Modelling the operation and maintenance of offshore wind farms

Iain Dinwoodie

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Centre for Doctoral Training in Wind Energy Systems

Department of Electronic and Electrical Engineering

University of Strathclyde

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Iain Dinwoodie

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Abstract

There are ambitious plans for renewable energy sources to provide a significant contribution to the future energy mix. The huge potential capacity and relative maturity compared to other offshore technologies has resulted in a strong commercial focus on offshore wind, particularly in Europe. However, costs of offshore wind remain significantly higher than conventional generation approaches as well as onshore wind. Reducing the cost associated with operations and maintenance of offshore wind remains a key challenge in decreasing lifetime cost of energy and achieving cost parity with alternative generation technologies.

The combination of nascent turbine and infrastructure design, moving into more challenging sea state and wind environments and the highly commercial nature of the industry has prevented the maintenance costs of offshore wind being adequately reduced through early operating experience alone. In order to accelerate the reduction of costs and critically to understand the uncertainty associated with future sites and novel operating strategies, it is necessary to simulate maintenance operations. This thesis has developed an offshore wind operations and maintenance expenditure model and specified a decision support methodology for this purpose. The models enable the quantification of the influence of cost drivers for current and future offshore wind farms and provide an improved understanding of the uncertainty associated with operating decisions.

Using the developed models, a detailed sensitivity analysis of the influence on lifetime costs from operational climate, failure behaviour, wind farm configuration and external cost drivers has been carried out to provide new insights on the industry. Operational climate and failure behaviour are identified as the critical cost drivers and sources of uncertainty currently. In addition, a detailed analysis of operational strategies for major repairs that involve the use of high cost, specialist vessels has been carried out for the first time, identifying the strengths and weaknesses of different strategies. Finally, a case study demonstrating how decision support models can be used to determine the optimal strategy choices for operators and reduce uncertainty has been performed.

The analysis in this thesis provides new insights on the industry and the developed methodologies have the potential to deliver significant financial savings in the future.

Acknowledgements

There are a large number of people I am indebted to for their help during the writing of this thesis. I would firstly like to thank Dr David McMillan for his invaluable guidance throughout my time as a PhD student, first as unofficial then as official supervisor. A number of other academics have provided assistance through early guidance on PhDs or informal discussions on wind energy, for this I would like to thank Professor Graham Ault, Professor David Infield, Dr Julian Feuchtwang, Dr Victoria Catterson and Dr David Hill in particular. A number of discussions with industry partners in particular at SSE, SPR and Siemens were also invaluable.

The marine operations aspects of this thesis were informed through work with colleagues in Naval Architecture, Dr Iraklis Lazakis and Yalcin Dalgic. The management science related aspects of the thesis would not have been possible without the help and guidance of Dr Matthew Revie, it has been a pleasure working with you all. The specification of a baseline wind farm was carried out in collaboration with Dr Matthias Hofmann and Iver Bakken Sperstad at SINTEF, Rebecca Martin at EDF and Ole-Erik Endrerud at the University of Stavanger, the conference calls were always enlightening and enjoyable, providing they worked.

To my fellow 'DTCers' thanks for making office life bearable and allowing me to be an occasional Dolphin. Specficially, thanks to Laura Kane, Mark Keegan and Conaill Soraghan for providing images used in Chapter 1.

Finally, thank you to friends and family for their encouragement and patience for a seemingly perpetual student. Most of all thanks to Lynsey for sticking with me throughout and sorting out the commas. I couldn't have done it without you.

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Nomenclature and Abbreviations

Symbol	**Definition**
t	Time
$\lambda(t)$	Observed failure rate
F_t	Number of failures observed
N	Number of turbines in population
$N_f(t)$	Number of turbines operating at time t
$Q(t)$	Cumulative failure distribution
$R(t)$	Reliability function
$f(t)$	Failure probability density function
$h(t)$	Hazard rate
ρ	Weibull scale parameter
β	Weibull shape parameter
u(t)	Failure intensity function
$R_c(t)$	Conditional Reliability function
r	Uniformly distributed random number from [0:1]
H	Number of components effected by failure
c	Modified Weibull scale parameter
a	Modified Weibull shape parameter
T	Transfer Probability Matrix
p(x|y)	Probability of x occurring, having observed y
n	Time step
$S^{(n)}$	System state at time step n
B	Variance between streams
v	Scalar summary
W	Within stream variance
$\hat{R}$	Gelman-Rubin convergence coefficient
Δt	Transition period
z	Time dependent variable
k	lag
γ_k	Autocovariance at lag k
ρ_k	Auto correlation function at lag k
μ_z	Mean of time series
Φ_k	Partial autocorrelation function
P_k	PACF matrix
P_k^*	Modified PACF matrix
X_t	Modelled time data
μ	mean
σ	variance
ε_t	White noise disturbance

φ_t	AR coefficients
θ_t	ARMA moving average parameter
ω	Frequency
$F(\omega)$	Fourier series fit
a_k	Fourier series coefficient
b_k	Fourier series coefficient
Y_t	Transformed time series
Hs	Significant wave height
$\hat{\mu}_{\ln(Hs_t)}$	Fourier Series fit of log means
Λ	Box-Cox transformation coefficient
LR	Lost revenue
RC	Repair costs
SC	Staff costs
IC	Infrastructure costs
VC	Vessel costs
MP	Market value
U(t)	Wind speed at time t
η	Efficiency
p(u)	Power at given wind speed from power curve
P(t)	Delivered power at time t
EP	Electricity price
A(t)	Availability
T	Number of turbines
F	Number of failures
FC	Failure cost
S	Number of staff
SC	Staff annual salary
V	Vessel cost component
R	Repair duration
D	Day rate of vessel
M	Mobilisation cost
s	Skewness
E(x)	Expected value of x
W(u)	Annual distribution of u
CTV	Crew Transfer Vessel
FSV	Field Support Vessel
AR	Auto-Regressive
ARMA	Auto-Regressive Moving Average
CBM	Condition Based Maintenance
TBM	Time Based Maintenance
CM	Condition Monitoring
O&M	Operations and Maintenance

Preface

During the course of writing this Thesis, the energy market in the UK and beyond has undergone significant technical and political changes. A sustained period during the 1990s and early 2000s of stable electricity and gas prices along with minimal investment in infrastructure came to an end. High wholesale prices together with closure of aging traditional coal and gas power stations and the extension of elderly nuclear power stations beyond their original design life has resulted in increased consumer prices and energy policy becoming a key political issue. There is a pressing need to build new energy infrastructure while keeping costs down and limiting the use of fossil fuel generation. As the most mature and therefore lowest cost renewable technology, onshore wind has seen widespread deployment during this period. However, the best sites for large scale wind farms have already been developed and there is increasing political and public objections to new onshore developments and an increasing focus on offshore wind.

With over 11000 miles of coastline, large areas of shallow seas and strong wind resource the UK is ideally located to make the most of offshore wind. Consequently, the UK has taken a world leading position in terms of offshore wind farm development, if not commercial offshore turbine technology development. As wind farms have moved further offshore and into deeper waters, the increased technical challenges have caused costs to increase rather than decreased as previously predicted. Relative to conventional power sources and onshore wind, there is a larger proportional cost of operations and maintenance (O&M) of offshore wind farms and greater penalty from lost revenues associated due to down time. Obtaining a greater understanding of the key influences and exploring novel operating strategies in order to bring down the O&M costs has been the principle motivation for this thesis.

Due to the immature nature of the industry and high entry costs there are only a small number of developers and operators which has resulted in a lack of operating experience. This situation is exacerbated as many existing sites are still under warranty where original equipment manufacturers (OEMs) perform maintenance rather than wind farm owners. This has led to the unusual situation where developers are having to make large investment decisions on future projects that are critical to the UK's energy security with limited understanding. Consequently, there has been an opportunity to work with developers, operators and service providers to provide modelling expertise during this project.

This has given wind farm operators improved clarity on the impact of current operational parameters and the consequences of adopting different strategies in the future. In return, it was possible to obtain a clear understanding of current operational practices and the key issues faced by the industry to ensure that the research carried out was as pertinent as possible. This collaborative approach highlights the relevance of the research in meeting the needs of industry and society at large to help offshore wind power reach its huge potential.

Chapter 1

Introduction

Offshore wind has rapidly developed to become a commercial source of electricity. However, compared to traditional fossil fuel generation and onshore wind the technology is still immature and key challenges remain in improving performance and reducing cost. The operation and maintenance (O&M) of offshore wind farms contributes significantly to the current high cost of energy. There is a requirement to improve understanding of all aspects of O&M as well as look towards future innovations in the area; this is the focus of this thesis.

Chapter 1 describes the structure, motivation, objectives and research output of this thesis. There is then a brief review of the progress of wind power and more specifically offshore wind as well as the current state of the industry and technology involved.

1.1 Objectives of research

A growing body of research is emerging in the field of offshore wind turbine O&M however, significant gaps in the knowledge remain; particularly in the peer-reviewed academic community. A full understanding of the key contributors to costs of O&M and the implications this has on optimum operating strategies at different sites has not yet been achieved. This requires a full analysis of the sensitivity of costs to various parameters at both the design and operation stage. This will allow an understanding of the costs which need to be controlled in order to effectively minimise the risk associated with offshore wind farms and to what extent controlling those costs will reduce risk to developers. A more detailed understanding of the degree to which overall O&M cost is influenced by the following is therefore required:

- Component reliability including failure categories.
- Component repair time.
- Impact of climatology on downtime.
- Operational strategies, in particular for the use of specialist O&M vessels.
- Vehicle and staff capability and availability.
- Resource availability and prices.
- Forecasting accuracy.

The major academic research and development into the field has produced two pieces of commercial software, [1.1, 1.2] identified in the literature review and various commercial companies offer modelling tools for O&M. However, due to commercial sensitivity, results have not always been subject to academic scrutiny. This PhD aims to develop a modelling methodology that can be used to address these gaps in the knowledge as well as provide an alternative source for independent verification. The model that is produced in this research will be described in adequate detail to allow it to be used for this purpose.

One area of key importance for the industry is to determine under which configurations and conditions different operating strategies are optimal. Various operating strategies are considered in this thesis covering the use of crew transfer vehicles (CTVs), helicopters and an in-depth investigation into the use of heavy lift vessels in order to provide greater clarity to the industry.

The application of advanced asset management techniques to the offshore industry is beginning to receive interest from the academic community. Development of these techniques for offshore wind will be aided by improved understanding of the key factors influencing costs identified in this research. The business case for these techniques has been more clearly defined and there is a particular focus on decision support methodologies. These approaches combine simulation with expert judgement to provide a stronger understanding of the underlying cost drivers for offshore wind.

1.2 PhD structural overview

In order to achieve the objectives of this research, an overall working structure was determined with key stages to be completed. This work structure is identified in Figure 1.1.

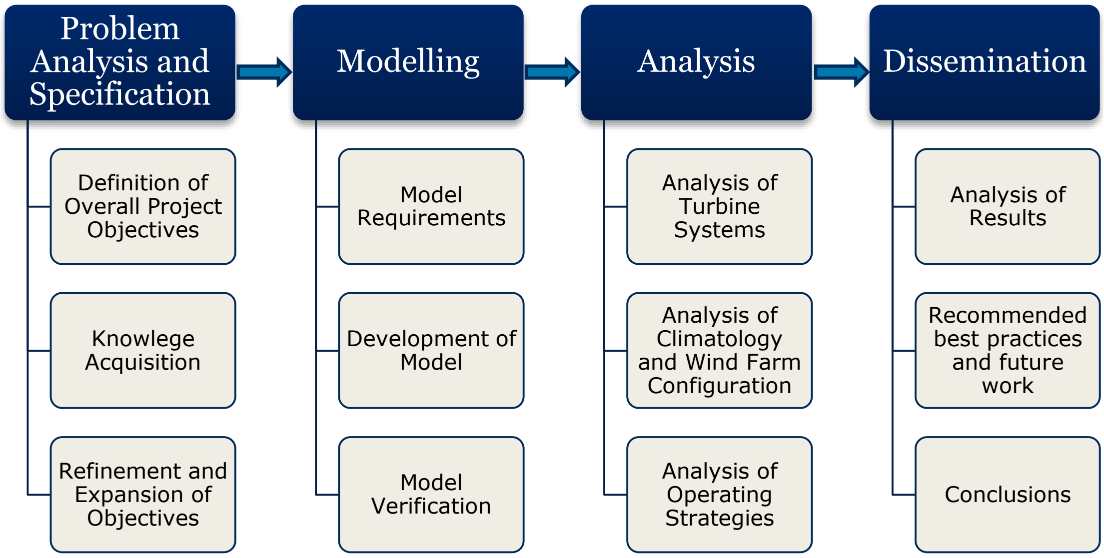


Figure 1.1: Overall research methodology structure

The clear identification of an overriding set of objectives is critical to determining the direction of any research project and influence the nature of all subsequent work. The key PhD research question was specified as:

"Which factors need to be controlled most effectively to minimise operational costs in wind farms and to what extent can operational modelling support the goal of minimising costs and risk?"

Following the specification of this objective, it was necessary to analyse the current literature followed by a focussed literature review which is presented in Chapter 2 . Having identified the areas where research would add the most value to the industry and where gaps in the knowledge existed, the original objective was then refined and expanded.

1.3 Novelty of research

In order to produce a model flexible enough to be used to investigate the range of objectives specified, an adequate degree of fidelity was required. The novelty of this research therefore comes from both the development of a new O&M operational expenditure (OPEX) model and the analysis performed with it. Furthermore, as the model is intended to be used for independent verification of other tools, it has been built from first principles rather than on top of any existing model. By building a model in this manner it was therefore possible to identify differences in model predictions during development. This allowed identification of how assumptions and simplifications impact model outputs.

The modelling approach builds on previous work carried out on engineering system maintenance and decision support models. The fundamental modelling approach has been applied to a wide range of industries, including onshore turbines but has been developed to incorporate the added complexity that exists in the offshore environment. It is becoming evident that the use of onshore O&M practices in the offshore market is not economically feasible and this has led to an interest in applying advanced maintenance strategies such as condition based and opportunistic maintenance. Before these practices can be implemented successfully there is a need to fully understand the underlying cost drivers and establish the business case of these techniques. This work addresses this knowledge gap.

1.4 Overview of thesis

A detailed literature review of relevant work is presented in Chapter 2. This covers the more widely applicable subject areas of asset management as well as reliability and failure modelling in addition to a more detailed focus on these areas in the context of offshore wind specifically. A detailed review of climate and operational modelling techniques is covered and gaps in the existing literature are identified.

The underlying principles and methodology of the developed model and analysis are described in detail in Chapter 3. The underlying theory covers reliability and climate model and developed cost model. There is a detailed explanation of the structure, functionality and key assumptions adopted for the combined OPEX model.

The focus in Chapter 4 is the importance of the offshore environment on offshore wind performance both in terms of availability and production. The wind and wave climate are analysed with a focus on variability. The parameterisation of the developed climate model is explained and used to perform a detailed single site investigation. A demonstrative multi-site analysis performed showing the relative impact on future sites.

Chapter 5 presents a rigorous sensitivity analysis of operational parameters influencing the performance of offshore wind. A base case is established and used to quantify the impact of operational choices and wind farm specification. Strategies for minor repairs are explored and the effect of externalities are also considered.

An investigation into different operational strategies for major repair and replacement actions that require specialist heavy lift vessels is performed in Chapter 6. A particular focus is given to the consequence of late life failure behaviour of wind turbines and strategies that can be used to mitigate risks posed from deteriorating behaviour. Finally, a decision support methodology is demonstrated using the previous results and the benefits of this approach are highlighted.

The final chapter reviews the key learning outcomes from this thesis. The major challenges that remain for the offshore wind industry going forward are discussed and benefits the work in this thesis has for the industry identified.

1.5 Research output

The following peer reviewed journal articles and conference proceedings have been output during this PhD:

Operational strategies for offshore wind turbines to mitigate failure rate uncertainty on operational costs and revenue.

I. Dinwoodie, D. McMillan, IET Renewable Power Generation, Volume 8, Issue 4, May 2014, p. 359 – 366

Development of a Combined Operational and Strategic Decision Support Model for Offshore Wind

I. Dinwoodie, Y. Dalgic, I. Lazakis, D. McMillan, M. Revie, Energy Procedia Volume 35, Pages 157-166 (2013) DeepWind'2013 – Selected papers from 10th Deep Sea Offshore Wind R&D Conference, Trondheim, Norway, 24 – 25 January 2013

Reference Cases for Verification of Operation and Maintenance Simulation Models for offshore wind farms

I. Dinwoodie, OE. V. Endrerud, I. Bakken Sperstad, M. Hofmann, R. Martin, Wind Engineering, volume 1, 2015

Heavy Lift Vessel Strategy Analysis for Offshore Wind

I. Dinwoodie, D. McMillan, European Wind Energy Association Annual Conference, Vienna, 2013.

Sensitivity of Offshore Wind Turbine Operation & Maintenance Costs to Operational Parameters

I. Dinwoodie, D. McMillan, 42nd ESReDA Seminar Risk and Reliability for Wind Energy and other Renewable Sources, Glasgow, 2012.

Analysis of Offshore Wind Turbine Operation & Maintenance Using a Novel Time Domain Meteo-ocean Modeling Approach

I. Dinwoodie, D. McMillan, F. Quail, ASME Turbo Expo, Copenhagen, 2012.

Forecasting long term jack up vessel demand for offshore wind

D. McMillan, **I. Dinwoodie,** Safety, Reliability and Risk Analysis: Beyond the Horizon – Steenbergen et al. (Eds), Amsterdam 2013, ISBN 978-1-138-00123-7

Optimum CTV Fleet Selection for Offshore Wind Farm O&M Activities

Y. Dalgic, **I. Dinwoodie,** I. Lazakis, D. McMillan, M. Revie, European Safety and Reliability Association 2014, Wroclaw, Poland, 2014

Wave height forecasting to improve off-shore access and maintenance scheduling

V. Catterson, **I. Dinwoodie**, D. McMillan, 2013 IEEE Power & Energy Society General Meeting, Vancouver, BC, Canada, 21-25 Jul 2013.

An economic impact metric for evaluating wave height forecasters for offshore wind maintenance access

V. Catterson, D. McMillan, **I. Dinwoodie**, M. Revie, J. Dowell, J. Quigley and K. Wilson – Accepted for publication in Wind Energy

In addition, the following dissemination to academia and industry have been carried out while undertaking this thesis alongside internal research presentation day presentations:

Operation and Maintenance of Offshore Wind Farms

Peer reviewed article contributed to IET online engineering library, available at

http://digital-library.theiet.org/content/reference/10.1049/etr.2014.0022

Offshore Wind Energy Operations Research

Presented at One Day Workshop on Logistics and Operational Research for the Offshore Wind Farm Sector, Portsmouth University, 18th July 2013

Modelling wind farm operational expenditure for improved asset management – objectives and methodologies

Offshore Wind Turbine Optimisation Seminar, 3-4 February 2014, Dexter House, London, UK

Offshore Wind OPEX Modelling – Reducing Uncertainty

University of Strathclyde Risk Consortium Workshop, 1 May 2014,

1.6 The development of wind as an industrial power source

The wind has been harnessed by humans as a source of energy for thousands of years for applications such as powering boats, pumping water and powering mills. The use of the natural wind resource for electricity generation is comparatively a modern development. Sporadic development of wind turbines of various configurations took place during the twentieth century before the ‘Danish concept’ arrangement of a 3 bladed horizontal axis wind turbine emerged in the late 1950s and was established as the dominant design for electricity generation by the 1980s. A typical Danish concept turbine is shown in Figure 1.2. During the 1980s and early 90s various government funded research initiatives were launched to combat the rising cost of fossil fuels and a commercial wind turbine market was established.

Figure 1.2: Modern 'Danish Concept' Wind Turbine in Scotland

Since the mid-1990s, there has been an exponential growth in the world wide installed capacity of wind turbines from around 6GW, concentrated in Northern Europe and the USA in 1996 to almost 300 GW spread across the world at the end of 2012[1.3]. Annual growth of installed capacity is shown in Figure 1.3 and the installed capacity of selected countries is presented Table 1.1 as of June 2013. Although wind turbines with rating from a few kW up to several MW now exist, commercial onshore wind turbines are typically in the range 800 kW – 2 MW and this represents the most cost effective design size onshore [1.4]. The technical reasons for this convergence as well as a more detailed history of the wind industry including descriptions of different technology through time can be found in the first chapter of [1.5].

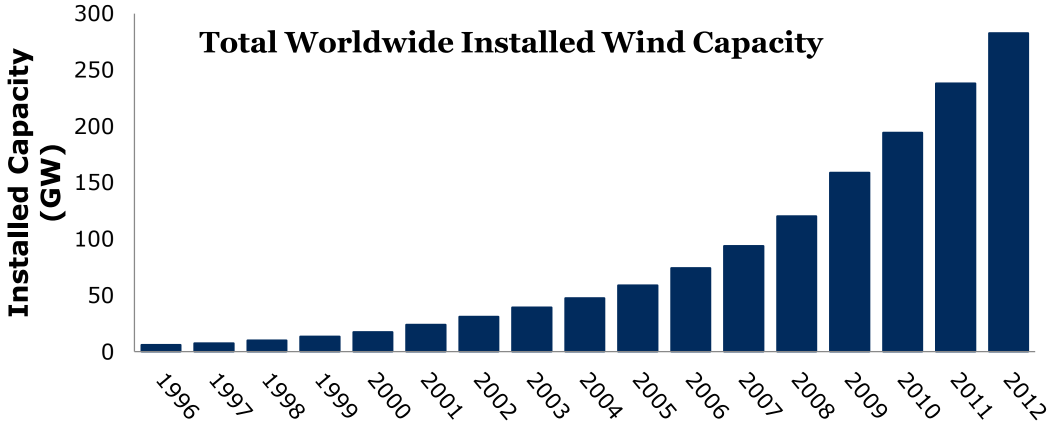


Figure 1.3: Total installed global wind capacity [1.3]

Table 1.1: Country installed capacity 2013 [1.4]

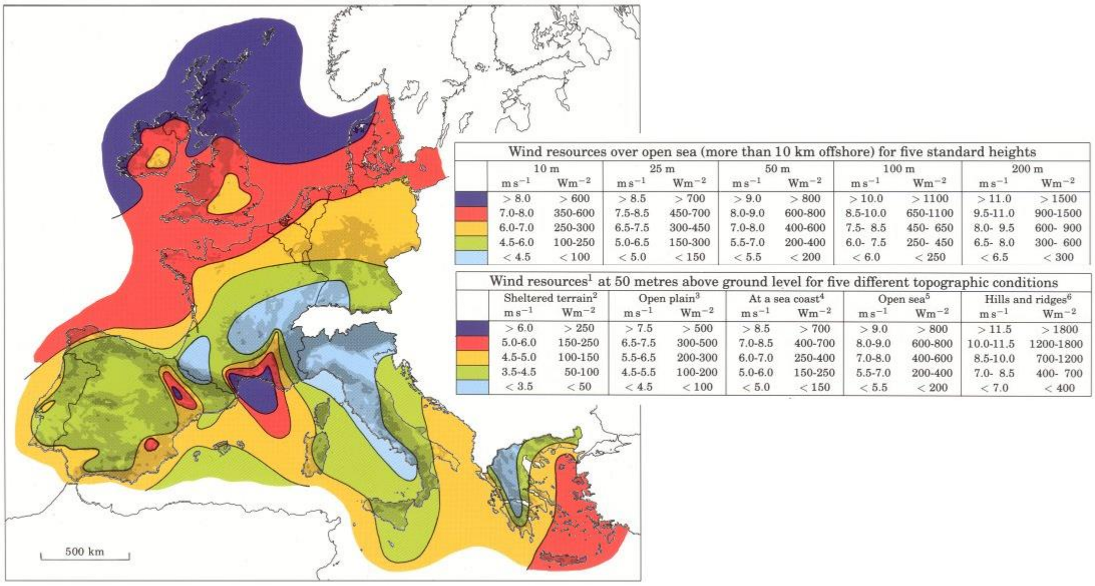
Country	Capacity June 2013 (MW)	Capacity end 2012 (MW)
China	80.82	75.32
USA	60.01	60.01
Germany	32.42	31.31
Spain	22.91	22.79
India	19.56	18.32
United Kingdom	9.61	8.228
Italy	8.42	8.15
France	7.82	7.62
Canada	6.58	6.2
Denmark	4.58	4.16
Portugal	4.56	4.54
Sweden	4.07	3.74
Australia	3.06	2.58
Brazil	2.79	2.51
Japan	2.65	2.61
Rest of World	26.2	24.17

1.6.1 The status of wind power in the UK

The principal driver for wind energy in the UK has been in the form of government incentives. The Renewables Obligation was introduced in 2002 to encourage electricity suppliers to diversify their energy portfolio to include renewable sources of generation [1.6]. Under this scheme, if suppliers failed to meet percentage targets that increase annually, they faced a financial penalty thus creating a market situation where renewable energy sources became financially practical. In December 2013 it was announced that the ROC scheme is to be replaced by the Contract for Difference which will guarantee a market price for different sources of power generation under the governments Electricity Market Reform [1.7]. Small scale developments of under 5 MW are covered by the feed-in-tariff initiative introduced under the 2008 Energy Act but this law is not relevant to large scale developments, particularly offshore.

There are two primary objectives behind these initiatives; firstly 'energy security' which aims to diversify the energy portfolio in order to reduce dependency on fossil fuels from foreign suppliers and secondly decrease carbon emissions as outlined in government energy white papers in 2003 and 2007 and reiterated in the latest policy document [1.7-1.9]. The climate change objective is in line with legally binding EU targets that require the UK to produce 15% of energy from renewable sources by 2020 [1.10].

Although the Renewables Obligation covers a diverse range of energy technologies, the practical implication has been the rapid growth of the onshore and offshore wind sectors in the UK. A principal reason for this is that the UK has the amongst the best wind resource in Europe as shown in Figure 1.4 and consequently wind power is the most cost effective method for meeting renewable generation targets, even with higher banding to less mature technologies such as wave and tidal generation.



Wind resources over open sea (more than 10 km offshore) for five standard heights										
	10 m		25 m		50 m		100 m		200 m	
	$m\,s^{-1}$	Wm^{-2}	$m\,s^{-1}$	Wm^{-2}	$m\,s^{-1}$	Wm^{-2}	$m\,s^{-1}$	Wm^{-2}	$m\,s^{-1}$	Wm^{-2}
	> 8.0	> 600	> 8.5	> 700	> 9.0	> 800	> 10.0	> 1100	> 11.0	> 1500
	7.0-8.0	350-600	7.5-8.5	450-700	8.0-9.0	600-800	8.5-10.0	650-1100	9.5-11.0	900-1500
	6.0-7.0	250-300	6.5-7.5	300-450	7.0-8.0	400-600	7.5- 8.5	450- 650	8.0- 9.5	600- 900
	4.5-6.0	100-250	5.0-6.5	150-300	5.5-7.0	200-400	6.0- 7.5	250- 450	6.5- 8.0	300- 600
	< 4.5	< 100	< 5.0	< 150	< 5.5	< 200	< 6.0	< 250	< 6.5	< 300

Wind resources[1] at 50 metres above ground level for five different topographic conditions										
	Sheltered terrain[2]		Open plain[3]		At a sea coast[4]		Open sea[5]		Hills and ridges[6]	
	$m\,s^{-1}$	Wm^{-2}	$m\,s^{-1}$	Wm^{-2}	$m\,s^{-1}$	Wm^{-2}	$m\,s^{-1}$	Wm^{-2}	$m\,s^{-1}$	Wm^{-2}
	> 6.0	> 250	> 7.5	> 500	> 8.5	> 700	> 9.0	> 800	> 11.5	> 1800
	5.0-6.0	150-250	6.5-7.5	300-500	7.0-8.5	400-700	8.0-9.0	600-800	10.0-11.5	1200-1800
	4.5-5.0	100-150	5.5-6.5	200-300	6.0-7.0	250-400	7.0-8.0	400-600	8.5-10.0	700-1200
	3.5-4.5	50-100	4.5-5.5	100-200	5.0-6.0	150-250	5.5-7.0	200-400	7.0- 8.5	400- 700
	< 3.5	< 50	< 4.5	< 100	< 5.0	< 150	< 5.5	< 200	< 7.0	< 400

Figure 1.4: European Wind Resource [1.11]

The excellent wind resource combined with the relative maturity of the technology has resulted in UK onshore wind capacity increasing from around 375 MW before 2004 to 6.8 GW in 2013. While this increase is considered a major success by the wind industry, to provide 20% of the UK's electrical energy needs from renewable sources, it is estimated that as much as 35% of the UK's electricity supply will be required to come from renewable sources [1.9]. At current usage levels that would be approximately 26GW of electricity supplied from renewable sources. Due to the comparatively lower capacity factor of wind power to supply 35% of the electricity supply, 33GW of wind capacity would be required [1.12]. Installing this level of wind capacity onshore is unfeasible due to land constraints in the UK, even if political and public will to do so existed. In addition, many of the best onshore resource is found over northern England and Scotland in particular, away from the large population centres in the South-East of England. Utilising the best onshore resource would require significant upgrading of the onshore transmission network which would be politically unpopular due to the aesthetic impact as well as expensive. These constraints do not exist for the offshore case. The UK is therefore in the optimal position to exploit offshore wind due to its strong resource, limited onshore growth potential and large electrical load.

1.6.2 The emergence of offshore wind power

Due to the high capital costs of installation and additional complexity of machines required, offshore wind power has only become technically feasible since the early 1990s and economically viable with the advent of multi-megawatt wind turbines in the 2000s [1.13]. Since the establishment of Middelgrunden Wind Farm in Denmark in 2001 [1.14], shown in Figure 1.5, there has been rapid growth in the EU market. Figure 1.6 shows the exponential growth experienced in EU market between 2000 and 2013. It should be noted that the installed turbines for 2013 comprise only

January to July and it is expected that total installation for the year will be a record high, exceeding that of 2012 [1.15].

Figure 1.5: Middelgrunden Offshore Wind Farm

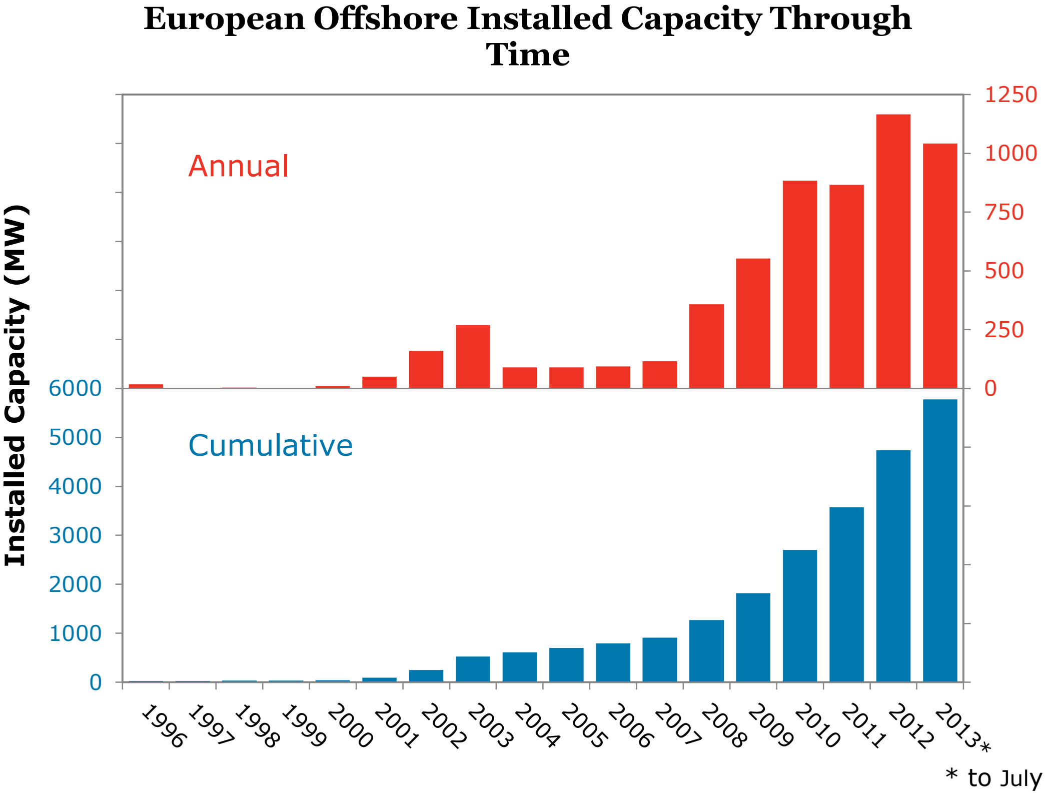


Figure 1.6: European offshore wind capacity through time [1.15]

In 2010, the UK became the world leader in offshore wind capacity including what was at the time the world's largest offshore wind farm. The 300 MW Thanet project came online, taking the UK's offshore capacity to over 1.3 GW, approximately a third of the total world installed capacity. The relative importance of the offshore market to the UK can be seen in Figure 1.7 comparing onshore and offshore installations. Unlike the global wind statistics where the onshore market dwarfs the offshore market, in the UK it can be considered that offshore developments only lag onshore by a small number of years. In addition, considering the projects under construction shows that while onshore development is reaching a plateau, offshore has significant potential for expansion. It should also be noted that these figures do not yet include projects in Scottish Territorial Waters which are expected to contribute significant additional capacity. The theoretical capacity in the UK for offshore wind that far exceeds current total energy consumption [1.16].

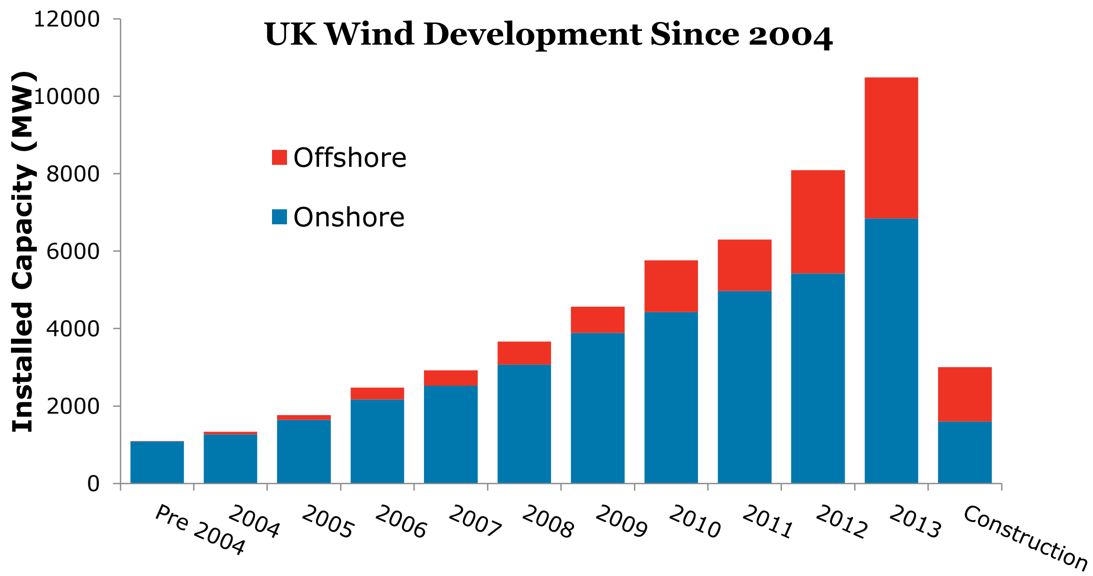


Figure 1.7: UK wind development since 2004 [1.17]

A summary of commissioned and under construction UK sites are shown in Table 1.2 where sites under construction have a blank year.

Table 1.2: UK offshore wind projects [1.17]

Wind Project	Turbines	Capacity (MW)	Developer	Year
Barrow	30	90	DONG / Centrica	2006
Beatrice Demonstration	2	10	SSE	2007
Blyth Offshore	2	3.8	E.ON UK	2001
Burbo Bank	25	90	DONG	2007
Greater Gabbard	140	504	SSE & RWE Npower	2012
Gunfleet Sands I	30	108	DONG	2010
Gunfleet Sands II	18	64.8	DONG	2010
Gunfleet Sands III - Demo	2	12	DONG	2013
Kentish Flats	30	90	Vattenfall	2005
Lincs	75	270	Centrica / DONG / Siemens	2008
London Array I	175	630	DONG / E.On / Masdar	2013
Lynn & Inner Dowsing	54	194	Centrica	2009
North Hoyle	30	60	RWE Npower	2003
Ormonde	30	150	Vattenfall	2012
Rhyl Flats	25	90	RWE Npower	2009
Robin Rigg	60	180	E.ON UK	2010
Scroby Sands	30	60	E.ON UK	2004
Sheringham Shoal	88	317	Scira Offshore	2012
Teesside	27	62.1	EdF ER	2013
Thanet	100	300	Vattenfall	2010
Walney I	51	184	DONG / SSE Ampere Equity / PGGM	2011
Walney II	51	184	DONG / SSE Ampere Equity / PGGM	2012
Gwynt y Mor	160	576	RWE Innogy / SWM / Siemens	
Humber Gateway	73	219	E.ON UK	
Methil Offshore Wind Demo	1	7	Samsung Heavy Industries	
West of Duddon Sands	108	389	Scottish Power/DONG	
Westermost Rough	35	210	DONG	

1.7 Technical introduction

Despite this impressive progress, the industry is still undergoing steep learning curves in terms of technological implementation and operations to reduce the cost of electricity produced. In order to explain why offshore wind energy is considered a less mature technology than onshore wind, as well as identifying the areas requiring further research and development, it is necessary to understand the basic design of a modern turbine as well as their method of operation. Detailed descriptions of the underlying electrical and mechanical principles can be found in various sources such as [1.5, 1.18] and are not covered in this thesis.

1.7.1 The modern offshore wind turbine

Onshore wind turbines can be found in a large range of sizes and configurations with vertical axis and horizontal axis types as well as varying number of blades, various electrical and control configurations existing. These variations reflect the onshore market where customers range in size from small single turbine owners up to developers of large wind farms. The high capital cost involved has resulted in a very different structure of the market offshore. This has led to a far greater uniformity between offshore turbine designs. Offshore wind turbines are in the megawatt range with the widest currently installed turbine in the 3-5MW stage and 7MW designs now undergoing commercial testing [1.19]. The blade diameters of these turbines are in the 60-80m range weighing upwards of 30 tonnes. Correspondingly, turbine hub heights are required to be at 90-100m. Performing maintenance on such large components at these heights require specialist staff and equipment and significantly add to the complexity of the logistics. An example of a current offshore blade is shown in Figure 1.8 demonstrating their huge scale.

Figure 1.8: Modern offshore wind turbine blade next to car for scale

Due to the high development costs involved with developing multi-megawatt turbines and the risk associated with bringing products to an emerging market, thus far only large companies with experience from the onshore industry have delivered commercial products. This is demonstrated in Figure 1.9 showing the domination of the market by two main manufacturers, Siemens and Vestas. The cost and resultant risk involved in developments has restricted the proliferation of other manufacturers. This is particularly due to the high insurance costs of using unproven technology and the difficulty and cost of certifying a new turbine type in the offshore environment.

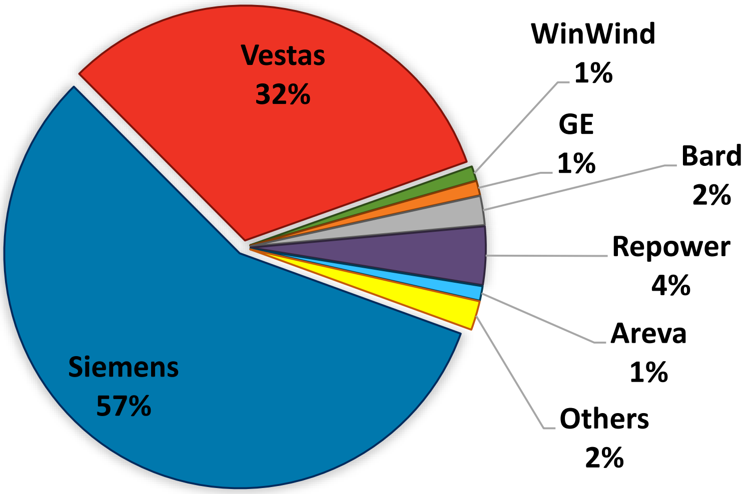


Figure 1.9: European offshore wind by manufacturer up to 2012 [1.15]

At the time of writing, every installed offshore turbine has been of the Danish Concept design; horizontal axis, 3 bladed upwind turbines. Although research projects have suggested that an alternative configuration may become the optimal design for offshore in the future, see for example [1.20], this work considers only the standard design. Modern large wind turbines are extremely complex machines and even considering a 'standard design' it should be noted that there is the possibility for large differences in system architecture. For example, the most recent Siemens offshore turbine design has moved to a direct drive design [1.21]. The consequences of such changes to operation and maintenance (O&M) have been considered in [1.22].

In order to perform a representative reliability analysis it is required to consider a wind turbine as more than a single machine. This requires a trade-off between representing the turbine in sufficient detail to identify key sub systems or components while keeping analysis practical. For the initial analysis, the complexity of the turbine chosen was determined by available failure data. Based on the subsystems reported in [1.23], the following subsystems were therefore used for initial reliability analysis: *Ambient, Blade, Brake, Control, Converter, Electrical, Gearbox, Generator, Pitch, Scheduled, Yaw, Structure and Grid.* The subsystems are identified on a typical offshore wind turbine in Figure 1.10. The consequences of this approach and alternative methodologies are discussed in detail in Section 5.4.

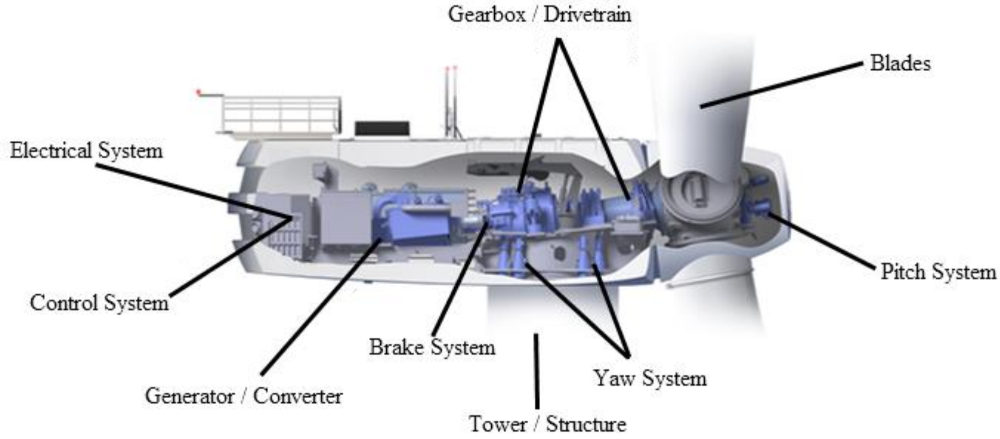


Figure 1.10: Subsystems of a modern offshore wind turbine [1.24]

1.7.2 Offshore wind power research

The current focus on research and industrial activity in offshore wind has concentrated on design and installation techniques as the emphasis has been on successfully constructing turbines offshore and getting them into the water and generating electricity [1.25]. There has been comparatively little research focussing on the longer term asset management of turbines in the offshore environment. Compared to onshore wind, operation and maintenance of offshore wind is more complicated due to more limited access windows, more complex logistical operations limited by port infrastructure and vessel availability and a lack of operating experience. Optimising the O&M costs offer a significant area of cost reduction which will be vital for long term financial viability of the industry. A detailed analysis of offshore wind power technology can be found in [1.26].

1.7.3 The importance of operations and maintenance to offshore wind power

Currently, the OPEX cost of offshore wind is estimated at 25% of the lifetime project cost which is likely to increase as even larger machines are installed further offshore in deeper waters [1.27]. On its own this represents a significant opportunity for cost savings and the importance of O&M increases when loss of production is considered. This can be demonstrated with a basic illustrative example. For simplicity, the effect of Renewable Obligation Credits (ROC) banding which currently are worth 1.5 for offshore wind versus 1 for onshore wind are considered rather than future support mechanisms. The following assumptions are made for a demonstrative calculation:

- Wholesale energy price of £55/MWh
- ROC value of £45/MWh
- Capacity factor of 35% offshore, 30% which are representative of a typical offshore site and an excellent onshore site.
- Offshore turbine size 5 MW based on average of Siemens 3 MW machine, Repower 5 MW machine and Vestas 7 MW
- Onshore machine size 1 MW

Table 1.3: Typical Lost Revenue with Downtime

Time Period	Onshore Losses Per Turbine	Offshore Losses Per Turbine
1 hour	£ 30	£ 173
1 day	£ 720	£ 4155
1 week	£ 5040	£ 29085
1 month	£ 20160	£ 116340

Onshore, downtime of a month is highly unlikely unless a serial defect was identified and there was a resulting delay in replacement components. Offshore, particularly in winter months when the wind resource is likely to be better, access delays of months due to wave climate are possible [1.28]. As Table 1.3 shows, the financial consequence of a single turbine going offline is significantly greater offshore than onshore. However, the relative costs of repair action also vary hugely when comparing onshore and offshore. Onshore repair actions are typically carried out by a single service engineer with only large components such as blades, gearbox and generator requiring specialised heavy lift equipment. Offshore, any repair action that cannot be carried out remotely is dependent on an access window that allows transfer to and from the site as well as adequate time to perform the repair operation.

Offshore, heavy lift vehicles are extremely expensive to build or hire and have limited availability. The current costs for a vehicle large enough to replace a blade is between £100 -£200m [1.29] and cost tens or even hundreds of thousands of pounds a day to hire for maintenance actions. The result of the increased cost of losses, more restrictive access conditions and expense of offshore operations is that O&M of offshore wind farms is significantly more complex than their onshore counterparts.

Figure 1.11 shows an estimate for the lifetime costs of offshore wind while Figure 1.12, represents the estimated costs for future sites in more challenging locations. From Figure 1.11 and Figure 1.12 it can be seen that O&M currently comprises a quarter of all total lifetime costs and this percentage is likely to increase. With O&M costs representing up to a third of total lifetime costs, it is a vital that they are optimized to reduce the lifetime cost of energy. In addition, unlike the other cost components that cannot be altered post construction of the wind farm, the O&M costs represent a potential area of saving during the entire operational lifetime of the wind farm. These factors contributed to the choice of O&M as an active area of research with tangible benefits to the industry.

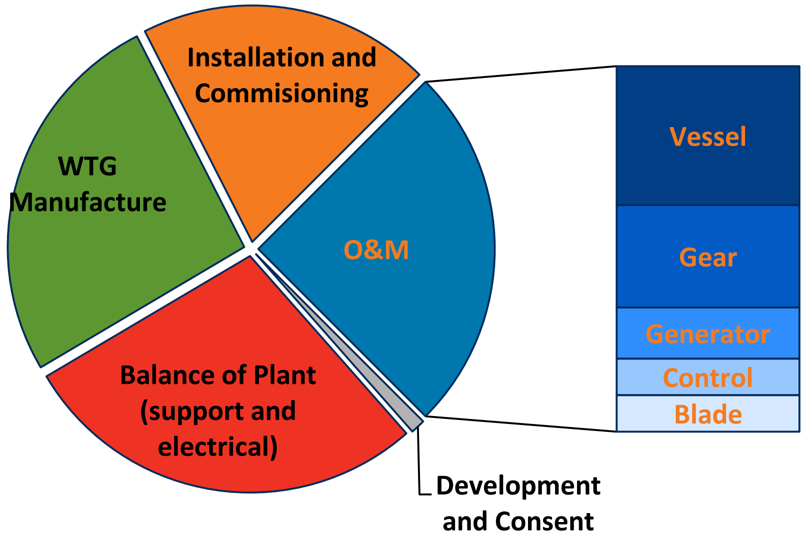


Figure 1.11: Estimate of lifetime costs of offshore wind (2009) [1.30]

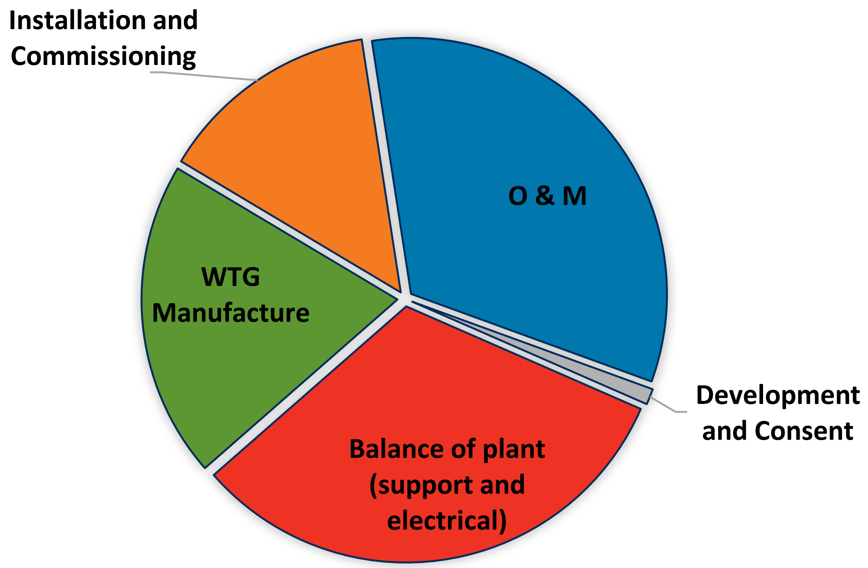


Figure 1.12: Predicted future breakdown of offshore wind lifetime costs [1.27]

1.7.4 Costs and trends in offshore wind farms

The UK offshore wind market consists of various rounds of development. The location and size of proposed developments are shown in Figure 1.13.

