.

The approximate values from Scroby Sands and Kentish Flats are £26,500 and £14,000 respectively. However, the values from Table 5.2 do not include SIM costs.

5.3.3. Discussion

This model offers several reasonable improvements to the model and has allowed the output of the model to become closer to the reference case. The two major improve-

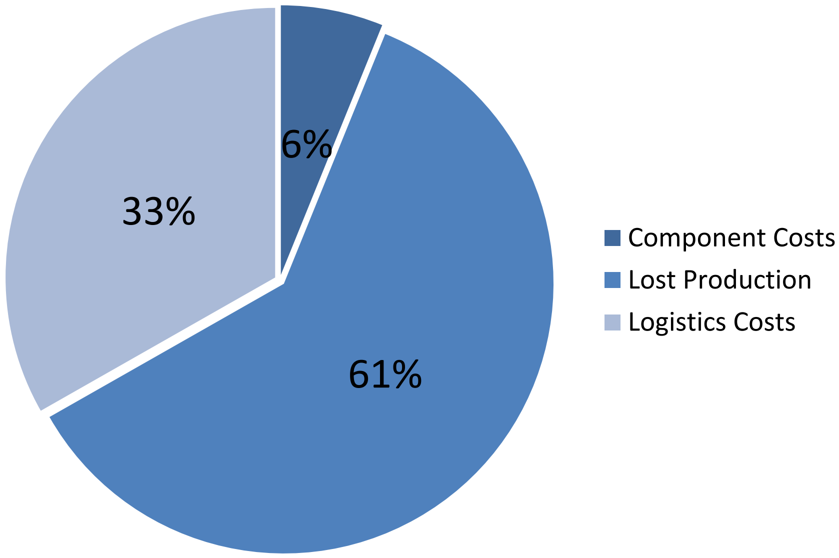


Figure 5.18.: Breakdown of Average Annual Costs with CM and SHM System

ments being the inclusion of a SIM plan and improved CM modelling.

The production of actual and risk based costs for structural components have allowed for an improved understanding of the benefits of SHM systems.

The improved P-F curves are rather bluntly deployed with simple detection profiles and limited deployment across assemblies. In their implementation on this model there has been a loss of some CM parameters used previously in other models. These include effectiveness and reliability. Another lost feature of the previous Markov model is a variable hazard rate.

While the SIM plan is an improvement over previous models and a good basis for understanding the cost benefit of the implementation of SHM, it is far from an accurate representation of an actual SIM plan.

5.4. Final Presented Model

The final model presented in this thesis is an improved version of the previous DBN based O&M model.

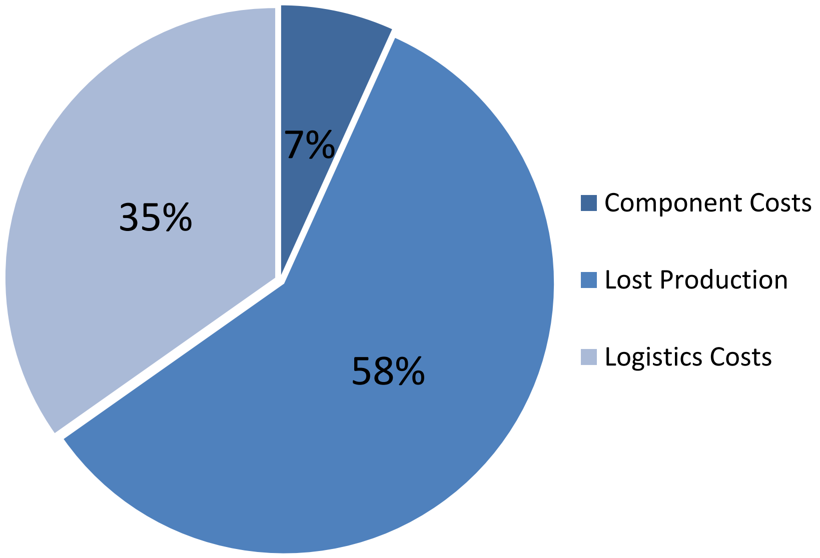


Figure 5.19.: Breakdown of Average of Annual Costs without CM or SHM System

5.4.1. Code Development and Modifications

Discussions with industrial partners have suggested that there are some general detection profiles with major failures. When the large main bearing develops a fault, this is normally easily detectable several months before failure. However, a developing tooth failure of a gear in a gearbox is harder to detect until the final few months before failure where it rapidly develops. These detection profiles have been estimated and that estimation has been used in this model. It is presented in Figure 5.20.

Parameters that have been used in previous models have been added again. When an assembly is operating normally with a CM system, there is a 99% chance that it will show no developing faults. False alarms will occur 1% of the time and incur the same penalties as discussed earlier. The CM effectiveness values have also been added again. This will check whether the fault can be detected at failure but before the model generates a CM detection profile for the particular failure instance.

The hazard rate modifications, to show learning and burn-in used in the final Markov model, have been reintroduced using the same parameters. Convergence has been observed throughout the development process of each model. A sample of this convergence for the final DBN model has been produced and is shown in Figure 5.21. The CoV for the streams for 100 simulated year intervals starting at 1,900, 3,900 and

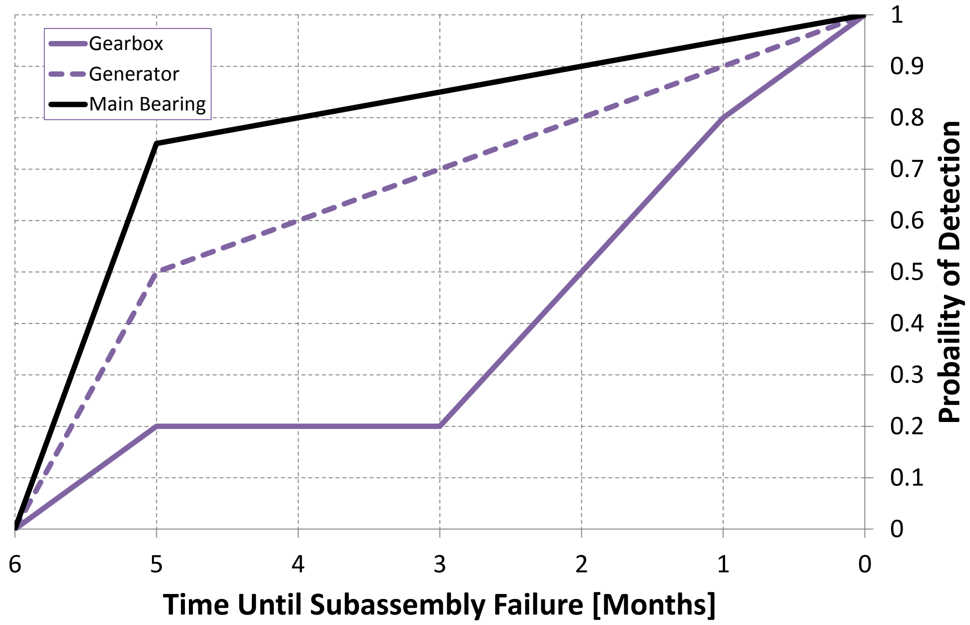


Figure 5.20.: Probability of Detection Profiles for Various Assemblies

4,900 was 1.6%, 1% and 0.57% respectively. A value of 2,000 Monte Carlo years was selected again for simulations.

Further insight was gained in how minor faults are dealt with in industry leading to an increase in downtime for minor failures from 24 hours to 48 hours for all assemblies. This highlighted an issue with how the DBN model dealt with minor downtime and was corrected which resulted in a large increase in availability.

5.4.1.1. Structural Integrity Management Plan

The SIM modelling has been entirely removed from the model simulation and is handled separately. A lifetime probability of failure for fatigue is still produced for both the tower and foundation with the resulting annual probability of failure used to calculate the expected benefit using the methods described in Chapter 3. A sample tower probability of failure per year of service is shown in Figure 5.22 for both correlated and un-correlated failures. This is generated from the same 8 structural hotspots

The annual probability of failure is used to determine when an inspection needs to occur. In the design codes for offshore wind turbine structures - as long as personnel are not expected to be present in severe loading cases - the threshold annual

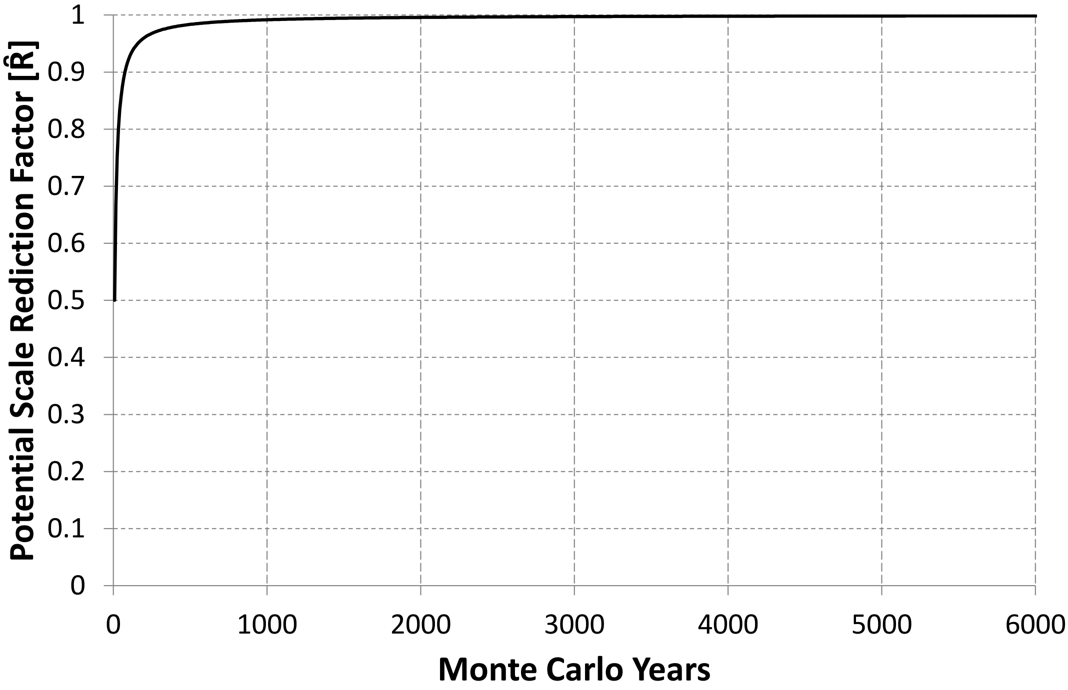


Figure 5.21.: DBN Model Convergence Using the Gelman-Rubin Criteria

probability of failure is 1×10^{-4} [5.29]. When this threshold is due to be exceeded an inspection occurs and the information from the inspection updates the overall probability of failure.

A short review of SIM plans for offshore wind parks in the public domain was conducted. These yielded sources for Egmond aan Zee [5.30, 5.31] and Kentish Flats [5.32]. Both these sites carried out annual surveys to examine the structures for corrosion, damage, growth and the surrounding waters for scour. Scour surveys are occasionally done by specially contracted bathymetry companies which is useful for monitoring seabed changes over time. Often, however, scour is performed as a visual inspection by Remotely Operated Vehicle (ROV) or using a sonar device on vessels when the rest of the foundation is being assessed. Egmond aan Zee aim to check each turbine every 3 years [5.30].

Divers have been used for most of the initial subsea work regarding offshore wind foundations but, due to speed and safety concerns, they appear to be being replaced with ROVs. Oceaneering International Inc. is a company that regularly provides ROV inspection services to the oil and gas industry and have published day rates for their

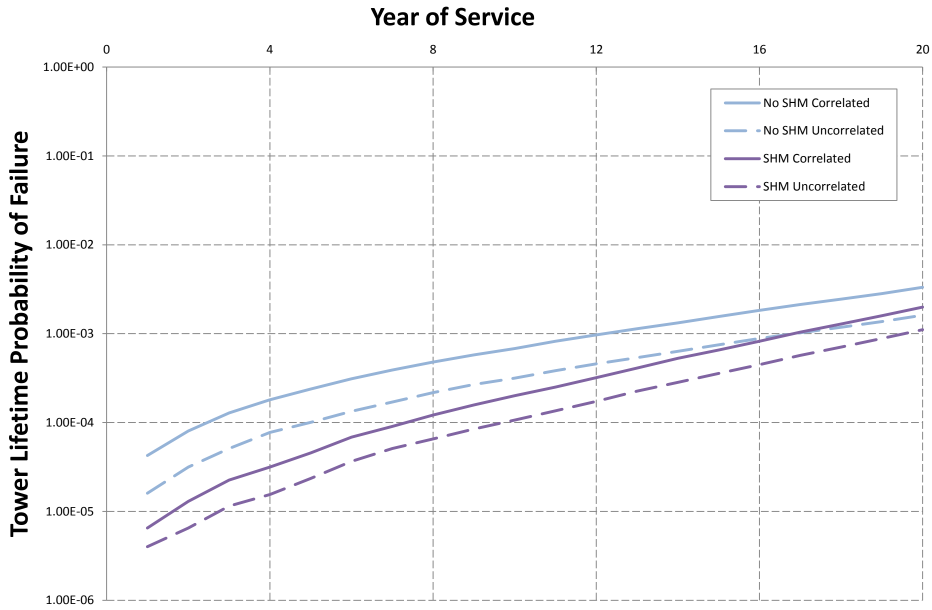


Figure 5.22.: Tower Lifetime Probability of Failure

equipment and crew [5.33]. For cost modelling purposes, an inspection action requiring an ROV is added to the hire costs of an FSV. This means that an inspection event is classified as a type 2 maintenance action as described in Table 4.7.

It is assumed that every foundation must be examined with an ROV every three years. It is also assumed that an ROV can examine 2 turbines per 24 hours and a less extensive survey can be completed when using the improved knowledge of the structure from an SHM system allowing for 2.5 turbines to be examined a day. All the necessary inspections of the tower and foundation are completed during these ROV visits or during the annual turbine service.

5.4.2. Outputs

5.4.2.1. Benchmarking

This model produces an average PBM cost of approximately £19,800, £222,100 and £120,200 per turbine (excluding SIM and annual service) for component costs, lost production and logistic costs respectively. This becomes £1.98 million, £17.77 million and £9.88 million respectively for an 80 turbine wind farm with annual inspections. Using the reference case, annual service costs of £18,600 the component costs become £3.07 million. The availability is 84.3%. These numbers are presented in Table 5.14.

Table 5.14.: Comparison of Output with Published Reference Model

Simulation Output	**Reference Case**			**Final DBN**
	Min	**Average**	**Max**	**Model**
Availability - time	80.82%	83.16%	84.30%	93.91%
Annual Lost Production	£15.48m	£17.01m	£18.64m	£10.32m
Annual Repair Cost	£3.00m	£3.76m	£4.39m	£3.07m
Logistics Cost	£10.9m	£16.24m	£20.78m	£9.88m
Total	£29.38m	£37.01m	£43.81m	£23.27m

The correction of the minor downtime handling in the code has led to a large increase in availability and a resulting reduction in lost production costs. This means that earlier versions of this DBN model over-stated the availability of wind parks and gave pessimistic results. However, the costs for logistics and component costs are close to the reference.

5.4.2.2. Results

The annual CBM costs for a wind farm consisting of 20 turbines of 3 MW in size and using SHM and a Drive Train CM system are approximately £470,000 for component costs, £1.20 million for lost production costs, £2.50 million in logistics costs and £215,000 for SIM costs for the first 3 years including annual servicing. These numbers are shown for comparison in Figure 5.23 and a breakdown of annual costs for the CBM strategy is shown in Figure 5.23. The SIM costs without using an SHM system have been calculated as £255,000.

The change in lost production costs relate to an increase in availability of 0.28% for the first few years of operation. Similar gains in availability are shown over the other operating years.

Over the lifetime of the wind farm the levelised cost becomes £37.80 million compared to £39.74 million - a difference of 5% when using a discount rate of 8.2%.

The expected benefit of the SHM system is approximately 35.5% and 37.5% for correlated and uncorrelated failure respectively. The risk was reduced from £141,000

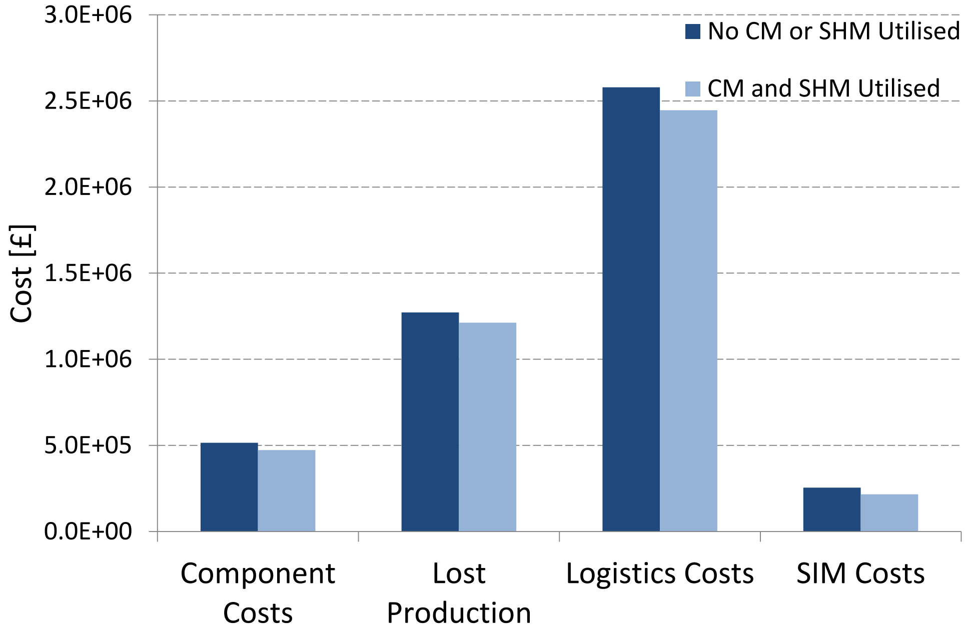


Figure 5.23.: Comparison of Annual Operating Costs with and without CM and SHM systems

per turbine to £91,000 for correlated failures and likewise from £92,000 to £58,000 for uncorrelated failures.

Adding a vibration based blade monitoring system to the blades and hub increases this saving to 5.7% over the lifetime of the wind park.

5.4.2.3. Additional Simulation Scenarios

This section contains additional scenarios that have been simulated using the model described above. Each scenario is outlined below and the simulation output is shown in Table 5.15.

The failure data of Egmond aan Zee - both failure rates and downtime - were adjusted to remove the apparent serial defects as detailed in Appendix A. Otherwise the simulation remains the same as the previous section with a SHM system for the tower and foundation. The simulation was run both with and without a blade monitoring system.

An offshore wind farm was simulated to investigate the implications of CM and SHM on larger wind turbines that are further from shore in a scenario that more closely relates to some of the large offshore wind parks. This simulated wind park used 30

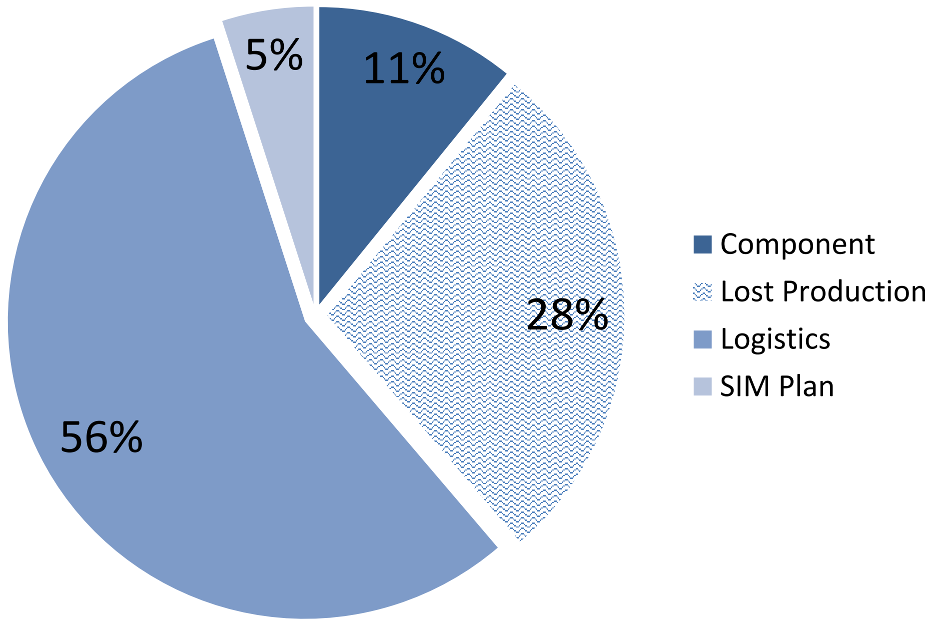


Figure 5.24.: Breakdown of Annual Operating Costs with CM and SHM systems

larger 5 MW turbines around 50 km from shore. A higher capacity factor of 45% was used.

The implications of a variable financial market was also investigated. The ROCs that have been commonly used have been 'grandfathered' and replaced by Contracts for Difference (CFDs). This is a 'pot' of money that will be used to top up the market price of electricity to the agreed upon 'strike' price. If the market price exceeds the strike price then the generator pays back the difference to the government. In the first round of CFD auctions in 2015 two bids were awarded at £119.89/MWh and £114.39/MWh. If there is less competition for the 'pot' then the strike price reverts to an administrative price of £140/MWh [5.34].

In the previous simulations, the price of energy has been calculated as £119.33 /MWh. Simulations were run with a low CFD strike price of £110/MWh - a figure chosen to possibly represent the next CFD auction round and increased competition - and the administrative strike price of £140/MWh. The results are referred to as 'Low CFD Price' and 'High CFD Price' in the table.

There are a range of vessel charter rates discussed in Chapter 4. A lower set of logistics costs were chosen from Bjerkseter and Ågotnes [5.7].

Table 5.15.: Overview of Additional Simulation Scenarios

Scenario	Lifetime Costs [£million]		Savings	
	PBM	CBM	Absolute	Percentage
New FR	33.43	31.88	1.55	4.64%
New FR + Blade System	33.43	28.59	4.84	5.33%
5 MW Wind Farm	76.45	73.81	2.64	3.45%
Low CFD Price	34.42	32.78	1.64	4.76%
High CFD Price	37.09	35.34	1.75	4.72%
Lower Vessel Costs	31.58	30.48	1.10	3.48%

5.4.3. Discussion

The model presented above has improved on the previous iteration and removed many of the outstanding issues.

The improved detection profiles have added a more realistic interpretation of CM capabilities. However, these are only estimations of detection profiles based on conversations on developing failures. Further research is required to validate the shapes of these profiles. The reintroduction of several key parameters used to evaluate how a CM system work is also an important addition. The model now has the capability to define the likelihood of false alarms, failures that cannot be detected and the period of time between detection and failure.

The SIM plan is an important and useful addition to the model, showing how SHM can both directly effect the operating and the risk based costs. These costs will be of interest to different users - operators will be interested in minimising operating costs while insurers or owners will be interested in minimising risk.

The model does well when benchmarked against both real operating cost data and a standard reference case. It also shows that in the majority of cases tested further integration of CM and SHM is warranted.

The model is weakest at matching availability levels and the resulting lost production levels. As a result these costs should be taken only as indicative of possible savings. As there is limited benefit in the model for CM systems for minor failures this is likely to make little difference in the comparison of two maintenance strategies.

It is likely that while previously the model was over-estimating minor downtime it is now under-predicting minor downtime. As the model does not allow for simultaneous failures per turbine, the downtime of major failures reduces the time available for minor failures to occur. If minor failures accounted for a further reduction in availability of 4% - a value chosen to bring availability under 90% - then this would equate to an additional average 7.3 visits per turbine per year. The results for comparison to the reference case would then be 89.91% availability, with an additional £2,100,000 in logistics costs, £7,500,000 in lost production costs and minimal impact on the repair cost. These values, when added to those already in Table 5.14, are all closer to the reference case ranges.

5.5. Overall Conclusions and Discussion

A model has been developed that is technically novel and allows for the exploration of factors associated with the deployment of condition monitoring and structural health monitoring systems. The development of the model has been shown in this chapter.