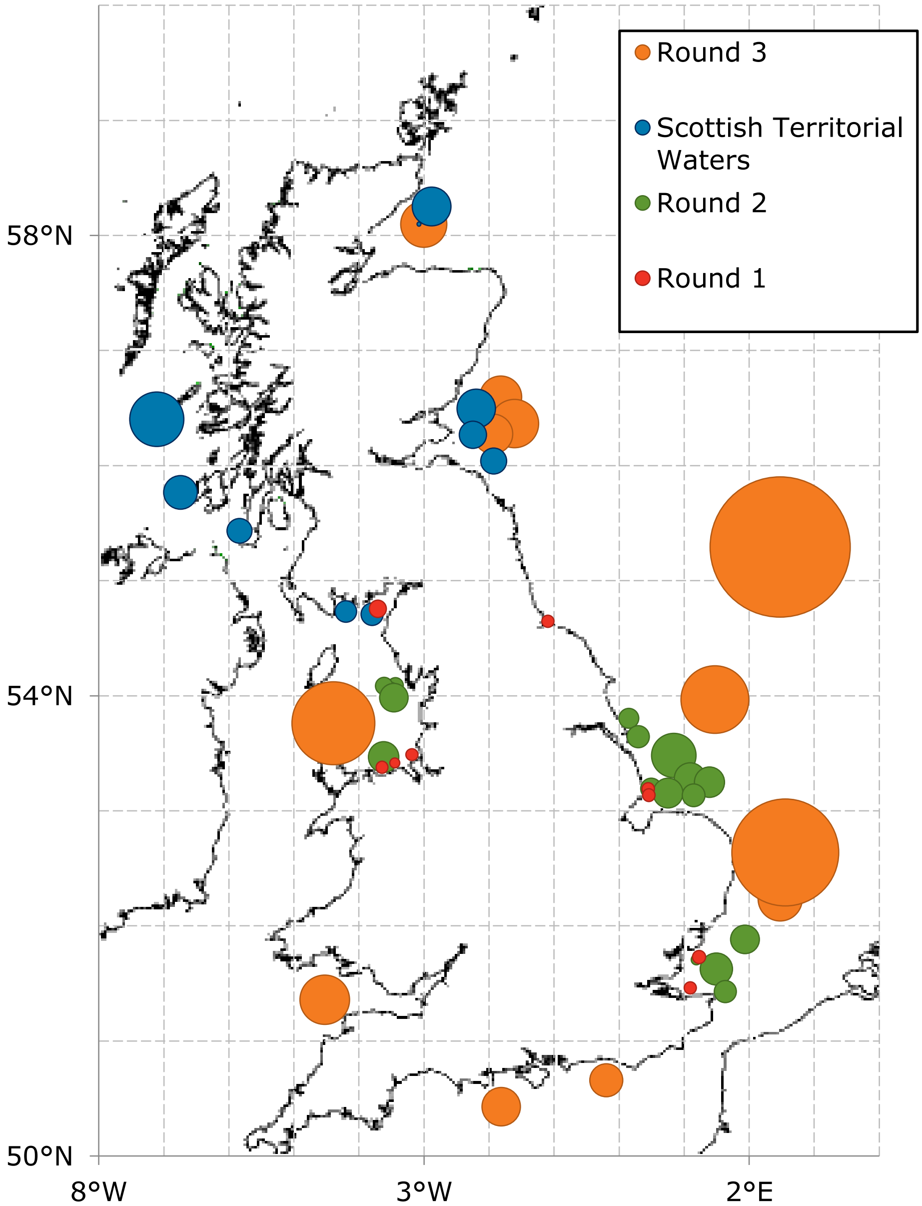


Figure 1.13: Location of UK Offshore Developments based on [1.31]

The majority of wind farms built in the UK to date have been part of the Round 1 and Round 2 developments with the commissioning of Greater Gabbard and the London Array in 2012 and 2013 constituting the largest at 504 and 630 MW respectively. As well as the increasing size and distance from shore of future developments identified in Figure 1.13, depths of projects will also increase. All three of these factors will contribute to an increase in O&M complexity and cost if current practices are applied to future offshore wind farms.

Comparing the costs of energy supplied from various sources is complex and with significant uncertainties from factors such as wholesale commodity prices, carbon and CO_2 offset costs, decommissioning costs and operating costs. Furthermore, there is significant variation between the costs of energy at the completed sites around the UK which makes an accurate estimate of the overall cost of offshore wind unpractical. A recent analysis of different power sources in the UK and attempts to predict future costs is provided in [1.32]. The report finds that offshore wind is typically 1.5 – 2.5 times the cost of onshore wind and conventional sources and this is likely to persist up to 2020. A more detailed analysis of costs involved specifically in offshore wind has been presented in [1.33] with similar findings.

1.7.5 Technical Outlook

As offshore wind farms increase in size, move further offshore and into deeper waters, the investment costs will become unfeasible for single developers. For example, in the round 3 projects in the UK, all 9 development zones have been leased to consortiums of developers of up to 4 large scale utility companies [1.31]. The current market structure, consisting of just a few key developers, presents opportunities as well as risks and has significant implications for operations and maintenance.

Onshore, the diverse range of operators, wind farm size and location has led to the adoption of basic maintenance strategies. In the extreme case of small private developments, turbines are simply run to failure. For larger commercial wind farms a combination of scheduled maintenance and reactive maintenance when faults are detected or failures occur has been used. Availability of over 97% for commercial onshore wind farms is currently achievable [1.34] resulting in modern onshore wind farms being economically competitive with conventional generation technology [1.35]. Adopting similar strategies offshore has proven to be an inadequate strategy with availability of initial UK and Netherlands sites achieving only 81% availability [1.23, 1.36]. This has been largely due to machine reliability and the access constraints associated with current vessels.

Improved turbine design is evidently needed and future offshore turbines will aim to significantly improve reliability. However, in the harsh offshore environment, complex rotating machinery will always be prone to faults. Improving the robustness of components will result in an increased manufacturing cost and may not make financial sense. Additionally, machines already in the water and those currently being deployed are required to operate for a 25 year life cycle with existing designs. Retrofitting or complete overhauls are expensive and wasteful approaches to achieving this and should be considered the last resort. There is therefore an urgent need to determine better methods of operating and maintaining wind farms and the research community is beginning to engage with this problem. The existing body of research is examined in the literature review section of this thesis.

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Chapter 2

Literature review

This chapter assesses existing pertinent literature and data sets that inform the analysis in succeeding chapters. There is a large body of research on the areas of asset management, operation and maintenance, failure simulation and climate modelling all of which are relevant to this thesis. However, there are various aspects and nuances associated with wind energy and offshore wind energy in particular that make many of the established approaches unsuitable. This chapter reviews prior work in the context of offshore wind rather than a general review of the topics. There is a focus on previous and ongoing offshore wind modelling projects. The growth in research in this area has followed the growth in offshore wind deployment and reflects the increasing priority O&M has within the industry. Figure 2.1 demonstrates this, showing the number of scientific articles related to wind turbine maintenance, using two citation sites.

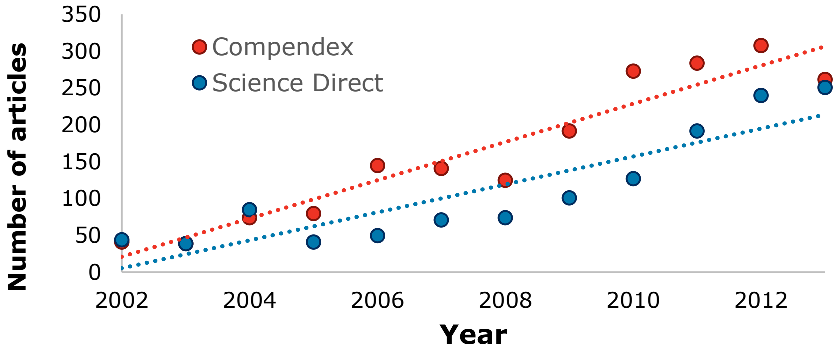

Figure 2.1: Articles containing 'Wind' and 'Maintenance' key word by year

2.1 Offshore wind O&M modelling projects

The first significant work undertaken to understand offshore O&M was carried out at Delft University under the development of CONTOFAX [2.1] as part of the Structural and Economic Optimisation of Bottom-Mounted Offshore Wind Energy Converters' (Opti-OWECS) project. The program simulated availability of the wind farm and the corresponding annual energy output and O&M costs by means of Monte Carlo Simulation. The simulation approach examines each subsystem of the wind farm and generates failures based on data provided by operators. This standard approach to simulation of system failures is built on by simulating maintenance actions under random failure, wind and wave data with predefined maintenance crew availability. Use of Monte-Carlo simulation to optimize simple O&M strategies has been demonstrated in [2.1] and predicted that by reducing failure rates by 25-45% and increasing maintenance, onshore availabilities are achievable offshore. CONTOFAX is listed as an 'in house development tool' by Delft University and has been superseded by commercially available programs. A key output from the Opti-OWECS project was associated with standardisation of data collection. The project recommended the development of a wind industry equivalent to the oil and gas Offshore Reliability Data

(OREDA) project which brings together competing companies to create a central database to improve safety, reliability and maintenance standards [2.2].

The first certified O&M program was produced by ECN as part of the FP6 EU funded ‘Recommendations for Design of Offshore Wind Turbines' (RECOFF) project. The RECOFF project involved the production of a software tool (ECN O&M Tool) for predicting and optimising the costs of offshore wind farms [2.3], health and safety guidelines for all stages of the wind farm life cycle [2.4] and proposals for a standardised approach to collecting failures and maintenance data [2.5]. The offshore O&M tool has been certified and has been used at the planning stage by more than 20 wind farms. The tool is based on probabilistic simulation in Excel and requires user input of failure rates, access constrictions and site climate conditions. It focuses on corrective maintenance, simulated from the user input and compares this with a deterministic preventative maintenance model but does not account for more advanced condition based maintenance (CBM) strategies.

Subsequently, ECN developed an operation and maintenance tool designed to optimise management over the whole life cycle (Operation and Maintenance Cost Estimator) as part of the Dutch Offshore Wind Energy Services (DOWES) [2.6] and we@Sea projects 2.7, 2.8]. OCME is a software tool designed to predict future O&M costs but is used at the operational stage rather than the planning stage. In order to do this, the program takes in failure data and uses it to continually derive up to date failure rates as well as MTTR before determining an optimal strategy. The ability to incorporate data from the operational wind farm allows traditional maintenance strategies as well as CBM in order to determine the most effective approach and the corresponding annual costs of O&M. OCME has been developed in MATLAB and was released to market in 2011.

DOWES is a European funded project to develop an integrated IT system for offshore wind farm monitoring. The we@sea project is a Dutch consortium that aims to gather knowledge and reduce the risk involved with offshore wind; O&M falls within their research remit and as well as the general tool previously mentioned the production of a tool specific to DarWinD turbines has been developed. As well as assisting the development of OCME, the project has funded relevant research under 'PhD@Sea'; in particular the development of a new design and maintenance philosophy based on functional redundancies [2.7]. A related commercially available tool is BazeField Wind [2.9] which automatically gathers field data to support the O&M decisions support. It has been used on Statoil wind farms and was developed for Baze technology & Statoil under CPI consultancy with help from ECN and SINTEF research institutes. The description of the software; modular software that monitors, analyses and advises as well as outputting data to MATLAB, is very similar to that of OCME.

Various consultant companies have independent cost models that are offered for consultancy and are discussed in more detail in [2.10]. The highest profile of these is the GL-Garrad Hassan commercial offshore wind operations and maintenance simulation tool O2M Plus [2.11]. The tool uses a time domain simulation approach in order to simulate the wind turbine failure and repair process. Due to the commercial nature of the software there are limited technical details and information surrounding underlying assumptions are not published although the general simulation methodology has been described. The company has presented summaries of several case studies at conferences and seminars, for example [2.12], that provide useful results.

The OffshoreM&R project undertaken by the Fraunhofer Institute for Wind Energy and Energy System Technology (IWES) aimed to 'lay the foundations for condition depending maintenance and repair (M&R) strategies for wind turbines in offshore wind farms' [2.13]. This project resulted in a certification of various condition monitoring and data acquisition systems and identified that CBM strategies are most suitable for offshore wind turbines but specific development of an operating strategy was not carried out.

A recent development has been the production of a failure detection, prediction and maintenance scheduling tool, WindMT, which is the result of the Reliawind project. The mission statement of Reliawind is 'Reliability focused research on optimizing Wind Energy systems design, operation and maintenance: Tools, proof of concepts, guidelines & methodologies for a new generation.' This project has not specifically focussed on offshore wind turbines or O&M but it has explored several of the more advanced maintenance tools that are needed to develop CBM [2.14-2.16].

Finally, a number of independent academic projects have recently looked at this project and built in house models [2.17, 2.18]. There has been a collaboration between this project and these academic partners in order to verify models and gain a greater understanding of the impact of modelling assumptions [2.19].

2.2 Advanced maintenance strategies for offshore wind

The areas requiring development for the offshore wind industry in order to implement asset management practices has been the subject of two recent reviews [2.20, 2.21]. A ‘road map’ focussing on general gaps in the knowledge is offered in [2.20]. The paper focuses largely on design and climatic challenges although it also highlights the relative lack of research on logistical and operational challenges.

In [2.21] various aspects associated with offshore maintenance strategies are examined for the particular case of the Norwegian market. This market is considered unique in Europe as future turbines are likely to be floating structures in deep waters. The authors propose a simple formalised model to determine whether preventative (PM) or corrective maintenance (CM) is the most cost effective strategy by optimising a total cost equation as a function of set up cost, effective failure rate and maintenance interval. The article highlights the benefit of a life cycle analysis approach and concludes with four proposed research areas. The use of life cycle tools such as Reliability Centered Maintenance (RCM), optimization of these strategies and integration of CM and deterioration modelling accurately have been highlighted by other papers covered in this review. A final recommendation raised is the need to quantify sensitivity of maintenance strategies to location and turbine design. For example, to what extent do distance to shore, vessel availability and redundant systems in turbines affect costs of both traditional and condition based maintenance strategies.

2.3 Asset Management

The term asset management (AM) is used within the context of the wind power industry to represent management of physical assets. Essentially, any developer or operator in the industry has a physical asset in the wind farm and AM is a set of tools that allows the assets to be used to optimally achieve an objective be it financial, environmental or social. An excellent overview of the growth of AM from a financial tool to maximise returns on investments to a toolset used by non-financial industries can be found in [2.22]. Various industrial case studies, including utilities are presented as well as an examination of the relevant British Standards and trends that are occurring in industry are included. The book defines AM in the following terms:

"Asset management is a strategic discipline which gives rigour and accountability to the way organisations decide:

- *What assets are most critical?*
- *What risks need to be managed?*
- *What demands must be served?*
- *What needs to be known?*
- *How this knowledge should be captured and disseminated?*
- *How organisations should be structured and led?*
- *What types and teams of people they need?*
- *How activities should be carried out?*
- *How actual performance should be measured?*
- *What improvements are needed?"*

This thought process has been implemented in the offshore Oil & Gas industry, recognising that remote and hard to reach plant requires additional analysis in order to run optimally. The offshore wind industry has begun to examine these processes. This has been done initially by attempts to model the O&M requirements, understand how and why wind turbines are prone to failure and then exploring the complete life cycle operation of a wind farm.

2.3.1 Asset Management strategies and tools

To move towards Condition Based Maintenance (CBM) requires the use of AM tools in order to establish how and where it is best to apply CM. Techniques to achieve this are reliability centred maintenance, (RCM) [2.23] developed in the aircraft industry; total productive maintenance (TPM) [2.24] developed by Toyota in Japan; risk based inspection (RBI) [2.25] and hybrid approaches [2.26] all allow the development of CBM. In particular, RCM has been applied to repairable, deteriorating systems and is potentially applicable to the wind industry.

Various tools are used within the above techniques in order to establish key components and failure consequences in order to direct maintenance to have maximum impact. The most widely used of these tools are Failure mode, effects, and criticality analysis (FMECA); Fault tree analysis (FTA); Critical task analysis (CTA); Event tree analysis (ETA); Critical task analysis(CTA); Hazard and operability studies (HAZOP); Quantified risk analysis (QRA); Root cause analysis (RCA); Structured What-if technique (SWIFT). None of these tools are industry specific and may have been implemented for the wind industry previously on an ad hoc basis. However, despite specific standards existing for the implementation of these tools for other industries, there is currently no standards specifically relating to the wind industry. The most thorough examples of FMEA being applied and verified as a valid tool for a modern large wind turbine are [2.14] and [2.27], a more recent comparison of applicability in the offshore environment is given in [2.28]. This paper uses the FMEA analysis method to study a 2MW wind turbine. It is shown that the subjective FMEA analysis correlates well with operational data implying that FMEA can be used with engineering expertise to help structure a maintenance strategy for future designs of wind turbines or when little data is available. FMEA ranks the severity and occurrence (and detection ability in this study) of failure modes to assign quantitative values. The higher the value the more critical the element allowing designers and operators to target key failure modes to determine how they can be prevented. There are various standards covering FMEA but the most widely available is [2.29], various software packages exist to assist with the process.

These tools allow a decision on what (if any) action should be taken when a failure is detected or to prevent failures and allow optimisation of periodic maintenance intervals. One area that has not been explored is the use of CBM to effectively operate assets under fault conditions. For example, curtailing energy production when a generator is at risk of failing until a new one is obtained rather than simply shutting down the WT could be a strategy. However, the sophistication of CM that would be required for such action to be safely carried out has not been reached and there is not yet any evidence that this sort of action would even prolong the asset life or is safe to perform.

In order for the developed tool to deliver tangible benefits and enable the asset management techniques described, a suitable decision making framework was identified. A decision making process based on the use of decision trees [2.30] and Dynamic

Bayesian Belief Networks (DBBN) [2.31, 2.32] was selected to achieve this.

2.4 Existing implementation of advanced maintenance strategies

A methodology to aid the decision on what the most appropriate maintenance strategy at discrete points throughout a wind turbine lifecycle based on a Markov Decision Process is presented in [2.33]. The approach is to create a seasonally dependant state space and transition probability matrix representing the deterioration of critical components. This allows an optimal maintenance action to be chosen based on the simulated condition of the turbine as well as the time of year. A case study is presented comparing current industry practice, standard CBM and the presented variable CBM approach to demonstrate the reduction in failures and O&M costs. This approach has novel benefits of incorporating time-varying weather conditions as well as partial repairs however for practical implementation, this approach is heavily dependent on accurate sensor results to correctly estimate the system location in state-space and this data is not currently available to researchers. Another approach based on CBM is described by [2.34] suggests it would be possible to optimize a CBM strategy using an Artificial Neural Network (ANN) to build a predictive model of the condition of the wind turbine.

The use of risk based operation and maintenance using Bayesian decision theory adapted from the oil & gas industry to the wind turbine has been carried out in [2.35]. This approach associates an uncertainty with observed deterioration such as fatigue and corrosion which can be determined using either CM systems or inspection. The methodology in the paper covers the design stage as well as the operational lifetime of a wind farm with the whole life cycle represented by a decision tree. An equivalent mathematical representation is presented to allow optimisation and an example is performed. The benefit of this approach when compared to traditional methodologies is not quantified. An opportunistic maintenance strategy that schedules maintenance based on weather forecasts is suggested in [2.36]. It is demonstrated that by scheduling preventative maintenance on days when power production is expected to be low, or when corrective maintenance is required, overall maintenance costs can be reduced. The optimisation approach is adapted from an opportunistic maintenance model proposed for the aircraft industry. A case study is presented demonstrating a cost reduction of 43% compared to traditional maintenance approaches. This approach requires accurate wind forecasting abilities. Wind forecasting is itself an extremely complicated subject, therefore a comprehensive introduction and review is included in [2.37].

The final approach considered to mitigate the huge costs of offshore maintenance is to significantly reduce the need for maintenance by improving reliability of critical components that cannot be remotely reset. Some initial work on the feasibility of such redesign has been looked at [2.38]. This study performed a FMEA analysis with a particular view to the development of an offshore turbine. Similarly, [2.39] develops a methodology that includes an FMEA stage to improve design and reduce failures and the need for maintenance visits.

2.5 Failure modelling and data sets

The modelling of engineering failures as a random occurrence following a known probability distribution was first developed for power system analysis in [2.40] and extended to the more general case of engineering systems in [2.41]. This approach has been widely used since and forms the basis for the model adopted in this thesis, a full description of which is included in the Methodology section. While this approach has been adopted, it requires simulation to converge to an answer which can be computationally intense. The alternative approach is to model failures using analytical expressions. This is an active area of ongoing research, for example [2.42]. This paper uses an on-line calculation of damage accumulation based on condition monitoring data in order to predict the likelihood of a failure at a given time as well as allowing identification of root cause of failure. Simpler analytical expressions and multi body models based on classic fatigue failure behaviour have been investigated for individual components such as the drive train [2.43]. However, such modelling approaches are not yet mature enough to capture an entire wind turbine system. Therefore, while they potentially offer a closed form solution that would significantly reduce computation time for sensitivity analyses, the physics of failure approach has not been considered in this work. The final approach to failure modelling is through the full finite element analysis of a system but this is currently unfeasible for life time operations simulations due to the high associated computational costs and knowledge requirements.

2.6 Reliability data and analysis

Any attempt to implement improved O&M techniques requires the ability to accurately assess the condition of components. In real turbines it is hoped that advanced condition monitoring (CM) systems can deliver this information. The current state of CM systems and the degree to which they need to be improved is considered later. When attempting to simulate operational strategies where failure behaviour is dynamic, the ability to correctly represent the condition of components is dependent on accurate reliability data. For reliability data to be of use it is not merely a large volume that is required, the data must be relevant to the turbines being modelled and consistent across the sample.

Onshore, it has taken a significant amount of time to produce enough data to accurately analyse the reliability of wind turbine subsystems [2.44]. There are various databases that exist containing reliability figures such as WMEP and LWK in Germany, the Windstats database reports Danish statistics [2.45], a Finnish database VTT and finally the Swedish data analysed in [2.46]. There is a lack of coherence between these databases but as previously discussed this is to be expected as there are a vast number of operators and turbine types. The objective of the databases has not been to develop maintenance strategies but rather to identify key component reliability and associated down time, for example [2.47]. Offshore, 2 manufacturers represent 89% of total installed turbines in Europe [2.48]. This is unlikely to change in the short term due to the perceived risk in installing turbines that haven't been proven over several years' operation; highlighting how different the market is.

The need to develop a central data source of failure and maintenance data in order to improve offshore operation and maintenance has also been established by the Offshore WMEP project (OWWMEP) [2.49]. OWMEP is part of the larger Research at Alpha Ventus (RAVE) project and is led by IWES [2.50]. The OWMEP project aims to develop a large statistical database by encouraging collaboration between operators, manufacturers and research institutes. This will allow statistically dependable predictions of reliability and maintainability of offshore wind farms although the database is not yet publishing results. The small number of manufacturers and operators is an advantage as a database requires cooperation amongst a relatively smaller number of partners than onshore. There is increased risk however as a single major manufacturer or developer refusing to participate could significantly impact the effectiveness of the database. The relative homogeneity of turbines means that a smaller sample size than the onshore case is required to build a reflective database. Caution must also be observed in the analysis of machines with a serial fault in early operational life such as that observed in Vestas V90 turbines [2.51]. Failure to do so could easily lead to maintenance intervals that are too regular, ultimately costing operators more than the traditional maintenance approaches. A final aspect that needs to be considered when examining reliability data is the influence of weather parameters on failures. Some work examining how wind speed effects onshore reliability exists [2.52] and an attempt has been made to link it to O&M costs [2.53] but there is a need to understand the effects of both wind speed and wave height in the offshore environment as it is the latter that determines access constraints.

Given the lack of an organised database at this time, various alternative approaches have been explored. The first is to use Supervisory Control and Data Acquisition (SCADA) data to estimate the state of the system. This approach has been explored in using various methodologies such as [2.54, 2.55]. SCADA provides a large amount of data but due to the random nature of the wind and inherent variation between every cycle of a turbine it has proven difficult to confidently predict faults without false positives which operators are unwilling to tolerate. A review of the different approaches taken is presented in [2.56].

Another approach is to apply more complex mathematical analysis to the available data so that it better represents the true behaviour of systems. For example, it has been suggested in [2.57] that by using a 3-paramater Weibull failure distribution as opposed to the traditional 2-parameter Weibull model, it is possible to more accurately represent the reliability growth of wind turbines where data is incomplete. This is demonstrated by considering the previously mentioned Windstats population where data has not been uniformly collected from the installation of the turbines. By using a time parameter the authors suggest they are able to account for past running time with little or no data points and reduced the error between the fitted models and observed data. A modification to the lifetime failure distribution model to incorporate serial defects in the early life of a wind farm or wind turbine population has been developed in [2.58]. These approaches also enable the analysis of changing populations where upgrades and new technologies are introduced and of data sets that begin measurement after the population has been introduced.

Physical modelling of the degradation of individual components can also be incorporated into failure modelling however; the failure physics of wind turbine subsystems are complex and not fully understood. Accurately modelling key subsystems along with probabilistic representation of less critical failures may become feasible in the future but has not been implemented to date. Finally, when matching data simply does not exist, authors have inferred from alternative populations or relied on expert judgement. The issues concerning lack of data can be overcome by industrial collaboration in projects such as Offshore-WMEP but as the need for more accurate reliability data increases, further intelligent analysis of available data will also have a role to play.

2.6.1 Wind turbine failure datasets

Limited sources of data have become publically available for analysis. Four of the first commercial wind farms in the UK, North Hoyle, Scroby Sands, Kentish Flats and Barrow received government funding under the UK governments 'Offshore Wind Capital Grants Scheme'. As a result, these wind farms were required to produce annual reports covering the first three years of operation [2.51]. Although these reports do not contain subsystem reliability data, they contain overall availability and various other data sets that has been thoroughly analysed in [2.59]. The Offshore Windpark Egmond aan Zee (OWEZ) development by Nuon and Shell off the coast of the Netherlands is committed to a six year research programme which has produced annual reports for the first three years of operation [2.60]. These reports include the number of annual 'failures' by subsystem. The subsystem and classification of a failure used by these reports is specified in Table 2.1.

Table 2.1: Classification of failures

Subsystem	'Failure' Description
Ambient	Ambient conditions (e.g. wind speed, temperature, lightning) outside design limits.
Blade system	Failures in the blades and blade bearings.
Brake system	Failures in the main brake and auxiliaries.
Control System	Failures in the main controller and associated equipment (like sensors etc.), including remote communication system.
Converter	Failures in the generator power converter.
Electrical	Failures in the wind farm cabling, turbine transformers, substation etc.
Gearbox	Failures in the gearbox including its lubrication systems.
Generator	Failures in the generator including its cooling systems.
Pitch system	Failures in the blade pitch system including hydraulic controls.
Scheduled	Stops as a result planned\scheduled service.
Yaw system	Failures in the yaw system (including yaw motors, yaw brakes and controls).
Structure	Failures in the support structure (foundations, transition pieces and towers).
Grid	Failures in the public grid.

The above subsystems have been used for the initial model presented later in this thesis as they represent the highest quality failure data available for an operational offshore wind farm.

Unfortunately, the reports do not specify their classification of a 'fault' state when an alarm is raised and 'failure' state when an action is required to be carried out. All incidents are simply referred to as failures with the 'majority' being fixed by remote reset. The number of visits to turbines is given however and this allows a scaling of the overall failure report to be performed so that a failure is classified as an incident requiring a visit to the turbine. The issue of classification of faults and failures in wind turbines has been explored in [2.54] and [2.61] and used in this work to determine failure rates that represent maintenance actions. .

Table 2.2 shows sources of data that exist in the public domain containing the required subsystem knowledge, developed from [2.16], [2.59] and [2.61].

Table 2.2: Empirical WT failure data sources

Source	Onshore/ Offshore	Subsystems	Failure Categories	WT Years	Relevant WT
Windstats – WSD & WSDK	Onshore	1	1	N/A	Limited
LWK	Onshore	14	1	5800	Limited
WMEP	Onshore	13	1	15400	Some
Reliawind Offshore Case Study	Offshore, *inferred from onshore	14	4	1400*	Yes
OWEZ Operational Reports	Offshore	13	1	102	Yes

From Table 2.2 it is identified that for the offshore case, sufficient knowledge to accurately model subsystem level failures does not currently exist. Where sufficiently large databases exist to provide confidence in failure rates at the subsystem level, the location, size and configuration of the wind turbine is inadequate. Conversely, the only source of detailed offshore WT subsystem failure rates is from a statistically unreliable sample size and subject to biasing from serial defects present in the early model of WT used at the site (OWEZ). An additional issue arises due to the different failure reporting mechanisms and subsystem classification between and sometimes within studies. This makes translating from one database to another difficult and unreliable. An alternative approach is to adapt the observed failure rates by eliciting expert knowledge of current offshore WT operators which has been performed for the Reliawind study [2.16]. Discussion with operators has identified that the observed failure rates from this study are in line with those experienced at early offshore wind farms in European waters.

It has been identified in Table 2.2 that there is a lack of a substantial offshore failure database but that there are several data sources available that can be used along with expert judgement in order to establish a baseline scenario for offshore wind. For classic reliability analysis, the other contribution to availability is Mean Time to Repair (MTTR). Despite the wide range of machine sizes and configurations onshore, there is a sufficiently large turbine population and uniformity of maintenance technique has allowed for MTTR values to be established. An analysis of the historical onshore failure rate and MTTR with a view to application of the offshore market has been performed in [2.61]. The paper identifies that more common, lower impact failures are required to be classified separately from less frequent, higher impact failures when considering the offshore environment. The original failure rates and MTTR identified in the paper are shown in Figure 2.2.

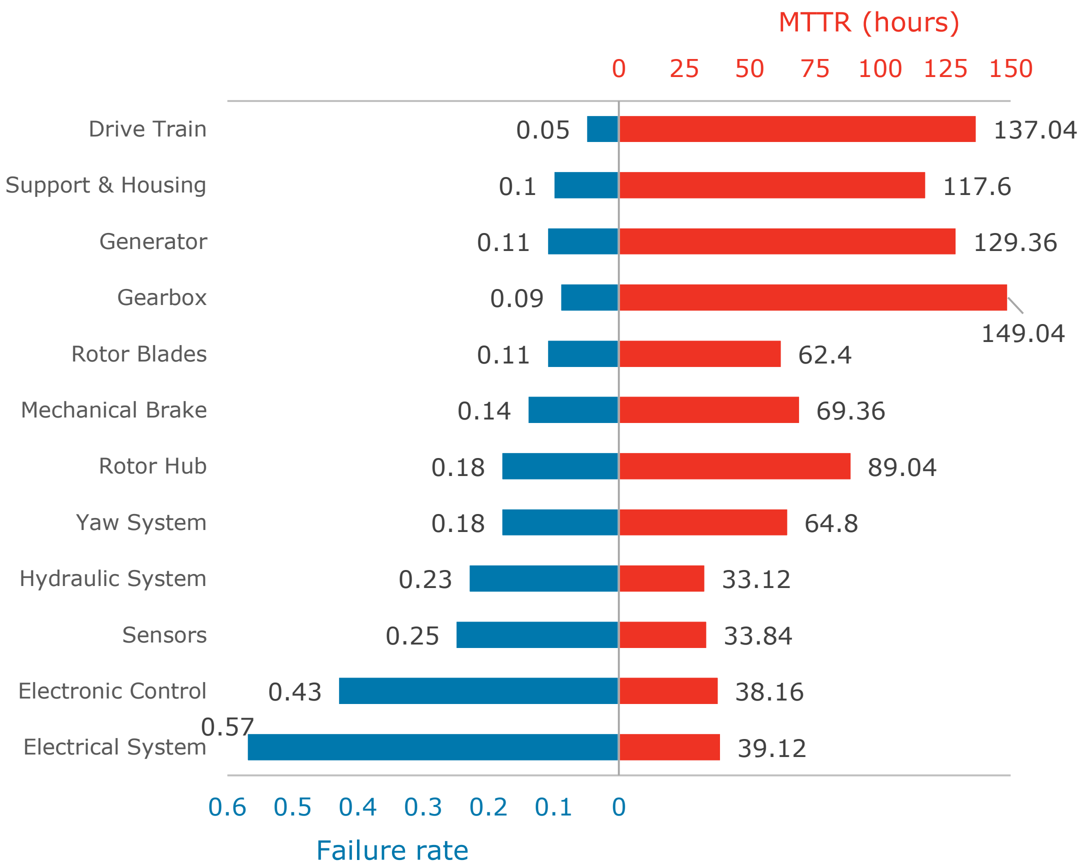

Figure 2.2: Onshore failure rates and MTTR [2.61]

The equivalent plot of failure rate and MTTR for OWEZ is shown in Figure 2.3. It should be noted that the relatively high failure rates of the generator and gearbox were attributed to a serial defect and replacement programme during the first three years of operation. The overall failure rate of 7.5 is based on reported visits to turbines.

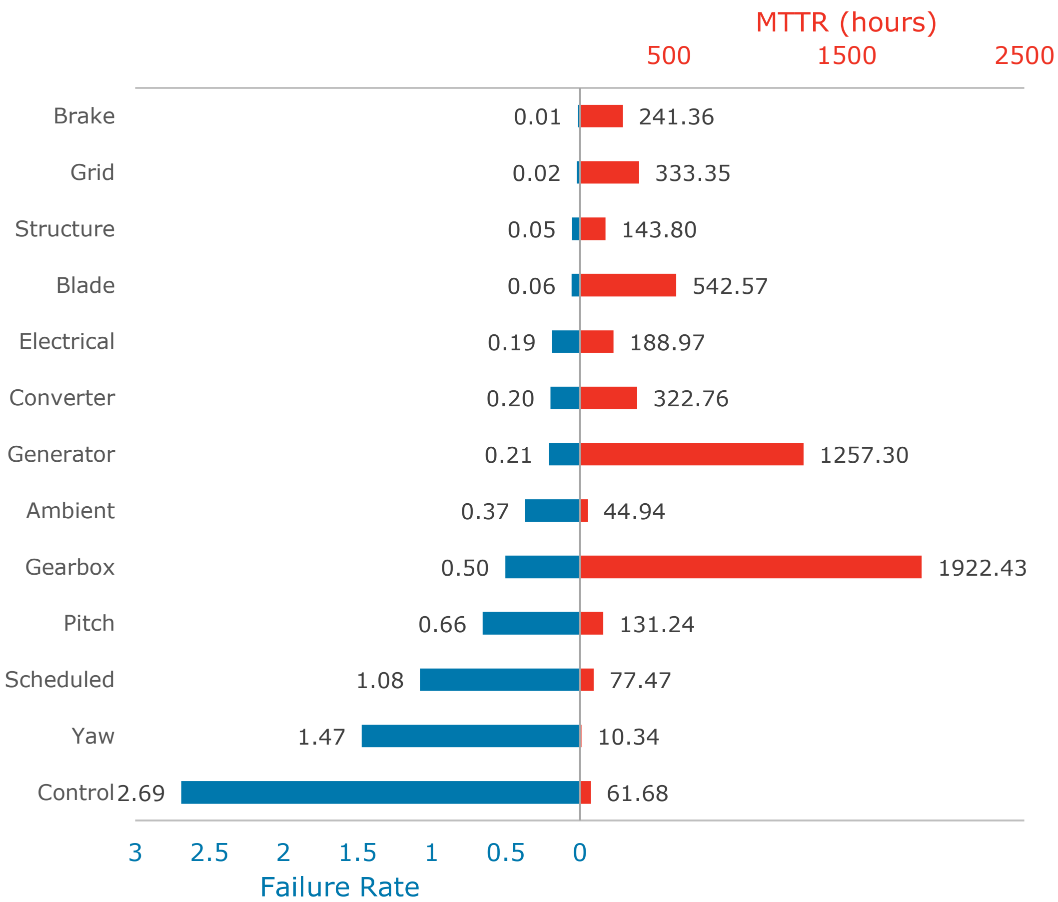

Figure 2.3: Offshore failure rates and MTTR at OWEZ

Comparing figures Figure 2.4 and Figure 2.3, it is immediately apparent that both failure rates and MTTR are significantly higher than onshore. Caution should be applied when attempting to draw definitive conclusions from this data set or extrapolating these failure rates to the future offshore turbine population. The uniform nature and relatively small sample size of the offshore data set shows clear evidence of biasing due to the serial failure rate of both the gearbox and generator. Additionally, the onshore failure data is based on a variety of machine sizes and configurations whereas a single large turbine type is present in the offshore data set. These factors may also contribute to the differences between the failure and MTTRs onshore and offshore. Taking account of the serial failures, the failure rate of both the generator and gearbox are of similar proportion to those observed onshore. Despite this there is a greatly increased proportional downtime; this observation is also true of the blade subsystem. Major replacement of drive train components and blades are the operations that will require jack-up vessels for their repair. This suggests that the need for specialised vessels significantly adds to the downtime and complexity of repair operations and must be considered in any thorough analysis.

Unfortunately, MTTR is also highly dependent on wind farm configuration and maintenance resources. Therefore MTTR for other wind farms may deviate significantly and simulation is required to estimate MTTR for future wind farms. However, the data provides an important benchmark for models. The relationship between failure rate and MTTR where subsystems with low failure rates have correspondingly high MTTR is consequence of design choices. Components that are complex and difficult to repair are typically designed to have greater life expectancy at a manufacturing premium. They therefore fail less often but still contribute significantly to overall downtime.

Table 2.3 identifies the predicted breakdown of failures by subsystem and severity based on the historical MW scale onshore wind turbine performance and detailed discussions with manufacturers and operators. The breakdown of this analysis into failure categories has significance for simulation modelling choices which are discussed in more detail in Chapter 3 when discussing the developed model structure.

Table 2.3: Reliawind offshore failure breakdown

Component Failures	Manual Restart	Minor Repair	Major Repair	Major Replacement	Overall Failure rate
Blade	0.00	1.48	0.08	0.04	**1.6**
Pitch System	0.68	0.08	0.032	0.008	**0.8**
Hub	0.00	0.185	0.01	0.005	**0.2**
Main Shaft and Bearing	0.00	0.185	0.01	0.005	**0.2**
Gearbox	0.68	0.08	0.02	0.02	**0.8**
High-Speed Shaft	0.0	0.19	0.01	0.00	**0.2**
Mechanical Brake	0.34	0.04	0.02	0.00	**0.4**
Generator	0.68	0.08	0.02	0.02	**0.8**
Control System	2.16	0.24	0.00	0.00	**2.4**
Yaw System	1.02	0.12	0.048	0.012	**1.2**
Hydraulic Services	1.02	0.12	0.06	0.00	**1.2**
Power Electronics	2.014	0.24	0.12	0.00	**2.4**
Transformer	0.17	0.02	0.008	0.002	**0.2**
Tower	0.00	0.19	0.01	0.00	**0.2**
Total	**8.79**	**3.25**	**0.448**	**0.112**	**12.6**

Failure Rates Per Year

A final piece of failure rate analysis on existing data is presented in [2.61]. This paper has analysed the onshore failure data displayed in Figure 2.4 to classify minor and major failures and the potential consequences this has for offshore wind operation.

A summary of the key output results from this analysis, the major to minor ratio reflected onto the available offshore data and a comparison with the totals from Table 2.3 is shown in Table 2.4

Table 2.4: Simplified failure matrix

Source	Minor Failures	Major Failures	Total
Onshore data	1.8	0.6	2.4
Offshore based on EaZ vessel operations and onshore major : minor ratio for failures requiring jack-up repairs	6.73	0.77	7.5
Offshore based on Reliawind data	12.04	0.56	12.6

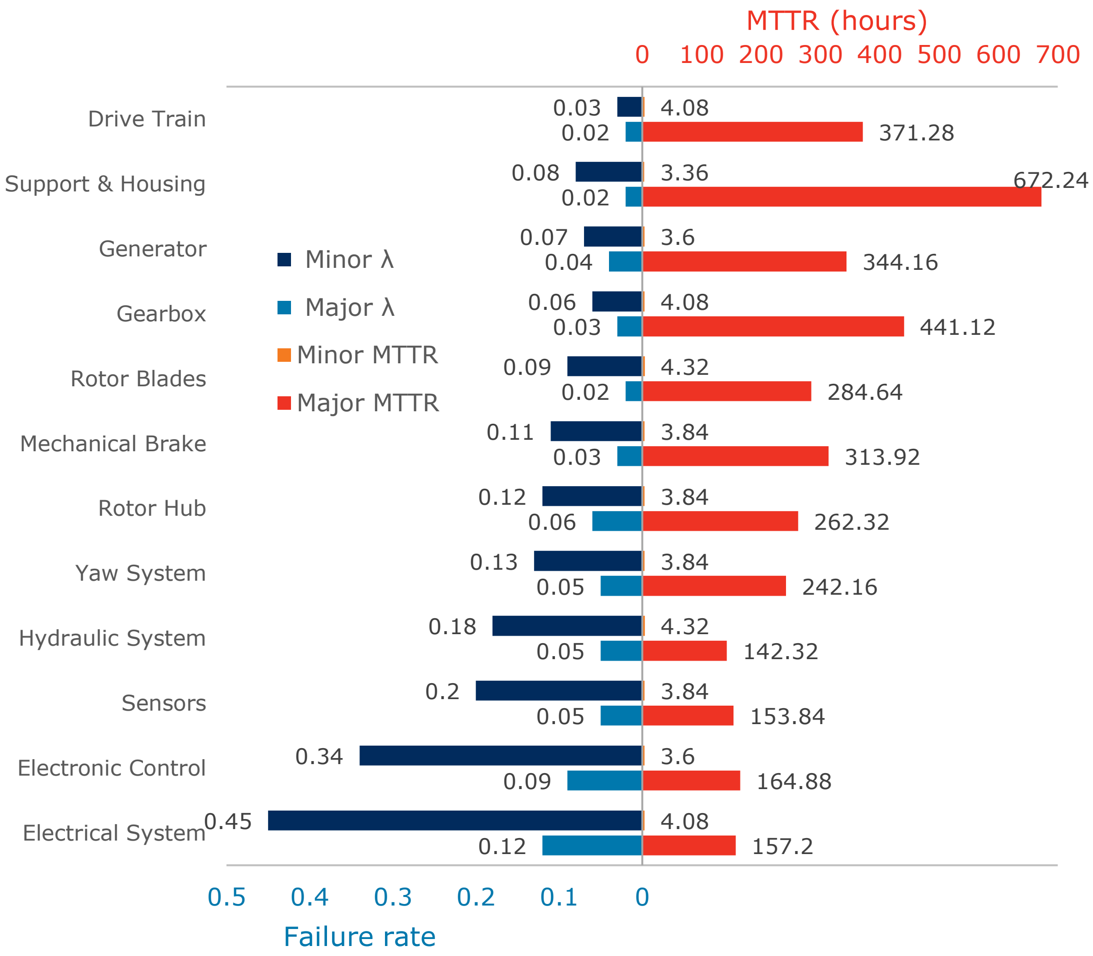

Figure 2.4: Onshore failure rates and MTTR based on [2.61]

From Table 2.4 it is evident that the reported data at Egmond aan Zee wind farm is subject to a significantly larger number of minor failures than observed onshore but significantly less than predicted from the detailed Reliawind analysis. This can be explained by the fact that as sites move further offshore, the challenges of operating in the marine environment with more complex turbines failures will be expected to increase. Although major failures are also higher than those observed onshore and predicted they are of a similar magnitude and considering the serial overhaul would be considered to be in line with those onshore and predicted for offshore.

The predicted offshore data set should therefore be considered the worst case scenario, while the long term objective of the industry should be to obtain onshore failure rates and ultimately surpass them by putting minimal maintenance at the forefront of design philosophy. From the operators viewpoint however, there is limited impact that maintenance can have on turbines that are already manufactured and operating. Therefore the driver for identifying a realistic and adequate range of failure rates is to allow an understanding of how different lifetime failure behaviours impact on operating strategies and associated exposure to risk that are within their control.

Due to the lack of data sets and inability to fully model the full physics of failure associated with subsystems, an alternative approach to modelling sub-assembly availabilities has been presented in [2.62, 2.63]. This approach, known as an availability growth model, is particularly suited to modelling the early operational life where there is lack of data and provides insight into the state-of-knowledge uncertainty associated with the system. The underlying failure mechanisms are considered and the impact of external actions such as innovations, operational learning and maintenance actions are used to inform the current state of the hazard function. This framework is highly flexible and provides useful insight into what is driving failure behaviour and the associated uncertainty. However, it introduces a significant subjective element into the modelling problem which requires significant expert judgement to successfully implement. Therefore, this approach has not been adopted but there is scope to combine the developed OPEX model with the availability growth model in future analysis.

2.7 Climate and operational modelling

2.7.1 Sources of data

This thesis has made use of weather data that is publically available or freely available for research purposes. Unlike wind turbine failure statistics, weather data in the North Sea area is readily available although not always at the required locations or with adequate quality of data. Satisfactory time series wave data in particular is difficult to obtain due to the harsh operating environment resulting in gaps in data and short measurement campaigns. The longest available simultaneous wind speed and significant wave height time series data was obtained from the FINO research platform database [2.64] located off the coast of Germany close to the location of the Alpha Ventus research wind farm. Several years of high quality time series data is available for academic purposes through this resource and was primarily used for wave modelling verification. Currently, no availability data is publically available for Alpha Ventus wind farm although it is due to be presented under the RAVE project. Therefore, it was necessary to source alternative wind and wave data that were located close to the wind farms with published availability for the analysis in Chapter 4. As well as operation reports, there is a large amount of climate data available at OWEZ [2.60] which has been extensively used in this work. For the UK Round 1 sites, wave data for access modelling was obtained from two separate databases; CEFAS Wavenet and BODC online data [2.65, 2.66]. It should be noted that the data extracted from these databases was not necessarily the data set located closest to the wind farms but rather the nearest with a sufficient duration and data quality.

The problem of collecting meteo-ocean conditions in the North Sea is one that has previously been encountered by the oil & gas industry. Due to the difficult and expensive nature of constructing a large offshore measurement network, the industry took a numerical modelling approach that was funded and shared by several partners in the form of The North European Storm Study (NESS) [2.67]. This database has been maintained and refined over time and contains 25 years of data covering the North Sea (1964 - 1989). The database is not publically available and therefore it has not been used in this work. However, a dissemination of the data in UK waters can be found in [2.68] that identifies the extent to which the sea climate varies around the UK.

2.7.2 Climatology modelling

The science of wind and wave modelling is in itself a large and complex field that is an active area of research. Wind speed forecasting in particular is subject to active research with different methodologies for different time horizons being investigated. An accessible review outlining the current development of different forecasting approaches, with an emphasis on the prediction of wind power is [2.69].The paper classifies forecasting methods into three essential classes, Persistence Method, Physical Approach and Statistical Approach. The Persistence Method is only accurate on the very small scale but is used as the benchmark for other approaches. Physical approaches are the most accurate methods but require vast amounts of data and are computationally demanding and therefore not suitable for the objectives of this study. Statistical approaches can be considered as either Time-series Models or Artificial Neural Networks. The relative merits and drawbacks associated with each are discussed in [2.69] with the emphasis on accurately predicting the weather at a given time horizon. An additional review, focussing on longer term forecasting with implications for wind power is [2.70].

However, for this work the requirement is not to produce a model that forecasts the upcoming wind but one that is representative of the resource at a given site. In this respect, the model must capture the short term correlation between simulated time steps, the medium term duration intervals observed and the longer term annual distribution. Therefore, the least computationally demanding modelling approach that captured these behaviours was identified as an auto-regressive modelling approach and this methodology was adopted. The alternative methods considered, including strengths and weaknesses of different approaches are outlined in Table 2.5.

Table 2.5: Modelling Choice Analysis

Model Type	Strengths	Weaknesses
Persistence Model	Extremely simple, requires little data	Poor accuracy except in extreme short term. No physical basis
Physical Simulations	Highest Accuracy	Computationally demanding, huge amounts of data required
Auto-Regressive (AR)	Based on physical process, widely used for similar applications	Requires stationary data for accuracy
AR Moving Average (ARMA)	Builds on AR to improve accuracy and applicability	Additional complexity that may not be required.
Artificial Neural Network (ANN)	Possibly improved accuracy over AR approaches	Lack of clarity in relationship to real data. Huge data set needed.

Sea state modelling is also an active area of research and an accurate representation of the surface profile of the sea requires a complex wave propagation model. Various approaches to modelling a stochastic time series of significant wave height exist and are assessed along with wind time series models in [2.71]. From this it was identified that with a suitable transformation applied to the time series values, an auto-regressive modelling approach can also be applied to sea state modelling, allowing consistency with the wind series model. The final methodology adopted for this investigation is described in the Methodology section of this thesis. The wind model is based on that presented in [2.72] and [2.73]. The wave modelling approach is based on the technique described in [2.74].

2.7.3 Wind farm access

The first major work on understanding the consequences of vessels and access constraints on O&M was undertaken as part of the DOWECS project [2.75]. This work recognised that simply increasing offshore wind farm availability to onshore levels by constructing access vehicles capable of operating in more severe conditions was not a cost optimal solution. The current access limitation at offshore wind farms in the North Sea is a significant wave height of 1.5m [2.51]. Various organisations and companies, for example [2.76-2.79] have suggested increasing this to above 3m would significantly improve availability by increasing access availability. No literature exists to determine if this is the most cost effective approach or to have established a direct relationship between access ability and wind farm availability in an actual operating context.

Logistical effects are considered in [2.80, 2.81] and [2.82]. In [2.80], the analysis is based on a theoretical 500 MW offshore wind farm to determine the intersection between increase in revenue and distance from shore against increase in O&M and connection costs with distance from shore. As this study is based on the US market with hypothetical floating turbines that don't exist, large numbers of assumptions are made that do not reflect the Northern European market. [2.81] and [2.82] represent more generic analysis of logistic delays identifying the potential for losses associated with the resourcing of large failure components with relatively low failure rates.

Where access constraints have been incorporated in previous studies, the methodology has been to simulate wave height rather than examine it analytically. This makes sensitivity studies to external factors like vessel availability time consuming and with an inherent uncertainty. One approach to overcome this is that of [2.83, 2.84] which has been to model access constraints as analytical expressions dependent on the wave distribution, storm duration and the time required for the maintenance operation. This allows for direct sensitivity analysis. The methodology has not been verified with operational data due to the lack of operational data in the public domain but could be. This would allow more efficient sensitivity analyses. An alternative analysis of the impact of climate access windows on operations and maintenance is presented in [2.85] and which draw similar conclusions.

Some attention has been given to the access problem in the context of construction and installation phase of the wind farms, for example [2.86] and [2.87]. One additional insight from considering installation is that there is the potential for additional seas state parameters to contribute to delays when using larger installation vessels, in particular currents and tides.