Table 5.16.: Comparison of Benchmarking Output at Each Stage of Development

Simulation Output	Prototype HMM	Improved HMM	Initial DBN Model	Final DBN Model
Availability - time	83.52%	86.92%	84.74%	93.91%
Annual Lost Production	£13.99m	£11.17m	£12.99m	£10.32m
Annual Repair Cost	£10.72m	£10.06m	£3.02m	£3.07m
Logistics Cost	-	£12.19m	£7.87m	£9.88m
Total	£27.71m	£33.42m	£23.88m	£23.27m

The benchmarking data for each model is shown in Table 5.16. Each stage of the development has built on the strengths of the previous, eliminating multiple issues and weaknesses culminating in a model that is both flexible and efficient. The model can be quickly updated for different farms - different failure rates and corresponding downtimes can be used.

There are several outstanding areas of the model that could be improved. The most basic would be an improved energy yield model. This would make the lost production figures more realistic. However, both the PBM and CBM lost production values would be improved so it is unlikely to have a significant impact on the cost benefit analysis.

More significant improvements would include the modelling of a logistics fleet, optimisation of maintenance actions and seasonality or the modelling of weather and sea state.

If a dedicated logistics fleet was modelled then maintenance actions could be assigned to a particular vessel and real constraints could be realised. This approach could also be used to optimise maintenance actions. The larger, more expensive vessels could prioritise work as suggested from CM and SHM output. If weather modelling was added then this would minimise the chance of failure during winter months where yield is likely to be higher.

However, the addition of these concepts would invalidate one of the major benefits of the model in its current state. The provision of site specific data from operators - failure rates and average downtimes for components - allow for realistic prediction of CM and SHM benefits. The average downtimes from real sources already include some of the factors mentioned above such as weather, logistics fleet constraints and others such as supply chain delay times.

It can be argued that the model in its current form is efficient and practical for addressing issues - most notably the spending of CAPEX and OPEX on CM and SHM systems - that both owners and operators face in selecting appropriate levels of condition monitoring.

5.6. Chapter 5 References

[5.1] A. May and D. McMillan. "Condition Based Maintenance for Offshore Wind Turbines: The Effects of False Alarms from Condition Monitoring Systems". In: *ESREL 2013*. Amsterdam, 2013.

[5.2] B. Lapeyre. "Introduction to Monte-Carlo Methods". Paris, France, 2007.

[5.3] S. P. B. Brooks and A. G. Gelman. "General methods for monitoring convergence of iterative simulations". In: *Journal of Computational and Graphical Statistics* 7 (4 1998), pp. 434–455.

[5.4] P. Lam. *Convergence Diagnostics*. 2008.

[5.5] M. H. Faber. *Statistics and Probability Theory*. Ed. by A. V. Gheorghe. Springer, 2012, p. 198. ISBN: 9789400740556.

[5.6] P. J. Tavner, H. Long, and Y. Feng. "Early experiences with UK round 1 offshore wind farms". In: *Proceedings of the ICE - Energy* 163.4 (Nov. 2010), pp. 167–181. ISSN: 1751-4223.

[5.7] C. Bjerkseter and A. Ågotnes. "Levelised cost of energy for offshore floating wind turbine concepts". MA thesis. NTNU, 2013.

[5.8] X-Rates. *Current and Historical Rate Tables*. 2015. URL: http://www.xe.com/currencytables/.

[5.9] R. Williams, C. Crabtree, and S. Hogg. "Quantifying the economic benefits of wind turbine condition monitoring". In: *Proceedings of ASME Turbo Expo 2014: Turbine Technical Conference and Exposition*. Dusseldorf, Germany, 2014.

[5.10] I. Dinwoodie, O.-E. V. Endrerud, M. Hofmann, R. Martin, and I. B. Sperstad. "Reference Cases for Verification of Operation and Maintenance Simulation Models for Offshore Wind Farms". In: *Wind Engineering* 39.1 (2015), pp. 1–14. ISSN: 0309-524X.

[5.11] A. Smith. *Capacity factors at Danish offshore wind farms*. 2015. URL: http://energynumbers.info/capacity-factors-at-danish-offshore-wind-farms (visited on 10/08/2015).

[5.12] R. Lema, J. Nordensvärd, F. Urban, and W. Lütkenhorst. *Innovation Path in Wind Power - Insights from Denmark and Germany*. Tech. rep. Deutches Institut fur Entwicklungspolitik, 2014.

[5.13] A. Juhl. *TCM ROI - Return On Investment*. Manufacturer's Study. 2010.

[5.14] D. Hatcher and J. Kirsten. "Considerations for Implementing a Highly Available or Disaster Recovery Environment". In: *SAS Global Forum 2011*. Las Vega, NV, USA, 2011.

[5.15] Noordzee Wind CV. *Operations Report 2007*. Tech. rep. OWEZ_R_000_20081023. NoordzeeWind, 2008.

[5.16] A. May, D. McMillan, and S. Thöns. "Economic analysis of condition monitoring systems for offshore wind turbine sub-systems". English. In: *IET Renewable Power Generation* 9 (8 Nov. 2015), 900–907(7). ISSN: 1752-1416.

[5.17] Mistras Group. *One Source for Wind*. 410B-14102-01. 2014.

[5.18] B. Morton. "The Value of Early Detection". In: *Wind Tech International* (2013), pp. 27–29.

[5.19] I. Dinwoodie, D. McMillan, M. Revie, I. Lazakis, and Y. Dalgic. "Development of a Combined Operational and Strategic Decision Support Model for Offshore Wind". In: *Energy Procedia* 35 (2013), pp. 157–166. ISSN: 18766102.

[5.20] P. J. Tavner. *Offshore Wind Turbines - Reliability, availability and maintenance*. 1st. The Institute of Engineering and Technology, 2012. ISBN: 978-1-84919-229-3.

[5.21] H. Guo, S. Watson, P. Tavner, and J. Xiang. "Reliability analysis for wind turbines with incomplete failure data collected from after the date of initial installation". In: *Reliability Engineering & System Safety* 94.6 (June 2009), pp. 1057–1063. ISSN: 09518320.

[5.22] L. Rademakers. *Fibre Optic Load Monitoring of Wind Turbines*. Tech. rep. ECN, 2012.

[5.23] GL Garrad Hassan. *A Guide to UK Offshore Wind Operations and Maintenance*. Tech. rep. Scottish Enterprise and The Crown Estate, 2013.

[5.24] J. Carroll, A. May, A. McDonald, and D. McMillan. "Availability Improvements from Condition Monitoring Systems and Performance Based Maintenance Contracts". In: *European Wind Energy Association Offshore Annual Conference*. Copenhagen, Denmark, 2015.

[5.25] H. Boudali and J. Dugan. "A discrete-time Bayesian network reliability modeling and analysis framework". In: *Reliability Engineering & System Safety* 87.3 (Mar. 2005), pp. 337–349. ISSN: 09518320.

[5.26] A. Van Horenbeek, J. Van Ostaeyen, J. R. Duflou, and L. Pintelon. "Quantifying the added value of an imperfectly performing condition monitoring system: Application to a wind turbine gearbox". In: *Reliability Engineering & System Safety* 111 (Mar. 2013), pp. 45–57. ISSN: 09518320.

[5.27] S. Thöns, M. H. Faber, and W. Rücker. "Support Structure Reliability Of Offshore Wind Turbines Utilizing an Adaptive Response Surface Method". In: *29th International Conference on Ocean, Offshore and Arctic Engineering*. Shanghai, China: ASME, 2010.

[5.28] European Wind Energy Association. *The Economics of Wind Energy*. Tech. rep. EWEA, 2009.

[5.29] Det Norske Veritas. *DNV-OS-J101 Design of Offshore Wind Turbine Structures*. 2011.

[5.30] E. Delnooz. "Offshore Windfarm Egmond aan Zee 4 years of Operation". In: *CUEN Offshore Wind Energy Conference*. June. Cambridge, UK, 2011.

[5.31] M. P. de Jong. *Results of corrosion inspections offshore wind farm Egmond ann Zee, 2007 - 2009*. Tech. rep. 50863231-TOS/NRI 10-2242. Kema, 2010.

[5.32] Vattenfall Wind Power. *Kentish Flats Offshore Wind Farm FEPA Monitoring Summary Report*. Tech. rep. 2009.

[5.33] Oceaneering International Inc. *ROV Services Rate Schedule UK & Europe*. Tech. rep. Aberdeen, UK, 2010.

[5.34] Department of Energy & Climate Change. *CFD Auction Allocation Round One*. 2015.

CHAPTER 6

Conclusions

There are many issues involved in operating and maintaining a wind park offshore. These include offshore weather access issues, obtaining specialist logistics vessels and the costs of major assembly failures offset against regular and sometimes unnecessary calendar based maintenance. A methodology for developing a cost benefit analysis for the inclusion of condition monitoring equipment on offshore wind turbines and using its prediction of assembly condition to aid with maintenance decisions has been presented.

This concluding chapter examines the contents of this thesis including a summary of all the key conclusions, the explored themes, the major contributions to knowledge and possible areas that the work can be expanded to either improve it or extend its use to other parts of the maintenance equation.

6.1. Key Contributions to Knowledge

A novel methodology has been developed that allows for the assessment of the cost benefit of utilising CM and SHM equipment for offshore wind farms. The methodology has been built on a strong foundation after analysis of existing literature and consideration of the strengths and weaknesses of this research. Its main areas of novelty are as follows:

Adaptable Independent application of CM and SHM systems with different properties and profiles to individual assemblies.

Flexible Application of multiple CM systems to individual assemblies - each CM system can have its own profile and abilities used to show its benefits.

Comprehensive Production of comprehensive annual costs for PBM and CBM strategies for offshore wind - risk, vessel hire, labour, components, lost production and SIM strategy.

Smaller but also key areas of novelty include:

- The completion of a survey of existing and near production CM technologies with estimations of their CAPEX and OPEX.
- Several techniques were used to allow CM systems to observe developing faults several months in advance and as a result reduce vessel costs.
- The formulation and integration of a SIM plan with mechanical component annual inspections to reduce overall operating costs.

The key benefits of the model are shown in Figure 6.1. The model produces a breakdown of costs that can be used to compare maintenance strategies. The model requires simple wind farm data and information about the desired CM and SHM system. If information is not known estimates can be used. The result is a tool that can show the possible benefits of CM and SHM integration.

6.1.1. Benefits for Operators and Owners

This flexible and comprehensive overview of OPEX costs offers a means to help both wind park operators and owners assess their decisions throughout an operating wind park's lifetime.

An operator can use this model to assess the value of service contracts that are offered from OEMs. If choosing to deploy additional CM/SHM hardware, the effects

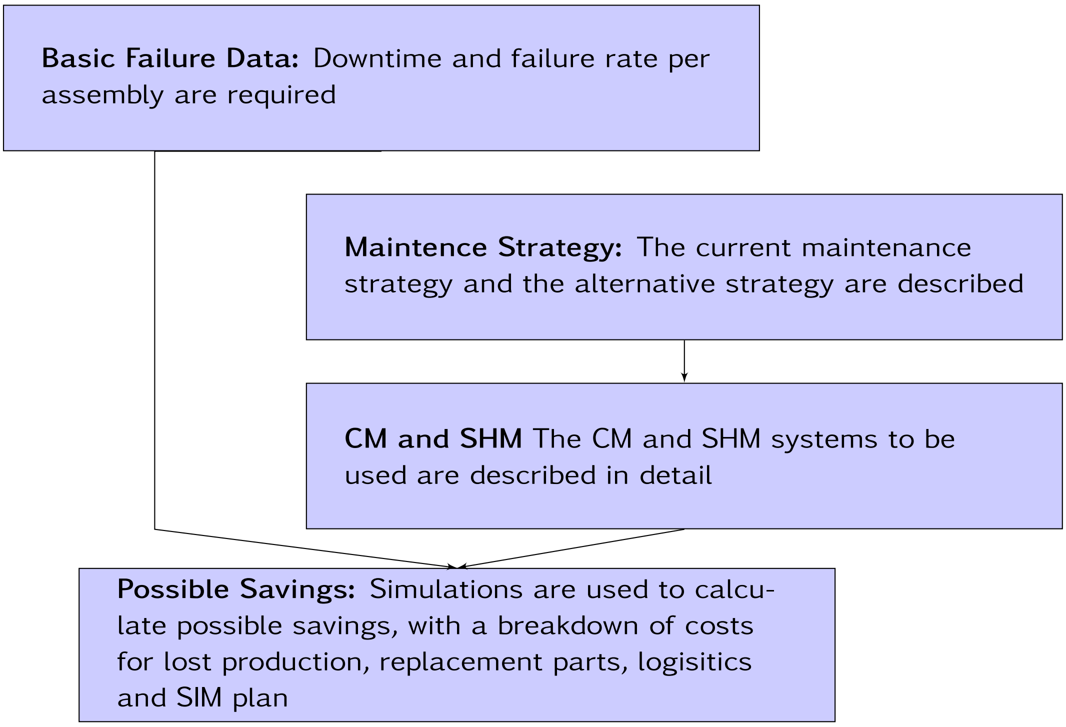


Figure 6.1.: Summary Diagram of the Model Benefits

on key operating parameters could be estimated and service providers can be held accountable for deviations in performance.

Various situations can be explored for modifying maintenance strategy, including when and to what extent to deploy CM systems. If an owner decides to deploy CM immediately, in tandem with a manufacturer monitoring program and service contract, then operating experience can be gained. The performance of the turbine can be benchmarked for several years and used to ascertain when components are operating in an unusual manner. This information could show that it is worthwhile assuming the risk of managing maintenance in-house.

CM/SHM systems could be deployed later in the life of the wind park. This could be used to aid in the extension of the life of assets or to help reduce risk as they come out of warranty.

6.2. Themes Explored

The key theme explored in this thesis is how one can define and analyse the capacity and capabilities of CM and SHM systems.

There are few forms of analysis that have been completed that allow for a full description of CM equipment to be developed for offshore wind. The information available in respect of the capabilities of CM equipment is normally restricted to particular failure modes rather than the total number of failures occurring.

In the final presented model, a P-F curve has been used to allow for times between a fault being detected and that fault causing a failure to be simulated. An effectiveness value allows for the number of detectable failures with a CM system to be observed and a reliability value allows for false alarms to be generated in simulations in a natural way. This approach benefits from being flexible and easy to update as new information becomes available.

The field of SHM analysis and simulation is slightly more advanced and one can model the reduction in uncertainty. However, a conclusion that has clearly emerged from this thesis is the difficulty in aligning maintenance strategies of structural and mechanical assemblies. This may be due to the difference in timescales of the operating lives of the components and the different goals of asset operators and owners. For example, an operator may not be interested in expensive monitoring campaigns that will only really begin to show value late in the life of the asset - their focus is much more short term and on ensuring the asset is available for generation. There are many opportunities that could be taken advantage of to harmonise the regular mechanical component access to the turbine and the more infrequent access required to complete structural assessments. The major benefit in this thesis shown for SHM is risk reduction which is of particular interest to an asset owner. It is through knowledge gained from SHM systems, with integration and feedback to operators, owners and insurers, that further cost of energy savings for offshore wind can be made.

Analysis completed on existing wind parks across the North Sea has shown that, overall, the expected increase in failure rate towards the end of life has not been observed. This simplifies the modelling process and appears to confirm research in other fields that suggests the typically used 'bath-tub curve' is useful for individual components but not the complicated combined electrical, mechanical and structural system that is a wind turbine.

6.3. Summary of Thesis

The major issues facing operators and owners in maximising their return on investment for offshore wind deployment are introduced in Chapter 1 with a focus on the difficulties in completing maintenance actions. This sets out the scope and definition of the project that formed the basis of this thesis.

Chapter 2 defined key indicators of reliability and showed the importance of taxonomy in understanding these key indicators between different wind parks and turbines.

Chapter 3 gave an overview of the key methods of modelling the deterioration of mechanical and structural components as used in this thesis. It also expanded upon these deterioration methods to show how monitoring equipment could be integrated for use in simulations. These methods of CM integration were documented previously but the combination of several methods is theoretically novel.

Chapter 4 developed a cost benefit analysis that can be used to assess an offshore wind farm utilising CM and SHM equipment. It begins by showing how this has been achieved by examining other maintenance literature both generically and specifically for wind. It shows the 4 major cost components associated with annual operating costs and the different ways that these costs could be reduced by using said monitoring systems.

Chapter 5 details a suitable methodology for combining the analysis from the 3 previous chapters into a probabilistic simulation model to give an output that suggests the possible benefits and disadvantages of implementing CM and SHM with the output as annual operation figures. The outputs are investigated, compared to the results of similar models in a reference case and the implications suggested. The imperfections of the model are shown and improvements are suggested and applied. The evolution of the model is shown and the effects on the output are analysed.

6.4. Key Results

6.4.1. Markov Models

Initial results from a prototype model using Markov models to deteriorate assemblies showed the possible benefits of having CM and SHM systems. This model suggested that by applying effective theoretical CM and SHM systems across all of the turbine's systems large savings in excess of 40% of the lifetime levelised costs could be observed compared to using a preventative based maintenance approach with limited CM applied. Smaller but significant savings are still possible even with a much lower effectiveness rate.

The same model was used to examine the effect of false alarms. Increases in false alarm rates have notable impacts on availability and costs. In this thesis, decreasing CM reliability values have been used to represent this increasing rate. A decrease from 99% to 70% in CM reliability shows a decrease in wind farm availability of approximately 0.5% from ~88.8% to ~88.3%. However, these impacts were far outstripped by the benefits from the CM systems (>1%).

These suggested savings were worth investigating further by improving the model so that it gave more detailed cost breakdowns and more accurately represented offshore maintenance actions. The focus of this model was accurate representation of commercially available and near-market CM systems with improved logistics modelling costs. Additional CM systems were added in order to improve detection capabilities and the hazard function was allowed to change over time.

The improved model showed similar trends to the prototype model but significantly smaller overall savings - 15% compared to 25% with a CM system used on the gearbox, drivetrain and generator - and was closer to other offshore wind O&M simulation reference cases. Increasing the effectiveness of the CM system monitoring the 3 drive train assemblies by adding additional CM systems increased the lifetime savings to approximately 30%. The addition of blade monitoring systems also showed increased savings. The more faults that a CM system was able to detect substantially in advance of failure created minor increases in savings.

For comparison, in the work of Williams, Crabtree, and Hogg [6.1], the authors predict a relative saving of 34% using a theoretical CMS over the lifetime of the wind park across all assemblies. This is when the CM system can reduce catastrophic failures to major by 75% and reduce major failures to minor by 25%. If the capabilities of the CM system are lowered so that they can only provide a 25% reduction of catastrophic failures to major failures then this becomes a 4% saving.

6.4.2. DBN Models

Two points from the previous work were highlighted for further investigation: (1) to capture the benefits of SHM, it had to be modelled in an alternative fashion and (2) the time from detection until failure was not being modelled in a realistic fashion.

The reduction in risk is a benefit of using SHM that was not captured in the model and the initial expense of SHM made it appear as a disadvantage. A new risk based model and a SIM plan were developed to try and observe the changes in risk.

Instead of a CM effectiveness value, a P-F curve with linear detection profiles was used that more naturally captures the combination of effectiveness and the time between the CM system alert and the failure occurring. The opportunity was taken to adapt the model to use DBNs and to limit the deterioration of other assemblies on a particular turbine when it is not operating.

The final evolution of the model improved the SIM plan based on reviews of commercially available SIM plans. This version also saw full integration of parts that had not been previously transferred from the Markov model to the DBN model including CM capabilities and an age specific hazard function.

This model gave outputs that fell within the simulation reference case for most values. The levelised lifetime costs for this model showed savings of around 4.7% without a SHM system and using a basic SIM plan. This increased to 5% with the SHM system and utilising an advanced SIM plan. This increased to 5.7% when a blade CM system is added to the farm.

In Wiggelinkhuizen et al. [6.2], repair costs are reduced by between 17% and 9% at 80% CM effectiveness for a range of false alarms per year. The lost production values reduce by between 15% and 7% for the same values. The final presented model suggests an 8% reduction for the repair costs and 4.6% reduction for lost production per annum.

6.5. Future Possibilities and Work

Ways in which the model could be altered to offer improvements or used to explore different areas have been highlighted in Chapter 5. In this section these alterations are revisited and expanded. It also highlights areas in which greater knowledge about various elements of the model could greatly improve either its accuracy or flexibility.

6.5.1. Advanced Financial Modelling

As has been discussed previously, the financial market that wind generators operate in is fluid and subject to market and governmental changes. Currently, the model assumes stationary conditions. Allowing greater flexibility in simulations to adapt electricity price and ROC levels would allow operators and owners to factor in this fluidity.

6.5.2. Additional Failure Modes

If further information becomes available about the capabilities of CM systems and the detection profiles then this could easily be incorporated into the model. One assembly could have multiple failure modes with different detection profiles. The failure mode for the assembly could be selected at failure by using the rate of occurrence of the failure modes.

6.5.3. Varying Maintenance Strategies

One of the major assumptions of the model is that minimal CM and SHM equipment are installed on the wind farm that the failure data is obtained from. However, the model could also be used to see where further CM and SHM would be useful. The model is built to compare two strategies regardless of which two these are. In this thesis, the base strategy has always been a PBM - utilising SCADA - but this can be adapted to represent a wind park with CM installed and the second strategy could have additional CM systems installed for comparison.

In highlighting this option, there is further opportunity to explore the Egmond aan Zee data. Egmond aan Zee have and use SCADA data and like all Vestas V90 turbines have a Vestas CM system installed. It was assumed that the long downtimes associated with gearbox and generators had rendered the CM system of limited use in the 3 years of operation. It was suggested in 2009 that the data from early offshore CM systems, including Egmond aan Zee, could be improved and allow for better integration of this data into maintenance [6.3]. If the model is adapted to deal with different maintenance strategies then this assumption could be examined.

6.5.4. CM and SHM Optimisation and Decision Support

The next step that could be achieved after completing the previous step would be to create an optimisation algorithm. This algorithm would analyse all possible CM and SHM options before suggesting the optimum solution. This optimisation should be based on the Value of Information as described in Thöns and Faber [6.4]. Taken further, different levels of CM could be implemented at different stages of the life of the wind park. This would allow operators to plan for different scenarios, such as when wind farms go out of warranty, to allow them to assess the different levels of risk they will take on.

6.5.5. Fleet Leader Concept

"Fleet leader" is a concept that is often discussed as a way to gain condition information for a wind park using an expensive and extensive instrumentation on only a few wind turbines in the wind park [6.5]. All turbines would still have SCADA and some CM systems - such as a vibration system on drive train, gearbox and generator - installed on them. Fleet leaders could have extended CM systems such as AE, blade monitoring systems and a wide deployment of SHM. How the additional information from a fleet leader is used to manage the condition of all assets would need to be determined but this concept could easily be applied to the model to reduce CAPEX and the impacts on on-going maintenance.

6.5.6. Integration with Logistics Modelling

A major alteration that would allow for more accurate and interesting results would be to model a dedicated logistics fleet. This would allow for realistic vessel constraints to be observed as well as additional modelling of weather windows at a site. However, there has been much work conducted in this field already by those such as Dinwoodie et al. [6.6] and Braam et al. [6.7] and in optimising vessel fleet type and size by Dalgic et al. [6.8]. In this situation it might be more valuable to find a way to integrate the condition monitoring modelling components presented in this thesis into these models.

6.6. Chapter 6 References

[6.1] R. Williams, C. Crabtree, and S. Hogg. "Quantifying the economic benefits of wind turbine condition monitoring". In: *Proceedings of ASME Turbo Expo 2014: Turbine Technical Conference and Exposition*. Dusseldorf, Germany, 2014.

[6.2] E. Wiggelinkhuizen, T. Verbruggen, H. Braam, L. Rademakers, J. Xiang, and S. Watson. "Assessment of Condition Monitoring Techniques for Offshore Wind Farms". In: *Journal of Solar Energy Engineering* 130.3 (2008). ISSN: 01996231.