2.8 Establishment of business case

As the size of onshore wind turbines has increased to the multi MW scale, it has become apparent that the associated cost of failures and downtime has also increased. This has led to investigations into applying alternative maintenance strategies. The first step has been to determine that there is an economic case for using alternative maintenance strategies. A methodology for establishing the failure consequences of key subsystems in financial terms is presented in [2.88] and it is demonstrated that for a sample 17.6MW wind farm there was a life cycle cost saving by using CBM versus TBM. Two case studies are investigated in [2.89], a single onshore turbine as well as an offshore wind farm in order to establish the degree to which condition monitoring systems would need to improve preventative maintenance in order to be economically viable. Both of these papers used a specific case study to demonstrate the benefit of condition based asset management. A set of models to quantify the benefit of condition monitoring are given in [2.90] and it is identified that in the majority of cases CM provides an economic benefit. Offshore wind has also been quantified in this manner and a required success rate for CBM to provide an annual benefit established [2.91].

2.9 Gaps in the existing literature

While various proposed condition based asset management techniques have been identified, a back to back comparison on several sites would be valuable to determine if there is a single optimum approach or under what conditions different approaches would become optimum. Certain key practical constraints to operation and maintenance strategies have also not been adequately explored. In particular, there are limitations on the availability and usability of vessels and staff along with the constraints from existing infrastructure and chartering procedures. Simply modelling accessibility and costs as a distance from shore is inadequate. A rigorous analysis quantifying these decision choices has not previously been carried out. There is a need to fully quantify the impact of the high uncertainty associated with variability of climate and the poorly defined failure performance of offshore turbines.

There is no literature pertaining to supply chain, spare parts holdings and decision making with regards to management of a fleet of offshore turbines; these areas can be considered under total life cycle analysis. Drawing conclusions from other industries that share some similarities, for example the oil and gas or aviation industries has some synergy but the degree to which conclusions can be drawn directly is limited. A literature review of spare parts inventories management, in particular age-based replacement, multi-echelon problems, problems involving obsolescence and repairable spare parts is provided in [2.92] but does not have a wind industry focus. They identified the development of automatic ordering and replacement systems and feedback from expired parts as critical developments for the field. The costs of holding spares compared to the cost of downtime out with the OEMs warranty period have not been sufficiently explored for example.

Having reviewed the literature, it was identified that there remains a fundamental need to understand the key cost drivers for offshore wind before more advanced asset management techniques can deliver tangible benefits to the industry. In particular, issues surrounding climate and failure data were recognised. Taking this into account, it was then possible to specify a modelling methodology that can operate with the constraints from poor quality data and still provide new insights. This methodology is described in detail in Chapter 3.

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Chapter 3

Methodology

After completing the review of existing literature and previously developed models, it was possible to define the most suitable modelling approach to achieve the objectives of this thesis. The model could then be constructed. This process was carried out by identifying the individual model components and the functional requirements that they have. A detailed specification of the underlying theory was performed and is presented in this chapter. The model was then built in the MATLAB environment. A secondary objective of this thesis is to provide a tool that can be readily used for future research without the requirement of detailed understanding of the underlying methodology. The input-output mechanism is through an intuitive excel spreadsheet to enable this. The developed model structure and key inputs are described in this chapter, in addition to the underlying theory.

3.1 Modelling overview

Having specified the research objectives and identified the need for a flexible model to enable relevant analysis, the requirements associated with different components of the model were analysed. The required structure and fidelity of the model were then specified and outlined in Table 3.1.

Table 3.1: Model overview and requirements

Model Component	Sub-Component	Description and Requirements
Climate Model	Wind Speed, wave height and wave period model	• Robust and quick • Reproduces key climate characteristics • Correlation between individual parameters
Failure Model	Subsystem failure model	• Allows identification of key subsystems • Clear to define • Adaptable to different turbine configurations
	Failure rates	• Failure categories by repair consequence • Adaptable to different failure distributions through time
	Failure costs	• Cost of component repair and replacement • Capable of predicting scaling cost
Operational Model	Access restrictions	• Access windows driven by climate model and vessel capabilities • Various categories of vessels including helicopters with unique properties.
	Access strategies	• Allow for assessment of different operational strategies for minor and scheduled maintenance • Allow for examination of strategies for specialist maintenance
	Operational costs	• Direct costs that are paid out • Lost revenue due to downtime

The most fundamental modelling choice for a complex system is whether to use an analytical or simulation based approach. Analytical solutions provide closed form solutions that can give definitive answers and allow quick sensitivity analyses. An analytical approach is therefore generally preferential. However, in order to use an analytical model, it must be able to accurately describe the system it represents. This can often be achieved by making simplifying assumptions that reduce the complexity of the equations describing the system which allows them to be solved. For example, assuming that weather delays are a fixed value would greatly simplify the modelling of the offshore repair process. The failure behaviour of individual components may be described using analytical expressions. However, an expression that represents the failure and repair behaviour of several subsystems in a modern wind turbine is not yet possible as the underlying physics of failure remains a research topic. Therefore, it is necessary to use a simulation approach in order to describe a wind turbine for O&M analysis.

When performing a simulation, it is necessary to appreciate that an exact answer with 100% confidence will never be reached but rather the simulation will converge to an approximation of the true answer. Methods for determining when a simulation has reached an acceptable level of accuracy varies depending on the simulation type, it is always a modelling consideration as to where the optimum trade-off between accuracy and simulation time is found.

3.2 Reliability modelling

The reliability modelling approach developed in [3.1] and [3.2] has been adopted in this thesis. It is necessary to understand and represent the failure behaviour of real world components and in particular those found in a modern WT system. Additionally, it is important to differentiate between the observed failure rate in a system population in the continuous time space and it's representation in a discrete simulation model.

Each subsystem within the turbine can be considered as a repairable system as when a failure occurs a maintenance action can return it to an operating state. Failure rate is defined as the number of failures observed in the population F_t, per turbine, in an observed time period Δt as shown in Eq. (3.1). For wind turbine systems it is normal for λ(t) to be failure rates per year and this convention has been adopted. Where failure rate is referred to in this thesis, it is therefore the annual number of per turbines failures at the population level.

$$\lambda(t) = \frac{F_t}{N \cdot \Delta t} \tag{3.1}$$

The true values of failure rate is not known but can be estimated by observing operational data. In order to simulate failure behaviour using the methodology in [3.1] and [3.2], it is necessary to analyse and represent observed data using probability density functions and cumulative probability distribution functions. The probability distribution describes the probability that a given component will fail within a certain specified time or survives beyond a specified time.

The reliability function, R, is the probability of a component surviving to time t and is defined in terms of Q(t),the cumulative failure distribution as:

$$R(t) = 1 - Q(t) \tag{3.2}$$

Q(t) can be described in terms of the number of turbines failed at time *t*, N_f and *N:*

$$Q(t) = \frac{N_t(t)}{N} \tag{3.3}$$

In the discrete simulation time it is necessary to consider the likelihood of a failure over a simulated time step, given that the system has not failed prior to this time interval. This value is the hazard function defined in Eq. (3.4) where *f(t)* is the failure probability density function. This distribution has to be fitted to the empirical failure data of the system being simulated, a detailed example of this process is presented in [3.2].

$$h(t) = \frac{f(t)}{R(t)} \tag{3.4}$$

The failure behaviour of mechanical components is commonly described using the 'bath tub' curve shown in Figure 3.1 [3.1]. The limitations of this approach are discussed in [3.3] and the consequences for this work are examined later in this thesis. The three phases in the curve represent the high initial failures resulting from manufacturing failures, design faults or transportation damage before operation; the working life of the component and then increasing hazard function as the component begins to approach the end of its design life and suffers from wear.

This observed failure behaviour through the design lifetime of many physical components follows the bath-tub curve shown in Figure 3.1. It can be represented by the hazard function of the

Weibull distribution defined in Eq. (3.6) with scale parameter ρ and shape parameter β.

$$h(t) = \frac{\beta t^{\beta-1}}{\alpha^{\beta}} \tag{3.5}$$

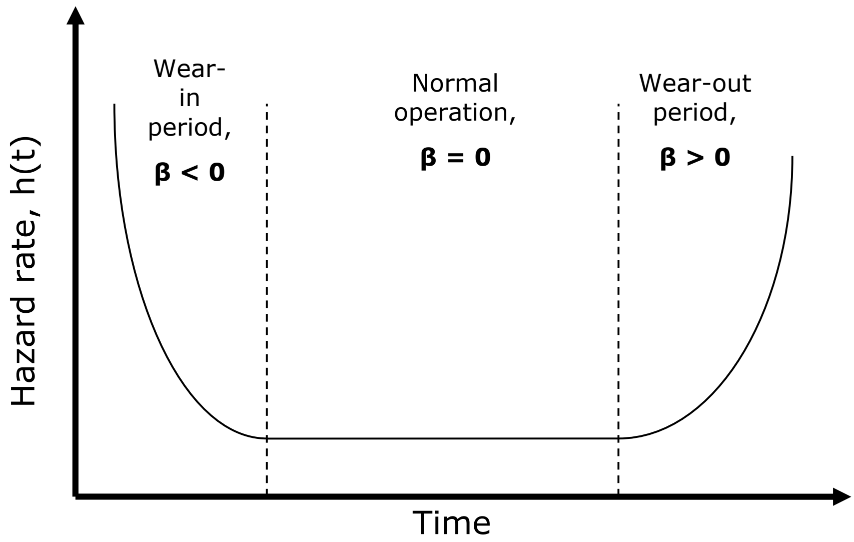

Figure 3.1: Electrical component failure behaviour [3.1]

The Weibull is a lifetime distribution and is only valid for the time to first failure or where the system undergoes a renewal process after failure and returns the system to 'as new condition'.

Wind turbines comprise of several subsystems and observations of failures are observed and reported at the population level. From this viewpoint, when a repair is carried out the wind turbine system returns to 'as good as old' condition within the population and the sequence of failures at the system level is a Non-Homogeneous Poisson Process (NHPP). The Power Law Process (PLP) is a particular case of a NHPP with the failure intensity described in Eq. (3.6). The PLP is proposed for reliability analysis of wind turbine subsystems in [3.4] as it can represent each stage of a bathtub failure curve when the intensity, rather than the hazard, function, is considered through time. The conditional reliability, R_c, that is the probability that a system will survive to a specified duration, *d*, from the current time *t*, is described in Eq. (3.33). A more rigorous mathematical exploration of representing wind turbine failure behaviour with this methodology, including fitting parameters to observed data can be found in [3.4].

$$u(t) = \rho\beta t^{\beta-1} \tag{3.6}$$

$$R_c(t) = e^{-[\rho(t+d)^{\beta} - \rho t^{\beta}]} \tag{3.7}$$

One alternative model for the failure behaviour applicable to offshore wind turbines has been proposed in [3.5]. Where a serial defect is present across the wind turbine population before normal life operation is achieved, the corresponding hazard function through the lifetime of the wind farm is shown in Figure 3.2.

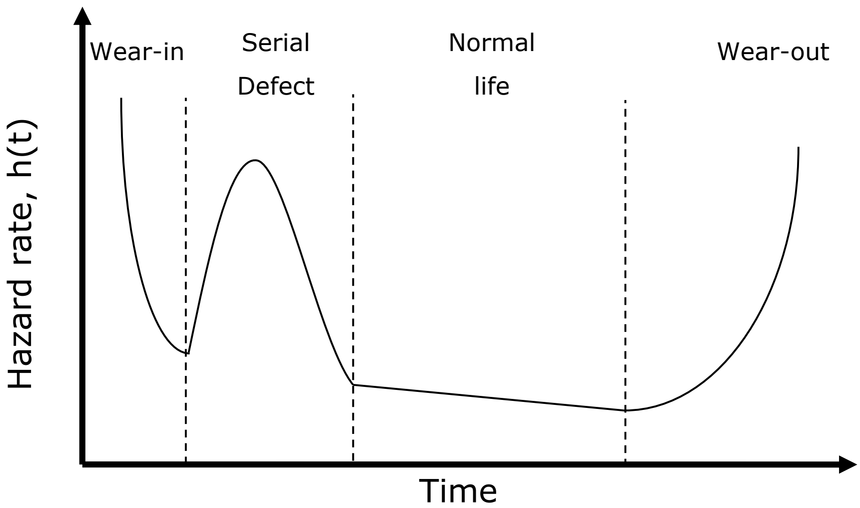

Figure 3.2: Madsen and Stiesdal lifetime failure distribution

This model is based on operational experience from Siemens but also reflects the failure behaviour witnessed at OWEZ where serial defects in the drive train were observed in non-Siemens machines [3.6]. The mathematical model used to describe this failure distribution is shown in Eq. (3.8) and the associated hazard function can be used in Eq. (3.33) in the failure modelling process that followed where H is the number of components effected by failure type, *yr* is the year of operation and a and c are scale and shape parameters respectively.

$$f(t) = \mathrm{H}\left[\exp\left(-\left(\frac{yr-1}{a}\right)^{c}\right) - \exp\left(-\left(\frac{yr}{a}\right)^{c}\right)\right] \qquad (3.8)$$

The consequences of different lifetime failure distributions on strategy choices and life time operational costs are examined in detail in Chapter 6

3.2.1 Markov Chain and Markov Process

Having considered the different operational methodologies available in Section 2.5 and specifying the failure modelling requirements in Table 3.1 it was identified that a probabilistic simulation approach was required. For discrete and continuous time domain repairable engineering systems, it has been demonstrated that Markov Chain or Markov Processes can effectively meet these modelling requirements [3.4]. This approach was therefore adopted for this thesis.

Markov chains are a mathematical system named after Andrey Markov. They transition between state spaces based on a transition probability in a random process. There are a wide degree of formal definitions and applications of Markov Chains but in the context of this thesis, they are considered a tool that is used to represent the state of an engineering system at a specified time and are formally in described in [3.7].

An engineering system can be represented as existing in a series of discrete states with each state representing the physical state of the system at a given time. The system can move from one state to another but can only ever be in one state and perform a single transition at a time. An important feature of Markov Chains is the

Markov Property which means that the transition to the next step is dependent only on the immediately preceding step and as such the Markov Chain is considered ‘memory-less’.

The simplest representation to consider is a binary model where a system is working (1) or not working (0) and can move only between those two states. From a known initial state, the system can remain in the current state or move to another state with a defined probability.

This simplest illustrative example is shown in Figure 3.3. In state A, the probability of remaining in state A in the next time step is $p_{(A, A)}$ and the probability of moving to state B is $p_{(A, B)}$. $p_{(A, A)} + p_{(A, B)}$ sum to 1 and similar relationships exist starting from state B.

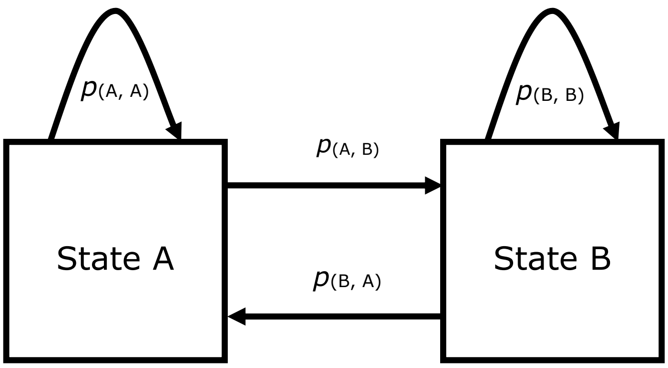

Figure 3.3: Basic Markov Chain system

This model can be represented by a transfer probability matrix (TPM) shown below in Eq. (3.9):

$$T = \begin{bmatrix} p_{(A,A)} & p_{(A,B)} \\ p_{(B,A)} & p_{(B,B)} \end{bmatrix} \tag{3.9}$$

If the starting state is a known matrix $s^{(0)}$ and, the system state after n time steps is $s^{(n)}$ a solution can be determined using Eq. (3.10).

$$s^{(n)} = s^{(0)}T^n \tag{3.10}$$

The TPM can be expanded to any number of systems as long as the transition probabilities between states can be estimated. However, if a state can be reached where the probability of moving to another state is zero or cannot be represented by a probability function the state is known as a sink or absorbing state and Eq. (3.9) cannot be solved. This is shown in Figure 3.4 and an alternative approach is required to determine the system state.

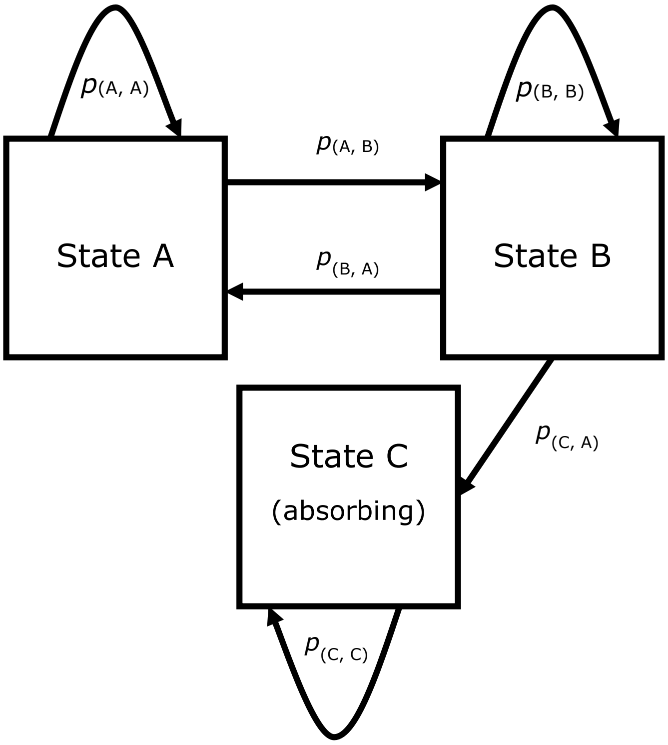

Figure 3.4: Markov chain with absorbing state

For systems with a MTTR that is fixed or has very little variation, two simple methods for determining the amount of time a system is in a failed state were considered. The model shown in Figure 3.3 can be used with a single MTTR value with a random (exponential) repair probability and analysed using Eq. (3.10). This effectively assumes that a repair can always be carried out and eliminates absorbing states. When an absorbing state is present, the simplest simulation method for representing downtime when an absorbing state is reached is to reset the state matrix to the original condition after a set number of time steps. The repair actions on an offshore wind turbine are too complex to be adequately described using these approaches. When a failure does occur, the repair action is dependent on multiple influences, the primary variables being the access restriction due to weather limits and maintenance resource availability.

To capture these dependencies of access thresholds and resource availability on downtime, and therefore technical availability, a modification of the simulation approach outlined above was adopted. When a failure occurs, the downtime is dependent on a sufficient access window for single action maintenance or windows for cumulative repairs being observed. If climate data for a significant period of time, required to perform a lifetime assessment of a system does not exist, a representative time series climate simulation is required. When a system fault occurs, the associated number of time steps before the system is reset is determined by the simulated wave height and wind speed time series. A description of the climate model used is presented in Section 3.3.

With adequate system knowledge the turbine model could be extended to include the relationship between subsystems as has been done for onshore turbines in [3.8] including degradation states. The model presented in this thesis does not use this approach due to a lack of such data. However, the general approach has been designed to allow the implementation of a fully developed degradation model if such data becomes available at a later date.

A Markov Process is a discrete process, with each step corresponding to a distinct time and the transition between each representing the passing of time. The actual system that the simulation is trying to capture on the other hand, takes place in continuous time space. When moving from a continuous time such as that shown in Figure 3.3 to a discrete time model, the transition probability is replaced with a transition rate, defined in Eq. (3.33). The transition rate is the likelihood that the system will move from its current state to another during the transition time step. In this simplest case where constant failure rates are assumed for a subsystem at a single simulated time step, the hazard function equals the failure rate and the transition likelihood is constant for the duration of the simulation [3.1].

This allows the failure behaviour described previously to be captured by the discrete Markov Process Model. Caution must be applied when representing a continuous system as a discrete process to ensure that the complexity of the true system is not lost. The key modelling decision in this respect is the size of the transition period, Δt. The smaller Δt is, the closer the Markov Process will be to the continuous system that it is attempting to represent but this comes at a computational cost. The value of Δt must be sufficiently small so that the probability of more than one transition event occurring in a single time step is statistically insignificant; for this application a probability of occurrence less than once in 20 years of simulated time. In this work, the value of Δt has been influenced by the nature of the climate and reported wind turbine failure rates in addition the model reports any instance of two transition events occurring in a single window to ensure that Δt is sufficiently small.

3.2.2 Markov Chain Monte Carlo Simulation

Markov Chain Monte Carlo (MCMC) is a methodology for analysing Markov Chains, it functions by running Monte Carlo integration for a suitably long time. A full and detailed introduction to MCMC including various examples and discussion is presented in [3.9]. Monte Carlo integration in this context is the use of randomly generated numbers to determine if an event has occurred. A sufficiently large enough simulation sample is then carried out in order to quantify variability and uncertainty of the process being simulated. The implementation of this is best described with an illustrative example. For this a simplified offshore wind turbine availability model is used where availability is driven by failure rate, repair time and accessibility due to significant wave height.

3.2.3 MCMC reliability simulation example

Each subsystem was modelled as an independent value either in the operating or failed state. A uniformly distributed random in the region 1-0 was then generated at each time step for each subsystem and failure is evaluated by comparing the random number to the failure criteria specified in Eq. (3.33).

If a subsystem is in a failed state, the turbine will remain in a failed state until an access period sufficient to perform a repair occurs in the climate time series. Repairs were assumed non-cumulative in this case. If one system is in failure state, the overall system is considered to be in failure state. The yearly availability is obtained by summing the number of time steps that all sub systems are working divided by the total number of time steps in a year. For the demonstrative case, simulation resolution of 3 hours was used and availability recorded at the end of each year during the 20 year life cycle of an offshore wind farm. As the number of years simulated increases, a moving average of the availability can be calculated and used to predict the expected availability of the system. An example of this process is shown in Figure 3.5 with a large number of wind farm lifetime simulations. Convergence in this example is based on OWEZ with serial defects of key components and isn't representative of the performance of the industry beyond very early sites.

This process is then repeated a large number of times to determine an overall availability for the system. Determining when to stop a Monte Carlo simulation can be a difficult process and again is a trade-off between accuracy and computational efficiency. Various methodologies have been suggested to determine when an adequate level of convergence is reached, see for example [3.10].

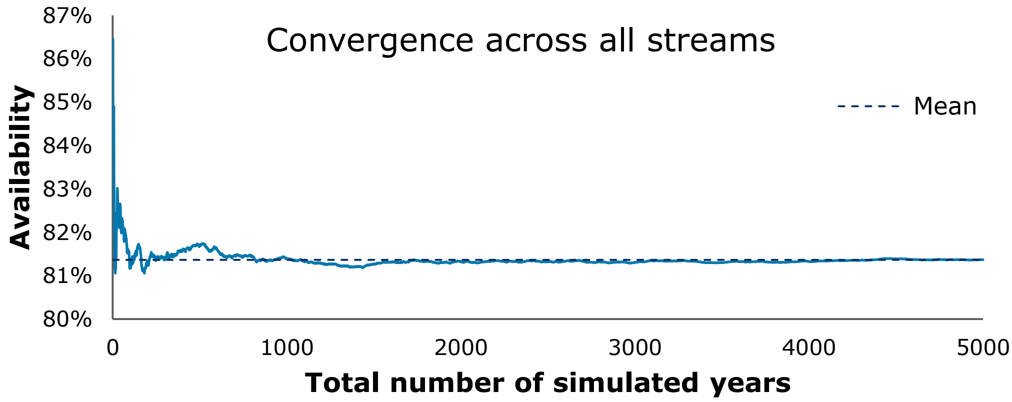

Figure 3.5: Monte Carlo simulation example showing convergence

The two most basic approaches are to carry out a single very long simulation and check how the answer is changing over time or to carry out multiple independent simulations and ensure they reach approximately the same solution. For this work, the Gelman-Rubin convergence criteria check was adopted [3.11] as it represents a well-defined, computationally simple and easy to implement methodology. The Gelman-Rubin convergence criterion combines both approaches and is described in detail in Appendix I, with further details in [3.12].

3.3 Climate Modelling

3.3.1 Nature of wind and wave climate

The difficulty in modelling wind and wave climate has been highlighted in the Section 2.7 identifying that various approaches exist and continue to be developed. For this work, the necessities for the model were that it is suitably representative of the real data, easily simulated and can be generated with available data. The key climate criteria for the climate model were identified as:

- Capable of simulating wind speed, wave height and wave period concurrently
- Replicates annual distribution of three climate parameters accurately.
- Reproduces short term (0-24 hours) correlation of climate models as well as longer term duration windows (24-72 hours)
- Captures correlation between different climate variables
- Preserves seasonality

Annual wind speed distribution has a direct relationship with annual energy production as well as heavy lift and helicopter accessibility, while wave climate determines accessibility for all other maintenance actions. Examination of the annual distribution also allows an understanding of the nature of the climate at a site and highlights several key differences between the nature of the wind and wave climate. The wind and wave distributions at the FINO offshore platform [3.13] are shown in Figure 3.6 with fitted two parameter Weibull distribution curves.

The wind climate is well characterised by a two parameter Weibull curve whereas the wave height distribution has a phase shift, this is due to the wave height never falling to zero. The wind speed distribution is closer to a normal distribution than wave height while wave period approximates a normal distribution; these climatic feature have implications for the modelling approach adopted which are analysed in detail in Section 4.3.

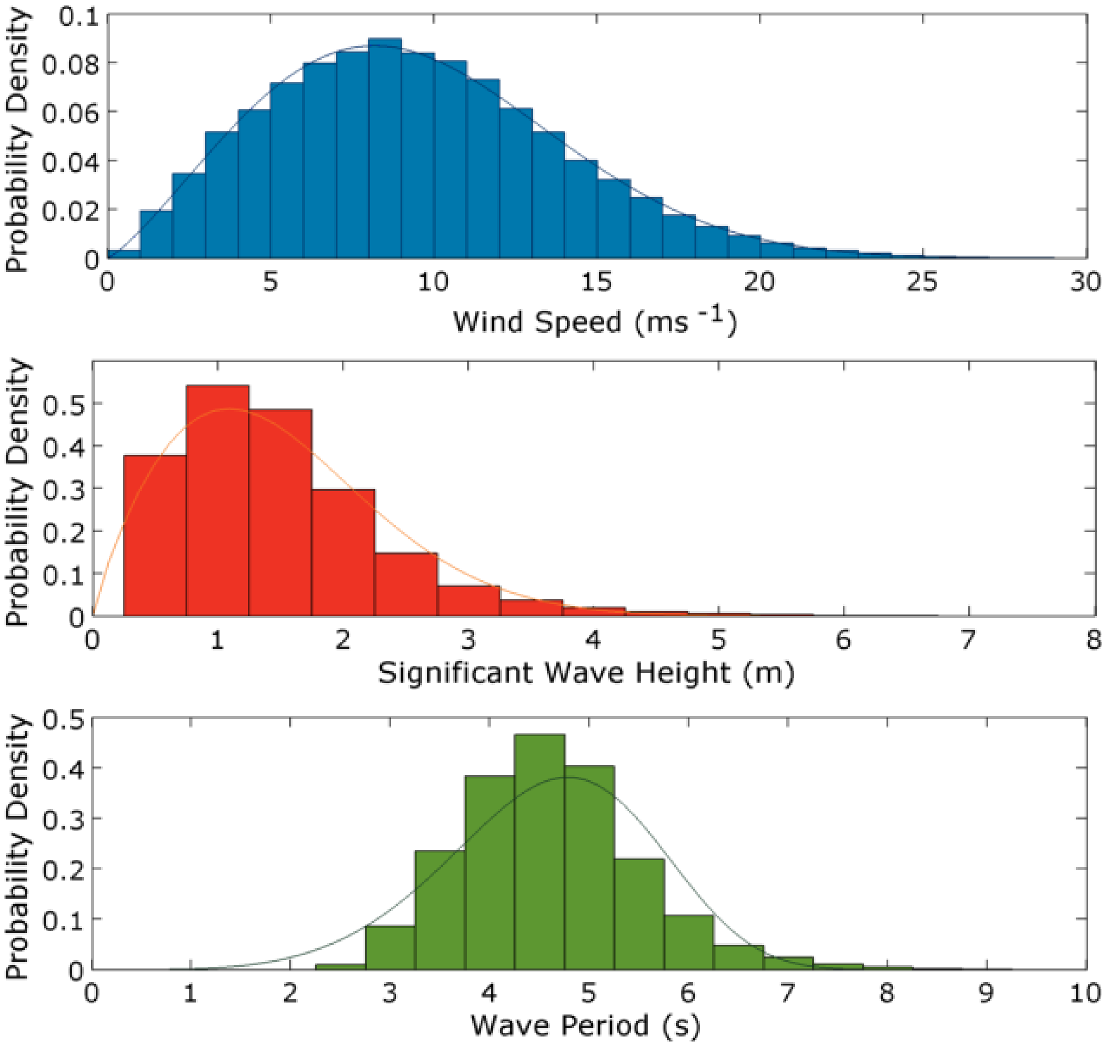

Figure 3.6: Wind and Wave Distributions at FINO met mast

The persistence characteristics of the climate model influence the waiting time that is to be expected before a sufficient weather window to perform a repair operation is observed and must also be captured in the model. Plots of mean waiting time for different access window lengths are shown in Figure 3.7 for both wind and significant wave height with access limits of 10 ms^{-1} and 1.5 m respectively at the FINO met mast location [3.13].

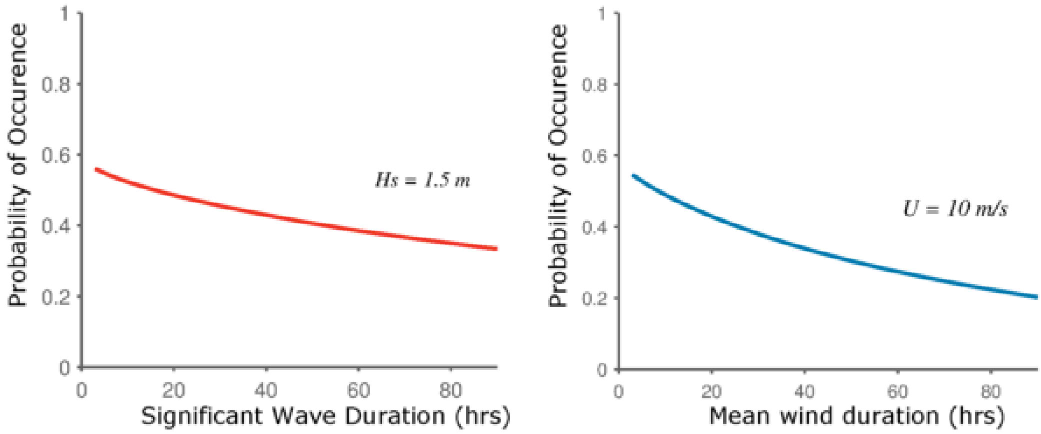

Figure 3.7: Probability of access windows based on wave height (L) and wind speed (R)

The short term duration is important for smaller repair operations, examining repair strategies and to ensure realistic losses due to downtime are captured. To analyse how strongly a current measurement is correlated to *k* previous measurements or lag terms, the autocorrelation function (ACF) can be examined. The ACF, ρ_k, is dependent on the auto-covariance, γ_k, mean, μ_z, and variance, σ^2_z, and is described in Eq.(3.11) + Eq.(3.12) [3.14].

$$\rho_k = \frac{\gamma_k}{\sigma_z^2} \tag{3.11}$$

where

$$\gamma_k = \frac{1}{N}\sum_{t=1}^{N-k}(z_t - \mu_z)(z_{t-k} - \mu_z) \tag{3.12}$$

Figure 3.8 shows sample ACF plots of the wind and waves at 1 hour time resolution. It can be seen that there is strong short term correlation in both climate parameters with wave height showing a slower rate of decay indicating it has stronger auto-correlation.

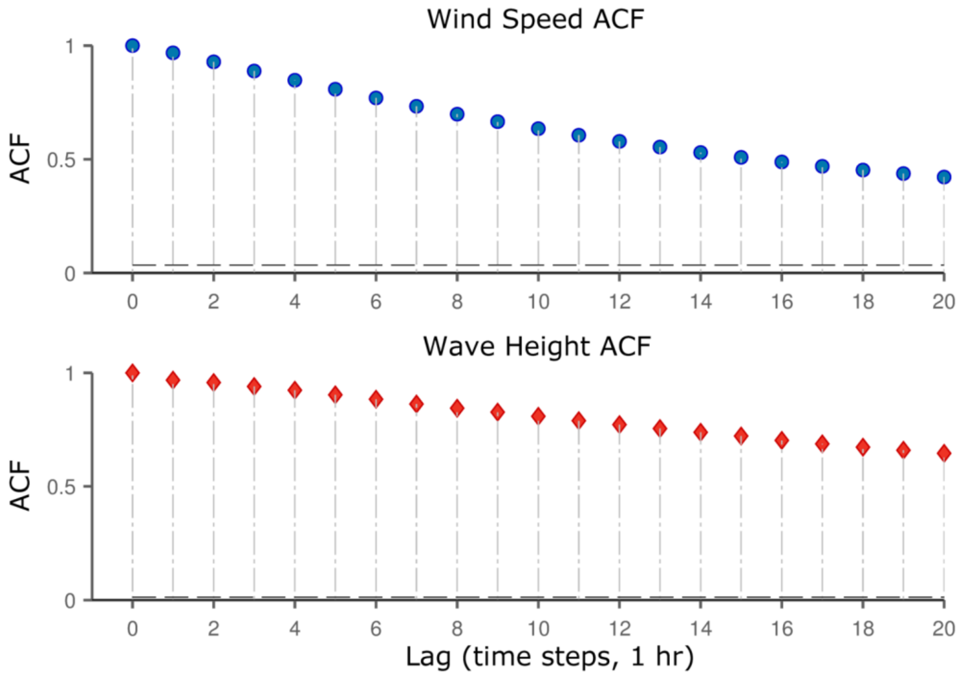

Figure 3.8: ACF for wind and wave Data

The ACF plots allow a visual assessment of the time step correlation and an automatic script has been produced to analyse any data set. In practical modelling terms, the ACF allows the identification of how many previous time step values are of significance to the current time step. However, if the autocorrelations are inter-correlated, the ACF plot can be prone to distortion and so a further metric, the partial autocorrelation function (PACF) needs to be introduced. Methodology for determining the PACF, Φ_{kk}, is outlined in Eq. (3.13) – Eq. (3.16).

$$P_k \Phi_k = \rho_k \tag{3.13}$$

where

$$P_k = \begin{bmatrix} 1 & \rho_1 & \cdots & \rho_k - 1 \\ \rho_1 & 1 & \cdots & \rho_k - 2 \\ \vdots & \vdots & \ddots & \vdots \\ \rho_k - 1 & \rho_k - 2 & \cdots & 1 \end{bmatrix} \tag{3.14}$$

$$\Phi_k = (\Phi_{k1}, \dots, \Phi_{kk})' \tag{3.15}$$

The last coefficient Φ_{kk}, is the partial autocorrelation of order k and is the only coefficient of interest for a PACF plot, the system of equations can be solved for Φ_{kk} using Eq. (3.16).

$$\Phi_{kk} = \frac{|P_k^*|}{|P_k|} \tag{3.16}$$

Where P_k^* is equal to the matrix P_k defined above with the k^{th} column replaced with ρ_k. If the value of the PACF is greater than the standard deviation of the coefficient series then that lag term is still considered important and must be considered when modelling. Example plots of PCF, corresponding to the ACF plots in Figure 3.8 are shown in Figure 3.9.

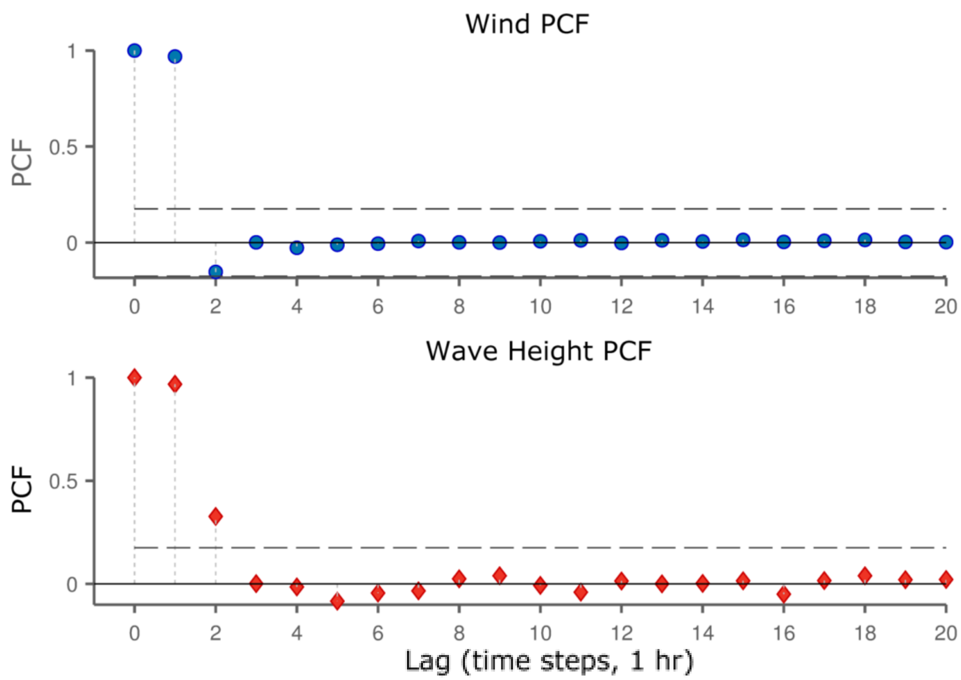

Figure 3.9: PACF for wind and wave Data

From Figure 3.9 it can be seen that in the above case only the previous 2 wind terms influence the wind whereas the first three influence wave height. In addition, a stronger structure is evident in the wave PCF corresponding to tidal influences. For an autoregressive model, empirical guidelines have been outlined in [3.15] and are outlined in Table 3.2. More mathematically rigorous techniques exist such as those outlined in [3.16]. The implementation in this work is detailed in section 3.3.2.

Correlation between wind and wave climate and seasonality are important in the context of offshore wind due to their impact on accessibility and power production. The power generated by wind turbines increases proportionally to the square of wind power; at higher wind speeds they generate higher revenue. The correlation between wind and wave height at the FINO met mast is shown in Figure 3.10 identifying that in general, higher wind speeds and higher wave heights coincide. Consequently, periods of poorest accessibility coincide with periods when it is most critical to have high turbine availability. This needs captured in the climate model. Through analysis of available data, in particular [3.17] it has been observed that typical Pearson Correlation coefficient values between wind and wave data are of the order of 0.5-0.8.

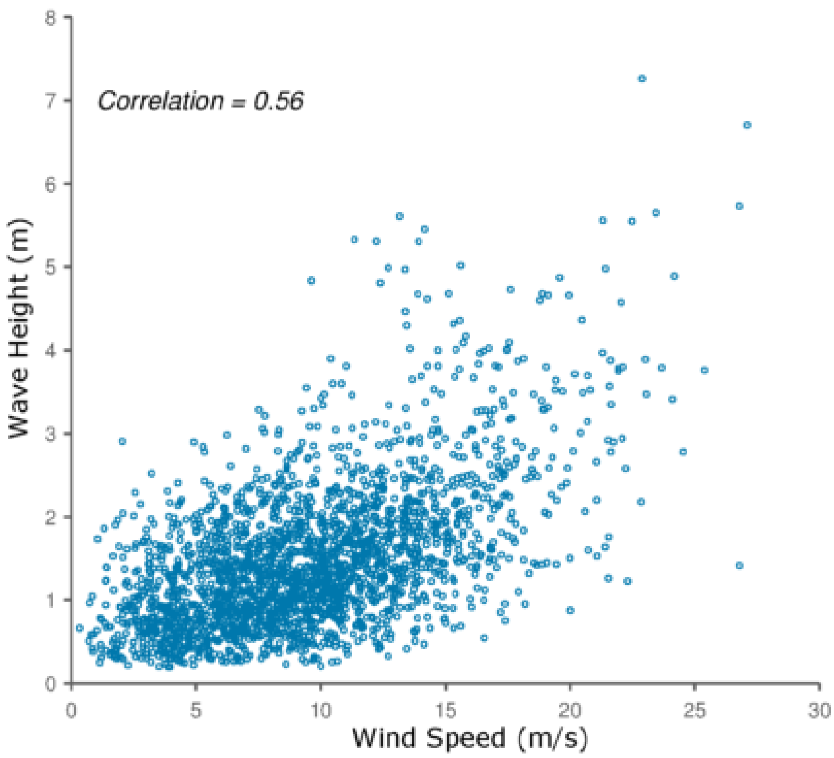

Figure 3.10: Correlation between wind speed and wave height

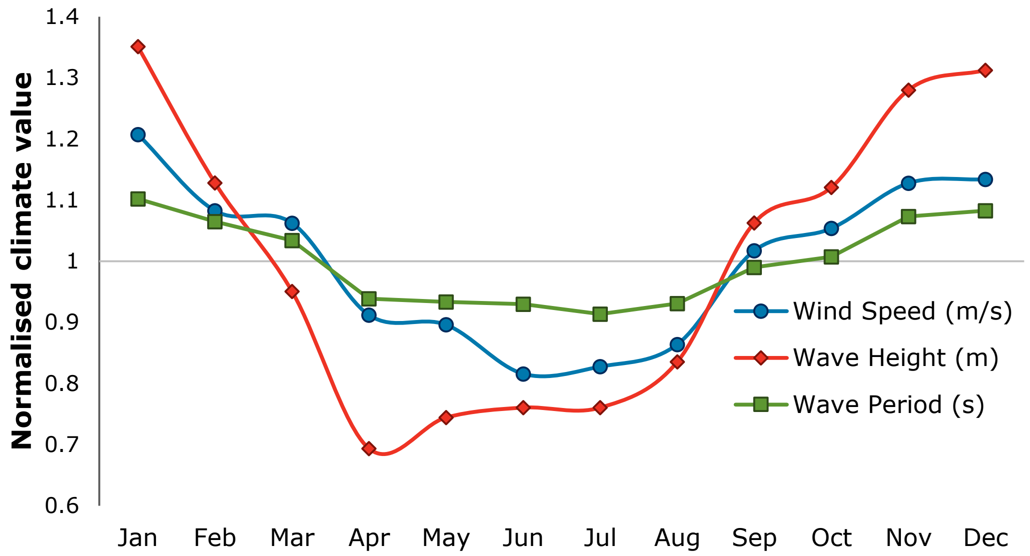

Figure 3.11: Seasonality in climate parameters

Figure 3.11 demonstrates seasonality of the three climate parameters, normalised to their respective means for the 8 years of available measured data. Seasonal variability will influence generation capacity as well as accessibility and must also be captured. There is particularly critical requirement for seasonality as it has the potential to directly influence operating strategies and provisions of resources.

3.3.2 Auto regressive modelling

Based on the analysis in Table 2.5, Autoregressive models were identified as the preferred modelling approaches from a selection of models that have previously been applied to climate models. Furthermore, there was pre-existing expertise within the Electrical and Electronic Engineering Department at the University of Strathclyde in this field of modelling which provided further weight to the choice, for example in [3.18, 3.19].

The general form of an AR model as described in [3.14] is shown in Eq. (3.17), normalised with respect to the mean, μ and in terms of model parameters φ_i and white noise term ε_t .

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{p} \varphi_i (X_{t-i} - \mu) \tag{3.17}$$

This model assumes that the data being modelled is stationary but can be extended to non-stationary data in the form of an ARMA model, the general form of which is shown in Eq. (3.18), again normalised with respect to the mean and with the additional moving average parameter θ_i.

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{p} \varphi_i (X_{t-i} - \mu) + \sum_{i=1}^{p} \theta_i \, \varepsilon_{t-i} \tag{3.18}$$

For wind and wave time series it has been observed that the non-stationary nature observed in data is primarily due to identifiable trends, in particular seasonality and diurnal variations. By de-trending the data before modelling, it has been shown to be possible to produce representative models using the simpler AR equation identified in Eq. (3.17). This methodology has been adopted in this work. Determining the order of the model, known as model classification was performed using the ACF and PACF assessment previously described along with the information presented in Table 3.2.

Table 3.2: Auto Regressive Model Order Classification [3.15]

Model	ACF Description	PACF Significant Terms
AR (1)	Exponential or oscillatory decay	$\Phi_{kk} \approx 0$ for $k > 1$
AR(2)	Exponential or sinusoidal decay	$\Phi_{kk} \approx 0$ for $k > 2$
AR(p)	Exponential and/or sinusoidal decay	$\Phi_{kk} \approx 0$ for $k > p$

For ARMA (p,n), n = p-1

Eq. (3.17) can be extended to capture the correlation between multiple data sets by extending to the Multivariate Auto-Regressive case developed in [3.20] and is shown in Eq. (3.19).

$$X_t = \mu + \varepsilon_n + \sum_{i=1}^{p} A_n(X_{n-i} - \mu) \quad (3.19)$$

Where n, is the number of variables, Xn is a variable state vector and An is a matrix of the AR model coefficients and ε_n is a noise vector with mean zero and covariance matrix of the data. The MAR modelling adopted has been carried out using the MATLAB function *ARFIT* [21] which can automate the process of model parameter estimation and generation of a new time series. The order of ρ is determined by optimising Schwarz's Bayesian Criterion. The methodology used for determining model parameters, φ and the variance of white noise ε, σ_a^2 is a least squares approach to solving the modified Yule – Walker equations shown Eq. (3.12).

3.3.3 Data pre-processing

A number of different approaches were considered when filling gaps in the time series in order to be used in a simulated AR process. The simplest approach is to fill gaps with the last observed value or use a linear interpolation between points. However, this was observed to have significant impact on the observed access duration windows that are important for this application. Therefore, an alternative methodology, using the historical average for the hourly time step was first used and any remaining gaps filled with a cubic interpolation. This process is outlined in Figure 3.12 for significant wave height values and preserved the access characteristics of the observed data. All climate data was pre-processed before an AR model was applied using a robust MATLAB code. The simulation process is described in the context of the full simulation model in Section 3.5.2.

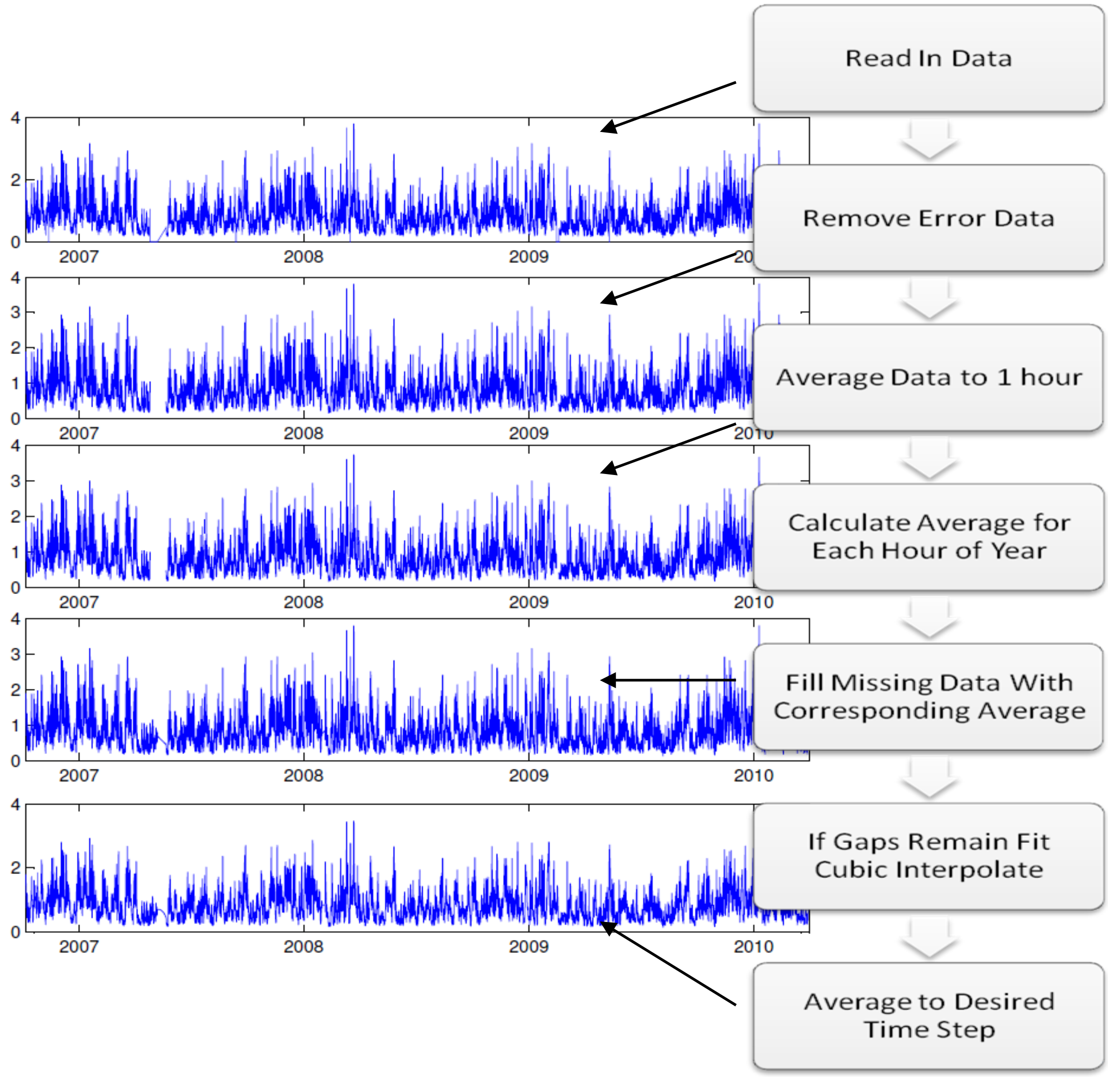

Figure 3.12: Adopted data pre-processing methodology

A Box-Cox transformation can be applied to the continuous data so that the distribution is approximately Gaussian [3.14]. The Box-Cox transformation is shown in Eq.(3.20) and Eq.(3.21) where shape parameter, Λ can take a value between -1 and 1, Y_t is the transformed time series. A discussion of the most appropriate transformation process for wave data is presented in [3.22], a detailed examination of fitting Λ and the modelling consequences are presented as part of Section 4.2.

$$Y_t = \frac{{Hs_t}^{\Lambda-1}}{\Lambda}, for\ \Lambda \neq 0 \tag{3.20}$$

$$Y_t = T(Hs_{t)} = \ln(Hs_t)\,, for\ \Lambda = 1 \tag{3.21}$$

Three months of significant wave height measurements before and after transformation are shown in Figure 3.13 to highlight the shift and smoothing effect of the transformation.