[6.3] W. Musial. "Offshore Wind O&M Challenges". In: *Wind Turbine Condition Monitoring Workshop*. Broomfield, CO, USA, 2009.

[6.4] S. Thöns and M. H. Faber. "Assessing the value of structural health monitoring". In: *Safety, Reliability, Risk and Life-Cycle Performance of Structures and Infrastructures*. Ed. by G. Deodatis, D. Frangopol, and B. R. Ellingwood. Taylor & Francis, 2013, pp. 2543–2550. ISBN: 9781138000865.

[6.5] A. Valland and V. G. B. Pedersen. *Industry Challenges Report – O&M*. Tech. rep. D4.1. LEANWIND, 2014.

[6.6] I. Dinwoodie, O.-E. V. Endrerud, M. Hofmann, R. Martin, and I. B. Sperstad. "Reference Cases for Verification of Operation and Maintenance Simulation

Models for Offshore Wind Farms". In: *Wind Engineering* 39.1 (2015), pp. 1–14. ISSN: 0309-524X.

[6.7] H. Braam, T. Obdam, R. van de Pieterman, and L. Rademakers. "Properties of the O&M Cost Estimator (OMCE)". 2011.

[6.8] Y. Dalgic, I. Dinwoodie, I. Lazakis, M. Revie, and D. McMillan. "Optimum CTV Fleet Selection for Offshore Wind Farm O&M Activities". In: *ESREL 2014*. Wroclaw, Poland, 2014.

Appendices

APPENDIX A

Egmond aan Zee Failure Data

The aim of this section is to show the techniques used to derive failure rates from the operational reports provided from Noordzee Wind CV for the years 2007 [A.1], 2008 [A.2] and 2009 [A.3] and how this compares to other available sources of operational data from different wind parks. It does this both for the early operational years and for the changes over the life of the wind park. The method described is based on the work of Dinwoodie, McMillan, and Quail [A.4].

A.1. Report Information

The reports give an overview of the performance of the wind park including availability and production. Importantly the total number of stops, downtime, and lost production is displayed per subsystem. This is shown in Table A.1. The type of stop is not recorded. Stops can include those that require significant physical intervention by an operator or are reset by the control room and cause almost no downtime. There are estimates on the number of visits to wind turbines and the resulting offshore personnel transfers to turbines. The last part of interest to a reliability engineer is work and construction notes, highlighting major ongoing projects to improve the wind park.

The taxonomy of turbines in these reports is different from the one detailed in Chapter 2 and before use with the model the failure rates are transcribed into the thesis standard taxonomy.

Table A.1.: The Combined Performance Statistics of Egmond aan Zee for 2007-2009 per Assembly

Category	**Lost Production [MWh]**	**No. of Stops**	**Downtime [h]**
Ambient	4,489	1,204	1,788
Blade system	3,714	180	3,228
Brake system	567	40	320
Control system	23,357	8,788	17,912
Converter	14,279	644	6,869
Electrical	3,796	615	3,840
Gearbox	134,998	1,607	104,367
Generator	42,404	682	28,333
Pitch system	15,762	2,145	9,303
Scheduled service	6,918	3,522	10,015
Yaw system	3,437	4,810	1,645
Structure	448	173	823
Grid	95	68	750
Total	254,264	24,478	189,192

There are approximately 800 vessel visits to the wind farm over the three years with the vessels visiting 1.5 turbines on average per trip. According to the reports, crews were "performing inspections, scheduled service, unscheduled service and punch list activities". Punch list activities are described as on-going construction items - such as laying concrete slabs to protect sub-sea cables. Inspections, punch list activities and some scheduled maintenance do not require there to have been a failure nor would they cause downtime. As a result it has been assumed that on average vessels makes a corrective action for a turbine once per visit. This gives an average of 7.4 visits per turbine per year.

The average number of failures per turbine per year are shown in Table A.2. The ratio of the number of stops per assembly is also shown - "Failure Ratio". It is this number that is multiplied by the average number of visits per turbine to give the intervention failure rate, λ. The downtime per turbine per year is also presented in the same table. The downtime per turbine per year figure is then divided by the intervention failure rate to give a scaled downtime. Alternatively, some of this data is presented in Figure A.1 which compares the failure rates to the hours of downtime per failure.

Table A.2.: Adjusted Failure Rates for Egmond aan Zee for 2007-2009

Category	Failures/ Turbine/ Yr	Failure Ratio	Inter- vention λ	Downtime/ Turbine/ Yr [h]	Scaled Down- time [h]
Ambient	11.15	0.05	0.36	16.6	45.52
Blade system	1.67	0.01	0.05	29.9	549.44
Brake system	0.37	0.00	0.01	3.0	245.05
Control system	81.37	0.36	2.66	165.8	62.42
Converter	5.96	0.03	0.19	63.6	326.82
Electrical	5.69	0.03	0.19	35.6	191.33
Gearbox	15.21	0.07	0.50	966.4	1946.47
Generator	6.31	0.03	0.21	262.3	1273.03
Pitch system	19.86	0.09	0.65	86.1	132.89
Scheduled service	32.61	0.14	1.06	92.7	87.41
Yaw system	44.54	0.20	1.46	15.2	10.48
Structure	1.60	0.01	0.05	7.6	145.75
Grid	0.63	0.00	0.02	6.9	337.92
Total	226.98	1.00	7.41	1751.8	-

The final stage is to generate 'Major' and 'Minor' failure rates. The defining characteristic of a minor failure is that it takes less than 24 hours to clear. The expected downtime for a minor yaw fault was significantly less than 24 hours and so was set at 6 hours [A.4]. The distribution of Minor and Major failures and their downtime is given in Faulstich, Hahn, and Tavner [A.5] and is shown in Figure 2.3. The ratio between Major and Minor failures is used to create the information shown in Table A.3.

A.2. Early Operational Issues at Egmond aan Zee

There are several important operational issues that occurred at Egmond aan Zee over the three years of this data that should be discussed. These issues mean that the data from this time period will not reflect on new wind parks without these defects or for the remainder of the Egmond aan Zee's operational life. Understanding these issues can allow for failure data to be produced that does not have these failures and can be used to represent new wind parks or parks that are not Egmond aan Zee.

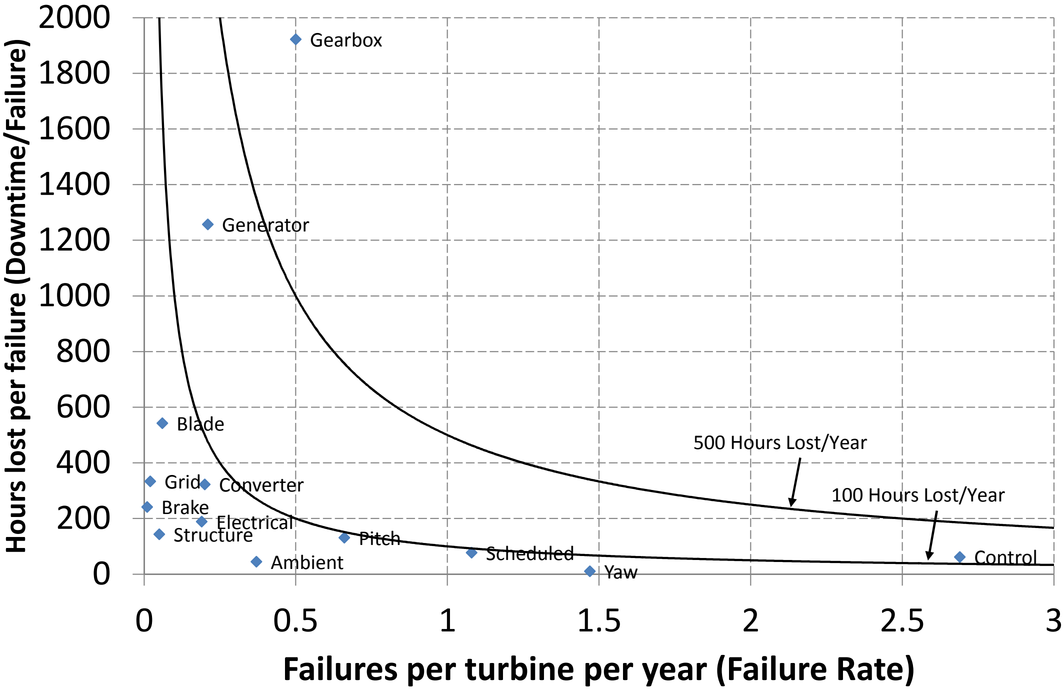


Figure A.1.: Rate of Failure vs. Hours Lost per Failure

One of the most interesting (from a maintenance model designer's point of view) is the very high gearbox and generator downtimes. The below is a quote from the 2007 report regarding gearbox wear:

> *"During July, the remote control system on one of the turbines showed a so-called "swarf" alert, implying that there was a higher than expected metal content in the lubrication oil of the gearbox.... During the following months, thirteen more wind turbines followed the same pattern."*

- **Noordzee Wind CV** [A.1]

Analysis of the faults showed that unexpected wear was occurring across the gearbox. The operators decided to replace all the gearboxes that showed this warning with a different type and began a replacement program in mid October. They were able to exchange 10 gearboxes and get 5 wind turbines operational again before the end of the year. During 2008 it became clear that the "swarf" alert would affect all gearboxes and they would all need to be replaced but poor vessel availability did not allow this to be completed in 2008. The replacement of all gearboxes was finished by

Table A.3.: Major and Minor Failure Rates for Egmond aan Zee for 2007-2009

Category	**Modified Failure Rate**		**Modified Downtime [h]**	
	Minor	Major	Minor	Major
Ambient	0.000	0.364	-	43
Blade system	0.045	0.010	24.00	2977
Brake system	0.009	0.003	24.00	1130
Control system	2.100	0.556	24.00	292
Converter	0.154	0.041	24.00	1397
Electrical	0.147	0.039	24.00	886
Gearbox	0.331	0.165	24.00	5786
Generator	0.131	0.075	24.00	3465
Pitch system	0.519	0.130	24.00	598
Scheduled service	0.000	1.064	-	87
Yaw system	1.050	0.404	6.00	37
Structure	0.042	0.010	24.00	725
Grid	0.016	0.004	24.00	1673

the 3rd quarter of 2009.

Generators also started to have major failure modes. There were 2 in 2008 and 8 in 2009 all with significant downtime - partially caused by the same jack up vessel constraints.

As detailed in Det Norske Veritas [A.6] in mid 2009 the industry became aware of a design issue with the grouted connection between the turbine transition piece and monopile foundations. A schematic of the grouted connection is shown in Figure A.2 [A.6]. The grout had been seen to fail causing the turbine to slip and rest on the jacking brackets - which had been designed only for temporary support during installation. There were no immediate concerns regarding the safety of the assets but several operators, including those at Egmond aan Zee, ordered repairs [A.3] and some installed monitoring systems [A.7]. There were repairs made to the transition piece in 2009 of 3 turbines and the remaining 33 turbines were scheduled to be completed in 2010 with "minimal impact on downtime".

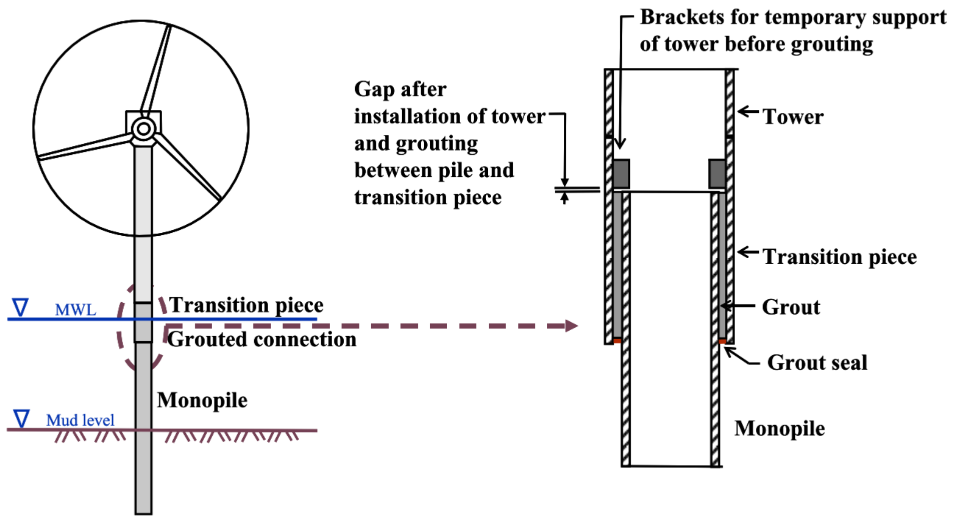


Figure A.2.: Grouted Connection in Monopile Structure [A.6]

A.3. Comparison to Other Offshore Wind Parks

A.3.1. Downtime

While Egmond aan Zee is one of the most useful data sets available for offshore wind, there are other less complete data sources from other farms. This data can be used to verify how representative the data from Egmond aan Zee is.