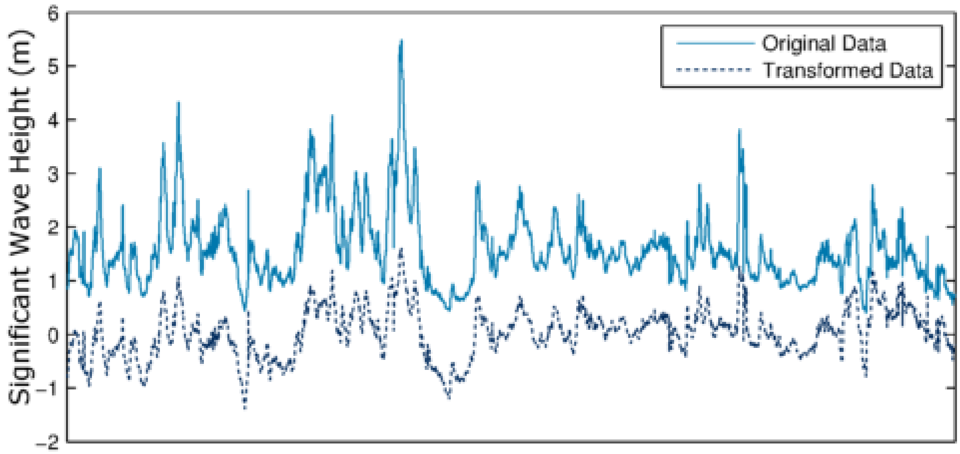

Figure 3.13: Example of original and transformed wave data

For wind and wave data, it is also necessary to remove underlying deterministic trends in the data before an AR model is suitable. For wind speed, these trends are the seasonal and diurnal trends, for wave height and period only, the seasonal trends were required, as diurnal trends in wave data were found to be negligible. The seasonality of the climate data was captured using a simple MATLAB script that determines monthly average wind speed values and fits a second order Fourier Series curve with period, ω = 12. The methodology is shown below in Eq. (3.22) – Eq. (3.24).

$$\begin{aligned} F(\omega) = \ &\mu + a_1 sin\omega + \ a_2 sin2\omega + \cdots + a_m \sin(m\omega) \\ &+ b_1 cos\omega + \ b_2 cos2\omega + \cdots + b_m cos(m\omega) \end{aligned} \tag{3.22}$$

Coefficients are given by:

$$a_k = \frac{2}{n}\sum_{i=1}^{n} y \cdot \sin(k\omega) \tag{3.23}$$

$$b_k = \frac{2}{n}\sum_{i=1}^{n} y \cdot \cos(k\omega) \tag{3.24}$$

The fitted values can then be subtracted from the data depending on the month the data is observed in. A similar process is repeated for diurnal trends with ω = 24.

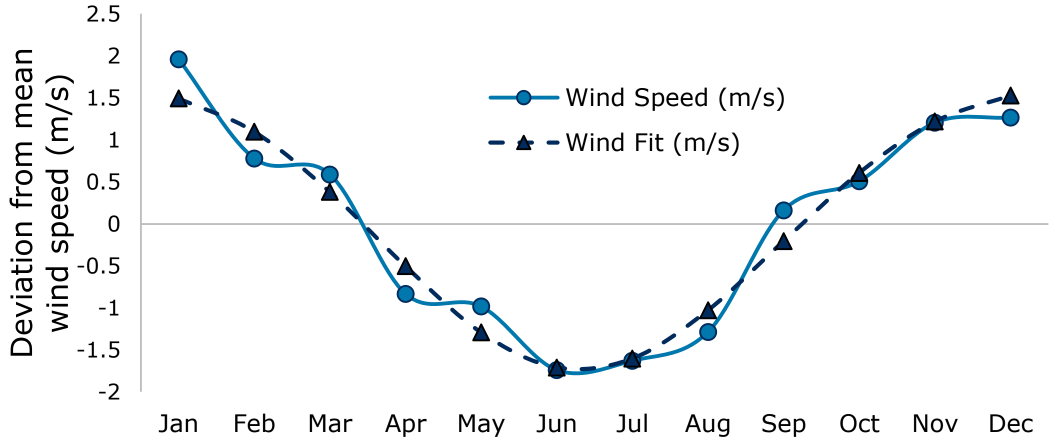

Figure 3.14: Seasonal wind speed observed data trend and fitted Curve

Figure 3.14 shows an example of fitted seasonality curves and averaged data overlaid on the raw wind climate data from Figure 3.11. The corresponding seasonal diurnal trends are shown in Figure 3.15 demonstrating that the variations observed throughout the day can exceed the magnitude of seasonal variations and are therefore important to capture for wind speeds.

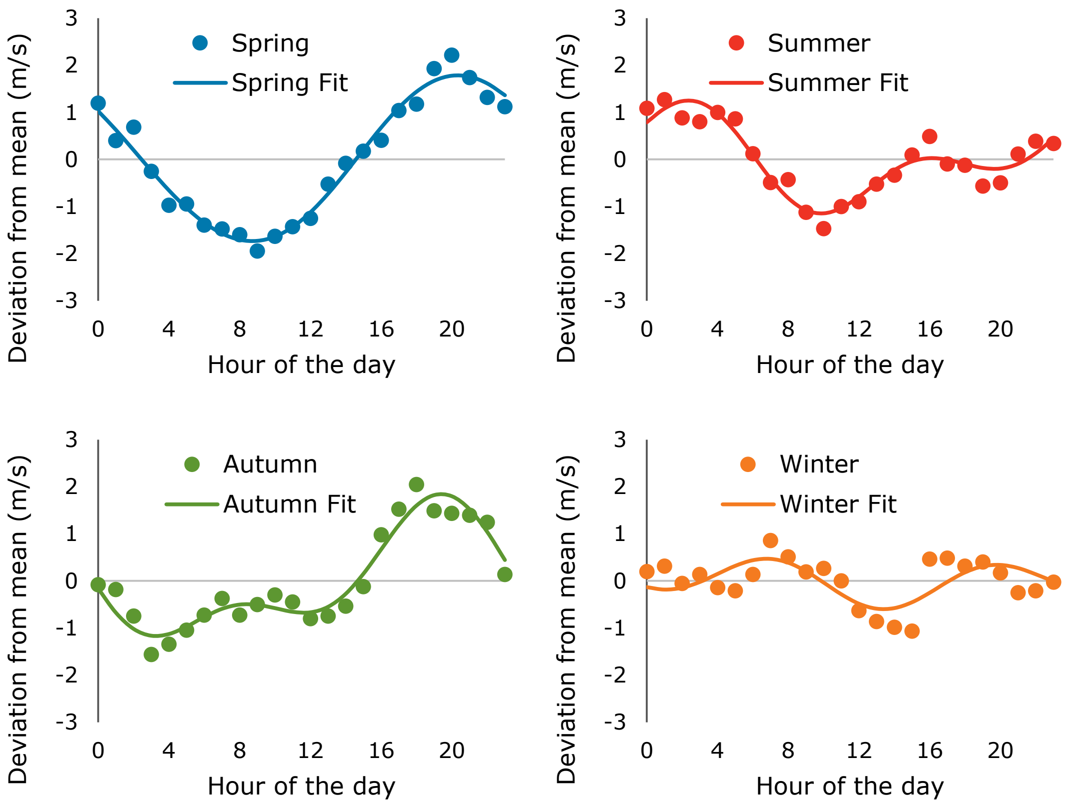

Figure 3.15: Diurnal variations for wind speed over different seasons

3.3.4 Combined climate model

Once a continual time series has been created it is necessary to transform and de-trend the data. When considering simulation of a wind time series only using AR models it has been demonstrated that a transformation is unnecessary and removal of deterministic trends alone is adequate [3.18]. When applying an AR modelling approach to wave data however, it has been identified that a transformation is required [3.23]. For this thesis, various combinations of data pre-processing were explored and the most robust methodology was adopted. The implemented process is to first transform all data and then remove the deterministic trends. This process is shown in Figure 3.16. For wind there is a requirement to remove seasonality, then diurnal variations. For wave height, firstly the Box-Cox transformation is applied and seasonality removed from the transformed dataset. For wave period, only seasonality is removed. The MAR co-efficient fitting and simulation process described in Section 3.3.2 can then be performed.

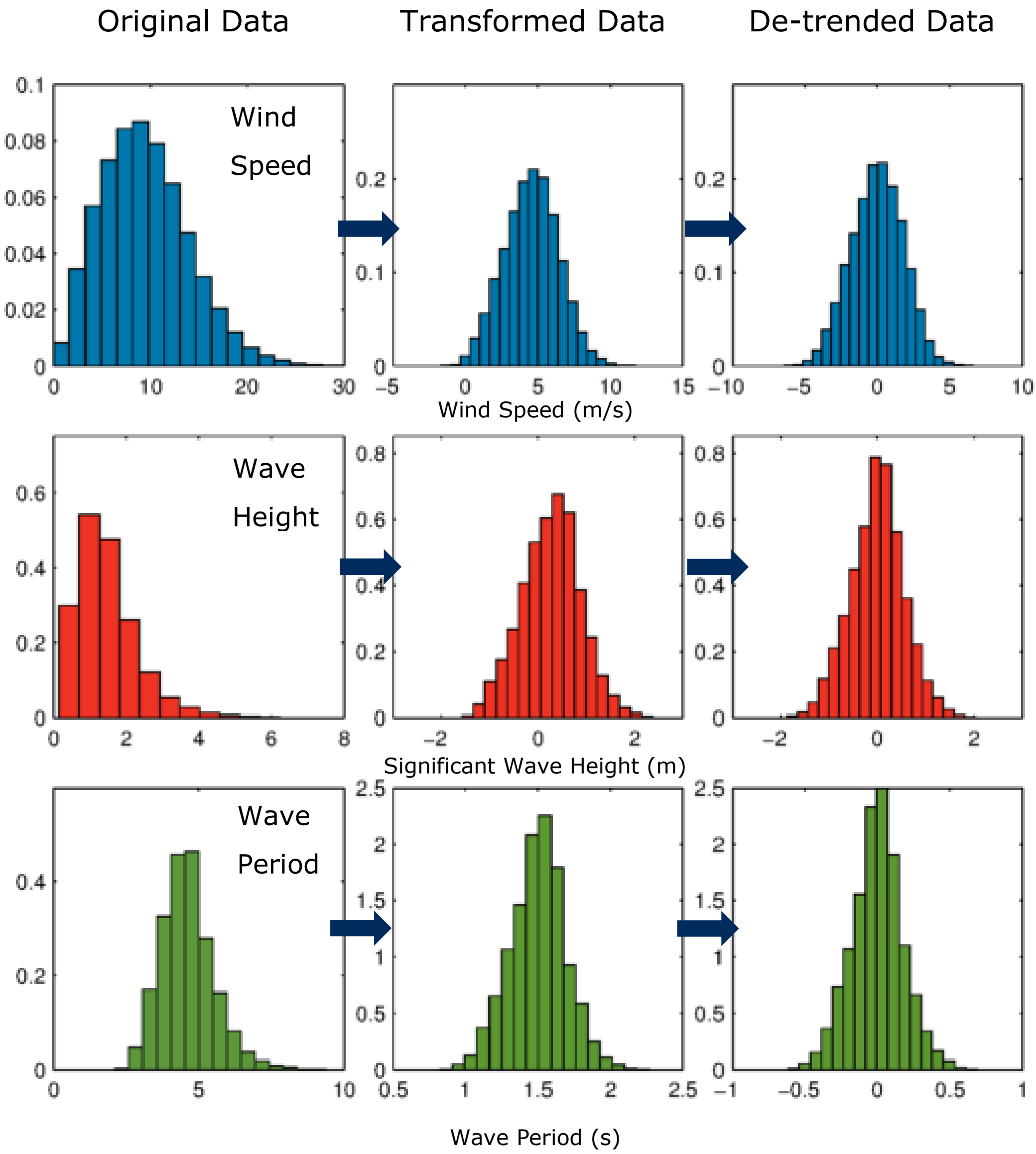

Figure 3.16: Transformation of data to enable MAR model

Simulated data is then re-trended and re-transformed to produce the final synthetic time series. Having established a methodology for combined climate modelling, two pieces of code were written to automate the process. The first code performs all the pre-processing action required to produce a continuous time series from supplied data. The main climate modelling code takes the output from the pre-processing script and produces simulated time series to pass to the availability model and is functionally described in Section 3.5.2.

One issue raised is that some generated data points are negative in value and are physically invalid. A discussion of different methods for dealing with this issue has been presented in [3.24]. In this work the values are simply set to zero. The justification for this action is that they will add no value to the loss of energy calculation while maintaining the value keeps the generated wind and wave time series consistent in length.

3.4 Cost model

The cost model comprises of various components outlined in Table 3.1 as failure costs, operational costs and lost revenue. The first two categories are considered direct costs as they must be paid out by wind farm operators while lost revenue is considered an indirect cost as there is no outlay. It is common in the wind industry to not only consider the direct costs but also the direct cost divided by total power produced which is known as the per unit cost [3.25], both measures are considered for the analysis in this thesis. Costs are an area of high uncertainty and are subject to large fluctuations over time. Costs will ultimately determine the success and long term viability of the offshore wind industry and therefore are vitally important to quantify.

Costs, providing health and safety is not compromised, will determine the provision of resources and choice of operating strategy. However, once resource and strategy choices are made, costs will not influence the resulting performance of the wind farm. Consequently, the cost model for this thesis is applied as a post process to the results rather than within the simulation. This allows the consequences of changing external conditions which may be outside of operator control to be rapidly assessed and greater understanding of the associated risks to project success.

3.4.1 O&M operations cost and associated loss of revenue

The repair operation of a wind turbine following a fault can be considered as taking several stages. In previous work, the total O&M mission has been classified as shown in Figure 3.17: Offshore WT Repair Process [3.26].

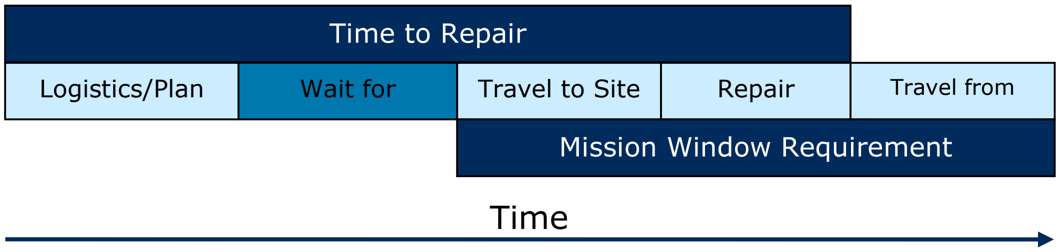

Figure 3.17: Offshore WT Repair Process

There will be associated costs with each segment of the repair process as well as loss of earnings corresponding to the time to repair. The costs associated with the mission window will be significant as they may involve expensive vessel hire.

Using the described climate and operation models, lifetime O&M costs can be predicted. Total O&M (OPEX) costs are considered to comprise of lost revenue (LR), repair cost (RC), staff cost (SC), infrastructure costs (IC) and vessel cost (VC) in Eq. (3.25) – (3.32).

$$OPEX = \ LR + RC + SC + VC + FC \tag{3.25}$$

Lost revenue is determined from (7) where p(t) represents the power produced at each simulated wind speed time step, U(t) based on a wind turbine power curve. Losses associated with electrical transmission and wind farm arrays are represented by efficiency coefficients, η. The value of power produced, EP(t) defined in (8) is a combination of the market price (MP_{elec}) of electricity and value of current UK support mechanism ($MP_{support}$).

$$P(t) = U(t) \cdot p(u) \cdot \eta_{farn} . \eta_{elec}, \quad for\ U_{in} < U(t) < U_{out}, else\ P(t) = 0 \tag{3.26}$$

$$EP(t) = MP_{elec} \cdot P(t) + MP_{support} \cdot P(t) \tag{3.27}$$

The lost revenue cost due to maintenance is calculated using availability, A(t) of the wind farm. This is defined as the number of operational turbines T_{on} divided by the total number of turbines, T_{total}, shown in Eq. (3.28) [3.25]. Lost revenue (LR) can therefore be calculated from Eq. (3.29)

$$A(t) = \frac{T_{on(t)}}{T_{total}} \tag{3.28}$$

$$LR = \sum (1 - A(t)) \cdot EP(t) \cdot T_n \tag{3.29}$$

Repair costs are calculated from Eq. (3.30) and are equal to the number of subsystem failures, F_n, multiplied by the cost of repair or replacement of the subsystem, FC_n. The methodology for deriving FC_n is outlined in Section 3.4.2.

$$RC = \sum_n F_n \cdot FC_n \tag{3.30}$$

Staff costs are calculated from the number of staff available and, S and annual salary of staff C_{staff} shown in Eq. (3.31)

$$SC = S \cdot C_{staff} \tag{3.31}$$

Vessel costs are described in Eq. (3.32). Any vessels purchased or leased for the duration of the wind farm life are represented as one off CAPEX costs. In addition, an annual fixed charge, V_{fixed} associated with vessels that covers costs such as fleet maintenance and docking fees is specified. The variable vessel costs are calculated based on the duration of repair, R_n for each subsystem and the associated vessel day rate, D_{vess} and mobilisation, M cost required.

$$VC = V_{CAPEX} + V_{fixed} + \sum_n (R_n \cdot D_{vess} + M) \tag{3.32}$$

A wind turbine is designed to operate optimally over a large range of speeds but this does not mean a wind turbine rated at 3 MW will produce 3 MW power output at all times. Detailed examinations of the design optimisation process, including the underlying power available in the wind can be found in various sources, see [3.27-3.29] for example. For power generated and loss of earnings calculations, the metric of interest is the power curve showing power output versus wind speed. An example from a modern offshore wind turbine is shown in Figure 3.18. The power curve may be thought of in three sections, cut in, variable operation and rated power operation, indicated by the dotted lines in Figure 3.18.

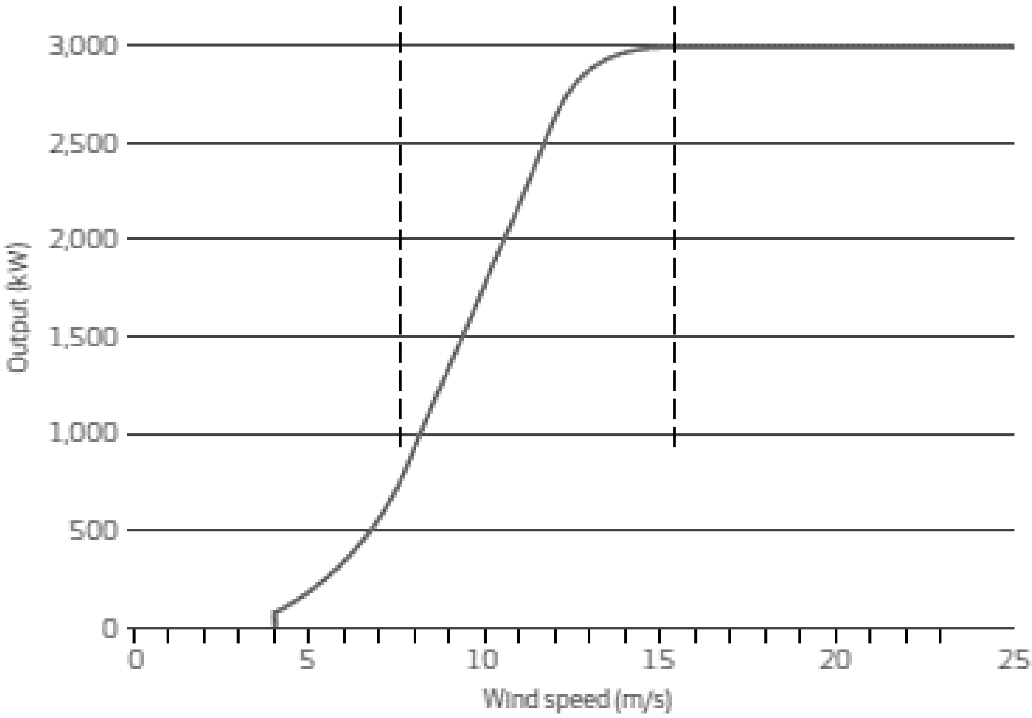

Figure 3.18: Typical wind speed power curve [3.30]

The simplest approach to calculating the losses associated with downtime is to take the hourly average wind speed when the modelled system is in the failure state and allocate losses based on the corresponding value of the power curve. Below cut in speed no losses are encountered and above rated wind speed the losses are equal to rated power.

To implement the power production and lost revenue calculations described, it is necessary to represent the manufacturers power curve which is often provided in discrete values as a continuous function, previously identified as *p(u)*. For this work the curve has been represented as a polynomial function using least squares regression between points in the varying operation section of the curve.

3.4.2 Component repair and replacement costs

Failure costs are the direct costs associated with partial or complete overhaul of components. There is a high level of uncertainty surrounding these costs for future wind turbine designs due to the unknown nature of their configuration as well as external cost drivers such as commodity and exchange rates. Future turbines are likely to be significantly larger and have different configuration to those widely deployed today. Current estimates of wind turbine components are reported in various studies [3.31-3.34], and serve as a baseline for a 5WM machine. It has also been established that the costs of different wind turbine subsystems do not increase proportionally to each other as the size of turbines increase and a set of empirical formulae relating subsystem size and cost has been developed and adopted for this thesis [3.35]. A study into the relationship between overall OPEX costs and wind turbine component size and costs has been performed in Section 5.6.2.

3.5 Developed simulation model

3.5.1 Model overview, inputs and outputs

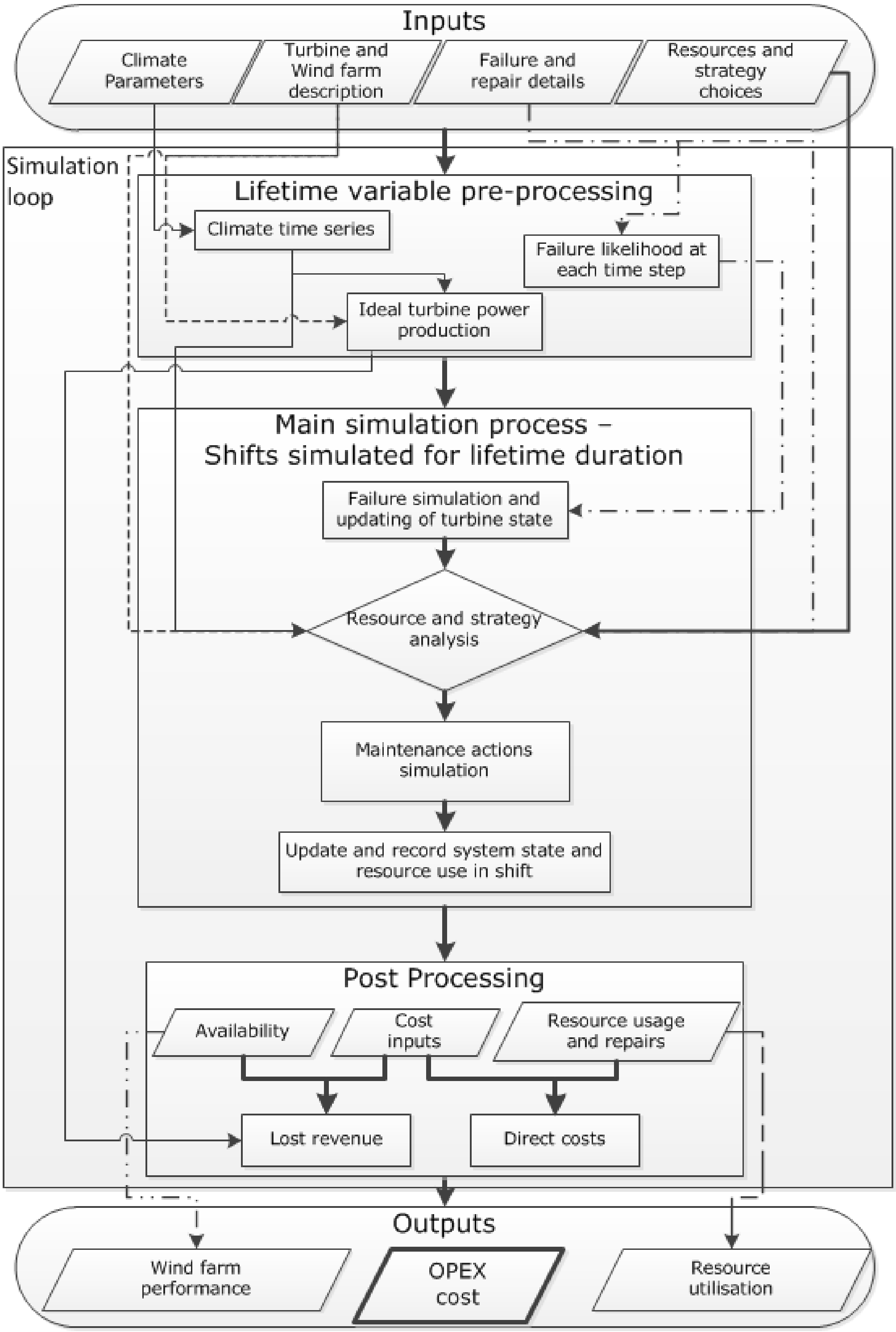

Figure 3.19: Simplified model structural overview and interdependencies

Figure 3.19 provides a simplified structural overview of the developed model. The main information path is shown by the bold arrows from inputs to outputs while direct inter-dependencies across functional blocks are shown with thinner lines. The developed simulation methodology can be considered in four stages. Firstly, all input blocks are completed in order to configure the scenario to be simulated. Lifetime variables which comprise of climate time series, corresponding ideal power production and the likelihood of a subsystem failing during each time-step are calculated in a pre-processing block and stored.

The operational simulation is then performed in a shift basis where the pre calculated values and user inputs are used to determine turbine failures and maintenance activity, if any, in that shift. At the end of the simulated shift, the condition of the wind farm is update and recorded along with the utilisation of resources. This process is repeated for the duration of the wind farm life. Calculation of wind farm availability and corresponding power production for this lifetime simulation is then calculated and stored. The entire lifetime simulation process is then repeated until convergence is observed based on the cross-simulation availability values. The cross simulation values are then passed to the output block for analysis.

The remainder of this chapter describes this model in detail. A summary of the key parameters for each of the input blocks is given in Table 3.3, cost inputs and all outputs along with a brief description and units are provided in Appendix II. The generation of a climate time series and corresponding ideal energy production are then described in Section 3.5.2. Modelling of the failure process is defined in Section 3.5.3. The main simulation process that takes the input configuration and lifetime variables and uses them to simulate the operations are then described in detail in Section 3.5.3.

Table 3.3: Summary of key inputs

Parameter	Description
Climate data	The model requires at least one year of wind speed and significant wave height time series data. If wave period is included this will be used to modify vessel capability calculation. If less than one year is present, it is not possible to capture seasonality.
Wind farm description	The location of the wind farm and operations base must be specified to determine transit time to and from the wind farm. The number and power curve of the turbine population must be specified in order to track availability, power produced and lost revenue due to downtime. The number of years the wind farm is expected to operate for must also be specified as it influences variable failure rates.
Failure rate and maintenance actions	The observed or predicted failure rate within the wind turbine population the life time of the wind farm for each subsystem, either a constant annual failure rate or fitted PLP model with specified wear in period and wear out start year. Weather window and vessel type required to perform repair as well as repair cost must be specified. The weather window can also be specified as cumulative of requiring a single operational window. The amount of time required to successfully complete annual scheduled maintenance and the month at which it begins must be specified.
Resources and strategy choices	The number of maintenance technicians and permanent transfer vessels must be specified for minor and scheduled maintenance. The mobilisation time and hire duration associated with specialist vessels must be determined if they are used and the contracting strategy adopted must be considered. A choice over whether a helicopter is used in conjunction with the vessels and the number of hours it can operate must also be made.
Costs	As well as the direct costs associated with staff, repairs and vessel costs. The value of power produced must be defined in order to quantify the relative value of different operational configurations.

3.5.2 Modelling of climate and power production

The climate simulation block is critical to determining power production and the extent to which maintenance actions can be carried out within an operational shift. The implementation of the climate simulation that is output to the repair process is shown in Figure 3.20, based on the methodology defined in Section 3.3.

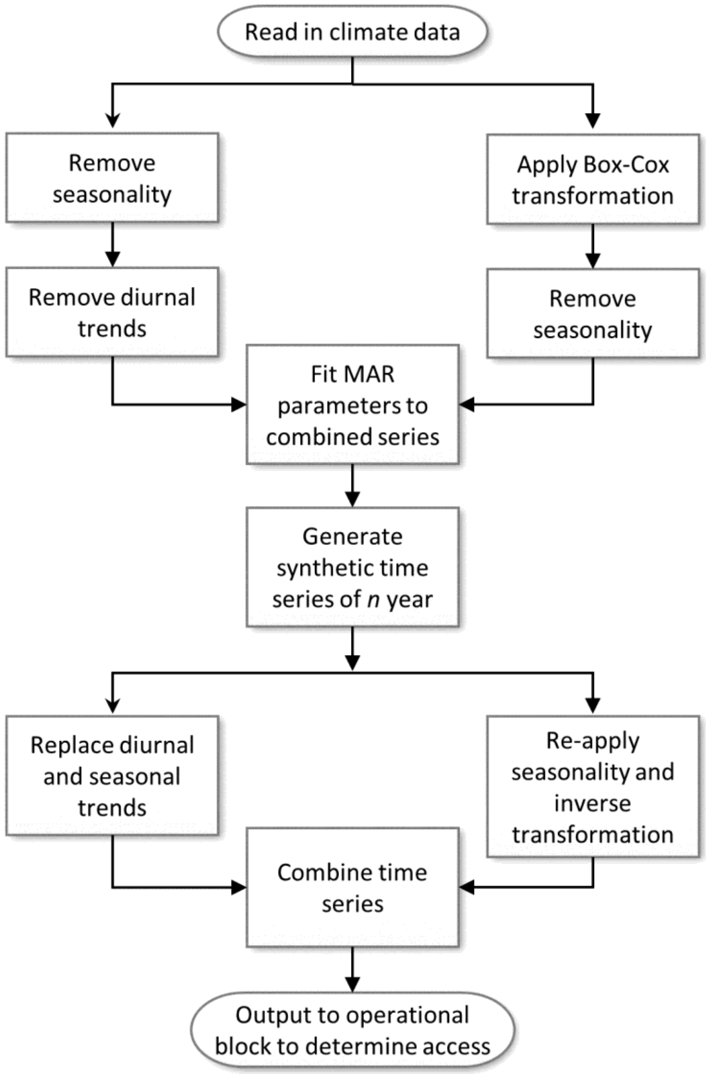

Figure 3.20: Climate simulation flow chart showing processing of data to output synthetic time series for operational simulations.

The output wind and wave time series are stored and are accessed in the main simulation block. Additionally, the wind time used to determine the ideal energy production for operating wind turbines at each state, this is done using the input power curve and Eq. (3.26). Once the state of each turbine has simulated throughout the lifetime of the wind farm, availability and the number of failed turbines are used with these values to determine energy production, lost energy due to downtime and their associated value in the post processing stage.

3.5.3 Modelling of failure process

A simulation model that is capable of representing failure behaviour at any stage of a bathtub curve is necessary to reflect the entire design life of wind turbines. The bathtub curve can be applied to the general population of wind turbines or individual components. If it is assumed that components have overcome any initial design problems and are being used in their intended environment, the normal life section of the curve becomes most appropriate. Similarly looking at the life cycle of a single wind turbine, the largest section is the on design normal life section.

Eq. (3.7) forms the basis of the failure modelling approach used in this research. The transition from an operating state to a failed state during any simulated time step is governed by Eq. (3.33) where *r* is a uniformly distributed number in the interval [0-1].

$$Transition\ if:\ r < 1 - R_c(t) \tag{3.33}$$

It can be seen from Figure 3.19 that the failure process is simulated in several stages. To avoid reading inputs in at each simulated operational shift, the failure criteria for each subsystem at each time step is determined from the input failure values in the pre-processing stage. This value is the likelihood of observing a failure in that simulated time step, calculated using Eq. (3.33). The process for determining the failure criteria, from operational data to model implementation is shown in Figure 3.21 and briefly described.

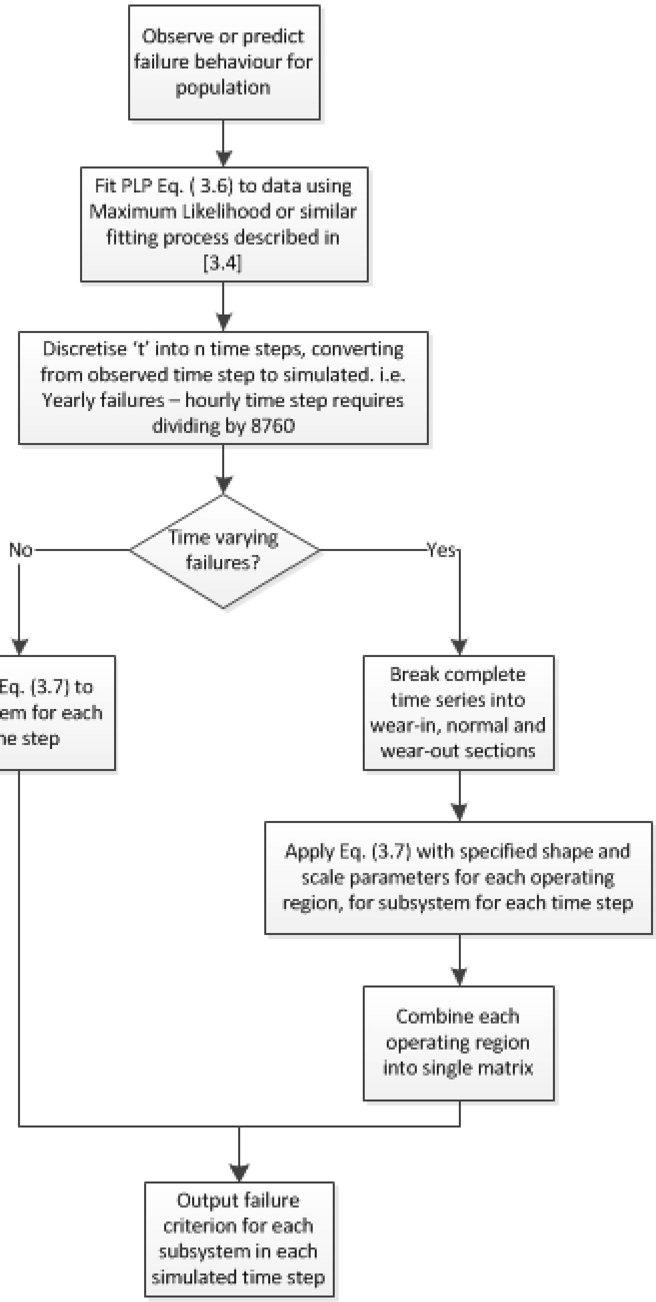

Figure 3.21: Failure criteria calculation

For all simulations in this thesis, the survival duration, *d*, used in Eq. (3.33) is one hour. Therefore, the continuous time variable t representing the duration of the wind farm life is scaled to hourly failure rates by dividing by 8760 and *d* set to 1. For the case of different operating periods corresponding to the bathtub curve behaviour, the duration of the wear in period, and start year for wear out behaviour are used in order to specify the changing shape parameter β over the duration of the wind farm lifetime. The failure criteria in each section is then calculated with the corresponding parameters.

The implementation of failure allocation to simulated subsystems is shown in Figure 3.22. The first stage of this process is to read the appropriate failure criteria from the previously calculated 'Failure likelihood at each time step' block.

This process is simulated for each operational shift, for each subsystem of each turbine, transitioning any working subsystem to a failed state when failures occur. The allocation of failures to operating turbines where a failed subsystem is observed at a failed turbine does not correspond to the physical reality of failure behaviour. However, it is a pessimistic representation of failures and preserves observed failure rates. Alternative approaches are discussed in Section 7.3. From a practical implementation viewpoint, the failure likelihood variable could be dynamically created or updated within each simulated shift to reflect operational history, for example increasing after high wind speeds, increasing due to a lack of completed scheduled maintenance or decreasing to represent a retrofit.

The adopted simulation of failure methodology allows the observed behaviour of wind turbine populations to be represented for operational simulations. However, as identified previously the model does not accurately describe the real world failure behaviour of individual engineering systems. As more data is obtained for operating wind turbines and further understanding of the physics of failures as well as the impact of maintenance actions, there is an opportunity to use more representative failure models. The modular nature of the overall OPEX model developed in this thesis would readily allow such failure methodologies to be incorporated for future work.

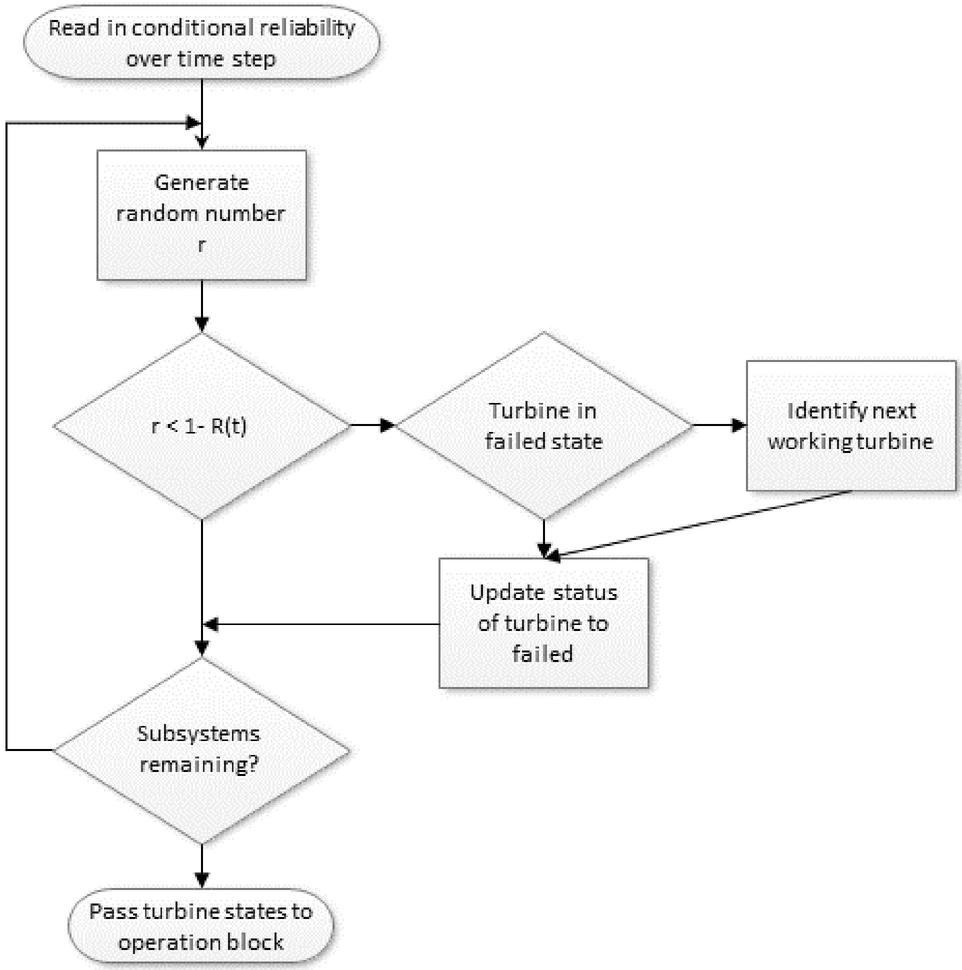

Figure 3.22: Failure simulation process flow chart, identifying preservation of failure rate

3.5.4 Resource analysis, maintenance simulation and recording of system state

Having simulated the failure process and updated the system state, an analysis for each vessel type is performed to determine if maintenance actions can be carried out. Following this analysis, the model either moves onto the next simulated shift or simulates the maintenance actions. The state of turbines throughout the shift as well as resource utilisation is recorded and output to tracking matrices which are used for post processing. This process is shown in Figure 3.23 and then described. For clarity the repair logic is shown separately in Figure 3.24.

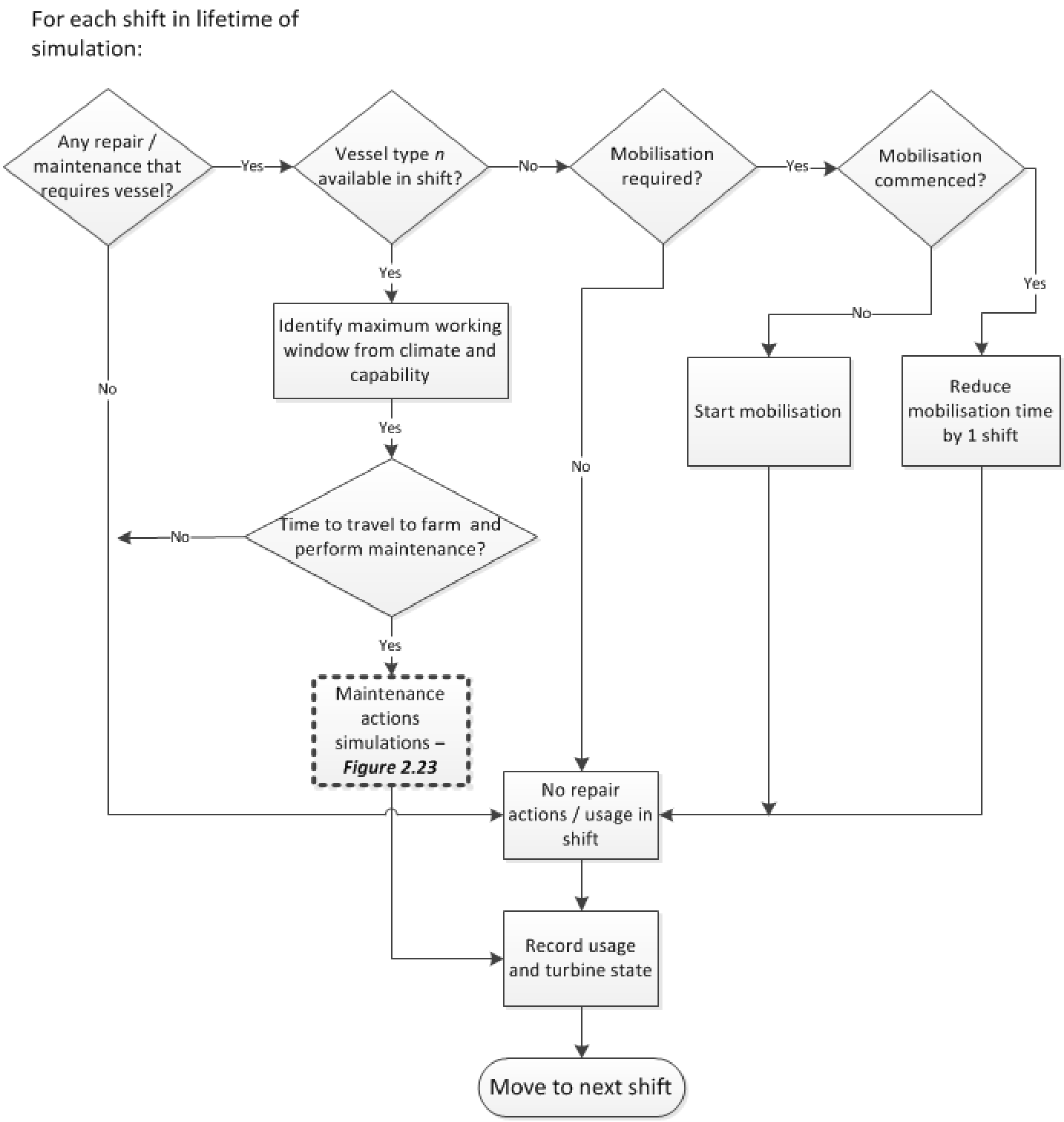

Figure 3.23: Repair process flow chart

Initially, there is a check to ensure that repairs or scheduled maintenance are required within the shift for each vessel type. If no maintenance actions are required, the simulation moves on to the next vessel type until all vessel classes have been considered. If repairs are necessary, the model checks whether the required vessel is available in this shift or not. This allows the limitation of day/night working conditions for smaller vessels, seasonal constraints and the mobilisation process for specialist vessels. If a vessel is not available and requires mobilisation, the right hand branch of the flow chart is followed and turbines remain in a failed state until the vessel is available. In the case of jack-up vessels, mobilisation time is highly variable and is therefore represented by a random value drawn from a triangular distribution with optimistic, expected and pessimistic values input.

Where vessels are available to perform maintenance in a shift the maximum available working shift is calculated, based on climate constraints, is identified. If sufficient time for transfer to the wind farm and perform maintenance is available the repair process is simulated as shown in Figure 3.24. The priority of the model is to maximise availability. Therefore, corrective maintenance is prioritized over scheduled maintenance and the vessel will visit the turbine that can be repaired in the shortest time first. A technician team may only visit a single turbine in a shift but CTV teams can perform scheduled maintenance having completed a corrective repair while waiting to be collected by a vessel.

Within the defined operational window at the wind farm, vessels travel to and from turbines and technicians are allocated to repairs until resources are fully deployed or there is insufficient time remaining. When a maintenance action is completed within a window. At the completion of the shift, the use of resources and status of repairs and scheduled maintenance is recorded.

Helicopter repairs are simulated using the same process as CTVs. However, access is limited by wind speed, there are a limit on the number of annual flight hours and priority is always to use CTVs if possible due to lower operating costs.

For number of available vessels:

For each hour in working window:

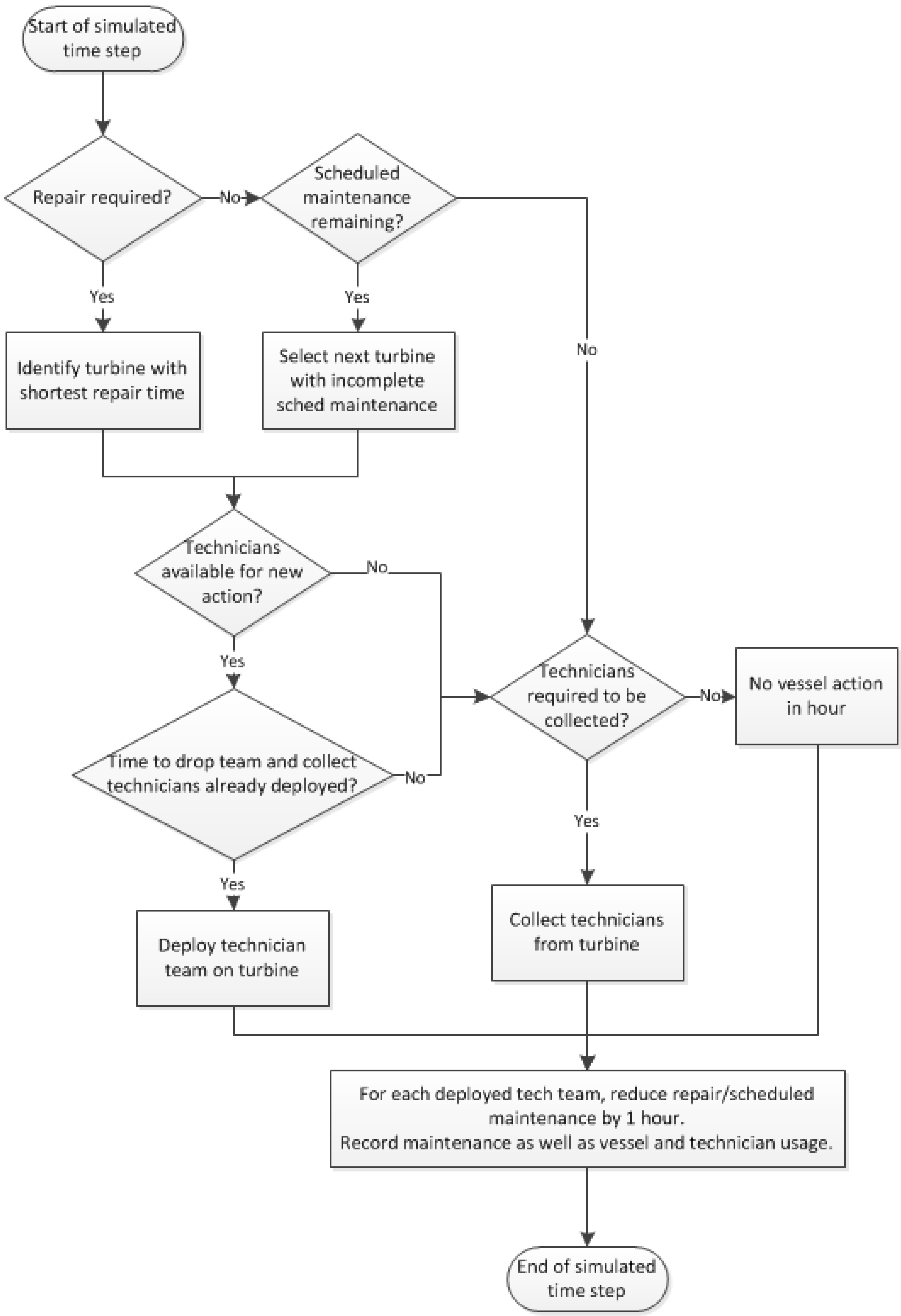

Figure 3.24: Maintenance actions simulation

Having simulated each shift in the life time operation and recorded the turbine state and resource utilisation in each step, it is possible to output lifetime performance metrics for further analysis. A turbine under corrective or scheduled maintenance is considered not operating for the purpose of availability calculation in Eq. (3.28) and is used as the key performance metric. By calculating the power production that an operating turbine would produce in each time step, the turbine state can be used to calculate power produced and the lost revenue associated with down time. Costs associated with repairs are informed directly by the number of completed maintenance actions. Vessel costs are calculated based on utilisation and the number of mobilisations which are recorded in each shift. The resultant values recorded for each lifetime simulation are passed to holding matrices and used for convergence criteria. The average values across all lifetime simulations are used for the analysis in this thesis.