The percent downtime caused per subsystem for both Egmond aan Zee and Horns Rev in Denmark is shown in Table A.4. The 3 or 4 highest values are highlighted. The information for Horns Rev is from the work of Besnard [A.8]. Horns Rev 1 is 15-20km off the west coast of Jutland and consists of 80 2 MW Vestas V80 turbines and the data is from 2009-2010. The numbers were estimated by the author based on the best information available and has been converted as much as possible to match the Egmond aan Zee category taxonomy.

It is the gearbox and electrical issues that are most prominent for Horns Rev. The converter, generator, control system and blade system are also significant contributors to the downtime. The V80s suffered severe electrical transformer issues as a result of using “dry-type“ transformers which suffered seismic vibration fretting. Vibration damage also effected the generators and there was damage seen on gears and bearings [A.9].

Table A.4.: Egmond aan Zee vs Horns Rev - Proportion Downtime per Subsystem

Category	**Proportion of downtime**		**Ratio**
	Egmond aan Zee	Horns Rev	
Blade system	1.82%	8.00%	4.40
Brake system	0.18%	1.00%	5.56
Control system	**10.10%**	8.00%	0.79
Converter	3.87%	**9.00%**	2.33
Electrical	2.16%	**23.00%**	10.65
Gearbox	**58.84%**	**33.00%**	0.56
Generator	**15.97%**	**9.00%**	0.56
Pitch system	5.24%	6.00%	1.14
Yaw system	0.93%	2.00%	2.15
Structure	0.46%	0.00%	0.00
Grid	0.42%	1.00%	2.38

The table highlights the dominance of the gearbox and generator issues mentioned above in the total downtime for Egmond aan Zee. The only other assembly with more than 6% of the downtime is the control system.

If the gearbox and generator downtimes are reduced by 50% then their ratios compared to Horns Rev increase to 0.67 (49.11%) and 0.68 (13.33%) respectively.

A.3.2. Availability and Capacity Factor

The most freely available information for offshore wind is the availability and capacity factor. The Round 1 offshore wind farms in the UK - Scroby Sands [A.10, A.11, A.12], Kentish Flats [A.13, A.14, A.15], North Hoyle [A.16, A.17] and Barrow [A.18, A.19] - produced annual reports for the first few years of operation each stating capacity factor and availability. Further capacity factor data for the UK sites is available from other sources such as the Renewable Energy Foundation [A.20] and is reviewed by Crabtree, Zappala, and Hogg [A.21]. Annual capacity factor data for four Round 1 UK sites is shown in Figure A.3.

The Danish Energy Agency (Energistyrelsen) keeps a register of all grid connected wind turbines and their output. If this is combined with information from the Danish transmission owner (Energinet.dk) then the capacity factor can be obtained [A.22]. Four of the older Danish wind parks' annual capacity factors are shown in Figure A.4.

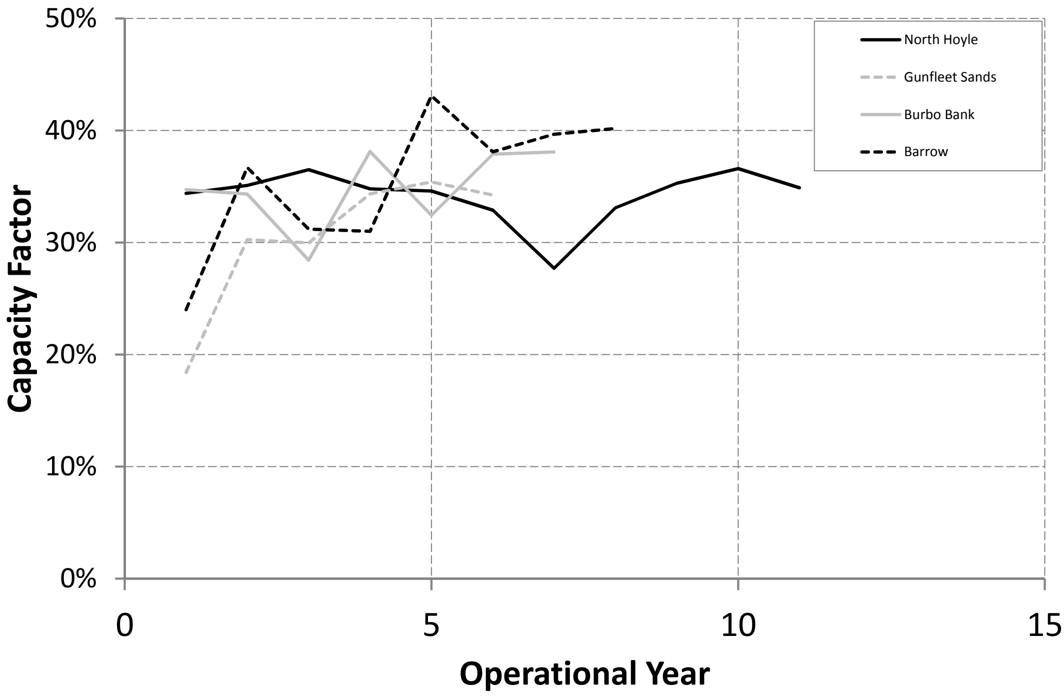


Figure A.3.: Capacity Factor Over Time for UK Round 1 Wind Parks

There appears to have been significant learning from the early Danish and British wind farms. Anholt I is a Danish wind park that produced significantly higher capacity factors in its first years - beginning operation in 2013 - than the others and has had far fewer technical issues than the earlier wind farms as detailed in Feng et al. [A.23]. Horns Rev is now 13 years old and had a capacity factor over 45% last year and it is the Horns Rev extension - Horns Rev II - that has the highest annual capacity factor of 51.2% in its 7th year of operation.

Figure A.5 shows the averaged annual capacity factor for the 8 UK and Danish wind parks. These values have been normalised against the lifetime average capacity factor for each wind park. It shows an increase of 30% in annual capacity factor over the first 5 years of operation. The capacity factors remain fairly consistent for the next 15 years.

The figure shows a marked increase in capacity factors for the first few years and this level remains constant for most of the life. As highlighted in Crabtree, Zappala, and Hogg [A.21] the Round 2 UK wind parks have immediately had higher capacity factors than their Round 1 equivalents. The same seems true for Danish farms. An-

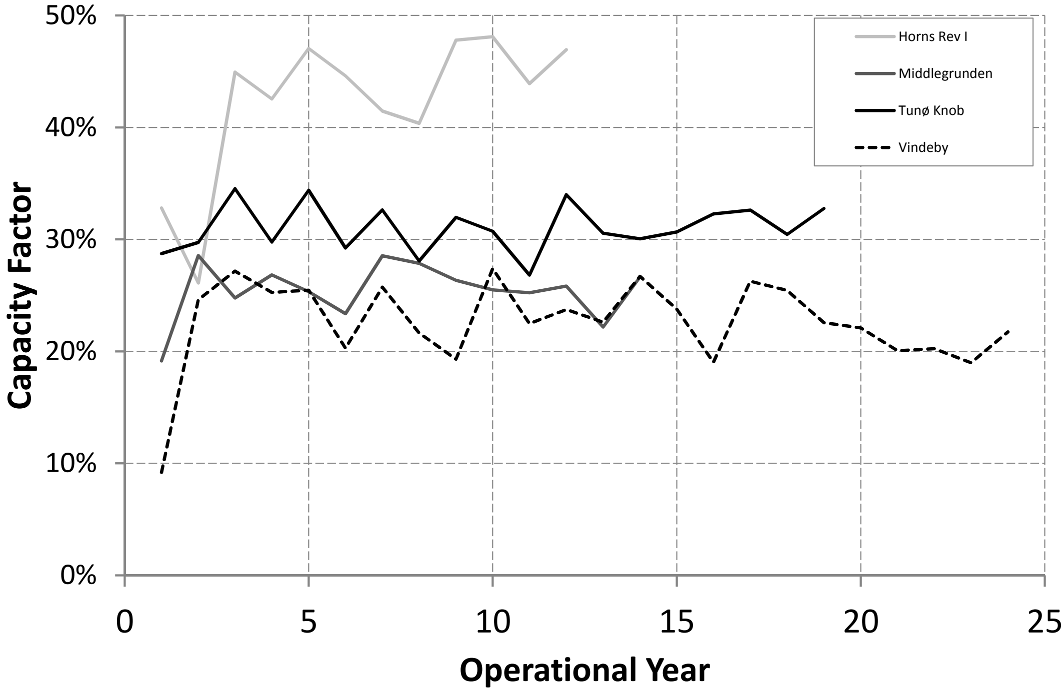


Figure A.4.: Capacity Factor Over Time for Selected Danish Wind Parks

holt I, as a relatively recent commission, has only seen slight increases in capacity factor in its early life and a lifetime capacity factor of 48.2%.

Vindeby is the earliest offshore wind farm from Denmark. It has the lowest recorded capacity factor over the last 12 months of 20% in its 25th year of operation. However, its lifetime capacity factor is 23% and it has never produced greater than 30% annual capacity factor [A.22].

The availability data for the Dutch and early British wind farms is shown in Table A.5. Here the myriad of issues mentioned above can be seen. Availability has been defined previously in Chapter 2. Technical availability is the proportion of time that the turbine is available out of the theoretical maximum and commercial availability allows for reduction in the maximum due for agreed reasons - weather, servicing etc. Availability in almost all cases reduces in the second year of operation but by the third operating year is higher than the first. In the table, all the availability rates are commercial availability excluding Barrow which is noted as technical.

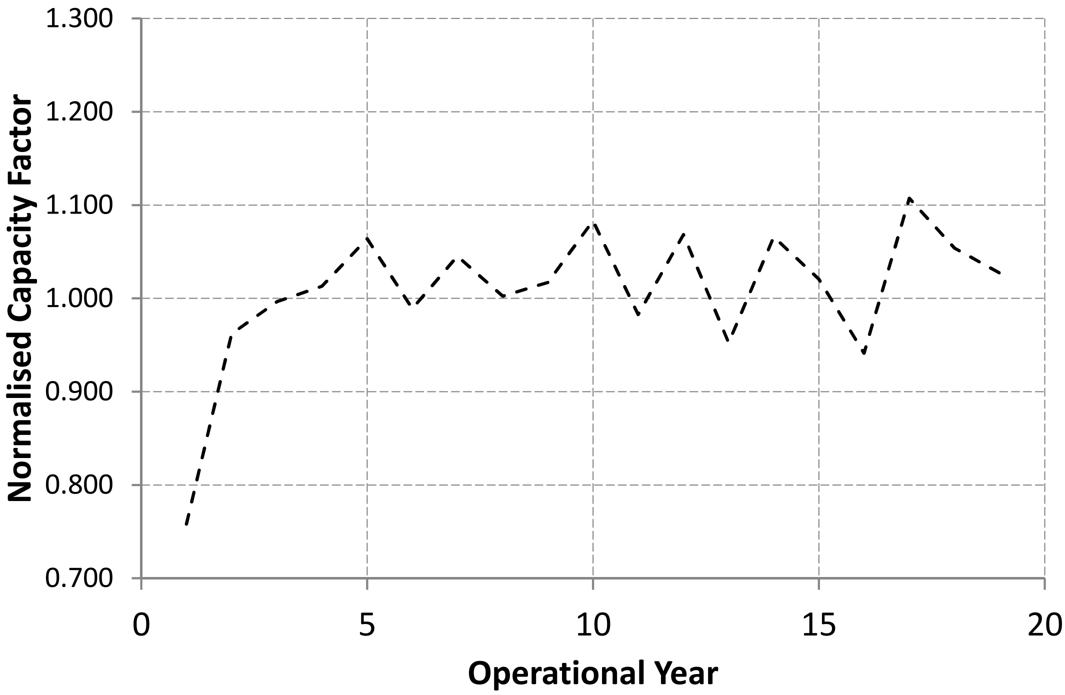


Figure A.5.: Capacity Factor Normalised Against Lifetime Average for Selected North Sea Wind Parks

Table A.5.: Availability Figures for Early Offshore Deployment

Operating Year	1	2	3
Egmond aan Zee	81.40%	76.30%	83.50%
Scroby Sands	84.18%	81.00%	87.00%
Kentish Flats	88.00%	73.50%	89.20%
North Hoyle	-	89.10%	87.40%
Barrow	67.00%	78.00%	-

A.4. Modifying Existing Data to Generic Data

Assuming that it took visits every day for 25 days to replace 10 gearboxes and get 5 of these replacements fully operational (based on the first round of replacements in 2007) then this could represent, 1 visit to prepare the old gearbox for removal, 1 visit to exchange gearboxes and 1 additional visit to commission the new gearbox. If the same work is required to replace a generator then this would mean 138 visits to the wind farm would be removed.

Reducing the downtime and number of stops is harder to estimate.

Generators caused a combined 3,090 hours of downtime in 2007 and increased to 14,000 in 2008 and 11,000 in 2009. If all generators operate normally then a downtime of 3,090 hours a year is assumed. The total number of generator stops was reduced by 30 - assuming that 3 stops were registered regarding this failure for the 10 replaced generators.

Gearbox issues effected each operational year for Egmond aan Zee. The lowest value recorded was 29,000 hours and the highest 44,500. An estimation of what a good operational year looks like is taken as 20,000 hours for the farm. The number of stops are also reduced by 108 for the reasons given above.

Structural downtime is assumed not to change - even with the issues noted above - as it forms such a small part of the total downtime.

The Table A.2 is repeated below in Table A.6 taking into account this modified data. The failures per turbine per year are reduced from 7.41 to 6.13. Additionally, downtime per turbine per year is also reduced from 1751.8 hours to 1164.5. These are significant reductions of 18% and 34% respectively.

Table A.6.: Reduced Failure Rates for Modified Egmond aan Zee Data

Category	Failures/ Turbine/ Yr	Failure Ratio	Inter- vention λ	Downtime/ Turbine/ Yr [h]	Scaled Down- time [h]
Ambient	11.15	0.05	0.30	16.6	54.49
Blade system	1.67	0.01	0.05	29.9	657.74
Brake system	0.37	0.00	0.01	3.0	293.36
Control system	81.37	0.36	2.22	165.8	74.77
Converter	5.96	0.03	0.16	63.6	391.25
Electrical	5.69	0.03	0.16	35.6	229.05
Gearbox	13.55	0.06	0.37	555.6	1504.42
Generator	5.85	0.03	0.16	85.8	538.05
Pitch system	19.86	0.09	0.54	86.1	159.09
Scheduled service	32.61	0.15	0.89	92.7	104.31
Yaw system	44.54	0.20	1.21	15.2	12.54
Structure	1.60	0.01	0.04	7.6	174.48
Grid	0.63	0.00	0.02	6.9	404.54
Total	224.85	1.00	6.13	1164.5	-

A.5. Conclusions

The operational data used in this thesis from Egmond aan Zee does appear to be in line with other offshore wind farms in the first few years of deployment for the middle to late 2000s and is relevant for simulating these types of wind parks. It also makes it seem logical that after the early defects presented in the data that failure rates would decrease and the capacity factor would increase. This is reinforced with longer operational evidence presented in this Appendix.

If actions are taken to remove the impact of the gearbox and generator replacement and then show some overall learning, it may be possible to estimate the failure rates for more recent periods of operation. These values, and some learning, could be used as the starting point for a new wind farm to be deployed in the coming years. This has been presented in Table A.6.

A.6. Appendix A References

[A.1] Noordzee Wind CV. *Operations Report 2007*. Tech. rep. OWEZ_R_000_20081023. NoordzeeWind, 2008.

[A.2] Noordzee Wind CV. *Operations Report 2008*. Tech. rep. OWEZ_R_000_200900807. 2009.

[A.3] Noordzee Wind CV. *Operations Report 2009*. Tech. rep. OWEZ_R_000_20101112. 2010.

[A.4] I. Dinwoodie, D. McMillan, and F. Quail. "Analysis of offshore wind turbine operation & maintenance using a novel time domain meteo-ocean modeling approach". In: *ASME Turbo Expo 2012*. Copenhagen, 2012, pp. 1–11.

[A.5] S. Faulstich, B. Hahn, and P. J. Tavner. "Wind Turbine Downtime and Its Importance for Offshore Deployment". In: *Wind Energy* 14.July 2010 (2011), pp. 327–337.

[A.6] Det Norske Veritas. *Summary Report from the JIP on the Capacity of Grouted Connections in Offshore Wind Turbine Structures*. Tech. rep. 2010, p. 42.

[A.7] Strainstall Monitoring. *Structural Monitoring for Offshore Wind Turbine Foundations*. SM109. 2010.

[A.8] F. Besnard. "On maintenance optimization for offshore wind farms". PhD thesis. Chalmers University of Technology, 2013. ISBN: 9789173858229.

[A.9] P. J. Tavner. *Offshore Wind Turbines - Reliability, availability and maintenance*. 1st. The Institute of Engineering and Technology, 2012. ISBN: 978-1-84919-229-3.

[A.10] E.ON Climate and Renewables. *Scroby Sands Offshore Wind Farm 3rd Annual Report*. Tech. rep. 08/P48. Department of Business Enterprise & Regulatory Reform, 2007, p. 15.

[A.11] E.ON Climate and Renewables. *Scroby Sands Offshore Wind Farm 1st Annual Report Capital Grant Scheme*. Tech. rep. 2005.

[A.12] E.ON Climate and Renewables. *Scroby Sands Offshore Wind Farm 2nd Annual Report - Capital Grant Scheme*. Tech. rep. 2006.

[A.13] Vattenfall Wind Power. *Kentish Flats Offshore Wind Farm 1st Annual Report Capital Grant Scheme*. Tech. rep. 2006.

[A.14] Vattenfall Wind Power. *Kentish Flats Offshore Wind Farm 3rd Annual Report*. Tech. rep. URN 09D/P46B. 2007.

[A.15] Vattenfall Wind Power. *Kentish Flats Offshore Wind Farm 2nd Annual Report*. Tech. rep. 09/P46. Department of Business Enterprise & Regulatory Reform, 2007.

[A.16] nPower Renewables Limited. *North Hoyle Offshore Wind Farm 2nd Annual Report Capital Grant Scheme*. Tech. rep. Department for Business Enterprise & Regulatory Reform, 2007.

[A.17] nPower Renewables Limited. *North Hoyle Offshore Wind Farm 3rd Annual Report*. Tech. rep. URN 08/P47. Department for Business Enterprise & Regulatory Reform, 2007.

[A.18] DONG Energy A/S. *Barrow Offshore Wind Farm 1st Annual Report*. Tech. rep. URN 09/P45. Department for Business Enterprise & Regulatory Reform, 2007.

[A.19] DONG Energy A/S. *Barrow Offshore Wind Farm 2nd Annual Report*. Tech. rep. URN 09D/P45. 2008.

[A.20] Renewable Energy Foundation. *Renewable Generators*. 2015. URL: http://www.ref.org.uk/%20generators/index.php (visited on 10/2015).

[A.21] C. J. Crabtree, D. Zappala, and S. I. Hogg. "Wind energy: UK experiences and offshore operational challenges". In: *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy* (Aug. 2015), pp. 1–20. ISSN: 0957-6509.

[A.22] A. Smith. *Capacity factors at Danish offshore wind farms*. 2015. URL: http://energynumbers.info/capacity-factors-at-danish-offshore-wind-farms (visited on 10/08/2015).

[A.23] Y. Feng, Y. Qiu, C. J. Crabtree, H. Long, and P. J. Tavner. "Use of SCADA and CMS Signals for Failure Detection and Diagnosis of a Wind Turbine Gearbox". In: *Proceedings of EWEA 2011*. 2011.

APPENDIX B

Literature Categorisation

The following appendix contains a visualisation of the categorisation of the literature presented at the start of Chapter 4.

The Selection of a Suitable Maintenance Strategy for Wind Turbines
Andrawus, Watson, Kishk and Adam
Onshore, LCC, Monte Carlo, Reduced Costs

Maintenance Management of Wind Power Systems using CMS
Nilsson and Bertling
Onshore and Offshore, LCC, Reduction Factor

On the Economic Benefits of using Condition Monitoring Systems for Maintenance
Besnard, Nilsson and Bertling
Either, LCC, Monte Carlo, Efficiency and Replacement

Quantification of CM Benefit for Offshore Wind Turbines
McMillan and Ault
Offshore, LCC, Monte Carlo, Risk modelling, CM Effectiveness

Assessment of Condition Monitoring Techniques for Offshore Wind Farms
E. Wiggelinkhuizen, T. Verbruggen, H. Braam et al.
Offshore, LCC, Monte Carlo, Time Series, CM Effectiveness

Framework for Risk-based Planning of Operation and Maintenance for Offshore Wind Turbines
J. D. Sørensen
Wind, Offshore, LCC, Limit-state, Inspections

Quantifying the added value of an imperfectly performing condition monitoring system: Application to a wind turbine gearbox
Van Horenbeek, Van Ostaeyen, Duflou, et al.
Onshore, P-F Curve, FMEA, LCC, Monte Carlo, Time Series, Effectiveness, False Alarms

Cost-benefit evaluation of remote inspection of offshore wind farms by simulating the operation and maintenance phase
Netland, Bakken Sperstad, Hoffman and Skavhaug
Offshore, LCC, Monte Carlo, Time Series, Effectiveness, False Alarms, Camera

Quantifying the economic benefits of wind turbine condition monitoring
Williams, Crabtree and Hogg
Offshore, LCC, Monte Carlo, Time Series, Effectiveness, False Alarms

Wind Specific

Continuous-time predictive-maintenance scheduling for a deteriorating system
A. Grall, L. Dieulle, C. Bérenguer, and M. Roussignol
Generic, Gamma Process, LCC, Time Series, Alarm Threshold

Discounted cost model for condition-based maintenance optimization
J. van der Weide, M. Pandey, and J. van Noortwijk
Generic, Poisson Process, LCC, Optimisation, Alarm Threshold

Condition-based dynamic maintenance operations planning & grouping. Application to commercial heavy vehicles
K. Bouvard, S. Artus, C. Bérenguer, and V. Cocquempot
Heavy Vehicles, Gamma Process, Minimum Availability, Monte Carlo

Maintenance optimization models and criteria
A. Van Horenbeek, L. Pintelon, and P. Muchiri
Generic, Gamma Process, LCC, Optimisation, Alarm Threshold

Generic

Cost-Benefits Analysis in SHM Projects
Inaudi
SHM, Generic, Cost-Benefit, Analysis Only

Towards life-cycle management of wind turbines based on structural health monitoring
K Smarsly, K. Law, and D Hartmann
SHM, Wind, Case-study, Life-cycle Management

Assessing the value of structural health monitoring
Thöns and Faber
SHM, Wind, Expected Benefit, Limit-state, Reduction in uncertainty, Monte Carlo

Structure Specific

Work Presented in This Thesis
May, McMillan and Thöns
Offshore, SHM, LCC, Monte Carlo, Limit-State, Time Series, Effectiveness, False Alarms

Time (not scaled)

APPENDIX C

FMEA

This appendix shows how costs are estimated for various failures and failure types in the model. Two FMEAs of wind turbines are used from General Electric Company and Bharatbhai. These are mapped to the WMEP taxonomy as detailed in Faulstich, Hahn, and Tavner and are as described in Chapter 2. They show the FMEA unit, its failure mode and the effects of the failure, if any, on the operation of the turbine. It is noted if the failure can be detected by either SCADA or CM/SHM systems.