Having explored various approaches, a final methodology that allows the key influences on offshore wind to be captured via simulation has been demonstrated in this chapter. With this modelling framework specified, the OPEX model could then be built to allow detailed analysis to be carried out. The initial focus of analysis, on the influence of wind and wave climate on operational performance and costs, is carried out in Chapter 4.

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Chapter 4

Analysis of operational climate on offshore wind OPEX

As part of the literature review, it was identified that operational climate has a significant impact on the accessibility, and consequently availability, of offshore wind farms. In this chapter, an initial analysis of sites around the UK is performed to determine the degree to which wave and wind characteristics vary and then used to determine what further investigation was required.

The development of the climate model required detailed scrutiny of publically available wind and wave data at offshore sites. This has provided new insights into nature of the climate at these sites and in particular the ability of the modelling approaches to adequately represent the variability observed in the data. The capacity of the model to capture variability between sites has then been studied and these findings are discussed.

Having explored the climate model, it has been integrated with the failure model and a detailed examination of the site with the most data, Egmond aan Zee (OWEZ) performed. The model was shown to be capable of accurately reproducing the observed operational performance.

Using the OWEZ wind farm as a base case, the influence of wave climate on availability at various sites was simulated and compared with available data. The results and implications of this are then discussed.

4.1 Initial analysis of wave climatology

Figure 4.1 shows the location of current and future wind farm developments in the UK as well as the location of the most relevant wind and wave datasets from [4.1], labelled 1-8 for analysis purpose.

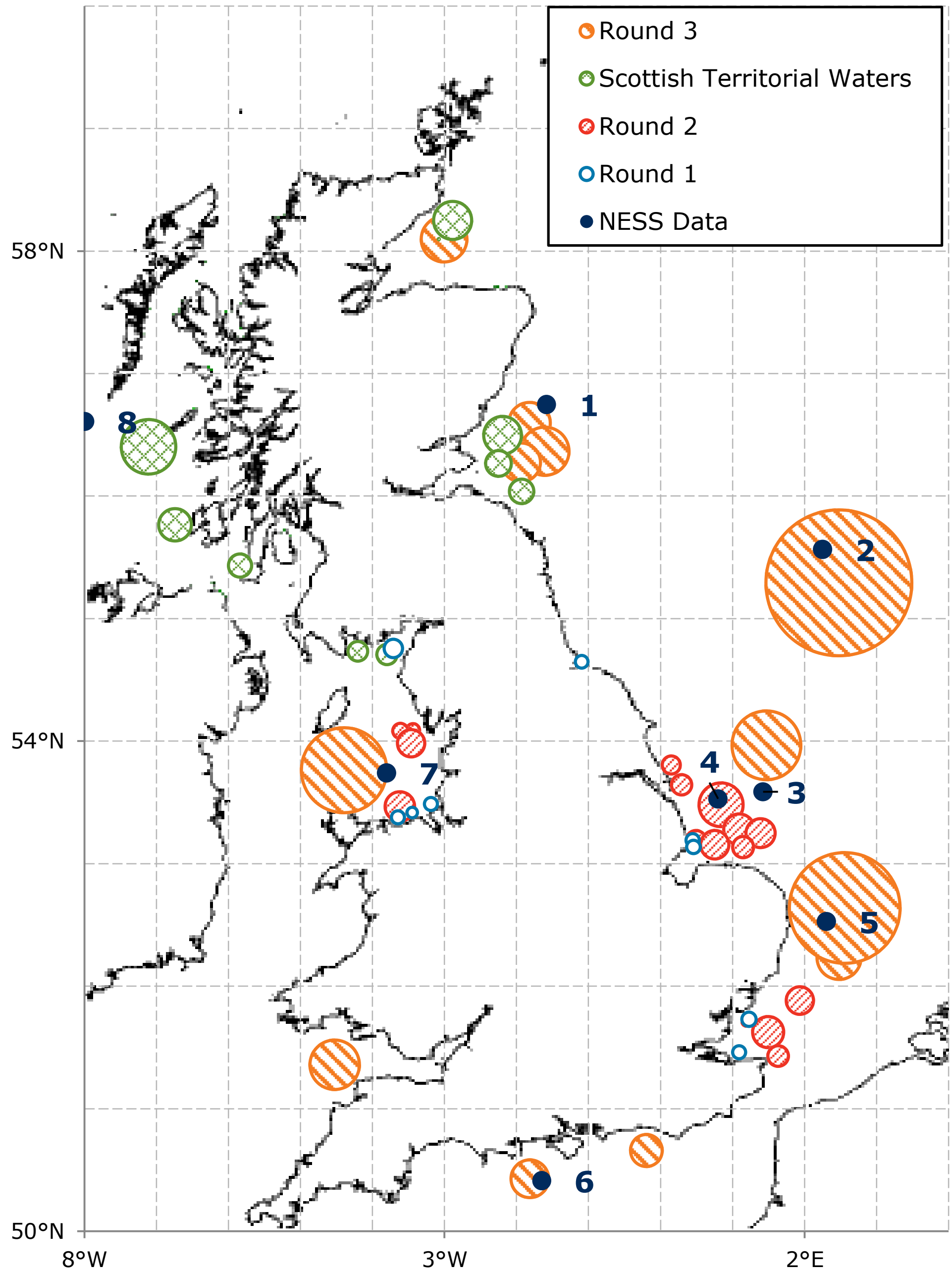

Figure 4.1: Current and UK planned wind farms sized by potential capacity and historic climate data points

Although time series data for these sites are not available, the monthly and annual exceedance distributions are. It is possible to produce a plot of accessibility versus wave height to give an indication of the importance of access thresholds and wave climate. It should be noted that important features such as duration windows are not captured in this simplistic approach.

Figure 4.2 shows an example for climate location '3' in Figure 4.1, located off the east coast of England close to several proposed Round 2 sites, Triton Knoll in particular. The overall and seasonal probability of exceeding various values and therefore being inaccessible at different significant wave height access thresholds are shown, highlighting seasonality. For a 1.5m wave height access threshold, winter accessibility is around 70% compared to 90% for summer.

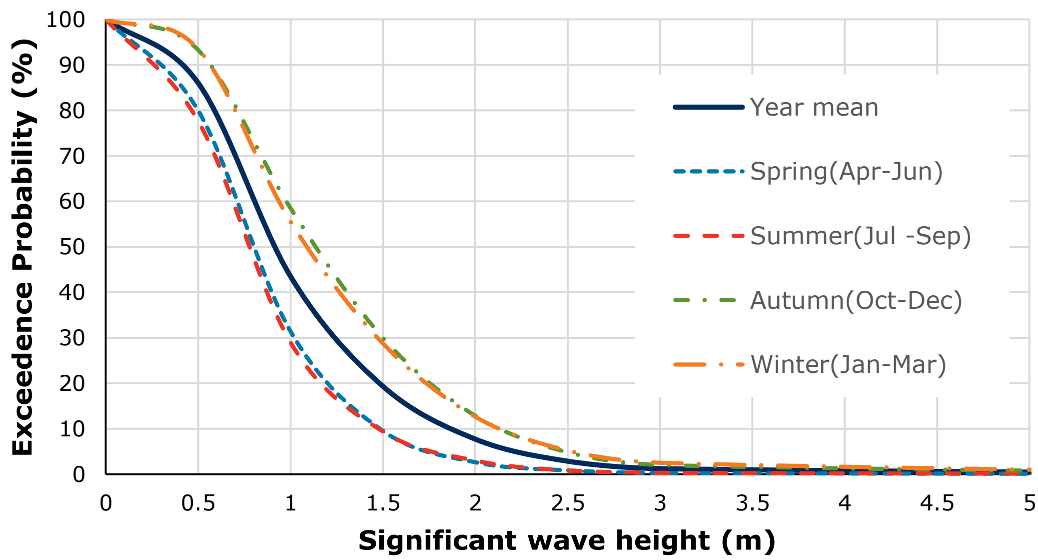

Figure 4.2: Accessibility against Hs height for different seasons

For the current industry standard access threshold of 1.5m [4.2], the probability of this threshold being exceeded is three times as likely in winter and autumn than summer and spring. Different access strategies and resource provisions are therefore likely to be optimal for different seasons.

In addition, the overall distributions at different sites were compared and is shown in Figure 4.3

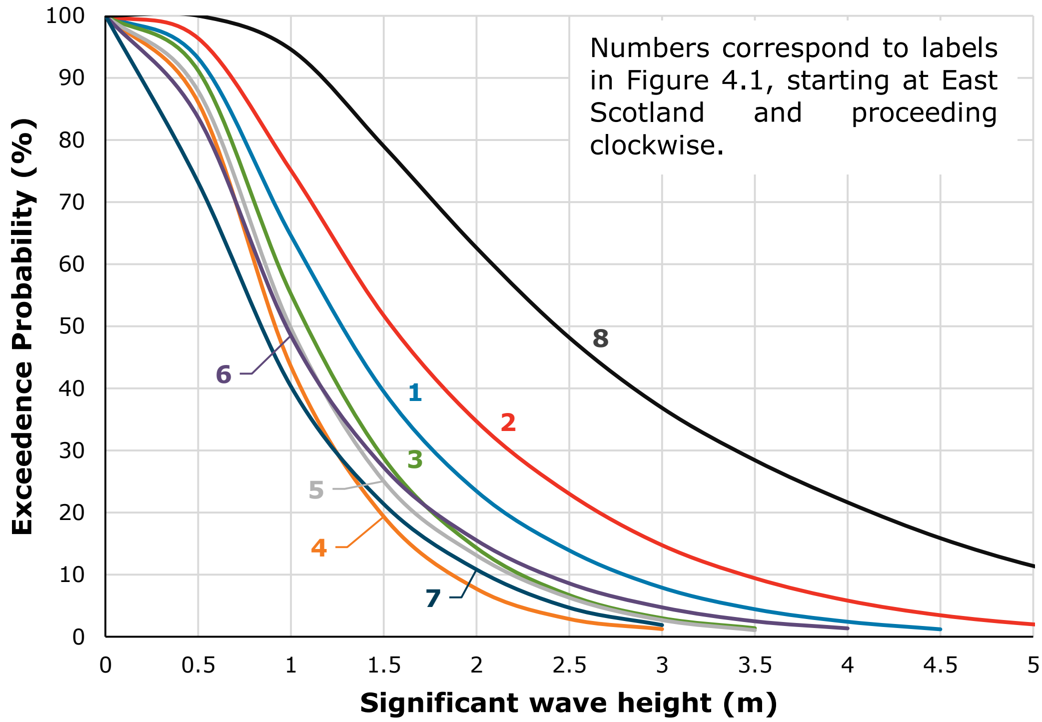

Figure 4.3: Variability in accessibility at different sea locations around the UK

The variability of wave climate at different locations around the UK is clearly significant, with a 60% difference between the best and worst sites at access threshold of 1.5m. This has implications for availability and operational costs at different sites. In particular, simply increasing the access threshold of maintenance ships to improve availability will have varying efficiency dependant on the site. The consequence of this has meant that several of the sites in more challenging conditions such as those off the west coast of Scotland are suspended until the technology involved has significantly matured [4.3]. It is also evident that while wave climate is influential, this simplified analysis approach does not provide sufficient insight into the overall influence on OPEX.

4.2 Climate model parameterisation

One characteristic of the climate model presented in Section 3.3.3 is that for different sites the optimum value of the Box-Cox transformation co-efficient Λ must be determined. Testing the model on various climate data sets has identified this value to be in the range of 0-0.3. The process of model parameterization is described below for the FINO met mast which represents the highest quality publically available measured data in the North Sea [4.4] and has been used for the climate for the baseline wind farm in this work. Several key metrics for identifying the performance of the model are identified and displayed for the possible range of Λ identified in Figure 4.4.

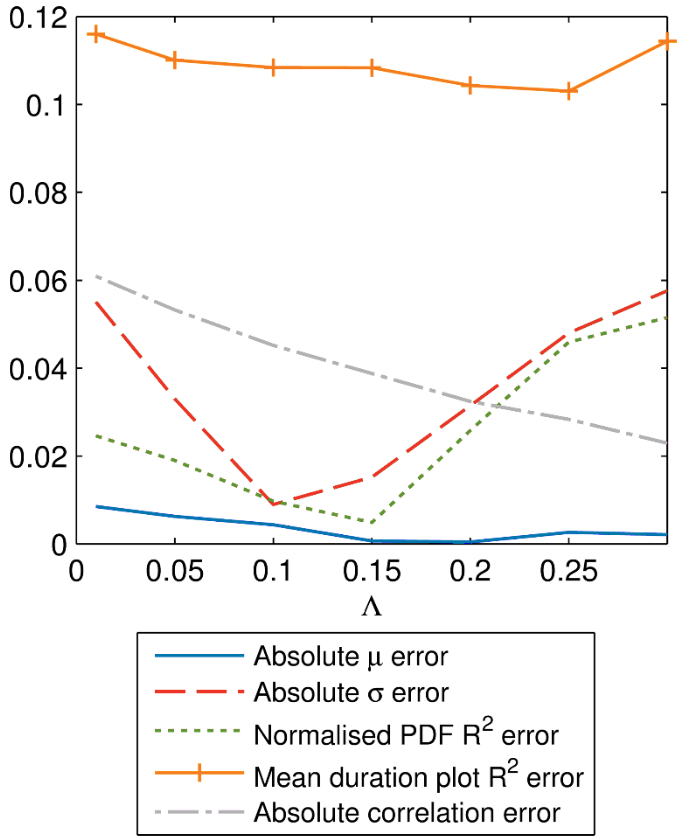

Figure 4.4: Model performance metrics for a range of transfer coefficient values identifying a preferred value of 0.15

The metrics chosen were defined as the absolute error in mean and standard deviation values of the lifetime dataset and simulation sets; the R^2 error of the normalized lifetime probability density function (PDF) which corresponds to the annual distribution of wave values; the R^2 value of duration probability windows at various access thresholds and the absolute error in the value of Pearson correlation coefficient between the wind and wave time series of the data set and simulation.

Figure 4.4 shows that over the identified range of Λ, the optimum value of 0, 0.15 or 0.3 varies depending on the chosen performance metric. Absolute mean, standard deviation and annual duration error are minimized in the range of 0.1-0.15 whereas the correlation error shows a linear improvement while increasing Λ and no clear trend is evident with duration plot error. Depending on the modelling requirement, different weighting or optimization on different performance metrics may be chosen. This challenge is demonstrated further in Figure 4.5 and Figure 4.6 which show the impact of changing Λ on annual distribution and access probability.

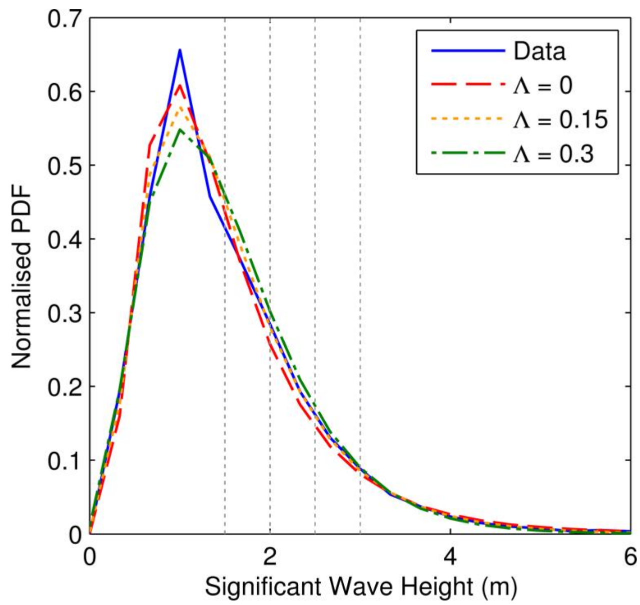

Figure 4.5: Normalized PDF plot representing annual distribution of the data set and model for three cases of Λ.

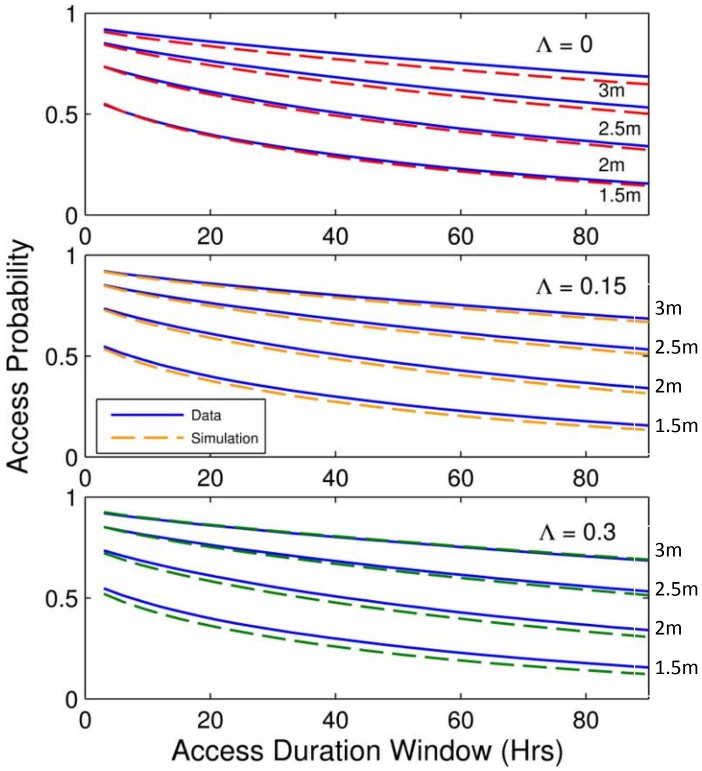

Figure 4.6: Access probability duration curves for a range of transfer coefficient values and wave climate access thresholds.

In Figure 4.5 the largest error observed in the model in all cases is at the modal peak value in the data set at 0.8 m. The error is smallest for a Λ value of 0 showing that this value best characterizes the lower value wave climate. However, the area of principle interest for the offshore wind application is in the range of 1.5m – 3m, representing typical current wave climate access thresholds of 1.5m and the targets for improved accessibility. In this region the model performance is best with Λ = 0.15. The ability of the model to better represent different areas of the overall wave climate is illustrated in Figure 4.6. The access probability curves represent the likelihood of a sufficient weather window being present at access thresholds from 1.5m – 3m. The distribution across this operation range is closely replicated with Λ = 0.15 whereas with Λ = 0 and 0.3, the access probabilities show errors at low and high access thresholds respectively. For maximum modelling flexibility a value of Λ = 0.15 is therefore the optimum parameter for this metric. However, if a study was focused on future access systems at an extreme site where access thresholds of 3m or greater were desired, Λ = 0.3 would become preferable.

It has therefore been identified that different transformations will be preferable depending on the analysis that is being carried out. It is computationally unfeasible to carry out a detailed optimisation study for each variable and every scenario to determine which parameter to optimise for and still produce a useable OPEX model. Therefore, for this thesis, a general approach based on the best transformation to normality, measured by skewness was adopted as described in [5.5, 5.6]. Skewness is defined in Eq. (4.1) where μ and σ are the mean and standard deviation of the data and E(x) represents the expected value of the quantity x. The skewness of the normal distribution is zero therefore the optimal value for Λ is the one that minimises Eq. (4.1) as shown in Figure 4.7 where the wind data is most skewed. All subsequent climate simulations adopt this procedure.

$$s = \frac{E(x-\mu)^3}{\sigma^3} \qquad \textbf{(4.1)}$$

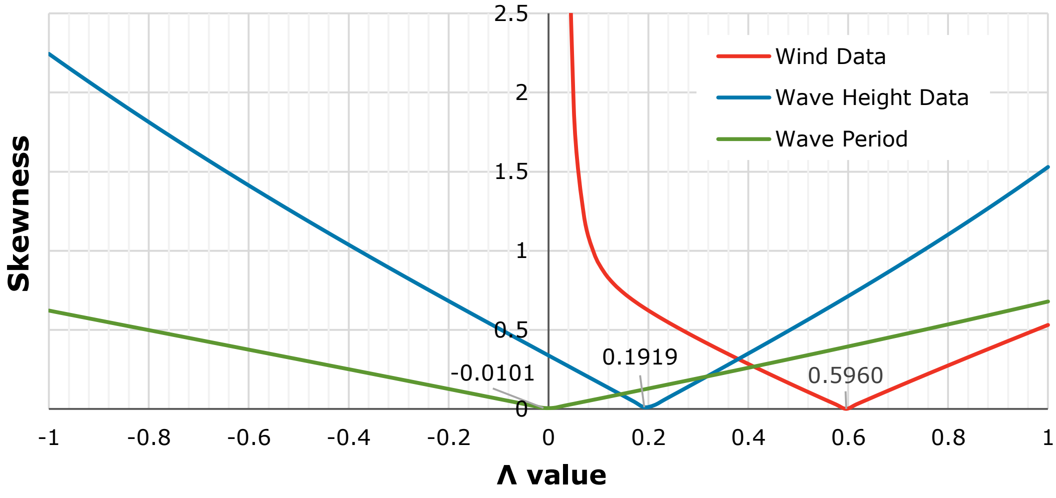

Figure 4.7: Lambda optimisation by minimising skewness

The same performance metrics for the observed and simulated wind speed time series are shown in Figure 4.8 and Figure 4.9 for a single Λ value. The annual wind speed distribution is replicated in Figure 4.8 showing close agreement between the model and data.

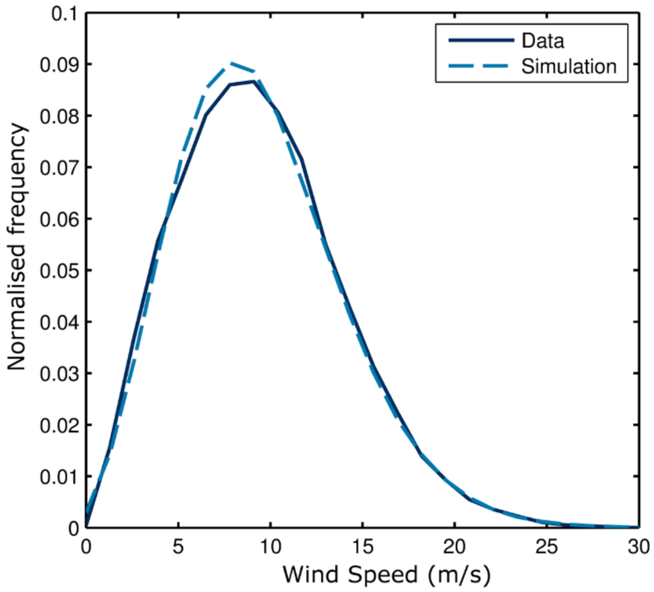

Figure 4.8: Normalized PDF plot representing annual distribution of the data set and model for wind speed

It can be seen in Figure 4.9 that the modelling approach replicates the access duration windows at 8m/s and 10m/s although the longer duration intervals at higher wind speeds are not characterized as well. This result suggests that the simple wind modelling approach does not fully capture the complex nature of calms and storms which are observed in the offshore wind environment. Additional de-trending, inclusion of a dimensional component and transformation of the wind data have been identified for future research.

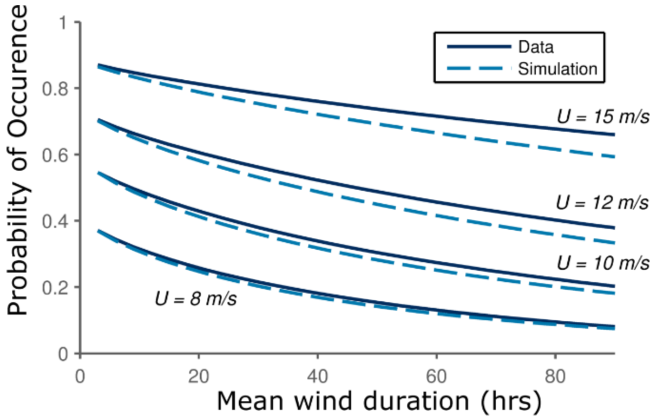

Figure 4.9: Access probability duration curves for a range of transfer coefficient values and wind climate access thresholds

The determination of optimal model order for this data set was found to be 16 using the *arfit* algorithm. This explains the model deviating from observed data at longer duration intervals. The poorer performance at higher wind speeds can be explained by the nature of the wind. High wind speeds are often associated with storm periods but have a low occurrence in total. The model preserves the occurrence probability but not storm behaviour and therefore the likelihood of a window without occurrence is higher in the simulation than data. Wind speed will limit two categories of maintenance. Access thresholds for helicopter based maintenance requiring short access duration or major replacements involving blades and drive train replacement which require lower wind speed thresholds. The model captures both these characteristics well. In all cases the modelled time series can be considered conservative in that the probability of observing an adequate access window is greater than that observed in the data. Increasing the order of the model becomes computationally inefficient and there is no requirement to capture the longer term duration windows.

The important short term dependency behaviour observed in the model and data is shown using an auto-correlation function plot in Figure 4.10. This figure identifies that for up to 24 hours the wind and wave models accurately replicate the structure observed in the data. The partial auto-correlation function plot, described in Section 3.3.2 is shown in Figure 4.11 demonstrating that the underlying lag structure in the auto-correlation function is captured and is not significant.

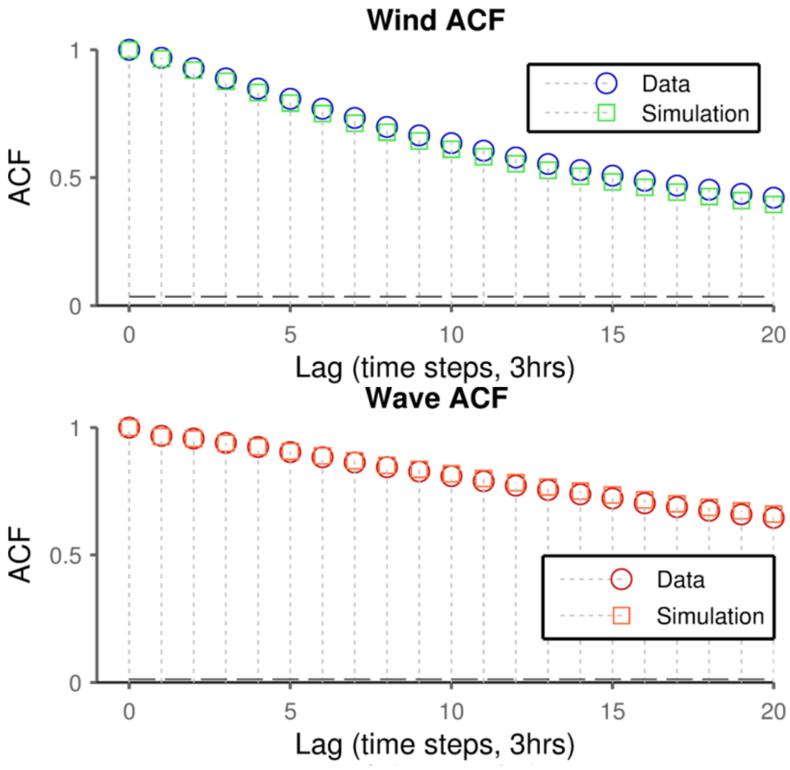

Figure 4.10: Autocorrelation function for wind and wave data and model series showing short term correlation is captured.

The correlation between wind speed and significant wave height is also required in order to capture repair operations that are dependent on wind and wave speed as well as the lost revenue associated with down time that is driven by wave climate access. This is demonstrated in Figure 4.12 which plots wind speed values and corresponding significant wave height as well as specifying the observed and simulated Pearson Correlation Coefficient. The measured correlation and general structure of the data is replicated in the simulated time series although the previously identified wind bias at zero wind speed can again be observed. Periods of high wind speed and wave height are also poorly reproduced as they represent abnormal, storm conditions that the model does not incorporate. These effects have limited implications for operational range considered in this work however extreme events may impact on failure behaviour and revenue and are identified as an area for future model development.

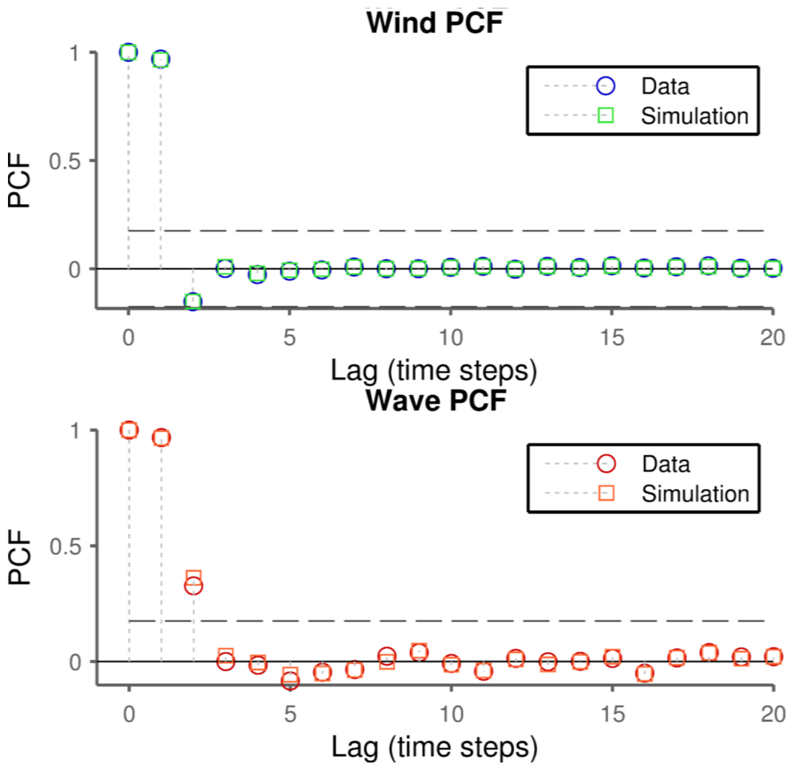

Figure 4.11: Partial autocorrelation function for wind and wave data and model series showing short term correlation is captured.

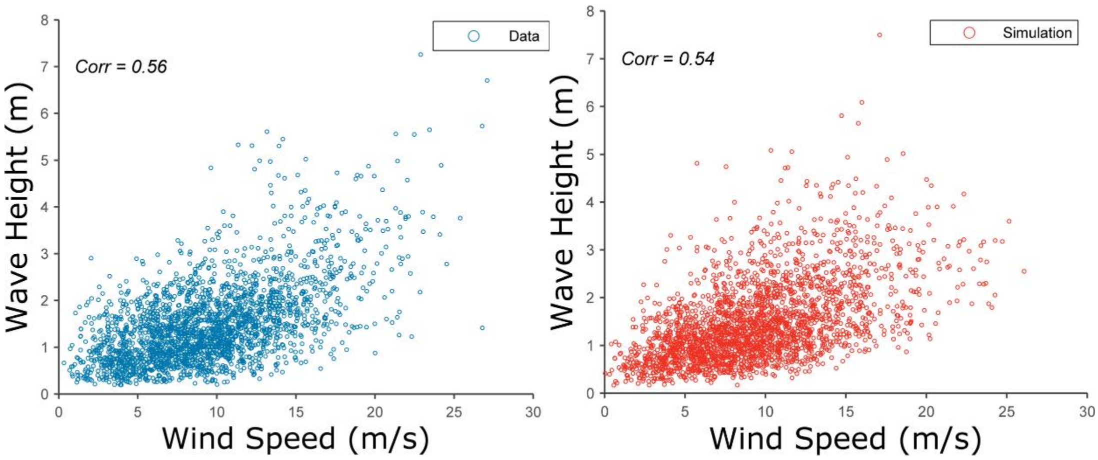

Figure 4.12 Correlation between wind speed and significant wave height for observed and simulated data sets showing structure is maintained

The final characteristic required for an adequate climate model is that seasonality is preserved. As previously identified, in summer months wind and wave climates are relatively calm and therefore accessibility is improved. However, this coincides with higher vessel market rates due to increased usage and a maintenance strategy based solely on spring and summer seasons may result in lower availability in autumn and winter seasons when lost revenue will be highest.

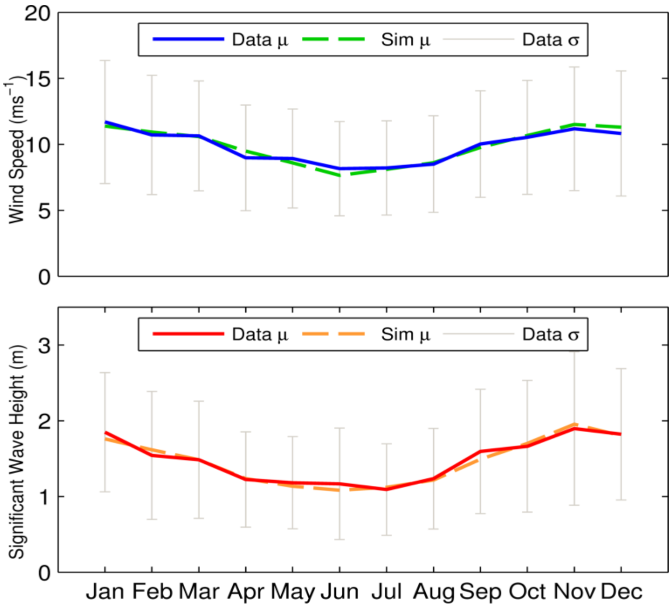

Figure 4.13: Seasonal means in data and simulation and standard deviation of data

It can be seen from Figure 4.13 that seasonality is strongly preserved between the data set and simulation results indicating that the presented methodology captures this characteristic of the climate. It can also be noted that there is a large standard deviation in mean wind speed and significant wave height relative to the mean values. This has implications for inter annual variability of accessibility and production and uncertainty associated with operational costs discussed later.

4.3 Variability of FINO wind and wave climate

The lack of quality, continuous wave height data for scrutiny has previously been discussed in Chapter 2 . Wind data of longer time spans is more readily available although not in the offshore context. The FINO measurement mast therefore provides an excellent source of data to study the offshore wind and wave climate [4.4]. Onshore, the subject of variability has been well studied and has been shown to lead to variations in ± 10 % in annual energy capture [4.7]. An assessment of the variability in offshore climate including wave height has been performed in order to provide a better understanding of the changeability and corresponding risks involved in the offshore environment. Simulation results for both wind speed and wave height have been analysed to see how well they capture the variability.

The availability and quality of data is shown in Figure 4.14, separated by year and with gaps where no data has been reported and the data is quantified in Table 4.1. The quality of wind data is significantly better than that of wave data with under 5% of data is missing whereas approximately a fifth of all wave data missing. Comparing the annual deviation from the overall mean value, the poor quality of the wave data results in higher average and extreme deviations. The consequence of this is that there is likely to be greater variability and uncertainty in availability predictions than power production for offshore wind farms.

Table 4.1: Quality of FINO dataset

Variable	Missing data (%)			Deviation from mean (%)		
	Mean	Low year	High year	Mean	Low year	High year
Wind	3.37	0.11	9.27	2.67	0.33	9.17
Wave (sig. wave height)	22.95	8.56	46.68	5.72	1.12	13.63

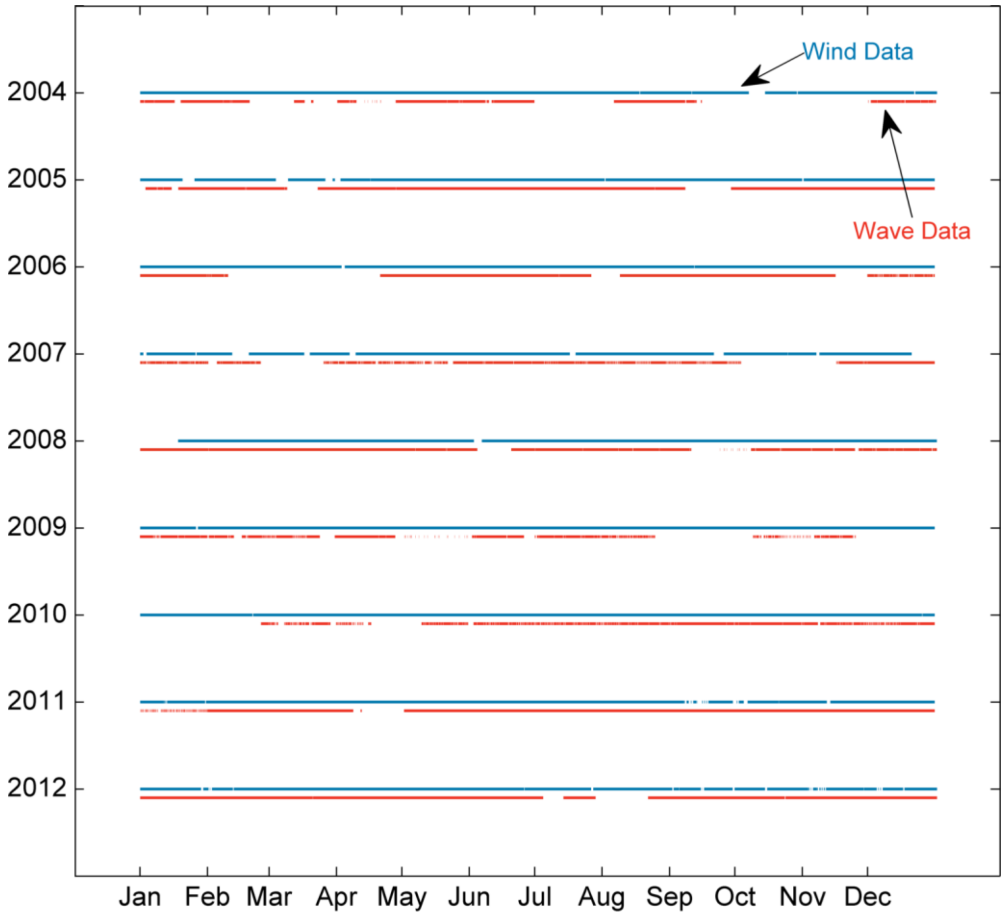

Figure 4.14: FINO climate data quality by year

These results highlight the difficulty in obtaining good quality wave data as gaps of weeks and months are not uncommon. This is due to the harsh environment wave buoys operate in and the difficulty in accessing them to perform maintenance. The poor quality of data in some years results in the potential for biasing if simulations are based on these data. For example, in 2009 there are large gaps in the data from September to December and the resulting mean is 13.6% lower than the global average. Any simulation model is only as accurate as the data it is based on. While the data sets cannot necessarily be improved, understanding the consequences of variable quality of data allows better understanding of risks. An investigation into this area was therefore performed as well as a study of how well the developed model captures this uncertainty.

4.3.1 Investigation of climate variability on availability and power produced

The variability in annual wind and wave distributions at the FINO platform are shown in Figure 4.15 and Figure 4.16. The thick dark line in both distribution pictures represents the mean annual distribution from the data.

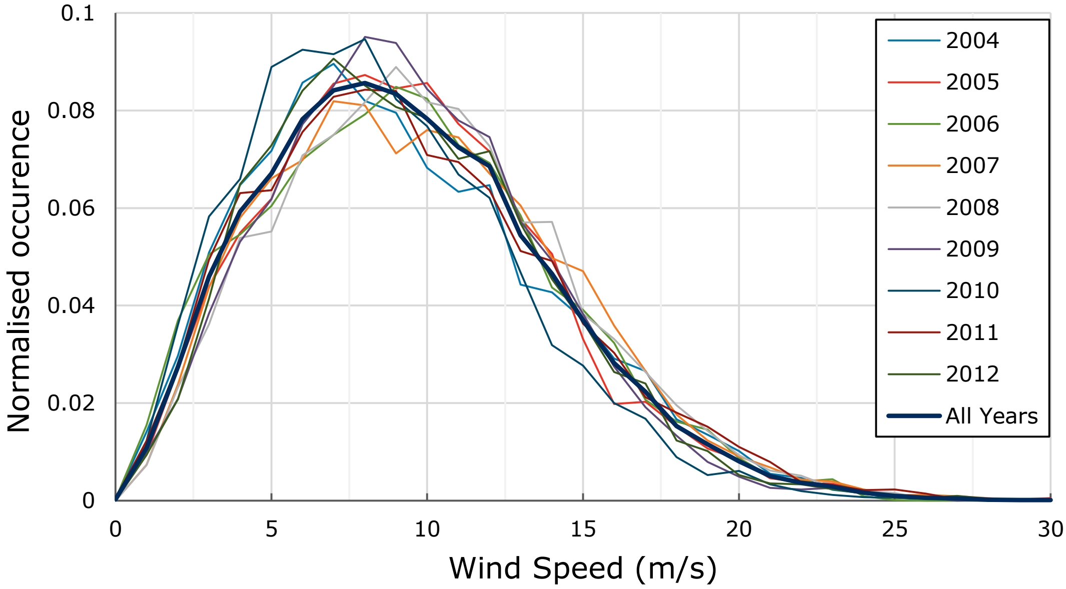

Figure 4.15: Annual wind speed distribution at FINO platform

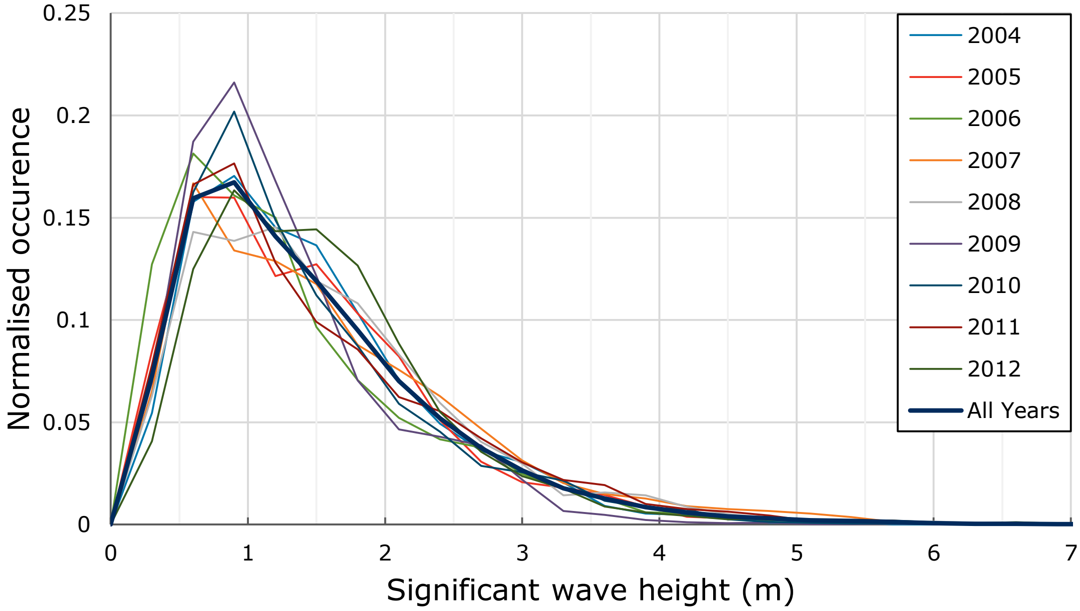

Figure 4.16: Annual wave height distribution at FINO platform

In order to assess the impact of this variability an estimation of the impact on power production for each year was estimated. This was done by taking the wind distributions at each bin, *W(U),* and multiplying them by the power produced in each bin for a 5MW wind turbine power curve, *p(U)*, to determine the expected annual power for the turbine given the wind profile. This is a simplified approach to solving Eq.(4.2) which is the average power for a wind turbine assuming 100% reliability [4.8]. Average power per hour (excluding hours with missing data) was calculated and multiplied by 8760 to estimate annual power production.

$$\overline{Power} = \int_{u=0}^{\infty} W(U) \cdot p(U) du \qquad \textbf{(4.2)}$$

The power curve used is the NREL 5MW turbine [4.9][1], the power curve for which is shown in Figure 4.17 and the resulting annual power productions are shown in Table 4.2.

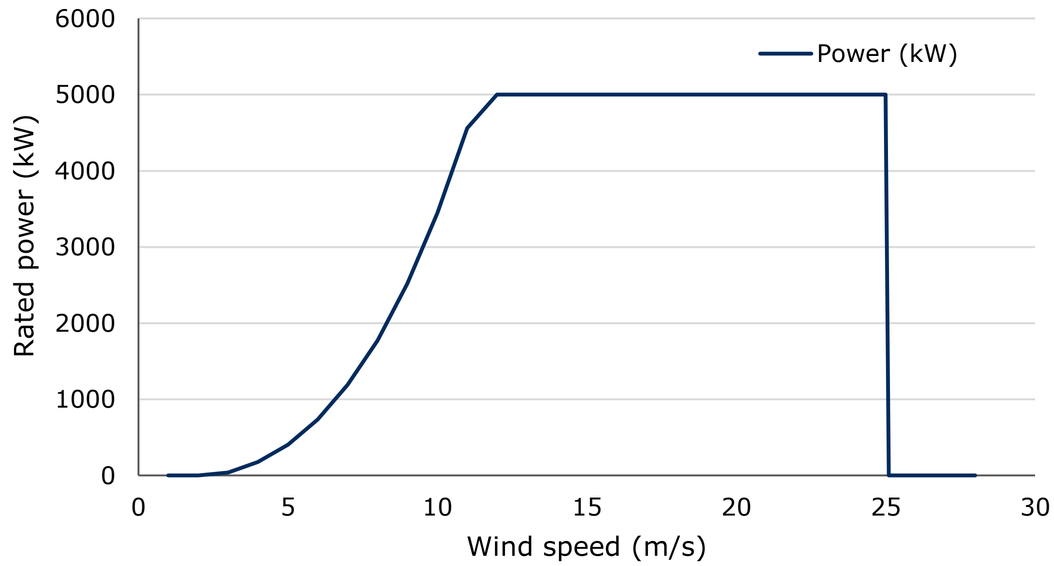

Figure 4.17: Power curve for the NREL 5-MW specification turbine

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[1] Numerical values used for specification of this turbine were provided directly by the author of [4.9] for which the author of this thesis would like to express gratitude.

Table 4.2: Estimated annual power production for single turbine at FINO

Year	Power produced (MWhr)	Deviation from mean
2004	2.27E+04	-3.92%
2005	2.39E+04	1.31%
2006	2.41E+04	2.07%
2007	2.47E+04	4.82%
2008	2.56E+04	8.37%
2009	2.41E+04	2.14%
2010	2.06E+04	-12.87%
2011	2.36E+04	-0.15%
2012	2.34E+04	-0.95%
Average	2.36E+04	

This analysis ignores the influence of reliability and so over estimates the fluctuation in power that is expected at a single site. However, it provides an approximation of the range of values that should be expected over a wind farm life time. Using the full simulation model, a 10 year simulation run was simulated (with no failures) to demonstrate the ability of the model to capture the variability in the wind climate. The simulated equivalent of Figure 4.15 and the range power produced are shown in Figure 4.18 and Figure 4.19. Comparing Figure 4.15 and Figure 4.18, the model does not display as significant variability. However, there are inter-annual variations with a similar magnitude, particularly around the wind speeds from 5-15 m/s which are critical for this application. The reduction in variability is largely accounted for by the smoothing effect of the gap filling process. The critical requirement is that the model reproduces the inter-annual variability on power produced to provide a greater understanding on the uncertainty associated with OPEX. Analysis of this is shown in Figure 4.19.

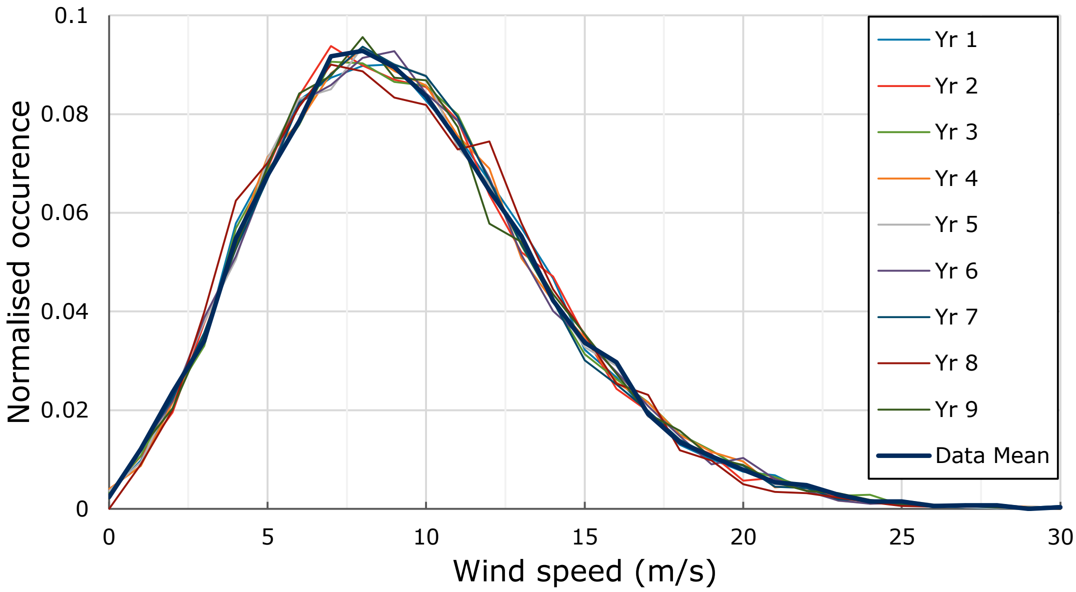


Figure 4.18: Simulated annual climate variations

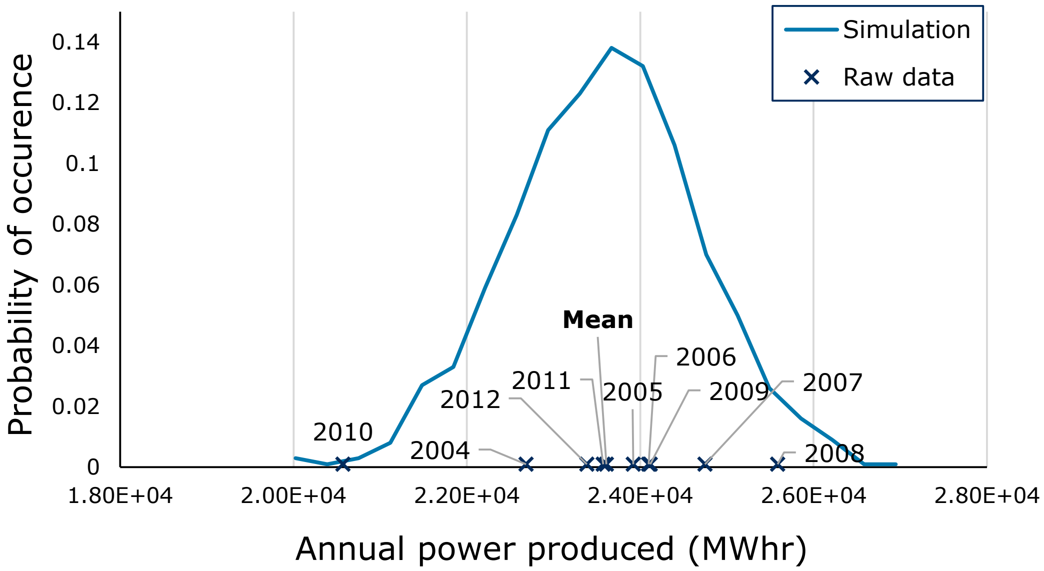


Figure 4.19: Power production simulated and calculated from FINO

Figure 4.19 shows the distribution of simulated annual power production as well as the calculated annual power production from Table 4.2. The results show that the model is accurately capturing the variability due to inter-annual wind variation. It should also be noted that the mean wind speed of 2010 is particularly low due to lack of data in January to March but even this extreme case falls within the limits of the simulation.

A similar analysis of the wave climate and model based on availability is not possible as availability is not purely driven by wave climate. Therefore the variability of wave climate is best examined purely by a direct comparison of the observed and simulated annual distributions and monthly mean values. This was done by comparing Figure 4.16 and Figure 4.20 and examining Figure 4.21. It can be seen that the wave model is more representative of the inter-annual variation observed in the annual distribution and mean than the wind model; the inconsistency in availability due to climate is therefore captured.

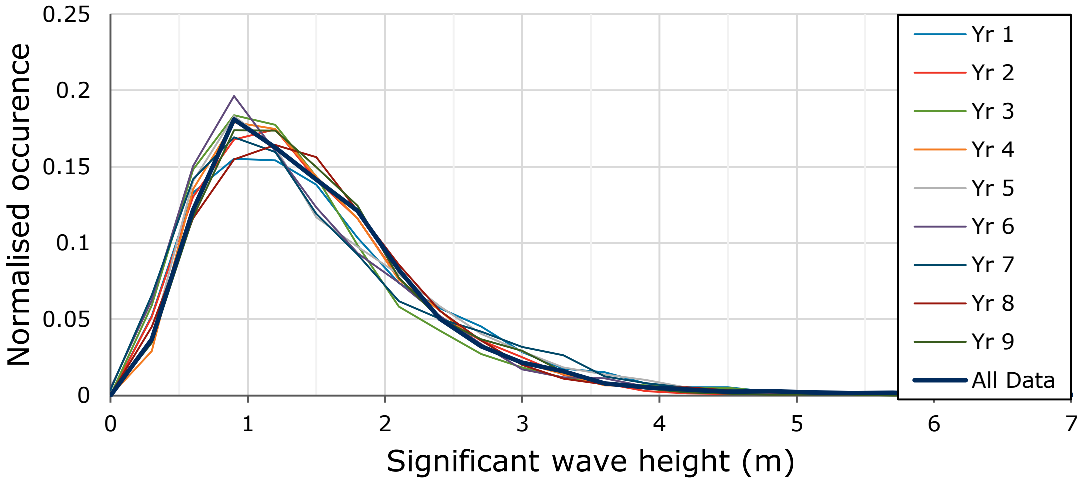


Figure 4.20: Simulated wave height annual distributions and average data distribution

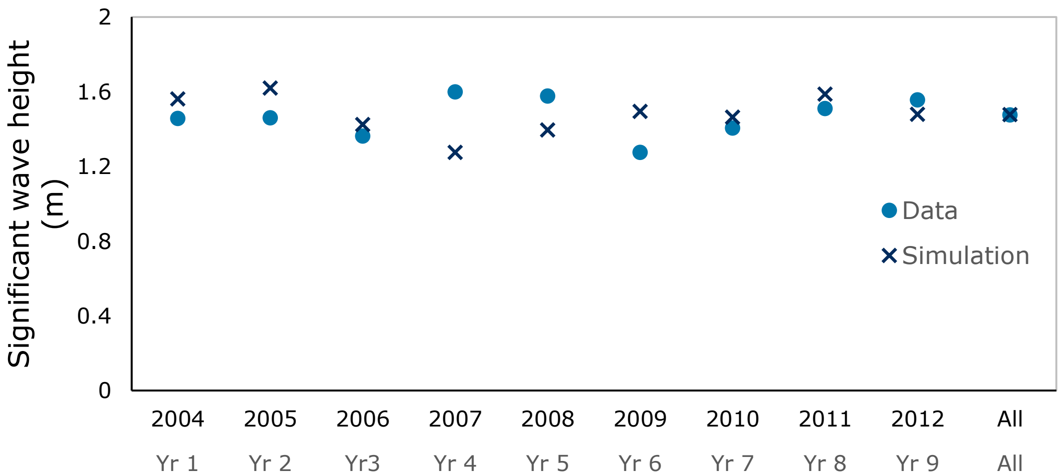


Figure 4.21: Observed and simulated yearly mean wave height

4.4 Detailed assessment of OWEZ

Having fully developed the climate model for this work, it was possible to perform an initial analysis of the impact of wave climate on wind farm availability. As OWEZ provided both the most detailed annual operations reports and climate information [4.10], it was used to validate the model. Observed failures over the first three years of operation and resulting down time are displayed in Table 4.3 with availability, accessibility and climate shown in Figure 4.22.

Table 4.3: Failure Rates from OWEZ Reports

	2007-2009 'Stops'	Total/ Turbine/Yr	Downtime (hrs)	Downtime /failure
Ambient	1204	11.15	1788	1.49
Blade	180	1.67	3227	17.93
Brake	40	0.37	319	7.98
Control	8788	81.37	17911	2.04
Converter	644	5.96	6868	10.66
Electrical	615	5.69	3840	6.24
Gearbox	1643	15.21	104366	63.52
Generator	682	6.31	28333	41.54
Pitch	2145	19.86	9302	4.34
Scheduled	3522	32.61	9015	2.56
Yaw	4810	44.54	1644	0.34
Structure	173	1.60	822	4.75
Grid	68	0.63	746	10.97
Total	**24514**	**226.98**	**188184**	

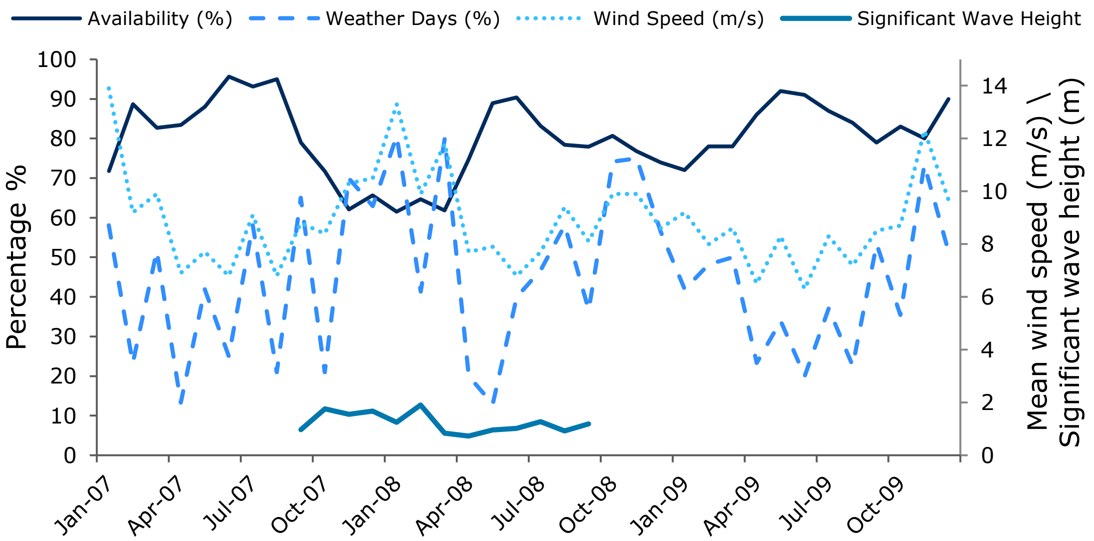


Figure 4.22: Summary of OWEZ performance and climate

It was established previously that the majority of reported stoppages were in fact remote resets and the figure of over 200 failures per turbine per is simply not feasible if each repair required a visit to the turbine. In fact, over the three years of operation, the total number of transfers was in the region of 800, or 7.5 per turbine per year. This includes the transfers that were for local resets, or minor repairs. For the validation modelling approach, the ratio of overall faults along with the downtime per subsystem was maintained but the number of failures were scaled to represent 7.5 transfers, per turbine per year. Additionally, various categories of maintenance may be applicable to each subsystem but this level of detail is not provided in the reports. The major drive train and replacements have MTTR over 1000 hours suggesting they required specialist heavy lift vessels. Based on adjusted MTTR, three failure classes were assigned to provide final inputs for the OPEX model. The resulting scaled failure rate and *MTTR* values are displayed along with the vessel categorisation in Table 4.4 where minor repair uses CTVs, major FSV and replacements use heavy lift vessels. The drive trains on this model were subject to a replacement campaign which is captured in this data set. Subsequent performance reported at sites using the same turbine such as Horns Rev in Denmark have significantly higher availability, above 90%.

Comparing this with published values for onshore turbines, most recently examined in [4.11] where observed annual failure rates are 2.4, this value seems high. However, other failure data does not include scheduled maintenance action and the values at OWEZ also include the repair campaigns for gearbox and generator. In addition, the harsher nature of the offshore environment is likely to contribute to higher failure rates until wind turbine design has been fully adapted for the marine environment.

A final step before carrying out the availability simulation was to determine the repair operation times for each subsystem. This would ideally be based on operator experience at the site. In the absence of this data. a similar approach to that of [4.12] was adopted where the operation time is inferred from the accessibility at the site.

Table 4.4: Adjusted failure behaviour and classifications

	Adjusted λ	Adjusted MTTR	Failure category	Repair win (hours)
Ambient	0.37	44.94	Minor repair	5
Blade	0.06	542.57	Replacement	12 (Single)
Brake	0.01	241.36	Major repair	12
Control	2.69	61.68	Minor repair	8
Converter	0.20	322.76	Major repair	20
Electrical	0.19	188.97	Minor repair	36
Gearbox	0.50	1922.43	Replacement	48 (Single)
Generator	0.21	1257.30	Replacement	36 (Single)
Pitch	0.66	131.24	Minor repair	18
Scheduled	1.08	77.47	Minor repair	1
Yaw	1.47	10.34	Minor repair	24
Structure	0.05	143.80	Minor repair	21
Grid	0.02	333.35	Major repair	5
Total	7.5			

The key outputs from the simulation are compared to the observed results in Table 4.5 and Figure 4.23 - Figure 4.25.

Table 4.5: Key observed and simulated results

	Data	Simulation
Availability	80.4%	79.83%
Power produced	320.2 GWhr	340.3 GWhr
Power lost	84.8 GWhr	78.3 GWhr

The overall mean availability for the simulated wind farm is 79.83%, consistent with the observed at OWEZ of 80.4%. This is as would be expected since the failure and climate data is based on the site and the repair windows have been calibrated with the modelling assumptions as described. There are more significant deviations between simulated and observed results for power produced and lost although they are of similar orders of magnitude. These differences can be explained by examining the simulated and observed availability in Figure 4.23.

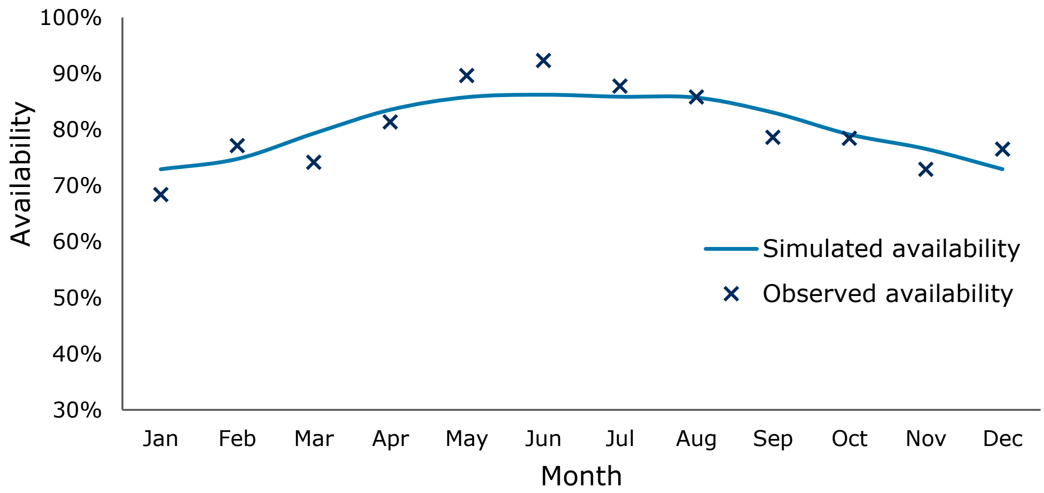


Figure 4.23: Observed and simulated seasonality

The model predicts lower summer availability and higher winter availability which would result in greater power produced and lower lost power due to downtime. This can be explained by data quality issues and a general smoothing effect of the simulation approach. There is less than three years of climate data and significant gaps in the wave time series which has lessened the magnitude of seasonal variation in the climate data used for simulation. In addition, large scale refurbishment work took place on key components in late summer and the failure simulation model does not take this into account. The wind farm therefore has lower availabilities in winter months than the model. However, the simulation does capture the variation observed throughout the year and the degree to which monthly variation occurs is of similar magnitude. The discrepancy in the results highlight that there will always be operational practicalities that simulation models fail to capture and these must be accounted for when models are used to influence operational decision choices.

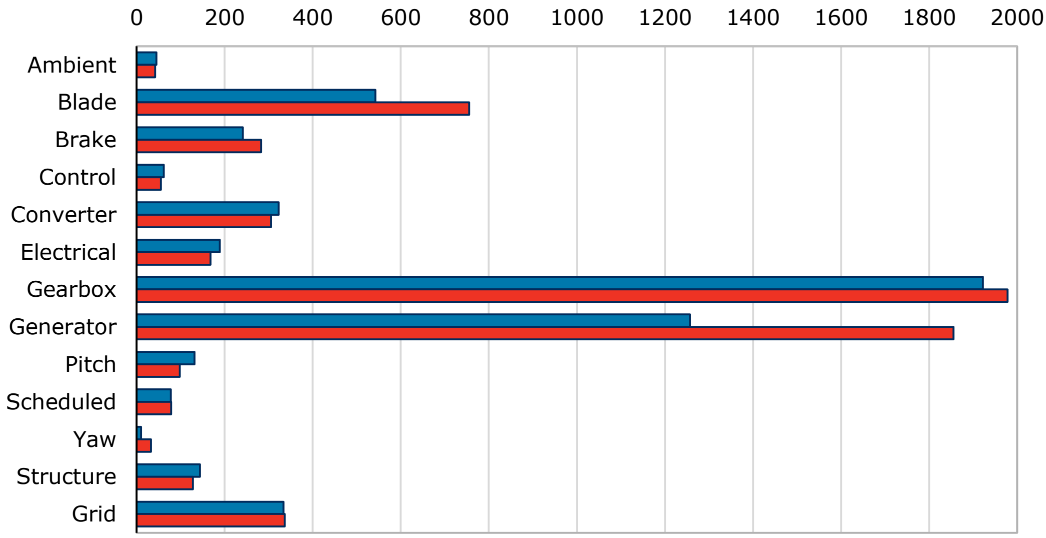


Figure 4.24: Observed and simulated MTTR by subsystem

The slightly lower simulated availability when compared to operational data can be explained by examining Figure 4.24 which shows the observed and simulated MTTR. There are a large number of factors which contribute to MTTR for offshore wind, in particular when specialist vessels are required and the vessels have to be chartered. The 'major replacement' failures were therefore less sensitive to repair window lengths than mobilisation time. The result is that the generator and blade MTTR is higher than that observed and contributed to the overall lower availability. Greater knowledge of the operational procedures would be required to fully capture this behaviour. Comparing the simulated and observed contribution to down time in Figure 4.25 shows good agreement between the two with the higher contribution of generator down time re-confirmed.

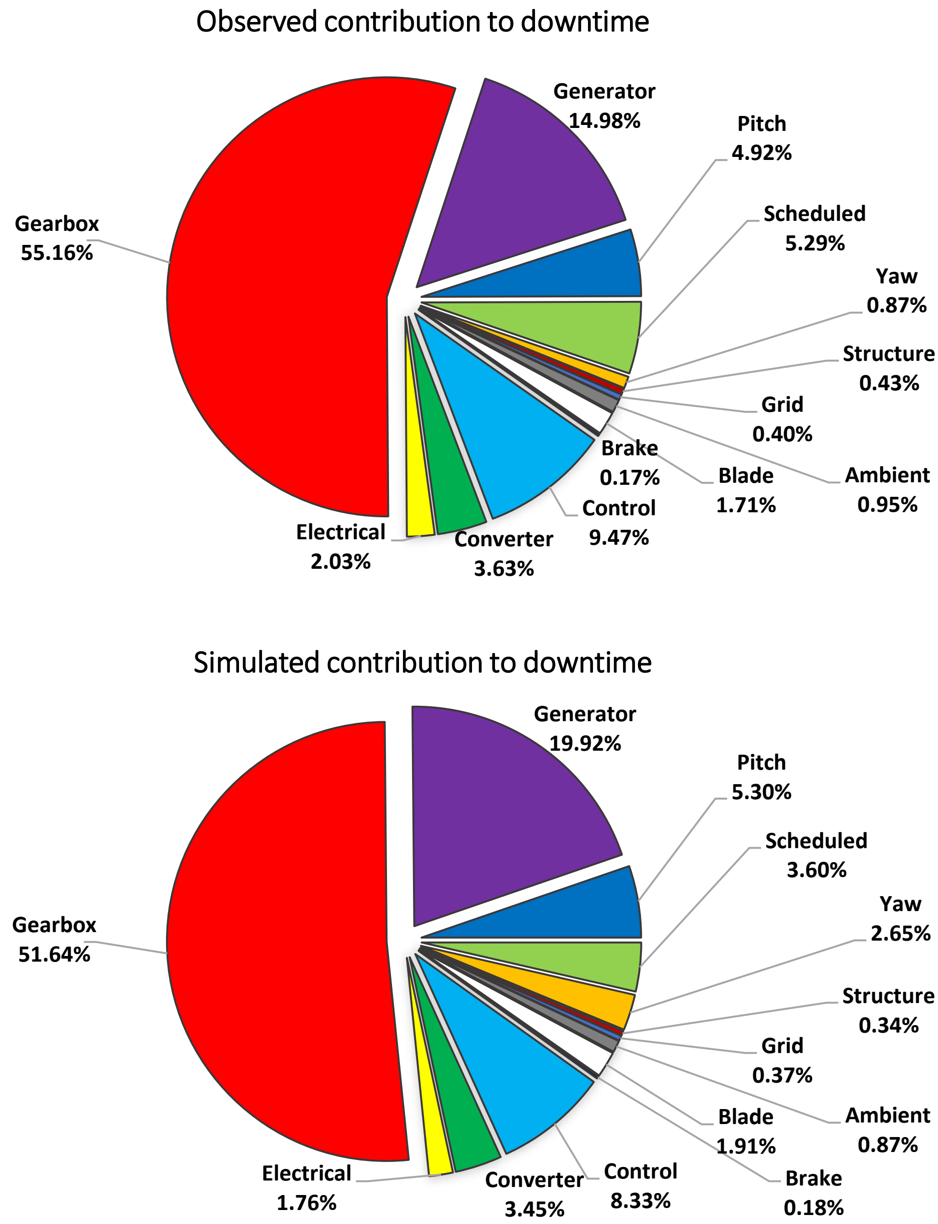


Figure 4.25: Simulated and observed contributions to downtime

This analysis demonstrates the ability of the model to replicate performance at a site when operational data is available. The data from OWEZ is only relevant to a small number of already operational wind farms with similar turbine design and wind farm size and distance to shore. The above analysis does allow the impact of climate under these conditions to be directly investigated and compared to reported operational data to provide further verification of the modelling approach. In addition, a greater understanding of the impact of climate on availability and how it can be mitigated is possible using the OWEZ failure data sets as a baseline. This analysis has been carried out in Section 4.5 for the early Round 1 sites in the UK and for a hypothetical wind farm at the FINO met mast.

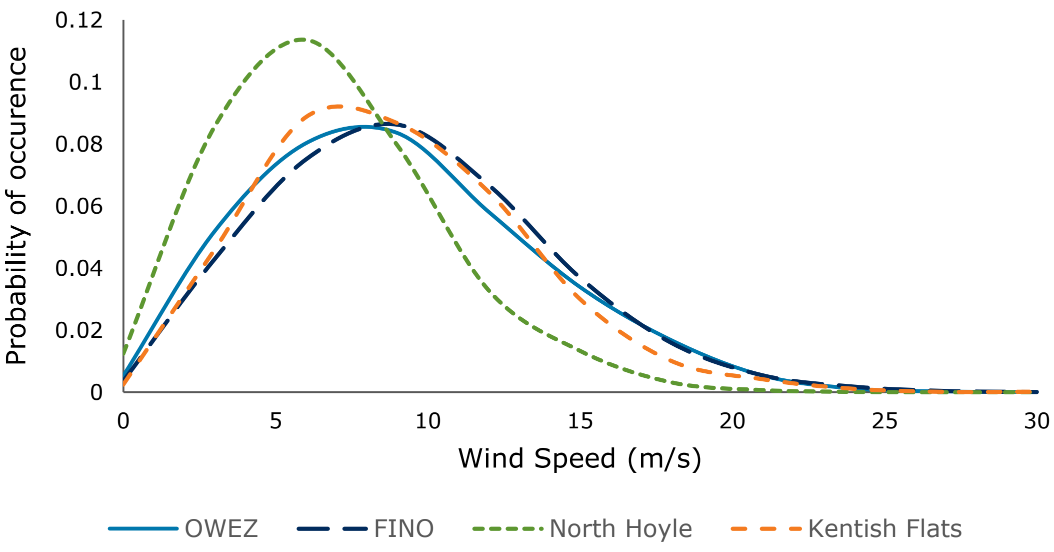
Performing detailed sensitivity analysis at the individual subsystem level has a high data requirement, is computationally inefficient and applicable only for similar wind farms. Therefore, for remaining analysis carried out on climate impact as well as the rigorous sensitivity analysis of OPEX sensitivity, the subsystem classification was changed to a maintenance action approach where the failure categories were reduced to four failure types.

4.5 Multi-site analysis

Having verified the ability of the model to replicate the performance of a well-defined site, an investigation into the influence of climate on availability could then be performed at different sites around the UK. This was achieved by using the OWEZ failure and repair data, excluding the major replacement failures, as a baseline and examining availability at other locations where climate and performance data was available. The exclusion of major replacements is due to the complexities in operations that are considered in Section 4.4. In order to validate the results, wave buoy sites were identified as close to wind farms with publically available failure data as far as possible. The exact location of the wind farms and wave buoys used in this study is shown in Figure 4.26 [4.13, 4.14].

Figure 4.26: Wind farm and weather buoy locations used for study

The observed climates at the Scroby Sands and Kentish Flats were comparable therefore for clarity only the Kentish Flats site is considered to represent both. The available performance data from Barrow was extremely limited therefore the performance data of North Hoyle was considered for this analysis despite being further away from the wave buoy. The wind and wave distributions at each site are shown in Figure 4.27 [4.4, 4.10, 4.14].



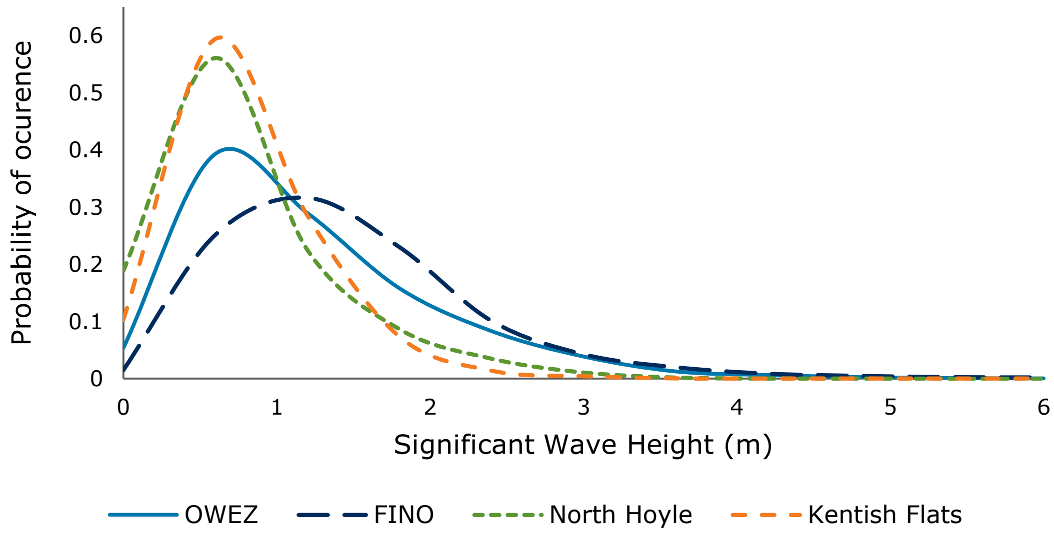


Figure 4.27: Wind and wave distributions at early wind farm sites

From Figure 4.27 it can be seen that there are two clear wind regimes while there is greater variation amongst wave conditions. The sites to the east of the UK in the North Sea have a similar annual wind speed distribution whereas the Irish Sea shows a much calmer distribution with higher probability of low wind speeds. The Kentish Flats site shows some reduction in high wind speeds due to the sheltering of mainland Britain however this effect is much more noticeable when examining the wave climates. A significantly larger proportion of total time is spent in the calm region below 1 m/s wave height is observed in the Irish Sea and close to the UK mainland than at the more exposed North Sea sites. In particular, the expected accessibility at the FINO site for a 1.5m access threshold is significantly lower and this has direct consequences for wind farm availability.

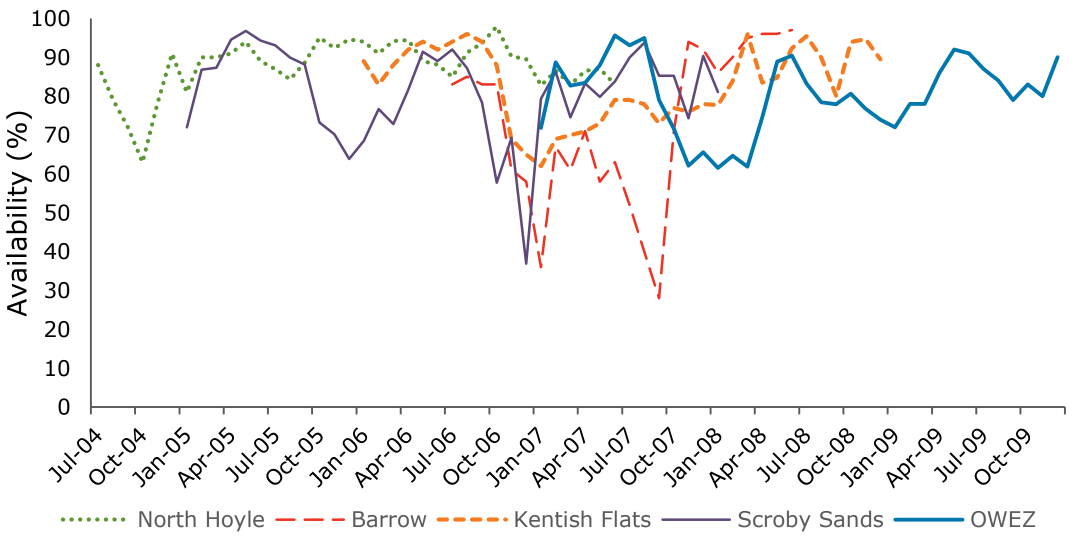


Figure 4.28: Observed availability at early wind farm sites

The monthly availability data across sites are shown in Figure 4.28. This figure is adapted from an initial analysis of UK offshore wind farm performance which also specifies issues surrounding the quality of performance data and is presented in [4.15]. There are particularly poor availability regions at Barrow and Scroby Sands which correspond to the periods when large component overhaul and replacement programs took place and therefore do not reflect the influence of climate. For the multi-site analysis, 4 sites were consequently considered. These correspond to the sheltered Irish Sea (North Hoyle), sheltered North Sea (Kentish Flats), North Sea (OWEZ) and exposed North Sea (FINO). It should also be noted that there are significant monthly variations at the observed sites, principally due to serial repairs. Climate is therefore not the only driver of availability and the model was not expected to fully recreate the observed performance. However, if general trends across existing sites are accurately replicated; future sites can be examined by extrapolating performance. It should also be noted that the wave buoys for the UK sites are a significant distance from the wave farms.

The availability of the sites, excluding major replacement of drivetrain components, were simulated with different vehicle access thresholds in order to determine the impact of weather at different operating locations. The results of this are shown in Figure 4.29 with the baseline values at 1.5m access threshold identified. The results show that the availability of an offshore wind farm is heavily dependent on the wave climate and access limits. As sites are developed in more extreme climates there will be a greater direct impact on availability. For the baseline case, a reduction in performance of 4% is observed purely driven by accessibility. This difference would be exacerbated if major replacements were included. These effects can be limited by increasing the access threshold of maintenance vessels but this will come at a potentially significant operational cost. Improved access capability can be seen to reduce variation between sites. This has the potential to reduce exposure to climate and thus uncertainty for sites in more extreme environments. Improving access constraints therefore has a benefit to the entire industry as well as individual project developments.

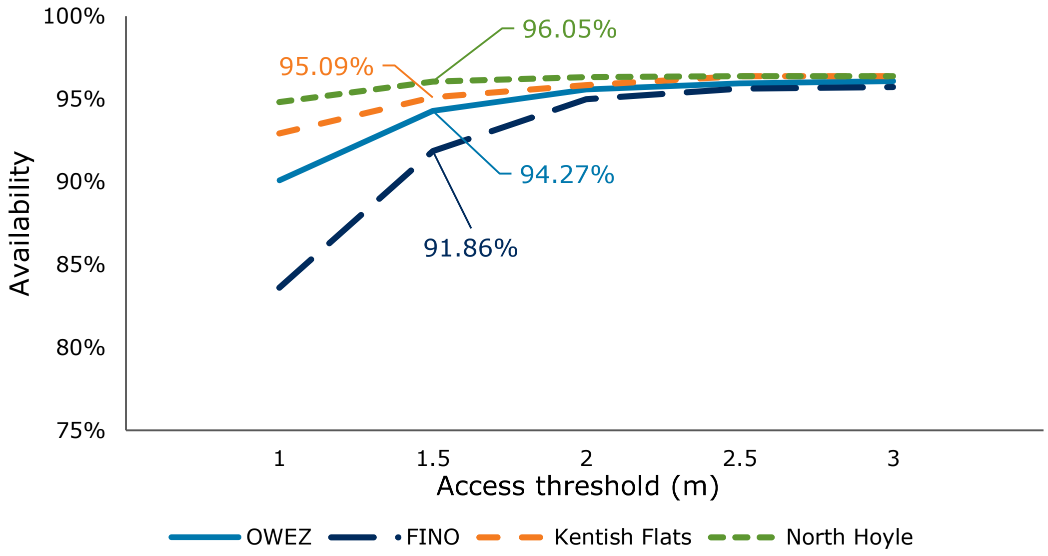


Figure 4.29: Simulated availability at R1 sites with varying access thresholds

In addition to this, simulated and observed seasonality at each site was examined and results are displayed in Figure 4.30. The simulated and observed failures are scaled to absolute failure ratios to accommodate for the removal of drive train failures in the simulation.

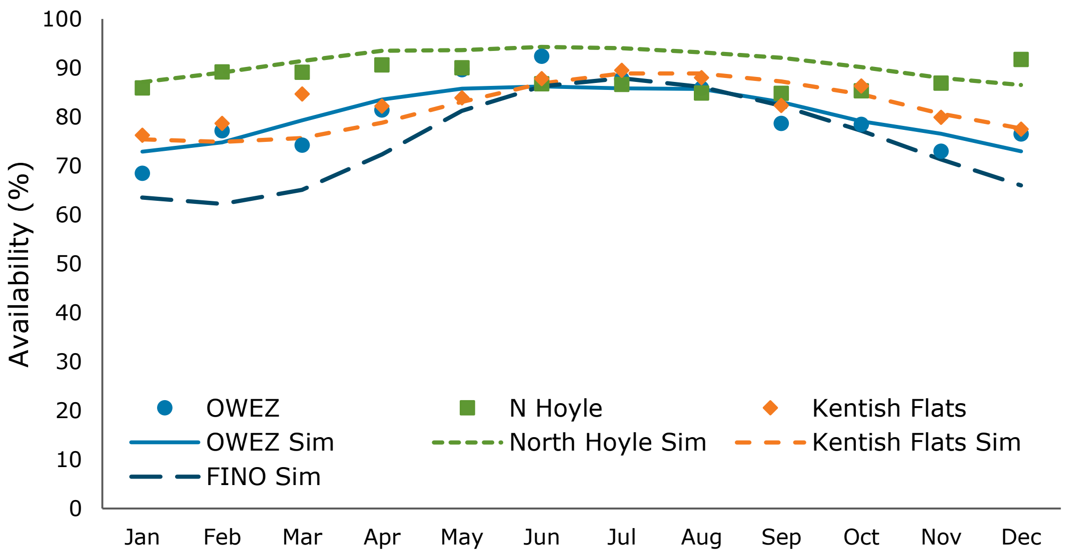


Figure 4.30: Simulated and observed seasonal trends at R1 sites

From Figure 4.30 it can be seen that there is a clear relationship between seasonality and availability. The relative extent of this variation is captured at each of the three locations where operational data exist although there is some deviation between simulated and observed seasonal trends. The deviations can be explained as being a consequence of the small data sets used, large refurbishment and from the fact that with exception of OWEZ the climate data and operational data are not concurrent. It is also evident that as sites are built in harsher climates with higher wind speeds and significant wave height, the impact of seasonality becomes more significant. This relationship can be seen more clearly in Figure 4.31.

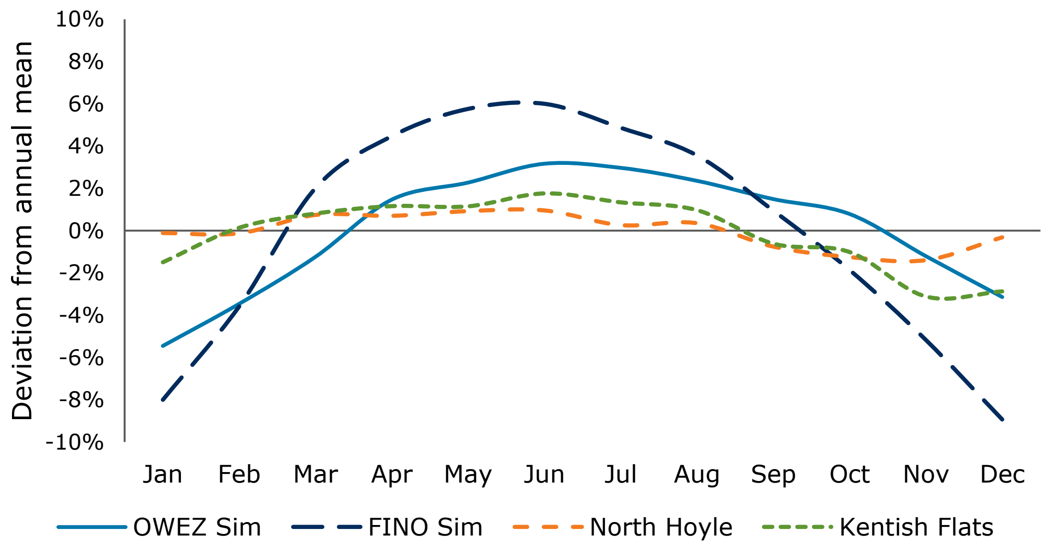


Figure 4.31: Normalised seasonal variation

From Figure 4.31 it can be seen that the relative seasonal variability at the FINO site is around 15% over the year compared to only 3-4% at the UK R1 sites. This has significant implications for seasonal operational strategies as well as investment in access technology that reduces this variability.

4.6 Climate OPEX impact analysis

Having identified that there is a relationship between climate and availability, a study into the impact of climate on OPEX has been performed to determine sensitivity on lifetime costs and lost revenue. A baseline offshore wind farm and operating conditions were chosen, based on current development locations, turbine size and operational practices as well as relevant available public data sets. The baseline wind farm consists of 50, 5MW NREL reference wind turbines [4.9] at a North Sea location with wind and wave climate observed at FINO and 20 km from the nearest port. The turbine failure model inputs, operating costs and vessel resources are described in Table 4.6 and Table 4.7. The cost and operating efficiency variables are based on the offshore electricity market conditions in the UK along with wind farm array efficiency based on that reported at Horns Rev [4.16] is summarized in Table 4.6.

Table 4.6: Climate sensitivity OPEX values

Variable	Value	Description
MP_{elec}	55 £/MWh	Based on UK wholesale price
MP_{supp}	41 £/MWh	Multiplied by current ROC level 1.5
Technician cost	£80000 /yr	
η_{farm}	86 %	Based on Horns Rev array losses

As previously identified, a failure consequence approach has been adopted which simplifies the subsystem representation of the turbine allowing sensitivity analysis to be performed. This approach simulates failure class by the corresponding maintenance action rather than the physical subsystem. For a minor fault that results in a turbine stoppage that can be dealt with remotely, there is no direct cost but there is a lost revenue consequence. As this is weather independent it can be represented by a failure rate and associated downtime or directly as a reduction in overall farm efficiency and not simulated directly.

Maintenance actions that require simulation are grouped by the required vessel. These are minor and scheduled maintenance, carried out using a personnel transfer vessel, larger repairs requiring a field support vessel with an external crane and major repairs and replacement which require specialist jack-up vessels which are also used also used for installation purposes. In addition, for minor and major repairs that do not require a jack-up vessel there is the option to use a helicopter which reduces transfer time but is subject to a greater day rate.

Table 4.7 identifies the key failure characteristics and vessel features for the baseline scenario. The baseline failure rates have been determined by the most recent analysis of failure data in [4.17]. The costs of component repair and replacement based on weighted average values for different component types using the subsystem failure rates and costs estimated from [4.18]. Day rates, CAPEX costs and access restrictions for vessels and helicopters are taken from [4.2] and [4.19] and operator discussions representing the current market.

The duration of repair windows do not directly correspond to the minimum time a repair operation takes to perform. Rather, the repair window represents the time required in order to commit to carrying out the repair operation in the offshore environment. This is a conservative approach representative of the nature of offshore operations where vessels will only proceed with a repair operation if it is believed a sufficiently large period of accessibility will be present. The baseline costs for the described site are 0.0289 £/kWh and 0.0217 £/kWh with and without lost revenue, in line with costs reported on existing projects [4.20].

The mean wind speed of the dataset measured at 100m is 9.85 m/s. Comparing this with estimated wind speeds for the North Sea area [4.21] it can be considered a high wind site with a more severe wind and wave climate than the majority of currently developed 'near shore' sites. However, there are regions such as the West coast of the UK and the centre and far North regions of the North and Baltic Sea with higher wind speeds where future wind farms are planned. In addition, the variability of wind speed and wave height increases with mean value as shown in Figure 4.13 and individual years where wave climate is significantly higher than the mean must also be considered. The sensitivity of costs to a wide range of site conditions covering existing sites as well as potential future sites were examined.

Table 4.7: Resource provision and costs for climate sensitivity study

	Minor replacement	Major repair	Major replacement
λ	1.8	0.4	0.2
Component cost	£ 2500	£ 5000	£750 000
Repair Window	6 hrs	12 hrs	24 hrs
Vessel	Transfer Boat	Field Support Vessel	Jack-Up vessel
Day rate / OPEX	£ 1800	£ 10000	£ 200000
CAPEX	N/A	N/A	£ 101m
Heli Alternative	Y	Y	N
Heli day rate	£ 10000	£ 20000	N/A
Access Limit	1.5 m	2 m	2.5 m Jack, 10 m/s lift
No. Available	5	2	1

Figure 4.32 shows the impact of changing the overall climate as well as wind and wave climate individually on operating costs. The relationship with wave climate is approximately linear with a positive or negative change in wave climate resulting in corresponding change in operational costs due to improved or decreased accessibility. Wind climate has a more complex relationship as wind drives both accessibility and revenue

generated and lost during down time. The opposing cost drivers are most evident in the region between -25% and 0% wind speed change, where there is no change in operational costs. This can be explained by improved accessibility and consequently availability being negated by a reduction in total power produced. Conversely, the increased overall production resulting from a 25% increase in wind speed does not compensate for the negative impact of reduced accessibility and increased lost revenue from down time resulting in an overall increase in costs.

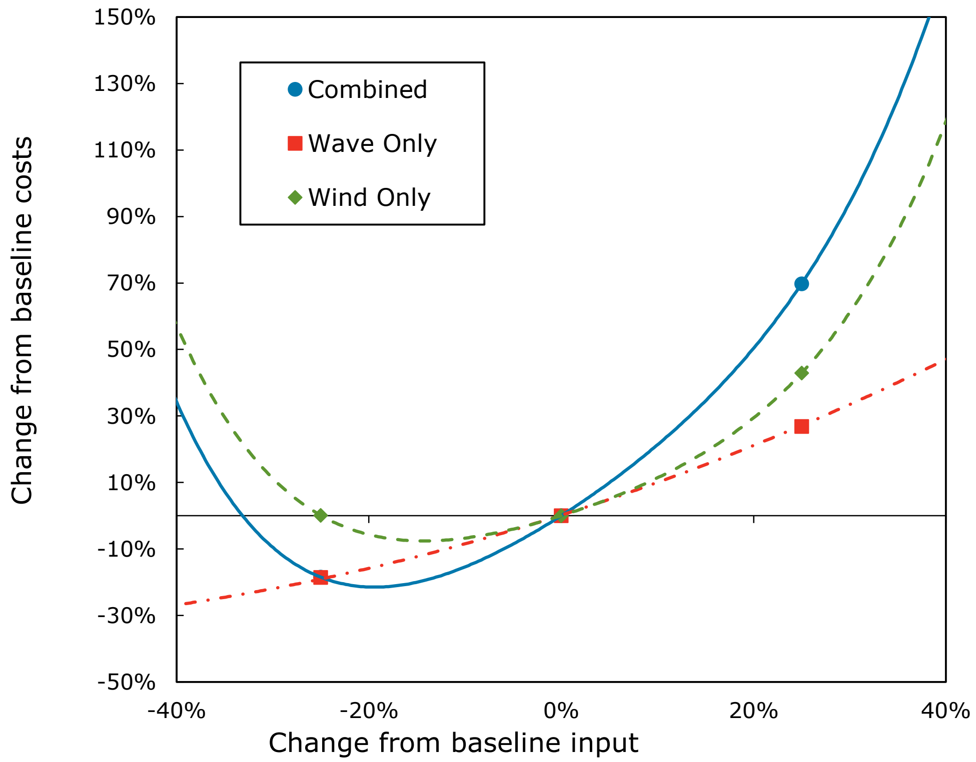


Figure 4.32: Variation of OPEX costs with change in wind and wave climate

This result highlights that there is a potential for increased operational costs at sites with harsher weather climates. The benefit of increase in revenue at these sites is insufficient to maintain the £/kWhr operational costs observed at the baseline site. It should therefore be a priority for both operators and OEMs to enable maintenance to take place at increased wind and wave speeds in order to reduce operational costs at sites with more extreme wave climates.

Using a combination of a measurement campaign and hindcast data, it is extremely unlikely that such a significant deviation in climate values would be observed over the duration of the wind farm life but as has been previously established, inter-annual costs are subject to this level of deviation. It is therefore vital to understand the risk associated with cost estimates based on a short term or poor quality site assessment offshore.

In this chapter the climate impact on wind farm availability and OPEX has been quantified. In order to do this, issues surrounding the inherent nature of the wind and wave climate and data were addressed and the robustness of the adopted modelling approach to accounting for these issues was demonstrated. It was identified that there is an increasingly important influence on availability from wave height as sites move further from shore and the degree to which improved access limits can overcome this has been established. Chapter 4 focused on the influence of climate, which operators have limited ability to control. The focus of Chapter 5 is on the degree to which availability and costs are driven by wind farm and turbine specification and resource provisions, which OEMs, developers and operators have the ability to impact.

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Chapter 5

OPEX sensitivity analysis and identification of key cost drivers

The previous chapters have specified a methodology for developing a robust model that allows all aspects of offshore wind operations and maintenance to be investigated. A rigorous examination of the impact of operational climate on accessibility and generated revenue was possible due to the availability of high quality, relevant data sets. However, there is significant variation and uncertainty surrounding the operational configuration and performance of current offshore wind farms and this is set to increase in the short term for future sites and new generation turbines. This presents a challenge when attempting to validate the ability of the model to capture the influence of different operational parameters on overall cost of energy. There are various means to address this challenge which are discussed and carried out in this chapter. A brief review of validation and verification approaches as well as modelling uncertainty is presented followed by verification of the model and a detailed sensitivity analysis of key OPEX drivers.

5.1 Validation and verification of models with inherent uncertainty

There are a large number of definitions for the words verified and validated in the context of simulation modelling. Rigorous consideration of this problem is presented in [5.1, 5.2]. There is a consensus that a model can be validated against a single set of modelling inputs or for a simple system where the entire domain can be simulated and compared with observations. The consequence of this is that for complex systems where it is impossible or impractical to model the entire domain of possible input scenarios a model can never be considered entirely 'validated'. Even when a model is considered validated against an observable system, in this case a wind farm with fully known climate, failure behaviour and operational procedures; when the model is used for predicting performance of alternative configurations, the underlying assumptions may no longer be valid. In this case, the best that can be achieved is to systematically investigate the output behaviour of the model to build confidence in outputs and provide credibility to predictive simulations [5.1]. This is considered as a verification process and is the strategy that has been adopted for the model developed for this thesis.

Where limited or no data exists, one approach to verifying models is to compare the outputs with other models. If the developed model is compared to a validated model, this process may be considered as validation. However, the same problems arise when applying the developed model to new scenarios as previously identified. Even when none of the compared models are validated, comparison of a range of scenarios serves to improve the credibility of the adopted simulation approach. This is achieved as consistent, independently arrived at results indicate that the underlying modelling assumptions and logic are representative of the problem. In addition, this approach allows the exchange of knowledge between experts and provides further insight into how models behave. This approach is referred to as inter-comparison or code-to-code comparison and has been shown to be effective in improving models in a variety of scenarios [5.3].

A relevant example of code-to-code comparison within the context of offshore wind research is presented in [5.4]. This project also aims to provide a greater understanding of future offshore wind turbine configurations using simulation models of the dynamics of floating substructures. Such inter-comparison or code-to-code comparison efforts may be regarded as verification efforts and not validation, since one is not observing the output of actual systems.

Within the scope of this thesis, there has been an opportunity to collaborate with industry professionals and other academic research groups to successfully carry out such a verification process. The objective has been to explore operational aspects of offshore wind where historic performance data does not exist or remains commercially sensitive. The results of this collaboration are presented in [5.5] and inform the base case scenario and initial analysis for this chapter. This has provided greater confidence in the more speculative scenarios that are explored subsequently. However, as simulations increasingly diverge from the configurations present at existing operational offshore wind farms, there will be increased uncertainty in the results. Before examining the baseline wind farm scenario in detail and examining how sensitive wind farm performance is to different operational parameters, the inherent uncertainty in the simulation model has to be considered.

5.2 Sources of uncertainty in offshore wind operations and maintenance

When attempting to model any physical system using a probabilistic model there is always an inherent uncertainty. Sources of uncertainty that contribute to this can be considered in two discrete classes as either aleatory or epistemic [5.6].

5.2.1 Aleatory uncertainty

Aleatory uncertainty, also classified as natural, stochastic or statistical uncertainty is a fundamental property of the system that is being modelled and can never be fully reduced. The variability in climate, failure behaviour and external cost drivers will exist in real world offshore wind farm performance. Monte Carlo techniques allow this natural variability to be quantified but results will only ever produce a range of predicted performance values. In this regard, aleatory uncertainty is an inherent property and cannot be eliminated. There is however, significant value in fully quantifying aleatory uncertainty in order to understand risk associated with projects.

5.2.2 Epistemic uncertainty

In addition to aleatory uncertainty, epistemic, systematic or subjective uncertainty [5.6, 5.7] can be accounted for. This is the uncertainty that arises from underlying assumptions that the model is built upon based on how well the system is understood. It should be noted that there is an epistemic uncertainty associated with the prediction of aleatory uncertainty, such as failure rate and climate parameters. If the state of a system is well understood then the epistemic uncertainty can be reduced and there may be a corresponding economic benefit to reduction of this uncertainty. In the context of offshore wind, the operational configuration represents epistemic uncertainty that can be removed if the wind farm and resource configuration is well defined. Epistemic uncertainty that informs the natural uncertainty such as failure rates, site climate variability and long term cost trends can be reduced during the operational period of the wind farm. In general, deterministic models allow for consideration of situations where only epistemic uncertainty exist and probabilistic models are required when the system is poorly understood or depends on expert opinion to inform it.

5.2.3 Quantification of uncertainty

Quantification of uncertainty is performed by considering the probability density function (PDF) of key variable performance across simulations. Uncertainty associated with different input parameters will impact the overall uncertainty of the system through a process known as propagation of uncertainty within the Monte Carlo Simulation [5.7]. An illustrative example of this is shown in Figure 5.1. Statistical measures such as standard deviation or p-value confidence limits on the output function allow quantification of uncertainty and is the approach adopted in this thesis. For example, adopting a strategy that results in a higher predicted cost but reduces the distribution of costs may be more desirable as it reduces the uncertainty and associated investment risk of the project.