Finally, the four categories of failure are shown for use with the model - these are major failures detected in advance by a CM system and without a CM system and minor failures detected in advance by a CM system and without a CM system - with the components that fail in each assembly based on the parts list outlined in Poore and Walford.

Reading the Table

The components that have been identified as likely to require replacement depending on the failure type are shown in the appropriate column for each assembly. The justification for the highlighted components is based on the FMEA which is shown on the right half of each table.

For example, if the drive train in a turbine suffers a major failure (Table C.3.) then the components that will need to be replaced are the main bearing and high speed coupling. If the major failure is detected in advance by a CM system then only the high speed coupling will need to be replaced.

Appendix References

General Electric Company. *Mod 1 Wind Turbine Generator Failure Modes and Effects Analysis*. Tech. rep. DOE/NASA/0058-79/1. NASA, 1979, p. 95

M. G. Bharatbhai. "Failure Mode and Effect Analysis of Repower 5M Wind Turbine". In: *International Journal of Advance Research in Engineering, Science & Technology* 2.5 (2015), pp. 2394–2444

R. Poore and C. Walford. *Development of an Operations and Maintenance Cost Model to Identify Cost of Energy Savings for Low Wind Speed Turbines*. Tech. rep. NREL/SR-500-40581. NREL, 2008

S. Faulstich, B. Hahn, and P. J. Tavner. "Wind Turbine Downtime and Its Importance for Offshore Deployment". In: *Wind Energy* 14.July 2010 (2011), pp. 327–337

C.1. Gearbox

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
	Gears			Gearbox	Tooth Failure	Vibration damage	Vibration
Bearings - high speed only	Bearings all				Bearing Failure	Vibration damage	Vibration and Oil
Lube pumps	Lube pumps	Lube pumps	Lube pumps	Lubrication	Oil Loss	Bearing life	Oil & SCADA
					Oil Overheat	Bearing life	Oil
					Oil under temperature	Oil damage	Oil

C.2. Generator

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
	Rotor			Generator	Overheat	Decreased insulation life	Temp
Bearings	Bearings				Fault	Fire damage	Temp
					Bearing jam	Bearing life	Vibration
Coolant	Coolant	Coolant	Coolant	Excitator	No/Reduced output	Overheating	Temp
	Contactor			Stabiliser circuit	No signal	Loss of synchronisation	Damage to drivetrain

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
	Soft starter			Protection relays	No operation	Breaker fails & Shutdown	
Electronics	Electronics	Electronics	Electronics	Synchroniser	No output	Can't start	
				Motor control	No output	No startup	
				Battery back up	Loss of DC voltage	Trip power	

C.3. Drive Train

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
	Main bearing			Main bearing	Fails	Vibration	Oil & Vibration
				Drive Shaft	Fracture	Shutdown	Vibration
				LS Coupling	Slip	Fracture Drive Shaft	Vibration
					Bolt failure	None	Inspection
				Slip Clutch	Fails	Shaft/LS Coupling Failure	SCADA
					Slips a lot	Overheating	SCADA
HS Coupling	HS Coupling	HS Coupling	HS Coupling	HS Shaft Assembly	Fracture	Gearbox damage	SCADA

C.4. Rotor Hub

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
Blade bearing	Blade bearing			Blade Bearing	Surface break up	Roughness	None
					Structural Fail	Less blade restraint	Rotor Vibration
Hub	Hub			Hub Assembly	Structural Fail	Blades separate	Rotor Vibration
					Bolt failure	None	Inspection
				Oil Seals	Cut and wear	Hydraulic loss	Low oil
				Torque Plate	Structural Fail	Less hub restraint	Rotor Vibration
					Loss of torque	None	Inspection
				Rod End Bearing	Linear Wear	Shock in Pitch	Inspection
					Structural Fail	Loss of pitch control	Rotor Vibration
	Pitch drive			Rod	Structural Fail	Loss of pitch control	Rotor Vibration
				Adjusting Nut	Adjusted	Wrong pitch	Inspection
				Stud	Loose preload	None	Inspection
				Link	Structural Fail	Wrong pitch	Rotor Vibration
				Jam Nut	Loose preload	Fretting	Inspection
				Support Beam	Structural Fail	Wrong pitch	Rotor Vibration

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
	Pitch cylinder & linkage			Actuator Sleeve	Structural Fail of link	Wrong pitch	Rotor Vibration
Pitch position	Pitch position	Pitch position	Pitch position		Structural Fail of pitch rod	Uncontrolled pitch (1 blade)	Rotor Vibration
					Structural Fail of sleeve	Uncontrolled pitch (All blades)	Rotor Overspeed
				Pitch Change Bearing	Breakup of Rollers	Roughness	None
Pitch gear	Pitch gear			Thrust Ring	Structural Fail of link	Wrong pitch	Rotor Vibration
Pitch motor	Pitch motor				Structural fail of actuator	Lower actuator fail	Rotor Vibration

C.5. Rotor Blades

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
				Retention Bolts/Studs	Fails	None	Inspection
Blade Structural	Blade Structural			Spar	Crack	Blades separate	Rotor Vibration
		Blade Non-Structural	Blade Non-Structural	Spar ring	Crack	Blades separate	Rotor Vibration

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
				Spar tie	Fails	Blade unbalance	Rotor Vibration
				Tip weight	Fails	Blade unbalance	Rotor Vibration
				Spar valve	Fails ON	Blade damage	Inspection
					Fails OFF	Blade damage	Inspection
				Lightning Protection	Fails	Blade may become damaged	Inspection

C.6. Yaw System

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
	Yaw gear			Yaw bearing	Bearing failure	Increased power consumption	Yaw error SCADA
	Yaw calliper	Yaw calliper	Yaw calliper	Yaw drive motor	No torque	No yaw	Yaw error SCADA
	Sliding pads	Sliding pads	Sliding pads	Pinion	Fails	No yaw	Yaw error SCADA
Bearing	Bearing			Coupling	Fails	No yaw	Yaw error SCADA

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
				Pinion bearings	Fails	Increased power consumption & Damage to whole structure	
				Brake calipers	Damage / inclusion	Slow yaw	Yaw error SCADA
					Ice	Reduced braking torque and Increased excitement - structural loads	Vibration
				Yaw brake release	Fail OFF	Park brake remains off	Yaw drive pressure
					Fail ON	No yaw	Brake status
				Leakage	None	None	Pressure switch
				Motor control valve	Fails OFF	No power	
					Fails ON	Always attempts to yaw & Damage to hydraulic system	Yaw error

C.7. Mechanical Brake

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
		Brake calliper	Brake calliper	HS shaft brake	Low torque	None	None
		Brake pads	Brake pads		High torque	Larger torque & Increased excitement - structural loads	Yaw error SCADA
				HS Shaft brake control	Fail ON	Brakes locked & Emergency shutdown	
					Fail OFF	No breaking & No shutdown	

C.8. Electrical System

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
Main contactor	Main contactor	Main contactor	Main contactor	Utility	No voltage / loss of phase	No power exchange	Shutdown
Circuit breaker	Circuit breaker			Utility recloser	Out of sync	Current & torque surge & Fatigue increase on generator	
				Step up transformer	Overheat	Decreased insulation life	Oil Temp

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
					Loss of phase	Motors overheat & Shutdown	
				Aux Supply	Overheat	Decreased insulation life & Shutdown	
					Loss of phase	Overheat & Shutdown	
				Main breaker	No close	Can't start or Shutdown	
					No open	Slip coupling overheats & Shutdown	
					Close or open at wrong time	Generator damage & Shutdown	
				Slip ring	Jammed	Higher torque	None
					Fault / noisy signal	Breaker opens & Shutdown	

C.9. Electrical Control

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
Module	Module	Module	Module	Primary blade control system	Fails	Blade damage	Rotor Vibration

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
Boards all	Boards all			Nacelle Control	Fails	Shutdown / Damage	

C.10. Sensors

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
Static sensor	Static sensor	Static sensor	Static sensor	Low oil temp switch	Fails ON	No power & Can’t start	
Dynamic sensor	Dynamic sensor				Fails OFF	Pump damage & Slow response	
				Low oil level switch	Fails ON	No power & Can’t start	
					Fails OFF	None	None
					Inadvertent close	No power & Can’t start	
				LP alarm switch	Fails OFF	No power & Can’t start	
					Fails ON	None	None
					Inadvertent close	False indication & Shutdown	
				Pump failed alarm switch	Fails OFF	Shutdown	
					Fails ON	None	None

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
				Emergency feather accumulator pressure switch	Fails ON	None	Inspection
					Fails OFF	Can't start	
					Inadvertent close	Shutdown	

C.11. Hydraulic System

(including yaw hydraulics)

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
Accumulator	Accumulator			Accumulator Charging Pump	Lack of Flow	Inability to pitch	LP Alarm
Hydraulic pump	Hydraulic pump	Hydraulic pump	Hydraulic pump	Charge pump unloading valve	Fail ON	Hydraulics down	Oil temp
Hydraulic valve	Hydraulic valve				Fail OFF	Accumulator discharge & Shutdown	SCADA
				Slew Pump	Lack of Flow	Slewing disabled	SCADA

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
					Excessive Pressure	High power consumption & Wrong pitch	Oil temp
				Unloading valve control switch	Fail ON	Main accumulator depleted	SCADA
					Fail OFF	Relief valve opens	Oil temp
				Emergency Feather Accumulator	Air leak	Loss of feathering pressure	LP Alarm
					Piston seal leak	Air entering fluid	Reduction of stiffness
				Hydraulic Fluid Heater	Open circuit	Pump failure below -17.7 C	Low temp
				Main accumulator flow pressure regulator	Stuck open	Higher slew rates	SCADA
					Stuck closed	Slewing limited & Pitch slow	SCADA
					Body leakage	Fluid depletion & Shutdown	SCADA alarm
				PCM Servo valve	Fails	Uncontrolled movement & Shutdown	

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
					Slews to one side	Uncontrolled movement & Shutdown	
				PCM Main accumulator	Loss of pressure	Slewing limited	SCADA
				Feathering flow control valve	Flow doesn’t vary	Slewing constant	Rotor Vibration
				Feather valve	Fail OFF	Feather issues	None
					Fail ON	Feather issues & Shutdown	
					Inadvertent open	Feather issues & Shutdown	SCADA
				Feather solenoid valve	Fail ON	None	None
					Fail OFF	Shutdown	SCADA
				Pitch change actuator	Internal leak	None	None
					External leak	Fluid depletion & Shutdown	SCADA
					Binding of piston	None	None
				Feather dump valve	Fails OFF	High pressure	SCADA
					Fails ON	Stuck blade & Can’t start	
					Inadvertent open	Loss of pressure & Shutdown	

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
				Filters	Leakage	Loss of oil	Low oil alarm
				Yaw brake accumulator	Loss of pressure	Loss of all brake pressure & Shutdown	
				Brake system charging valve	Fails ON	None	None
					Fails OFF & No pressure	Shutdown	LP Alarm
				Yaw hydraulic supply	No pressure	No yaw	Low oil alarm / Pump alarm
					Pump fails on	Shutdown	Oil temp

C.12. Support and Housing

(including yaw structure)

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
Brace/ Joint repair	Brace/ Joint repair	Mostly lift faults	Mostly lift faults	Upper yaw structure	Fatigue crack	Loss of stiffness / Distortion	Vibration
	Larger repair			Lower yaw structure	Fatigue crack	Loss of stiffness	Vibration
				Lift	Fails	No maintenance	

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
				Brace	Buckling	Distortion	Tower vibration
				Joint	Fatigue crack	Reduced stiffness	Tower vibration
					Yielding	Distortion & Vibration damage	Tower vibration
				Joint for Bedplate	Fatigue crack	Reduced stiffness	Tower vibration
					Yielding	Distortion of gearbox mounting	Tower vibration
Nacelle	Nacelle			Nacelle panels	Structural failure	Loss of sensors	Temp
				Exhaust fan	Fan/Louvre failure	Hydraulic / Electrical shutdown	Temp

C.13. Foundation

Major		Minor		FMEA Unit	Failure Mode	Effects	CMS Detect
CMS	No CMS	CMS	No CMS				
Reduced risk	Whole turbine			Not included			