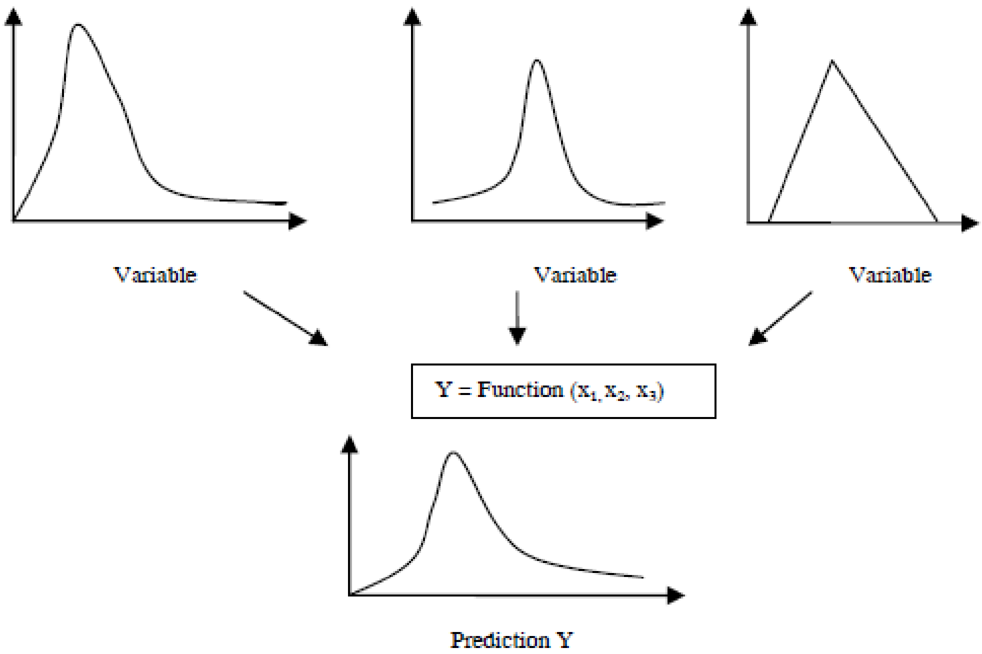

Figure 5.1: Uncertainty propagation [5.7]

Alternative modelling approaches focusing on separating the aleatory and epistemic risk associated with offshore wind has been developed and presented in [5.9] and provides an alternative approach to dealing with uncertainty.

5.2.4 Classification of key contributions to uncertainty in offshore wind

The key sources of uncertainty relevant to offshore wind are summarised in Table 5.1. One area of uncertainty associated with offshore wind that is not considered in Table 5.1 arises due to lack of standard industry definitions. In particular, this uncertainty exists with respect to the definition of availability which is used as a key performance metric. This issue has been considered in more detail, along with a review of general sources of uncertainty pertinent to offshore wind in [5.10].

Table 5.1: Principle sources of uncertainty in offshore wind

Source of Uncertainty	Epistemic / aleatory	Treatment in Model
Inter annual and seasonal variability of climate	Aleatory	The adopted climate model is able to reproduce the principle seasonal and inter annual variations observed. Extreme climate events are not captured but have minor impact on O&M.
Climate model parameterisation	Epistemic	Increasing the length of the time series used to fit climate model parameters significantly reduces this uncertainty. At least 1 year is required for successful modelling purposes however, the model is robust enough to incorporate longer data sets.
Component failure behaviour	Aleatory	Currently a complete turbine, physics of failure model of component failure is not sufficiently developed and can therefore be treated as a knowledge gap to operators.
Failure behaviour parameterisation	Epistemic	This uncertainty can be reduced by feeding back in observed failure behaviour at operational sites. This could also be reduced by creating a standardized industry failure database. Correctly identifying the state of components through inspection, condition monitoring will also reduce the uncertainty associated with failure rates.
Future site configurations, turbine designs and operational strategies	Epistemic	This uncertainty is a consequence of modelling a developing industry. Over time it will be reduced as standard industry practices are adopted such as the common failure database created in the oil and gas industry [5.8]. By ensuring the modelling framework is as flexible as possible only step change technologies or strategies will require re-development of the model.
External cost drivers	Both	External costs that are outside the influence of the offshore wind industry such as commodity prices can be considered as aleatory. Externalities such as electricity, vessel and turbine prices are subject to change but can be influenced by choices of the industry and as they are better understood the associated uncertainty will reduce. The model allows these costs to be changed in a post processing fashion to allow a rapid sensitivity analysis of how changing future costs will impact overall cost of energy.

5.3 Code-to-code wind farm specification

In order to carry out the code-to-code verification process a baseline wind farm was specified and a number of scenarios simulated. This made it possible to determine if different simulation models were consistent, what the key modelling assumptions influencing results were and identify which operational parameters required further, independent sensitivity analysis. The sensitivity analysis for availability and costs are shown in Figure 5.2. A brief description of the range of cases explored can be found in Appendix III.

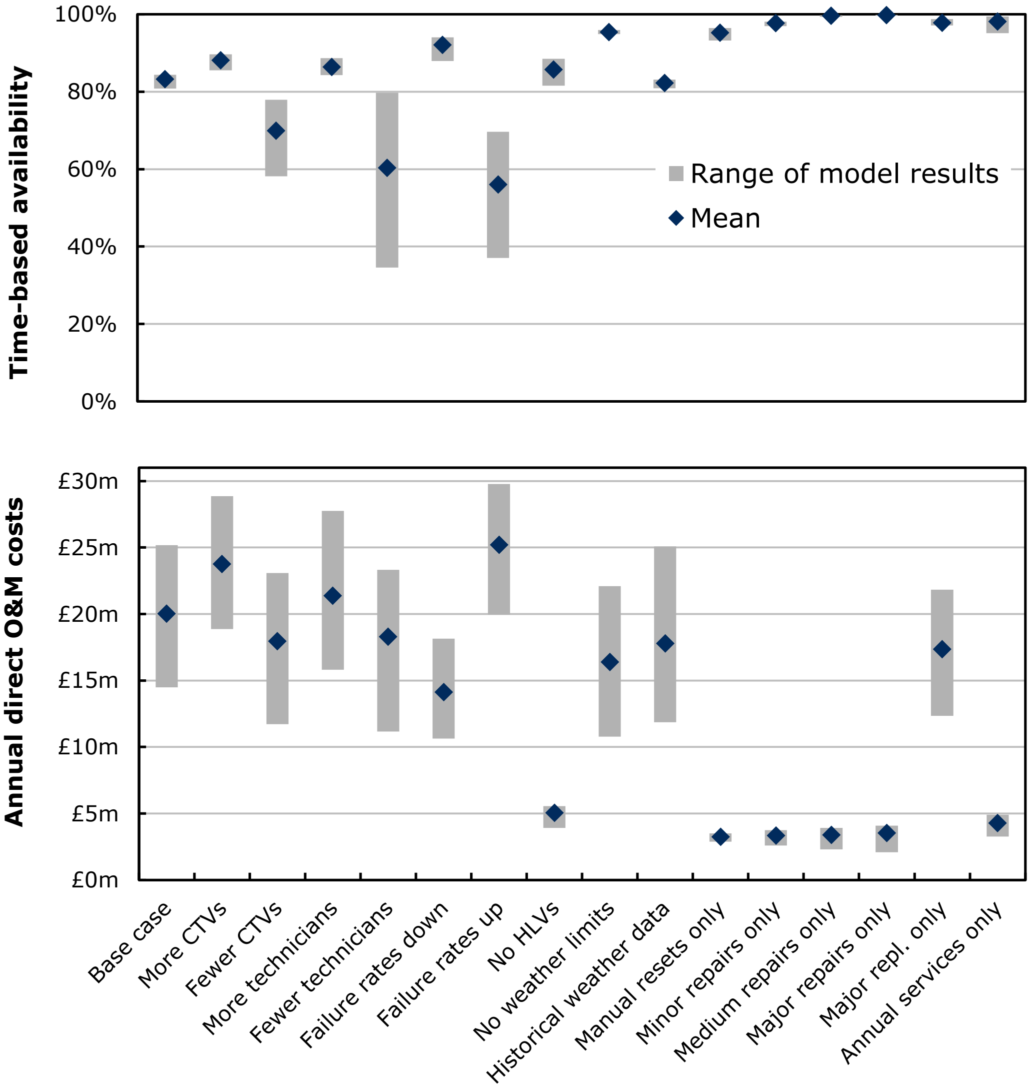

Figure 5.2: Results from Code-to-Code comparison study [5.5]

Considering availability in Figure 5.2, it can be seen that there is good agreement across models except for scenarios where resources are highly constrained. For example, having insufficient vessels or significantly increased failure rates with fixed resources. This deviation is primarily due to the assumptions that different models make regarding allocation of failures and how vessels are allocated when there are more turbines failed than CTVs available. In both cases, the model developed for this thesis takes the most pessimistic approach resulting in low availabilities. It would be financially impractical for a wind farm to be operated under such circumstances as the costs associated with additional technicians or vessels are significantly less than the huge lost revenue when availability is low.

There is significant variation between predicted annual direct O&M costs. This has been identified as being driven by the different charter periods for heavy lift vessels between different models. Models that assume a minimum charter period result in a significantly higher annual direct cost than those that assume that a vessel can be chartered only for the duration that it is required. When heavy lift vessels are discounted, there is close agreement between models as shown in the 'No HLVs' plot in Figure 5.2. This high impact on costs identified heavy lift vessels as an area requiring more in depth analysis which is the focus of Chapter 6 .

The baseline scenario used for the code-to-code verification process relied on modified failure rates that are similar to the Reliawind values but were determined by expert judgement based on operational experience in the North Sea. For consistency with previous analysis, for the baseline case and further studies in this thesis, the Reliawind values previously identified were adopted [5.11].

5.4 Baseline wind farm analysis

The base case scenario inputs used for this chapter as well as the key performance indicators of availability and direct costs are specified in Table 5.2. A full specification is provided in Appendix III.

Table 5.2: Specification and results of baseline scenario for this thesis

Wind Farm Overview		**Resources Overview**		
Number of Turbines	80	Number of CTVs	3	
Wind Farm Life (Yrs)	20	Number of Staff	64	
Wind Turbine Rating (kW)	5000	Helicopter Used	Yes	
Total Failure Rate (excl. remote resets)	12.59	FSV mobilisation and charter length	21 day mob 14 day charter	
CTV Travel Distance to Wind Farm (km)	10.18	Jack-up mobilisation and charter length	Mobilisation from triangular distribution, 30,60 and 120 days 30 day charter	
Climate	FINO 2004-2012	**Failure rates**	Reliawind values	
Availability and Production Overview		**Costs Overview**	**m£**	**£/ MWhr**
Availability Absolute	85.4%	**Lost Revenue**	459.7	16.48
Availability Excluding Scheduled Maintenance	86.0%	**Transport Costs**	438.8	15.73
Availability OEM Responsibility	96.5%	**Staff Costs**	102.4	3.67
Energy Produced (MWhr)	2.79E+07	**Repair Costs**	196.9	7.05
Energy Lost Due to Downtime (MWhr)	4.75E+06	**Fixed Costs**	41.0	1.47
Capacity Factor	39.88%	**Total O&M Costs**	**1398.7**	**42.97**
		Total Direct O&M Costs	**781.2**	**20.87**
		Total Revenue	**3632.8**	

The failure rates are pessimistic when compared to both the historic onshore rates and performance at Egmond aan Zee where there were serial defects. This has resulted in an availability that is lower than the historic onshore failure rate. However, the values for availability, capacity factor and direct O&M costs are consistent with the early performance of offshore wind farms in the North Sea. In this respect, the base case serves as a representative starting point from which to examine what is currently contributing to operational performance and explore alternative scenarios.

5.4.1 Availability and power production assessment

The availability of the base case wind farm is 85.4% and annual power production of 1400000 MWhr and annual lost power of 238000 MWhr. Figure 5.3 shows the variation of availability, produced power and lost power due to down time throughout the year.

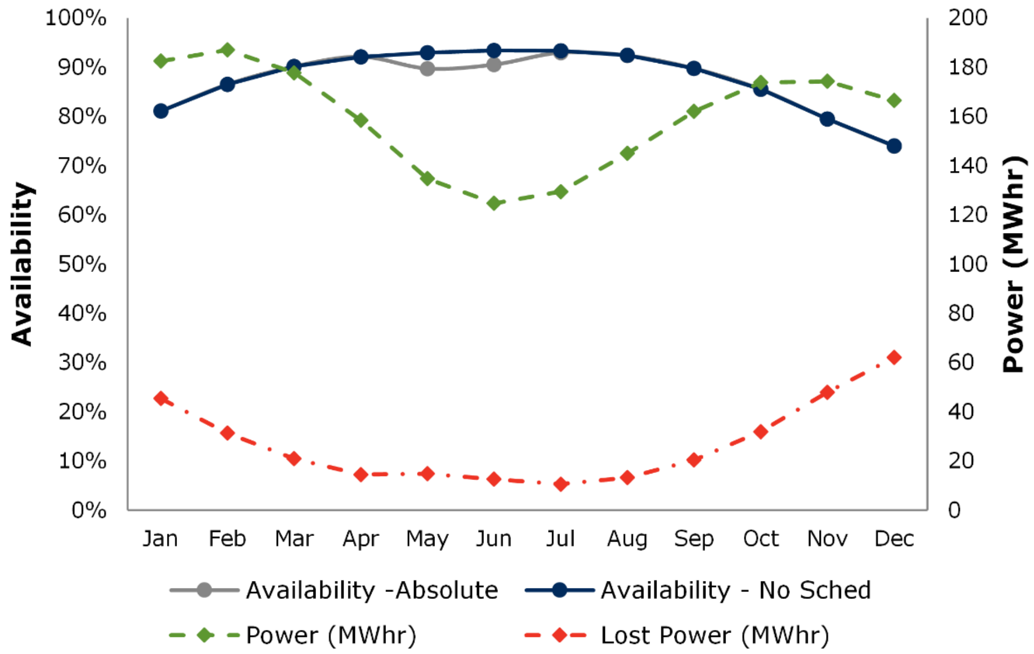

Figure 5.3: Variation in availability and power production throughout the year

The availability results are consistent with those identified in Section 4.3.1 showing strong correlation with wave and wind conditions. Additional insight into the importance of weather on cost performance is provided by considering the power production curves which are a function of both wind speed and availability. Lost power is approximately inversely related to the availability curve as periods of lowest availability correspond to the months of the year when wind speeds are greatest. However, the power production relationship is more complex. Despite the maximum availability in summer months, lower wind speeds result in lower power production than the rest of the year. There is a trade-off between availability and wind resource. Consequently, December and January have similar power production to March and October when availability is significantly higher. In both cases a peak in the middle months of February and November represent a local power production maximum.

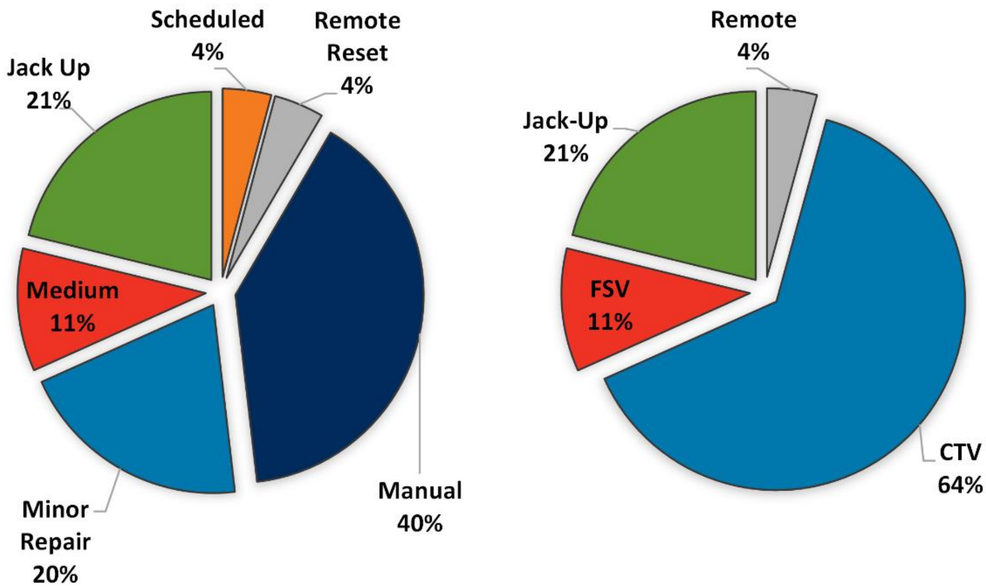

Figure 5.4: Contribution to downtime by failure and vessel type

The contributions to down time are shown in Figure 5.4 by individual subsystem category and access vessel type. The results of Figure 5.4 show that it is the large number of small repairs and scheduled maintenance requiring the use of CTVs that will result in the largest downtime. This result is in contrast to the observed contributions to downtime at the UK Round 1 sites and Egmond aan Zee where downtime was dominated by the major failures that would fall into the major replacement category performed with specialist Jack-Up vessels. The anticipated improved design performance going forward will eliminate serial replacement of major drive train components and this results in the significant change in the contribution to downtime.

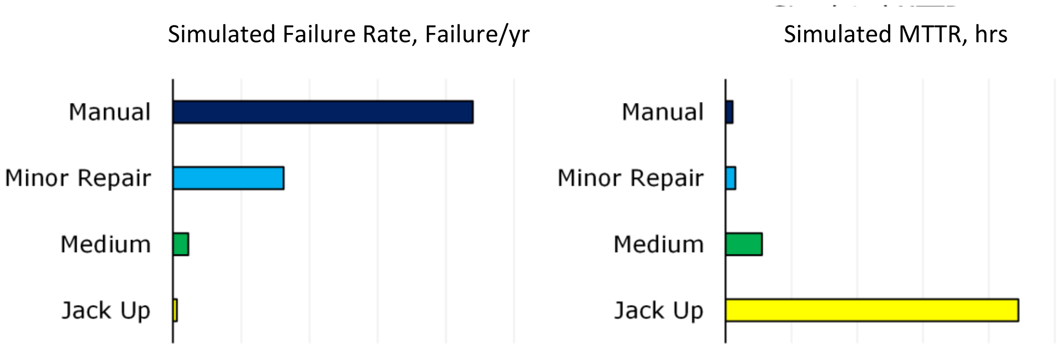

Figure 5.5: Simulated failure rate and MTTR

Examining the simulated failure rates and MTTR for unscheduled maintenance actions in Figure 5.5 shows that the historically observed relationship between the two is preserved. Relatively uncommon failures requiring complex repair operations have a corresponding high MTTR. It should be noted that while failure rates are directly related to the inputs, independent of the wind farm and resource configuration, MTTR will vary when these inputs are varied.

The simulation approach converges to single output values for the 20 year average of availability, power production and losses and resource usage which can then determine operational costs. However, the performance of real world wind farms are typically recorded on an annual basis and for resource and financial planning, it is important to understand the range of annual values that can be expected to be observed over the life of the wind farm. In order to output this, the availability and production values are recorded at the end of each simulated year in every simulation and then output as a histogram. These results have been normalised to produce PDFs and the inverse cumulative distribution function (CDF) as shown in Figure 5.6, Figure 5.7 and Figure 5.8. The PDFs provide an indication of the inter-annual variability and the range of operational performance that is reasonable to expect on an annual basis. In addition, if the observed performance of an operational wind farm falls outside of the predicted range, it is an indication of a modelling error or an extreme performance event that has not been anticipated such as a serial design defect. The CDFs allow p-value predictions of performance which are often used in financial planning and risk assessment of projects. P-value in this context is the probability that a result will be exceeded, an example 'P80' confidence levels are displayed on the CDFs below.

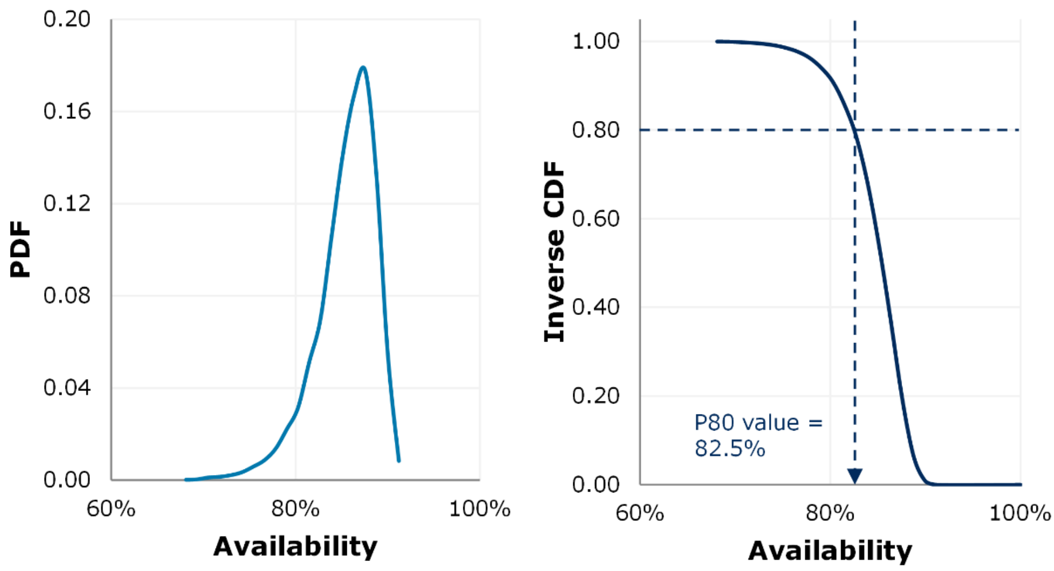

Figure 5.6: PDF and inverse CDF of annual availability

In the case of the baseline wind farm, annual availabilities could be expected in the range of 68-92% under normal operating conditions. A value of 82.5% availability correlates to a P80 level for financial and operating planning. This is significantly lower than the observed mean value, 85.4%, representing the more conservative assessment. It can also be observed that the annual variation is not normally distributed. This can be explained by two factors. Firstly, there is an upper limit that will be reached where observed failures are low and accessibility delays are minimal. Even when these favourable conditions are met, availability will never approach 100% and there is a convergence of performance. However, due to the annual distribution of wind and wave climate, there is the possibility for a large number of failures to occur towards the end of the year resulting in poor accessibility and corresponding low availability. Although such events are uncommon, they are responsible for the longer low availability tail on the distribution.

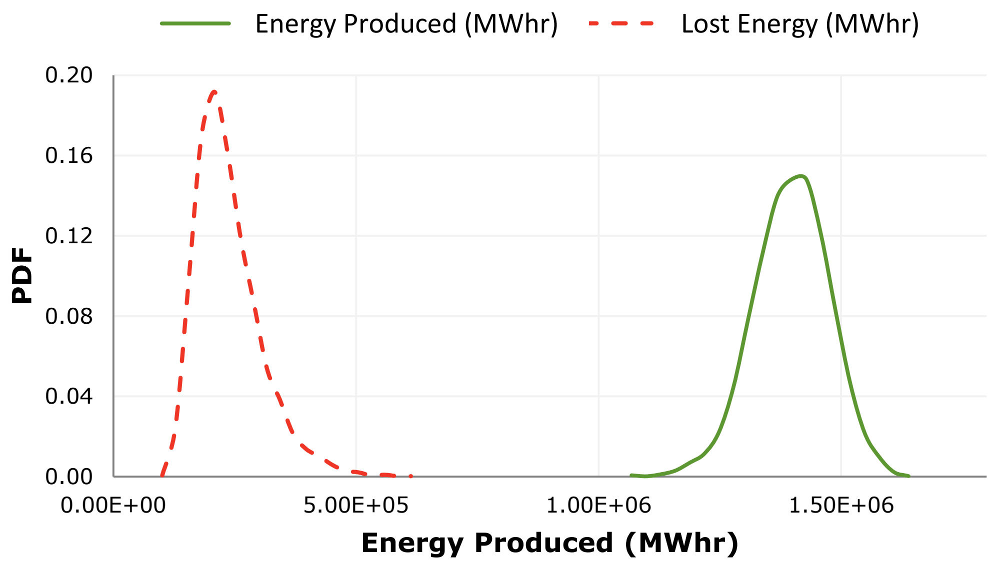

Figure 5.7: Annual energy produced and lost due to downtime PDF

Figure 5.7 shows similar trends to those observed in Figure 5.3. The annual distribution of lost power is inversely related to availability, when availability is low lost power is high. Annual power production is more complex as it is a function of both availability and wind speed. Consequently, the distribution of annual power production approximates a normal distribution more closely. The P80 value for annual power production can be identified from Figure 5.8 as

1300000 MWhr. This increased understanding of operational performance over single value estimates allows for significant improvement of uncertainty around projects and has a high value in reducing project finance risks.

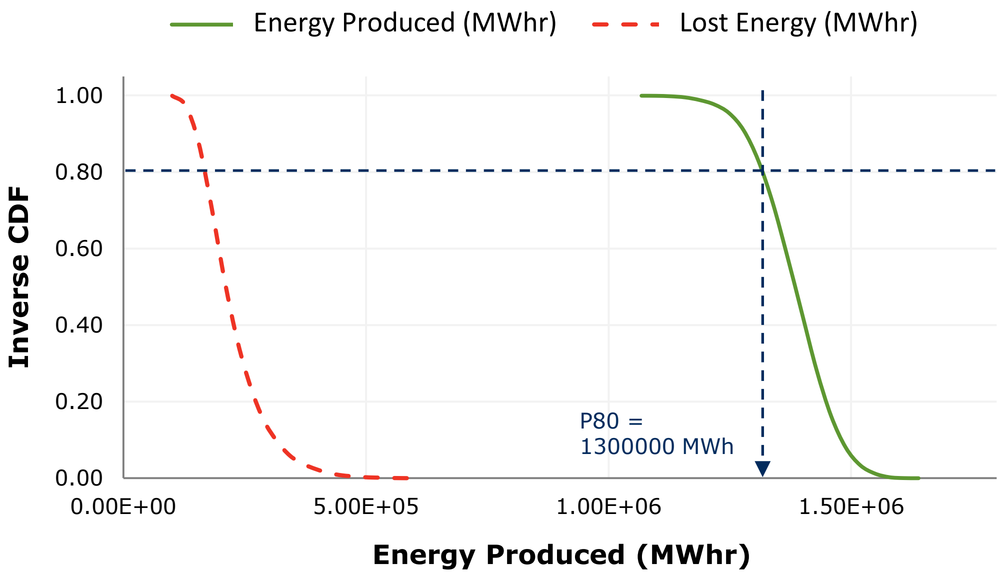

Figure 5.8: Annual energy produced and lost due to downtime inverse CDF and P80 values

In order to gain further insight into what is contributing to downtime, the contribution for each vessel has been identified and is shown in Figure 5.9. Considering CTVs, the largest proportion of down time is contributed from the current working practice of working in shifts where daylight hours are present. This supersedes other causes of downtime in the modelling approach so that even if the wave climate would prevent access to the wind farm this is ignored. Future access solutions may permit 24 hour working shifts but it is not current industry practice. Weather delays represent the largest down time contribution for minor failures. This problem has been recognized by the industry and work towards developing vessels and personnel transfer solutions that have greater access thresholds are being developed. This has the potential to significantly reduce this contribution as shown in Section 4.6. For the base case, there are small contributions from travel time, performing the repairs or waiting for vessels to become available. Improving the performance in any of these areas would result in only minor overall performance benefit. However, as wind farms move further offshore travel time may become increasingly important leading to alternative strategies being adopted.

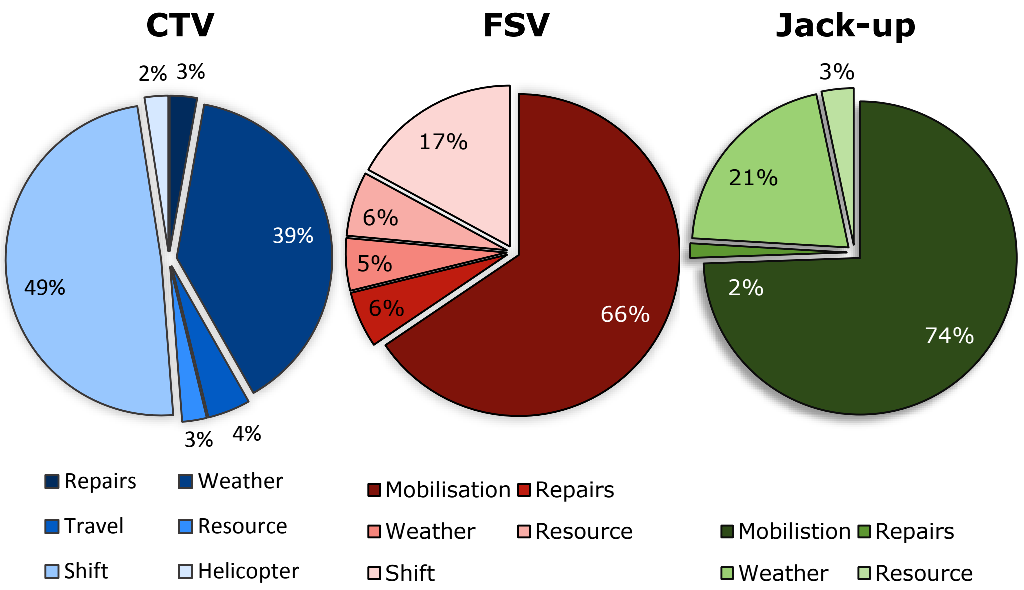

Figure 5.9: Breakdown of downtime contributions by vessel category

Examining the more specialist vessels, the majority of downtime is contributed to mobilisation time. In the case of Jack-Up vessels three quarters of the down time is associated with mobilisation time. If failure rates are high or as wind farms become larger, this delay will lead to unacceptable loss of production and alternative operational strategies for heavy lift vessels will be required. Detailed analysis of this problem has been carried out and is presented in Chapter 6

5.4.2 Operational cost assessment

As well as determining the operational performance of the wind farm, it is necessary to evaluate the operational cost and value of lost energy in order to determine the lifetime cost of energy for a project. Caution has to be associated with such analysis as costs are subject to significant changes over the predicted 25 year life time of a wind farm. In the case of up-front investment decisions, it is necessary to account for inflation and perform net present value calculations to account for these changes. However, for an initial analysis it is justifiable to assume that costs are constant as increasing costs of resources are matched by the increasing value of production and losses. Therefore, for the investigation in this chapter, it is assumed that all costs are fixed across the lifetime of the wind farm, based on the best available data and expert opinion of current market costs. Full details of the cost assumptions made are in Appendix III.

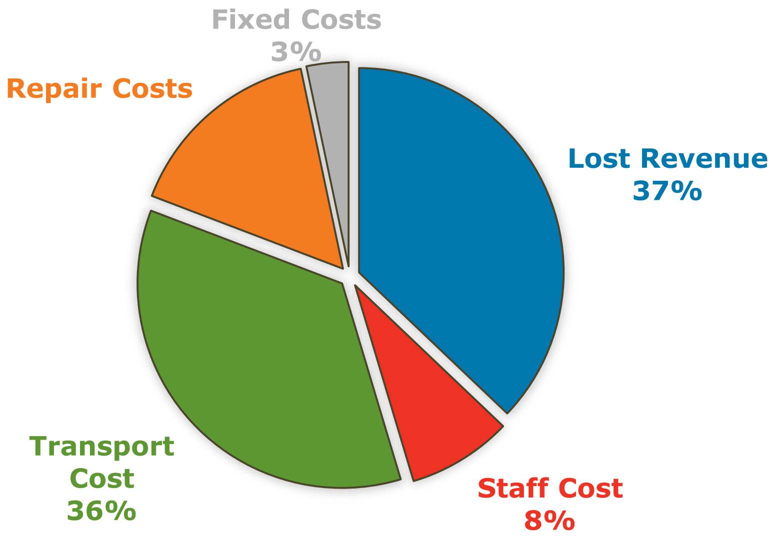

Figure 5.10: Lifetime cost of energy contributions

The breakdown of absolute costs are displayed in Figure 5.10 and the costs normalised by power production values are displayed in Figure 5.11. When considering lifetime costs there are two separate categories of cost. Direct costs are those that have to be paid out from revenue generated; repair, transport, staff and fixed costs while indirect cost don't have to be paid out but rather represent a lost revenue opportunity.

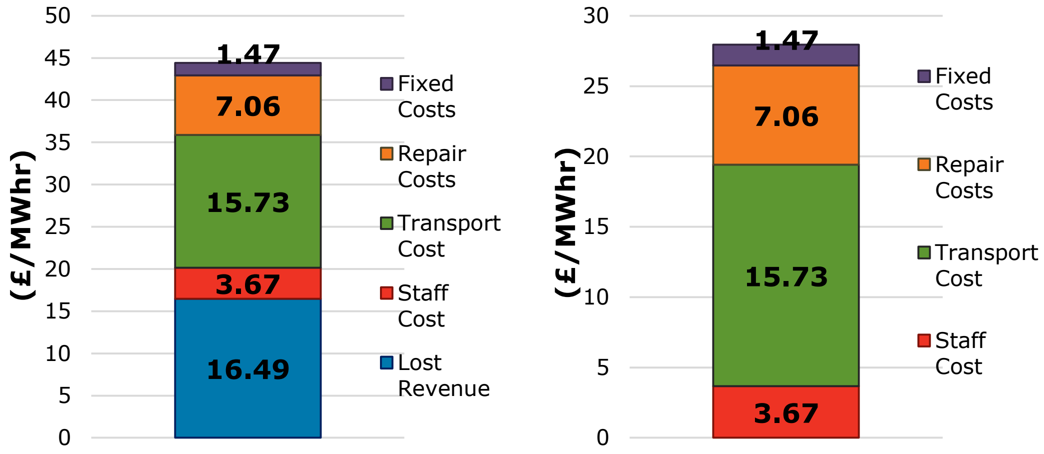

Figure 5.11: Per MWh operational cost breakdown

From Figure 5.10 and Figure 5.11, it can be seen that the areas of highest value are transport costs and lost revenue. Lost revenue is directly improved by improving availability. Any increased revenue must outweigh the cost associated with the improved performance for overall lifetime cost of energy to be reduced. Fixed costs account for infrastructure costs such as port fees and maintenance base running costs. Staff costs in this context are the engineering operations staff and technicians that are required for scheduled and minor maintenance actions but not vessel crew. Staff costs associated with specialist repairs that require specialist vessels are assumed in their daily charter rate. Considering only direct costs, the two largest components comprise of vessel costs and repair costs. Any reduction in these values will contribute directly to reduced lifetime cost of energy providing they do not have an adverse impact on availability.

The breakdown of transport and repair costs are shown in Figure 5.12. The cost breakdowns show significant contrast to the contribution to availability. Transport costs are dominated by the specialist jack-up vessels that are required for major component failures, despite the comparatively rare usage of such vessels. A similar trend can be observed when examining repair costs. The high costs associated with replacing major components comprise almost half of total repair costs despite the fact that they account for less than 1% of the total failure rate. Similarly, major repairs which are only 3.5% of total failures result in over a quarter of total repair cost.

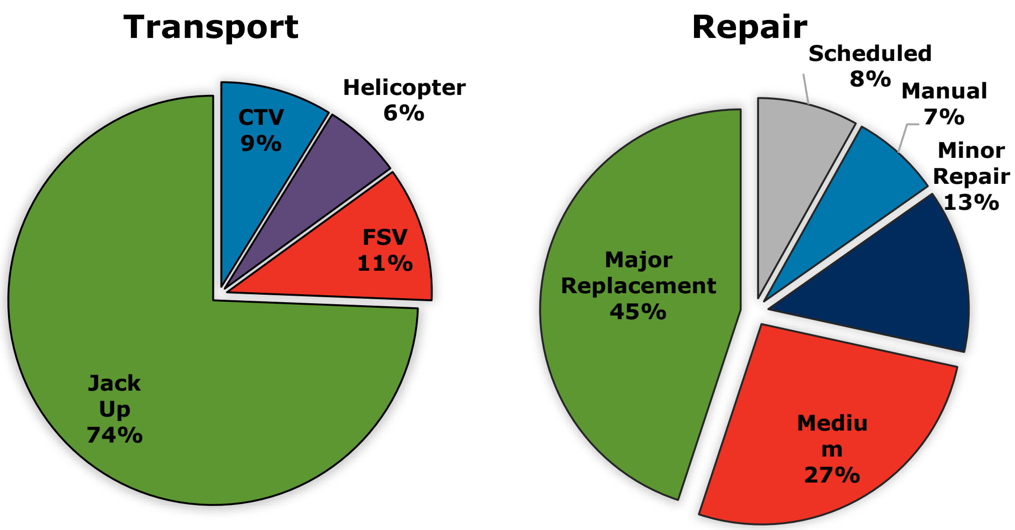

Figure 5.12: Breakdown of transport and repair cost by vessel and failure type

5.5 Failure rate sensitivity analysis

From Figure 5.2, it was identified that the operational area with the most significant impact on both availability and direct costs is failure rate. It has also been identified previously, that there is significant uncertainty surrounding current failure behaviour of offshore wind turbines. Therefore, a detailed sensitivity analysis of failure rates has been carried out on the baseline wind farm to ascertain an understanding of the influence of failure rate on costs and availability.

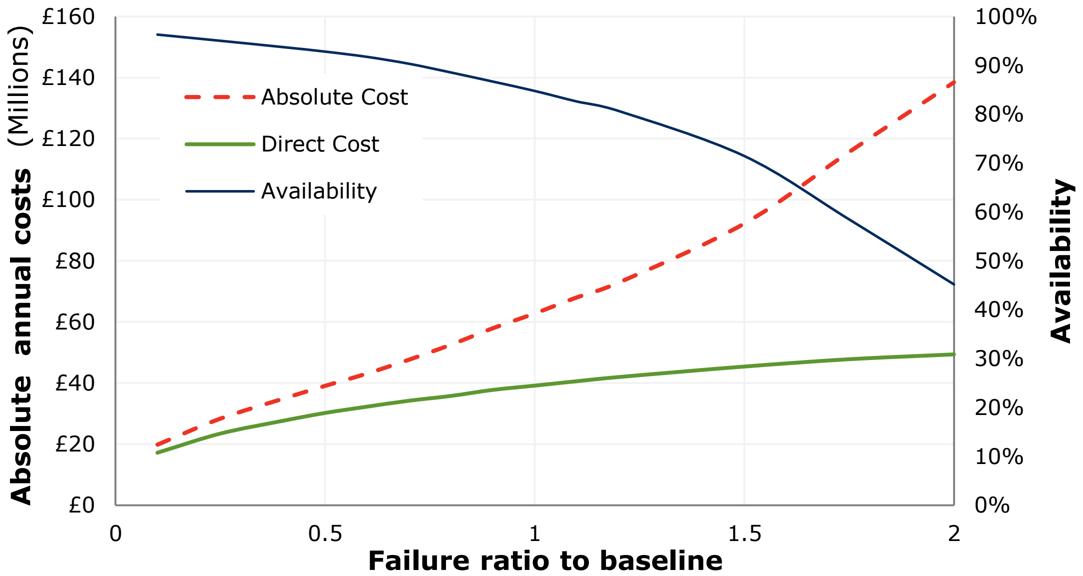

Figure 5.13: Availability and operational costs with changing failure rates

The first investigation considered only the Reliawind failure behaviour, varying the observed failures from 10% of the observed value to 200% while maintaining the same number of turbines and resource provisions. The resulting availability, direct and total costs are shown in Figure 5.13. Examining the availability sensitivity to failure rate shows that there is an approximately linear relationship from 10-140%. Beyond this range there is a steeper reduction of availability and correspondingly rapid increase in lost revenue. Operational costs are approximately linear across the range although there is a slight levelling off as there is a physical limit to how frequently the fixed resources can be used. In practice, the availability performance at higher failure rates would be unacceptable and if such low availability was observed it would make economic sense to increase the available resources.

In order to gain further understanding of the impact of failure rate, the same analysis was performed using the alternative failure distributions identified in Section 2.6. The resulting availability and direct operational costs for the three different scenarios are shown in Figure 5.14 and Figure 5.15

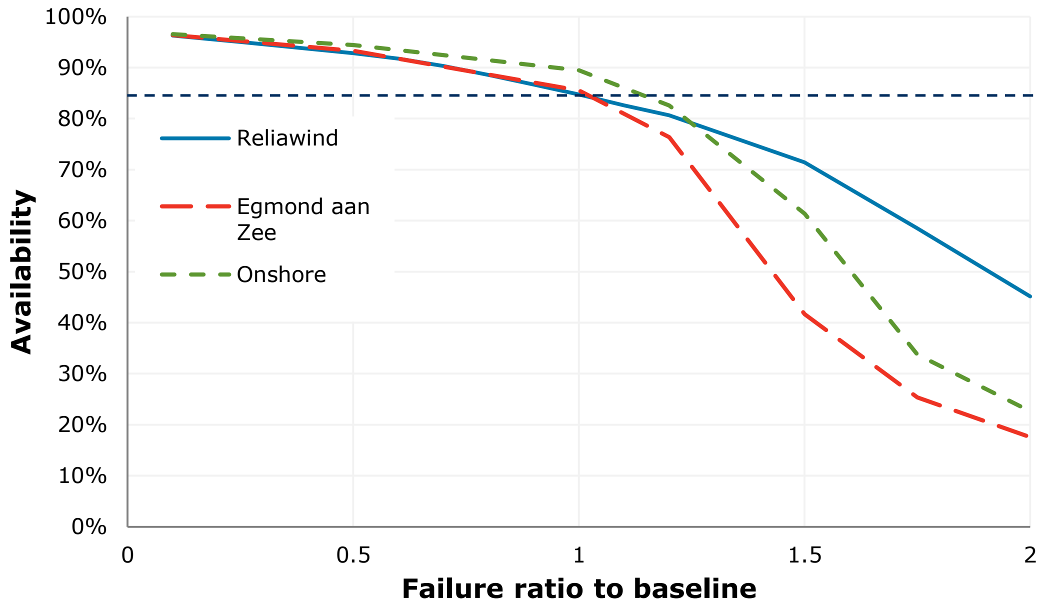

Figure 5.14: Availability against changing failure ratio for different failure distributions

From Figure 5.14, it can be seen that if the onshore failure performance was achieved offshore there would be a corresponding improvement in performance of 5%. The resulting availability is still lower than historic onshore rates however, to achieve historic onshore levels of availability, the failure rate has to reduce by 50%. When the ratio of the onshore and OWEZ failure distributions increase, the resulting decrease in availability is steeper and is onset more rapidly. Combined lost revenue and direct costs in Figure 5.15 demonstrate a similar trend to availability while the behaviour of direct costs are similar across scenarios and follow the same pattern as observed in Figure 5.13.

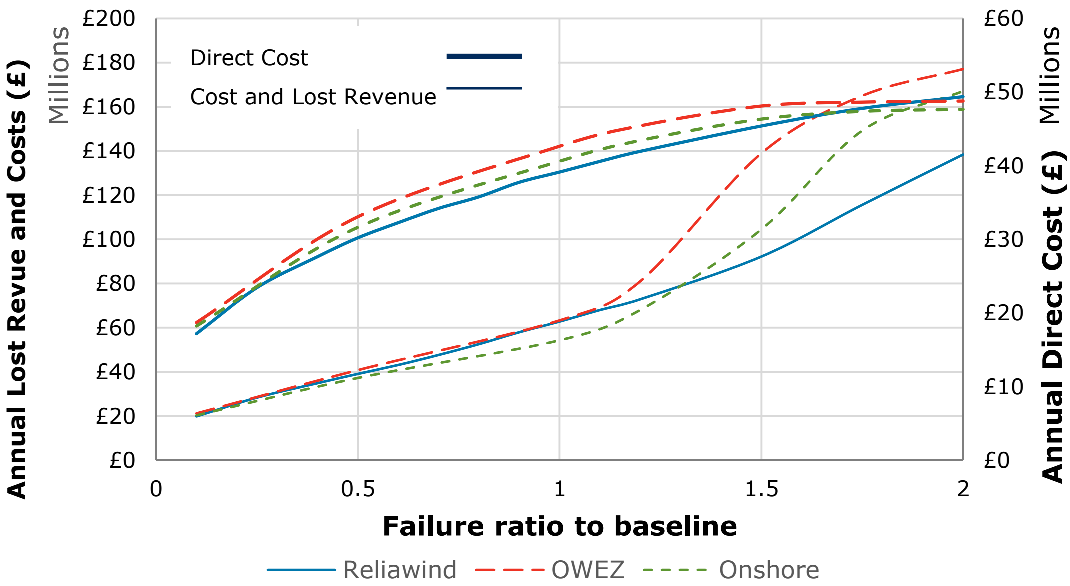

Figure 5.15: Direct absolute and normalised costs against changing failure ratio for different failure distributions

These results are not intuitively arrived at considering only absolute failure rates. Considering only failure rates, it would be predicted that the operational costs of the onshore failure profile would be lowest as the overall failure rate is lowest and availability is highest. This apparent contradiction is due to the influence of major replacement failures that dominate direct costs. It is also apparent that despite manual and minor failures dominating the downtime in the baseline scenario, there is significantly higher sensitivity to major failures and replacement.

The higher sensitivity to major replacements is explained further by considering the contribution to downtime and direct operational costs for the baseline scenario at 10%, 100% and 200% failure ratios shown in Figure 5.16 and Figure 5.17.

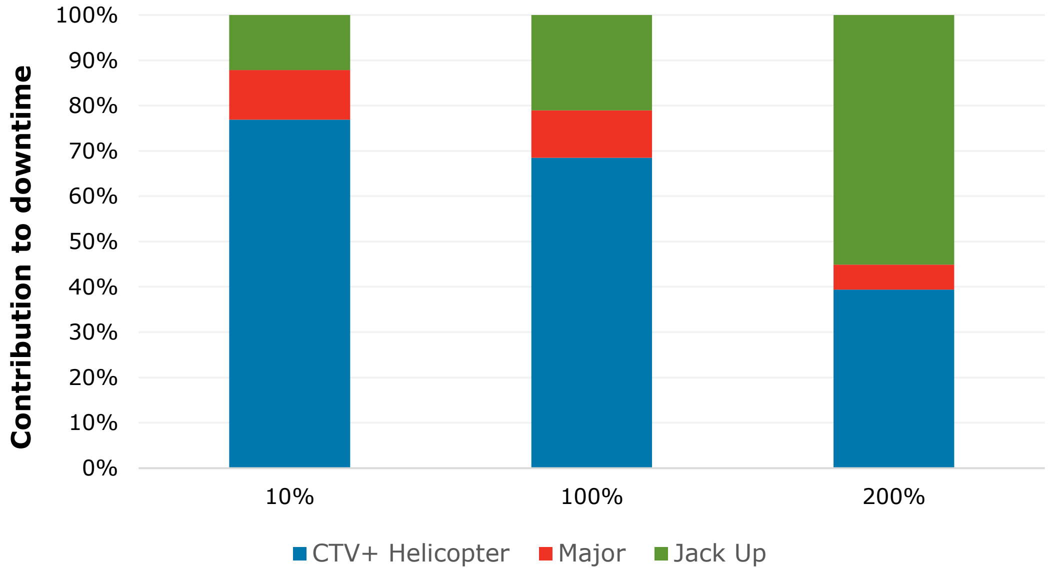

Figure 5.16: Relative downtime contribution per vessel type

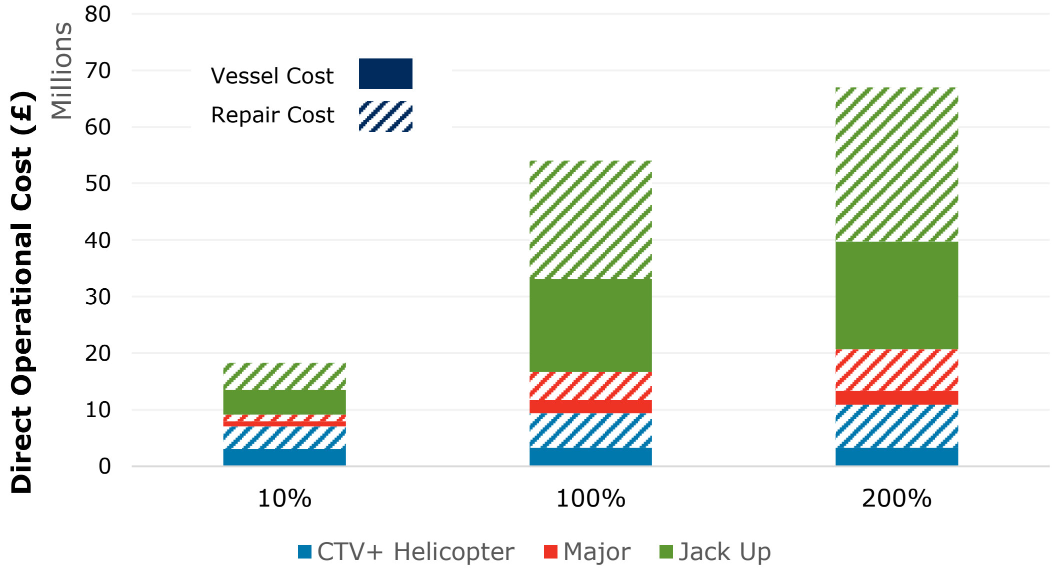

Figure 5.17: Costs contributions at different failure ratios

From Figure 5.16 and Figure 5.17, it can be concluded that although the frequent failures that require CTVs dominate downtime for the baseline scenario, failures requiring jack-up barges dominate when overall failure ratios increase. In addition, it is possible to tolerate variation in minor annual fail rate in terms of direct operational costs. Increasing the number or capability of CTVs will provide a cost effective solution to higher than anticipated failures. Reducing failure rates of this type will result in increased generation rather than significant reduction in direct operational costs. A brief case study identifying the cost benefit of increased vessel resources is presented in Section 5.6.1.

Jack-up repairs present a significant opportunity to reduce overall costs but also represent a critical risk to the financial viability of offshore wind. Comparing major and jack-up vessel costs it can be seen that FSV costs demonstrate a linear relationship with failure rates however there is a plateauing of jack-up vessel costs. This can be explained due to the limit imposed on their usage from mobilisation time. This further explains the increased contribution to downtime observed in Figure 5.17 and identifies that operating with conventional jack-up strategy will no longer be adequate and alternative strategies will need to be adopted. A further analysis of these operating strategies is carried out in Chapter 6

5.6 Sensitivity to wind farm specification

In addition to the key performance drivers of failure rate and operational climate that have been thoroughly investigated, numerous other operational factors contribute to overall wind farm performance. These can be considered as operational parameters that can be controlled by the operator during the lifetime of the wind farm and site characteristics that cannot be readily changed once the wind farm is commissioned. Sensitivity analysis to provide greater understanding of both types have therefore examined.

5.6.1 Identification of optimal CTV configuration

From Figure 5.2, it was identified that the level of resources, either directly considered by the number of CTVS or the associated number of technicians has a large impact in availability performance. The optimal number of CTVs and the impact on operations and lifetime revenue was therefore considered initially. This analysis is a simplified analysis considering only a single CTV vessel type and cost. Subsequent work investigating the optimisation problem when multiple vessels are available in the market has been performed in collaboration with colleagues with Naval Architecture expertise but is outside the scope of this thesis. That analysis considers vessel operations using a more complex offshore environmental model that impacts vessel capabilities as well as mixed fleets with different access threshold and technician capabilities [5.11].

Figure 5.18 shows the impact of availability and completed scheduled maintenance against number of CTVs available for the baseline wind farm specification. It is clear that there is critical drop in performance when insufficient vessel resources are available. Simply increasing the number of vessels available does not continue to increase operational performance however and a plateauing is reached beyond 5 CTVs. CTVs are assumed to be perfectly reliable.

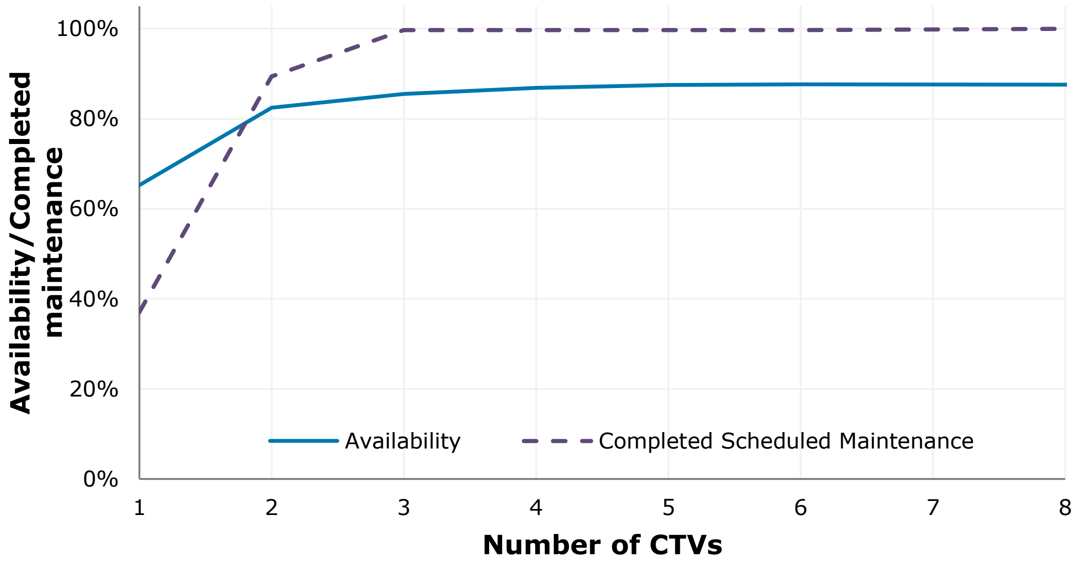

Figure 5.18: Availability and completed scheduled maintenance with varying number of CTVs

It can also be seen that the completion of scheduled maintenance serves as useful indication of whether there is sufficient vessel resource available for the given wind farm and failure rates. In the case where the lack of CTV resource is resulting in a significant reduction in availability, there is a corresponding failure to complete scheduled maintenance. In the modelling context, this is due to the prioritisation of corrective over scheduled maintenance in order to maximise availability. In practical wind farm operation, there may be contractual obligations or impact on failure performance that would result in this situation being considered unacceptable and availability would be lower in order to complete scheduled maintenance. In either scenario, increasing the number of CTVs would be desirable.

The resulting power production and lost power associated with the availabilities in Figure 5.18 was considered and is shown in Figure

5.19 and allows an overall lifetime revenue to be determined and plotted in Figure 5.20.

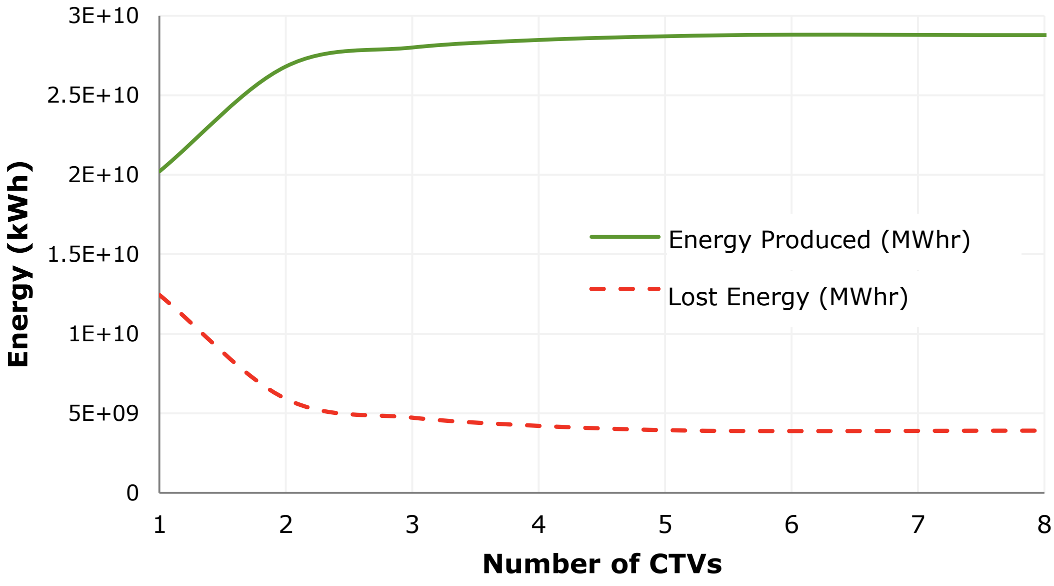

Figure 5.19: Energy produced and lost vs number of CTVs

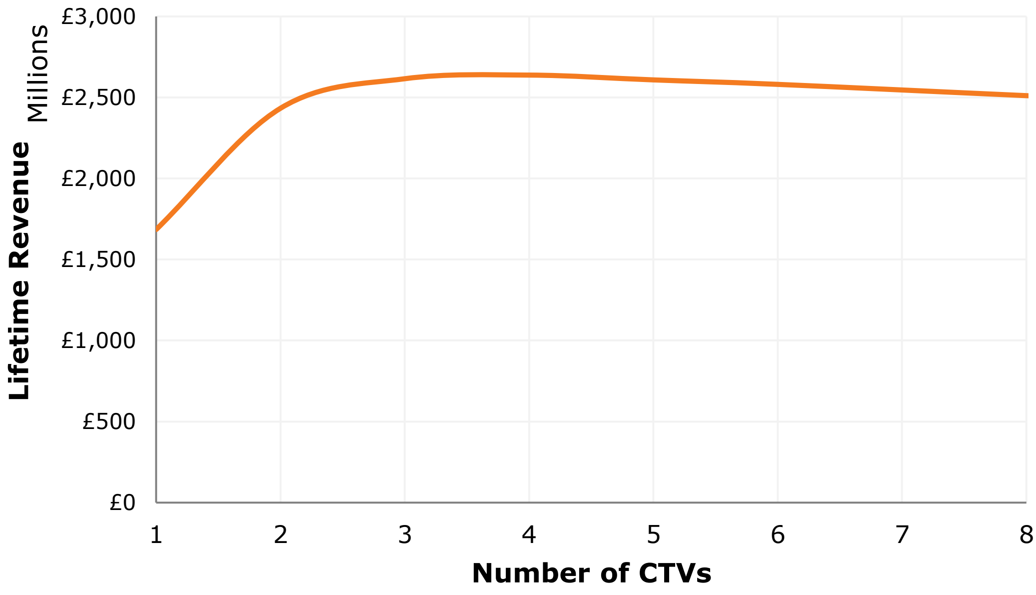

Figure 5.20: Lifetime revenue vs number of CTVs

Unlike availability and power production that tend to a maximum with increased resource, revenue shown in Figure 5.20 shows an optimum value to be identified. For this wind farm configuration it can be seen that the optimal number of CTVs is 4 where lifetime revenue is maximised. However, the gradient of the revenue curve at either side of the maxima should be considered when deciding on resource levels. The lifetime revenue using 3 CTVs is greater than 5 but there is a steeper drop in revenue below 3 than above 5. Effectively, this means that the consequence of over-estimating the resource required has a less significant impact than under-estimating. An operator may choose to adopt the higher resource configuration with a slightly reduced lifetime revenue in order to avoid the possibility of ending up with insufficient CTVs and consequently sudden drop off in lifetime revenue. This increased understanding of resource configuration on operational performance allows an important reduction in the uncertainty associated with offshore wind.

5.6.2 Impact of wind turbine rating on operational costs

As technology has matured, the feasible size of wind turbines has increased to the multi megawatt range with 5MW offshore technology in commercial operation and 10MW machines in the early stages of development. Much of the drive towards larger machines has been driven by the concept of 'economies of scale' reducing costs. It has been proposed that for a given wind farm capacity there will be a cost reduction from having fewer, larger machines. This is due to fewer installation operations costs and fewer turbines to maintain. Offsetting these benefits is the increased cost of each operation as well as greater loss of earnings associated with downtime for a large machine.

Using blade sizes from commercially available 3MW, 5MW and 7MW offshore turbines and estimating a 10MW blade size the cost of various components for 4 machine sizes were calculated and are shown in Figure 5.21 [5.13].

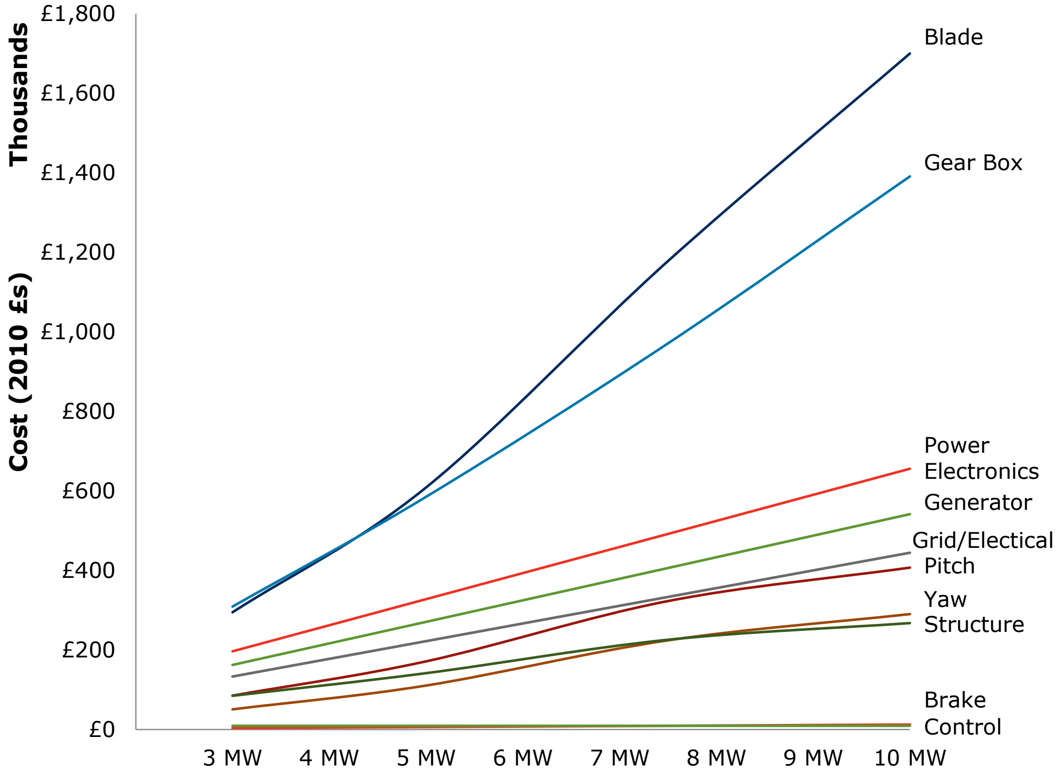

Figure 5.21: Component cost variation with turbine size

From Figure 5.21 it is evident that the blade and gearbox costs become increasingly significant at larger turbine sizes while the cost of some systems such as control are nearly independent of size. The increased cost of components is compensated for by the greater energy capture of larger machines. In order to determine the net result, the power produced by each turbine size must be considered. Turbines with the same nameplate rating may have significantly different power curves and power curves for very large turbines may be theoretical. For this investigation, the 5MW turbine power was selected as the reference, as it is well defined, and scaled to each of the other sizes.

Currently, there is uncertainty over the relationship between failure rates and turbine size in the offshore case, therefore failure rates were taken to be constant for each turbine size. However, it has been noted that for onshore wind turbines there has been an increase in failure rate as turbines have increased in size in the 50-1500 kW range [5.14] as shown in Figure 5.22. A similar analysis extending the result to the multi MW range is important going forward in order to fully quantify the analysis in this thesis. Potential novel solutions to overcome this scaling failure rate are discussed in Section 7.3.2.

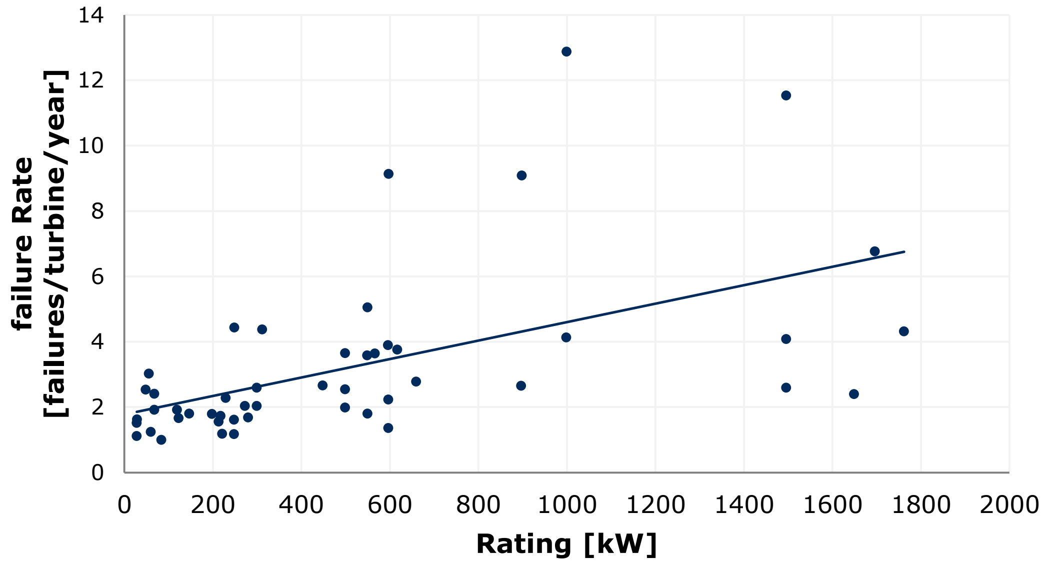

Figure 5.22: Failure rate vs turbine rating [5.13]

Maintaining the baseline scenario wind farm capacity of 400MW, a range of wind turbine ratings and number of turbines were investigated. Operational resources, climate and location of the wind farm were held constant; 133 x 3MW, 100 x 4MW, 80 x 5MW, 53 x 7.5MW and 40 x 10MW. The resulting availability and normalised O&M costs are shown in Figure 5.23. The absolute costs, broken down by contributions including and excluding lost revenue are shown in Figure 5.24.

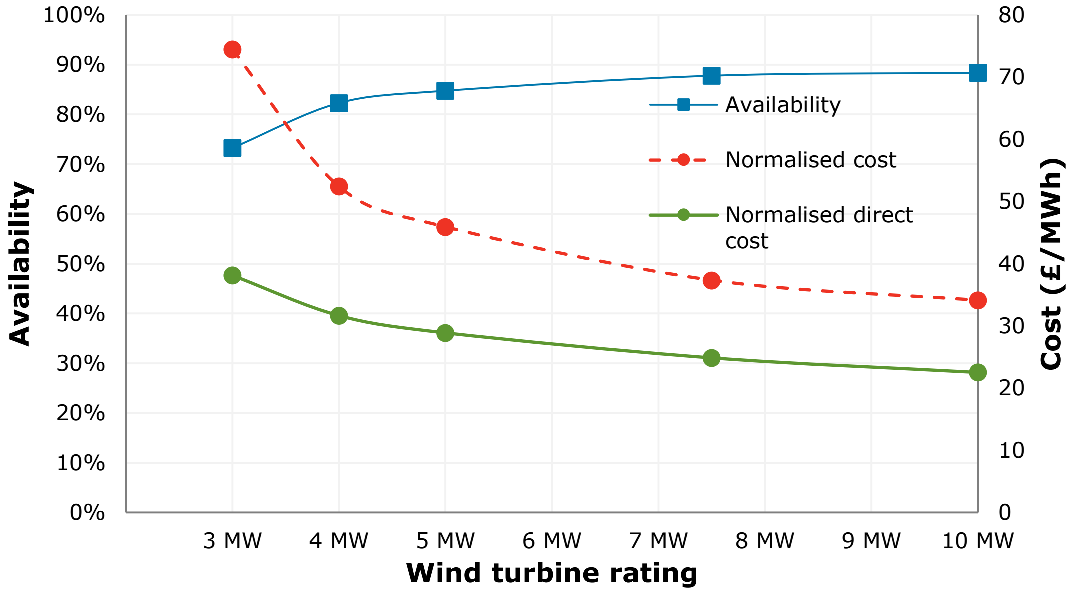

Figure 5.23: Availability and operational cost for different wind turbine size configurations

The results demonstrate that there is a clear improvement in availability and corresponding reduction in operational costs when moving to fewer, larger turbines. In real world operations, changing the size of turbines will not inherently lead to changes in performance; rather a similar level of performance is attainable with increased or decreased resources. However, by maintaining constant resource levels, it is possible to quantify the degree to which operational performance is related to the size and number of turbines. It can be seen that moving from 3MW to 5MW results in a 32% reduction in direct cost and moving from 5MW to 10MW results in a 28% reduction in direct costs. Considering lost revenue as well results in an even greater cost reduction.

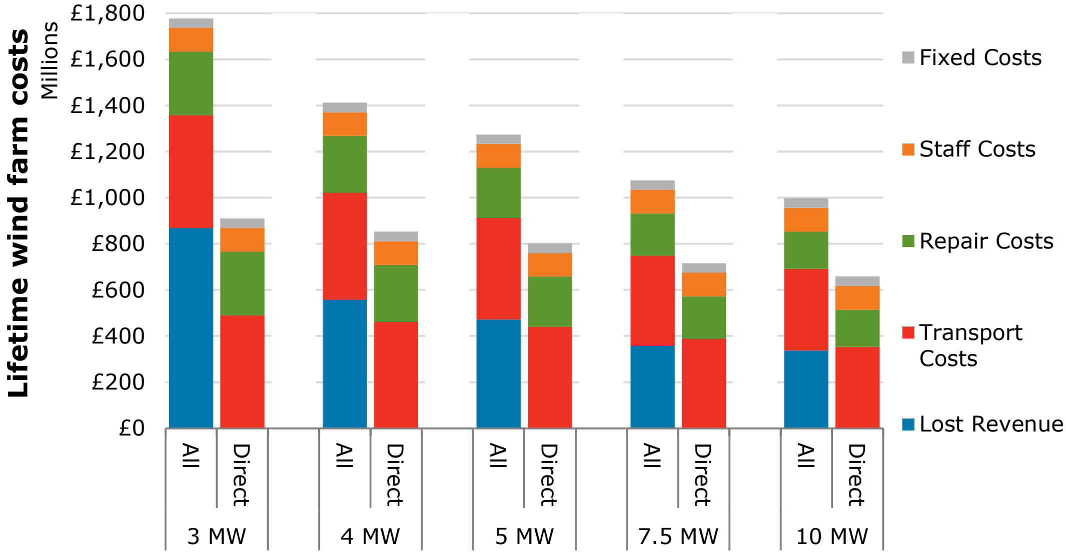

Figure 5.24: Breakdown of costs for different turbine sizes

The driver for this reduction can be seen in Figure 5.24. The reduction in lost revenue as wind turbine size increases is driven by having insufficient vessels with which to carry out the large number of maintenance actions. Considering the direct costs, the largest savings come from reduced vessel costs. This is driven by the lower usage for specialist heavy lift vessels and the ability of the same CTVs to be used regardless of turbine size. The reduction in repair costs is less significant as despite the lower number of repairs and replacements, each replacement has an increased cost, demonstrated in Figure 5.21. Despite this, repair costs are reduced.

5.7 Distance to port, operational strategy investigation

An additional cost driver for offshore wind is the distance from operational port that the wind farm is located. Although the location of the wind farm is a fixed value that cannot be altered once the wind farm is constructed, there are operational aspects that remain in the operators control; helicopter usage and operational port strategy. In this respect, the influence of distance to port can be considered as both a site and operational parameter and serves as an informative case study as to the degree to which operational strategy after commissioning can overcome physical limitations associated with a site.

5.7.1 Distance to shore operational analysis

The baseline wind farm was considered at a number of distances to port, ranging from 5 – 100 km. The results of changing the distance to port both with and without a helicopter in addition to the CTVs is shown in Figure 5.25.

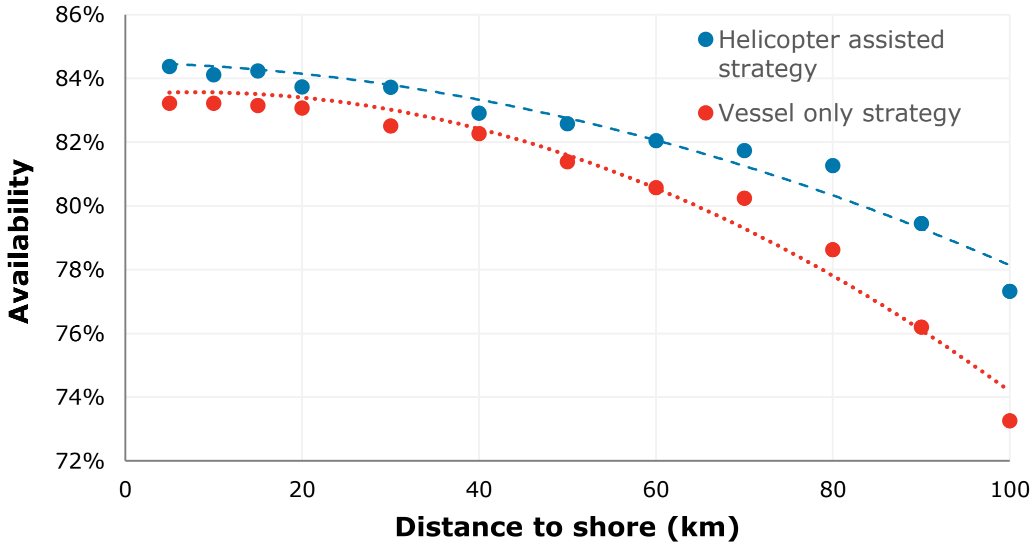

Figure 5.25: Availability against distance to shore with and without a helicopter

Increasing the distance to shore as expected reduces the availability of the wind farm. However, it is non-linear relationship and the use of a helicopter has a significant impact on baseline performance and the relative impact from increasing distance to shore. In the region 5-20 km, there is a very slight linear decrease in availability, with less than 0.25% change in absolute availability whether a helicopter is used or not. Comparing this to the 1.5% increase in availability obtained by the use of a helicopter, the importance of distance to port in this region is less significant.

Beyond the 30km there is an increasingly significant drop off in availability with increasing distance to port. In the case where a helicopter is present, a 6.8% reduction in availability is observed moving from 10-100km and when a helicopter is not available this increases to 9.96%. Various conclusions can be reached from Figure 5.25 and are discussed below.

Firstly, for a large wind farm with harsh North Sea conditions there is a significant benefit obtained from the utilisation of a helicopter in addition to CTVs. This is due to the increased accessibility achieved and corresponding significant improvement in wind farm availability. Secondly, there is a 'near shore' region where there is limited impact from changing distance to shore which is less than the impact of the operational decision to use a helicopter or not. Beyond this near shore region, the decrease in availability due to increased distance to port becomes increasingly significant. The impact can be mitigated by the use of a helicopter but the impact is still significant. Therefore, it will become necessary to adopt alternative operational strategies when the distance to shore becomes higher than the near shore region. The near shore region will be influenced by the size of the wind farm, climate and failure performance.

5.7.2 CTV and port operational analysis

In order to improve the operational performance and consequently reduce costs, unconventional operating strategies may become cost effective. Two such operating strategies for scheduled and smaller maintenance actions requiring the use of CTVs are the use of an offshore maintenance base or a 'mother-ship' (also referred to as 'Flotel') concept. The costs associated with these strategies are unknown as there is currently no operational examples for offshore wind and any assumed values have high associated uncertainties. Therefore, an accurate financial analysis identifying the circumstances under which different strategies are cost optimal is also not currently feasible. However, it is possible to investigate the potential performance improvement and quantify the financial benefit from improved power production and reduction in lost revenue. In addition, it is possible to quantify the sensitivity of different operational strategies to distance from shore and failure rate.

The use of an offshore maintenance base effectively reduces the transfer time between port and the wind farm and increases the operation window for performing maintenance. There is an associated logistical challenge involving transfer of crew and components onto the operational base. In this analysis, this aspect of maintenance has not been considered due to the additional modelling complexity required. This assumption can be justified by considering the working patterns of technicians to be flexible enough to accommodate delays in transfer and the operational base being sufficiently large to store a large number of components. This allows the number of access windows required between port and the operational base to be assumed low and have a negligible impact on operations. Larger repairs still require the chartering of specialist vessels under this operational strategy. A fully realised model of all operational aspects involved in these alternative operating strategies has been identified as an area for future research.

The mother-ship concept involves a maintenance ship that remains at the wind farm acting as a mobile maintenance base. Smaller CTVs are dispatched from this larger mother-ship in order to perform minor and scheduled maintenance and the mother-ship can be used to perform large maintenance actions using an external crane. There would still remain a small number of maintenance actions requiring specialist vessels however, the exact capability of a mother-ship would be highly variable and directly related to CAPEX and running costs. For this analysis, all failures requiring a field support vessel and 50% of those requiring a jack-up are performed by the mother-ship. Consequently, the mobilisation time is reduced to one week in all cases to reflect that there will be a delay obtaining components but not the specialist vessel itself.

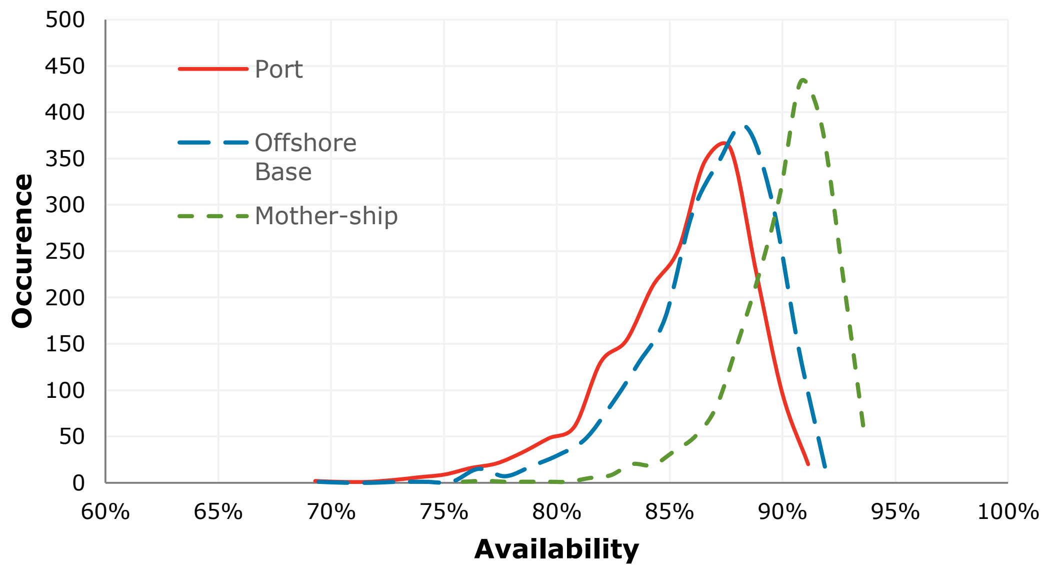

Figure 5.26: Distribution of annual availability for different operational strategies

The simulated annual performance for 100 lifetime simulations of the baseline with the different operational strategies described is shown in Figure 5.26. An improvement in availability performance is observed with both a maintenance base and mother-ship operational strategy when compared to the conventional use of a port. The improvement is greatest using the mother-ship strategy which results in a 4.8% improvement in availability compared to a 1.3% increase using a maintenance base. Equally as significant is the reduction in standard deviation of annual availability associated with the mother-ship strategy. Adopting this approach reduces the annual variability in availability and decreases project uncertainty.

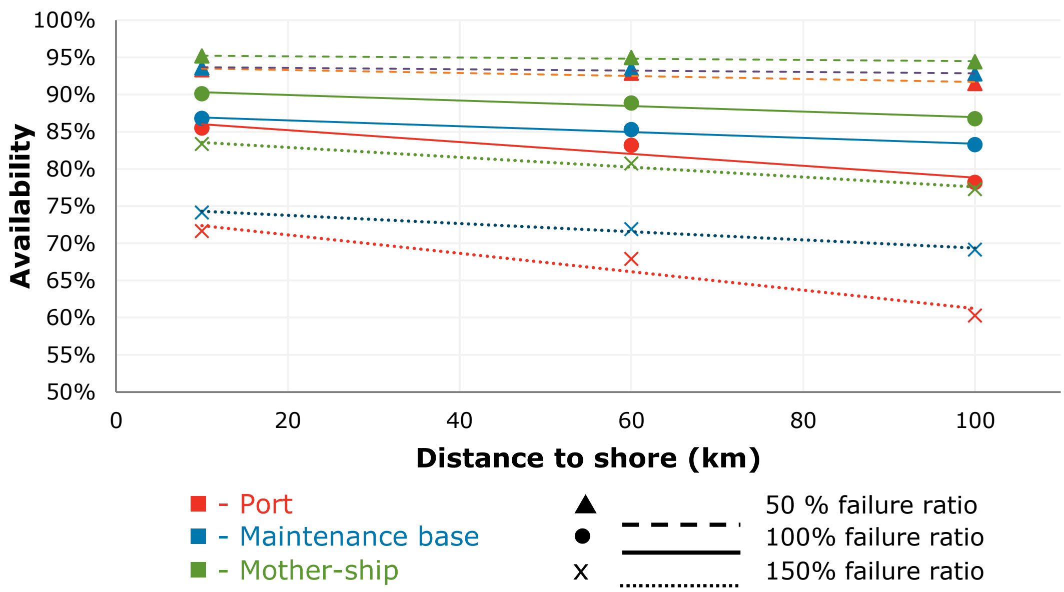

Figure 5.27: Impact on availability under different operational strategies and distances to shore

Prior to considering the financial implications of different strategies, an analysis of sensitivity to distance from shore and failure rates was performed. This analysis is shown in Figure 5.27 from which a number of conclusions can be drawn. Sensitivity to failure rate is more significant on availability performance than the operational strategy or distance to shore. However, the negative impact of increased failure rate on availability is increased as wind farms move further from shore. In the scenario where a wind farm experiences high failure rates and is located 100km from shore there is an availability improvement over the port strategy of 9% and 17% by adopting a maintenance base and mother-ship strategy respectively.

Table 5.3: Value of increased production from operating strategies

Distance to shore (km)	Failure rate	Annual production improvement over port	
		Maintenance base	Mother-ship
10	50%	£375,203	£3,223,806
	100%	£2,058,109	£7,604,201
	150%	£4,254,304	£19,210,516
60	50%	£747,619	£3,321,319
	100%	£3,239,056	£9,074,789
	150%	£6,386,058	£20,527,528
100	50%	£1,661,215	£4,700,410
	100%	£8,699,949	£14,216,890
	150%	£15,091,926	£28,235,512

Using an electricity value of £100/MWh, the resultant cost analysis of Figure 5.27 is presented in Table 5.3. The yearly performance benefits from using a mother-ship are in the order of several millions of pounds under all failure and distance to shore configurations which can be considered significant. The annual benefit of maintenance bases only reach comparable levels when the wind farm is at least 50km offshore and failure performance is at current levels or higher.

Although these revenue improvements are significant, the costs to achieve them have a high degree of uncertainty and are likely to be in the tens of millions over a wind farm life cycle. It is therefore not possible to clearly define the circumstances under which such strategy choices will represent the optimal solution to maximising lifetime project revenue. The methodology used however allows such an analysis to be carried out for a well-defined wind farm as the future costs become defined. This will allow operators to identify the optimal strategy for future projects.

The current range of costs for a jack up vessel would be in the range of £50m-£200m depending on the capability and operating depth [5.12]. If it is possible to procure a mothership vessel in the lower range of this cost window it would make economic sense to adopt this strategy. There will also be an annual cost associated with maintaining and operating the vessel. Although this would be higher than that of a conventional fleet, when the production performance benefit is in the millions of pounds range it is likely that there will an economic case for using specialist maintenance vessels far offshore.

5.8 Impact of external cost drivers

Throughout this thesis, the focus of analysis has been on the sensitivity of wind farm performance to wind farm configuration, operational parameters and operator decisions. These aspects are either defined prior to construction phase or can be influenced by operators during the life time of the wind farm. However, there are several cost drivers that are outside of the influence of wind farm performance or operator decisions. These costs have to potential to significantly influence the viability of a wind farm and an appropriate modelling approach is required to be able to capture this uncertainty. The adopted modelling approach has therefore been to apply costs that are not directly related to operational performance in the post processing phase of simulation. This allows a rapid sensitivity analysis of cost components to be performed.

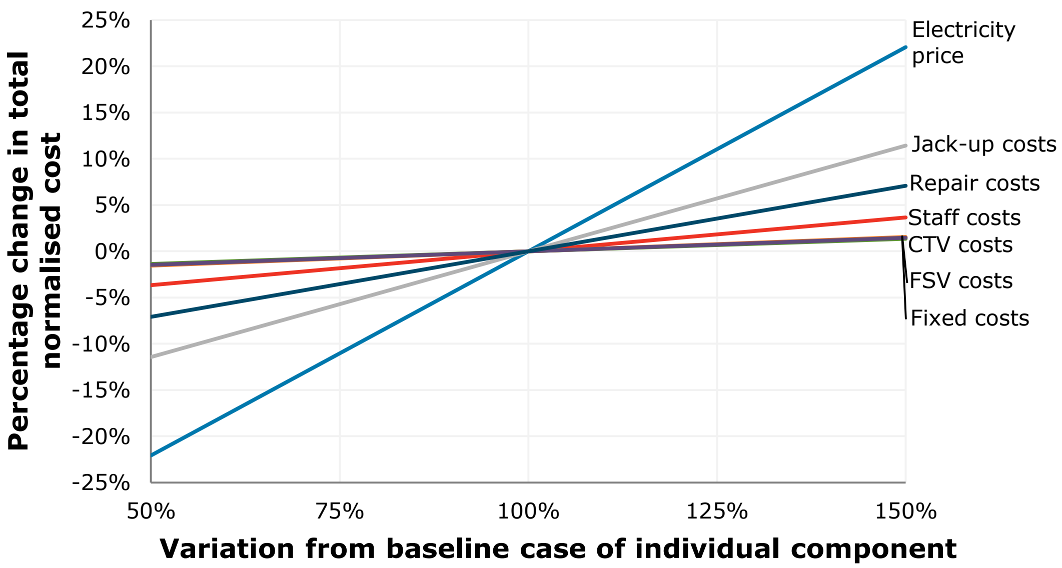

Figure 5.28: Cost sensitivity analysis for baseline case

Figure 5.28 shows an example sensitivity plot where costs of various components are varied and the impact on total O&M costs determined. This not only re-affirms the previously identified key cost sensitivities of electricity prices, jack-up and repair costs but provides their influence relative to each other.

This approach represents a simplistic cost analysis methodology and has the implicit assumption that over the lifetime of a wind farm all costs will rise or fall in proportion to each other. This limitation can be accounted for using discounting however, large uncertainties associated with future costs are not considered. More sophisticated approaches that attempt to quantify the impact of uncertainty and consider a range of future scenarios are considered in detail in Section 6.5.

Having considered the impact of failure rates and wind farm configuration, it has been identified in this chapter that there remains significant uncertainty associated with these variables. A particular area of high costs for offshore wind has been recognised as the use of specialist heavy lift vessels. A detailed study into operational strategies that can be applied to minimise these costs is therefore carried out in Chapter 6. In addition, a methodology is developed that allows the full range of uncertainties identified in this chapter to be quantified. This allows a fuller range of operating scenarios for a given wind farm to be considered and the value of understanding and controlling the key cost drivers to be determined.

Chapter 5 References

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Chapter 6

Advanced strategy analysis and development of a decision support methodology

For offshore wind there are several areas where a significant change in costs could occur due to a dramatic change in market condition, step change in technology, incorrect fundamental assumptions or adoption of significantly different operating strategies. The uncertainty of these changes cannot be captured using a simple sensitivity study and become computationally demanding to perform detailed sensitivity analysis on. Therefore, alternative modelling approaches are required.

For offshore wind, the operating strategy associated with specialist vessels represents an area with a high uncertainty and high impact on lifetime costs. It is an area that has not previously been considered in detail. Therefore, a thorough analysis on the impact of different strategies has been performed and is the subject of this chapter. Operational strategy, is then used to demonstrate a decision support methodology that can increase the value of the work in this thesis to the industry.

6.1 Heavy lift maintenance for offshore wind

As has been identified in Chapter 5 , there are high costs and potential delays associated with the use of specialist vessels which are required for repair and replacement of major components, principally the blade, generator, gear box and main bearings. These high costs are driven by use of specialist vessels with high CAPEX and day rate costs. An example of such a vessel is shown in Figure 6.1.

Figure 6.1: Example of a jack-up vessel being used for offshore wind turbine maintenance [6.1].

In order to minimise the impact from these operations, it is necessary to explore various potential operating strategies. This allows the identification of strategies that minimise cost, uncertainty and exposure to external cost influences or a combination of all these criteria. Previous analysis [6.2] of offshore wind vessel requirements has neglected heavy lift vessel strategies. For small wind farms, it has been acceptable to adopt a fix-on-fail approach to such repairs due to the relatively small numbers involved. This situation is changing due to the huge finance required for future projects with a larger number of turbines. A greater understanding of the circumstances under which different strategies are optimum and the key cost drivers associated with each approach has become vital to the success of large scale offshore wind projects.

In addition, adequate consideration has not yet been given to the different late life failure scenarios that are likely to be observed for offshore wind. In particular, the impact of late life wear out failures has been largely ignored. The financial implications for the industry as well as the degree to which operational strategies can mitigate the increase in operational costs have therefore been investigated in this thesis. The financial case for proactive maintenance strategies that avoid increasing failure behaviour can therefore be considered adequately.

6.2 Operational strategies

Discussion with operators as part of this thesis's research has established 4 operational strategies that are currently being considered by the industry and so formed the basis for the analysis below. Alternative strategies and external issues that may influence strategies are considered later in the chapter in Section 6.6. The strategies investigated, as well as perceived advantages and disadvantages were defined as:

- Fix-on-fail (FoF) - Charter vessel when fault is predicted or observed. Only pay a mobilisation cost and day rate for the duration of the vessel charter however, risks exposure to long mobilisation periods where the turbine will not be generating electricity.
- Batch repair - As FoF but operator does not go to spot market until a threshold number of failures have occurred. Reducing total number of charters but increasing exposure to lost revenue.
- Annual Charter - Short term (1-12) month yearly charter each year, failures falling outside the charter period do not receive maintenance until the start of the next charter period. Lifetime vessel costs established at beginning of project but this strategy is inflexible and has the potential for significant downtime.
- Purchase – Purchase (or lease) a vessel for the duration of the wind farm life. Inflexible, has high initial cost added to the CAPEX cost of a project and running costs are difficult to determine. However, permanent access to vessel will maximise wind farm availability, minimising lost revenue.

In order to model vessel costs under different contractual arrangements, expert knowledge has been applied to vessels currently operating in the North Sea that are suitable for offshore wind to estimate day rates depending on charter length. These are primarily derived from operational knowledge of the North Sea [6.1, 6.3] and values in [6.4, 6.5]. A more detailed description of this process along with a case study of the methodology in this chapter is presented in [6.6].

Figure 6.2 identifies the cost for vessels with varying capability under different operating contracts. This demonstrates that as the charter period increases in time, day rate costs are reduced. In addition, the day rate in the spot market results in the CAPEX cost of a vessel being met after approximately two years of day charters. This 'rule of thumb' ignores the operational costs of owning, maintaining and using a vessel but provides an insight into the high charter rates involved in the industry.

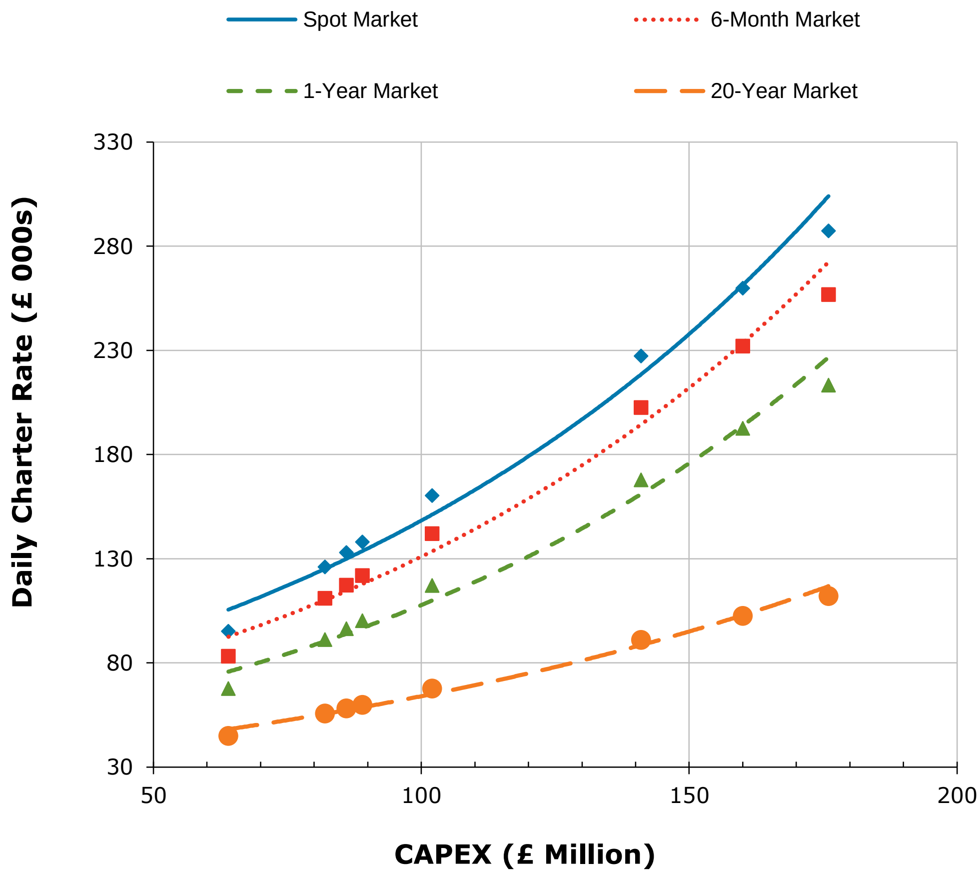


Figure 6.2: Vessel Day Rates under Different Operational Regimes [6.6]

6.3 Baseline analysis of heavy lift strategies

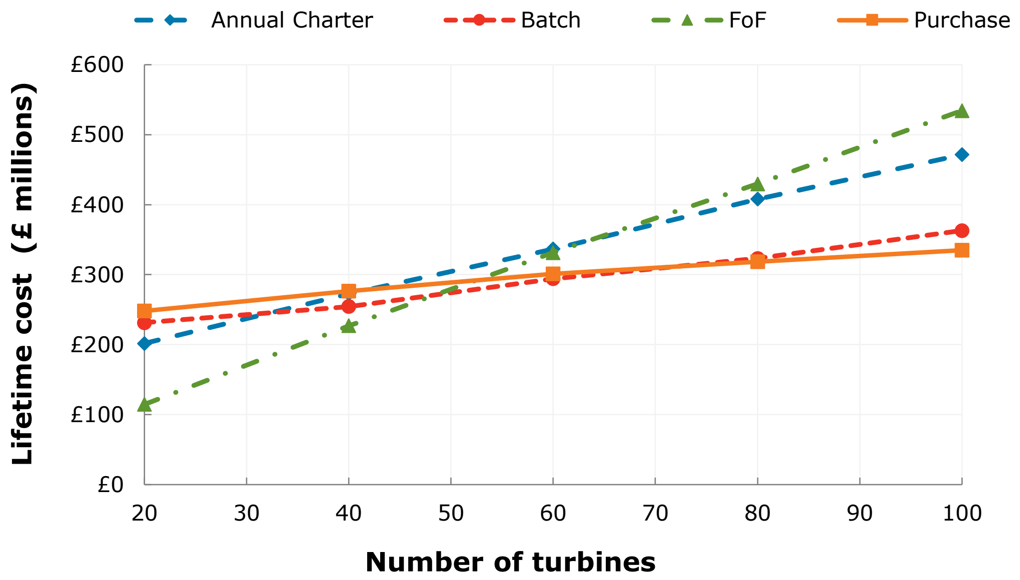
The initial analysis performed investigated sensitivity of lifetime costs to the size of wind farm and the failure rate of major components. Using the failure characteristics and costs in Table 6.1 a series of cases were simulated under different charter regimes, the results are shown in Figure 6.3 [6.2]. Component costs were estimated based on weighted average of observed failures and costs from [6.7].

Table 6.1: Heavy lift baseline costs

Failure type	Scheduled Maintenance	Manual repair	Minor repair	Major repair	Major replacement
Failure rate	1	5	2	0.25	0.067
Repair duration (hrs)	48	3	8	25	52
Vessel requirement	Crew Transfer (or Helicopter)	Crew Transfer (or Helicopter)	Crew Transfer (or Helicopter)	FSV (or large Helicopter)	Jack-Up
Day rate/ OPEX		£2500		£10 000	£150000 / £24000
CAPEX		N/A		N/A	£112.5 m
Number Available		5		1	1
Component Cost	£18500	£0	£2000	£75000	£450000

Figure 6.3 shows the sensitivity of strategies to wind farm size by absolute cost and costs per kWh produced. Costs in this figure consider only direct vessel procurement costs and lost revenue due to downtime associated with chosen strategy. When failure rates requiring specialist vessels are equal to the major failure rate observed onshore of 0.2 per year [6.8] and wind farms have more than 80 turbines, a purchase strategy becomes optimum. Using a batch repair strategy can achieve similar costs but with greater variability and exposure to the future price of electricity. This result identifies that with current market conditions and historic onshore

failure performance there is a strong economic case for purchasing a dedicated heavy lift vessel or adopting a batch repair approach. In order to determine if this result holds for a wider configuration of failure behaviour the sensitivity and key cost drivers associated with each strategy have been explored.



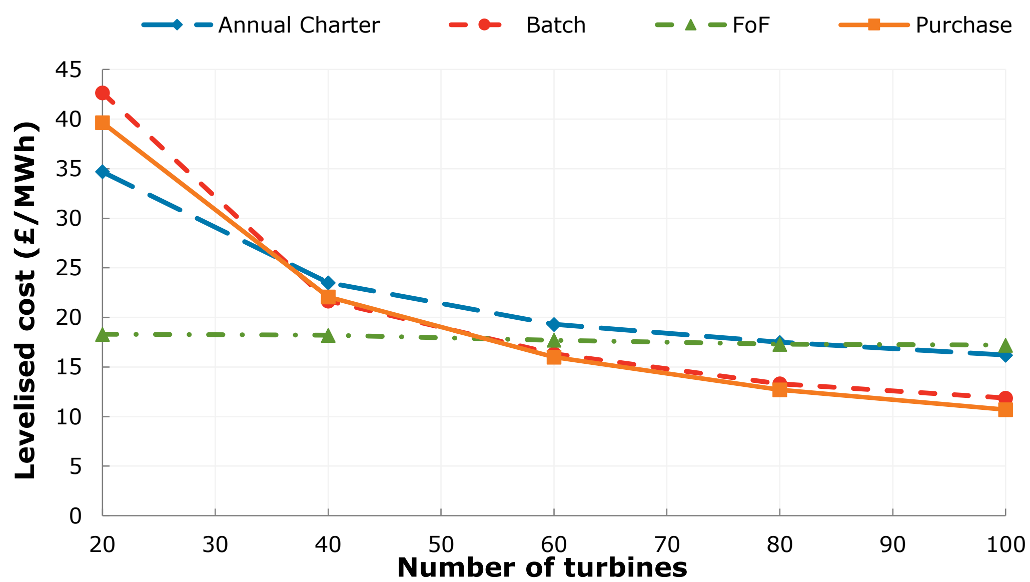


Figure 6.3: Absolute costs of strategies over a range of wind farm sizes and normalised Cost of Energy

Each of the proposed strategies was investigated for a 75 turbine wind farm of 5MW machines [6.9] using climate data typical of the

North Sea from [6.10]. The breakdown of cost contributions and the sensitivity to major replacement failure rates are shown in Figure 6.4 for each of the four strategies. Lost revenue values are based on 2013 UK offshore market conditions, staff wages are based on a cost of £80000 per maintenance personnel and wind farm efficiency of 90 % to account for array losses and transmission losses.

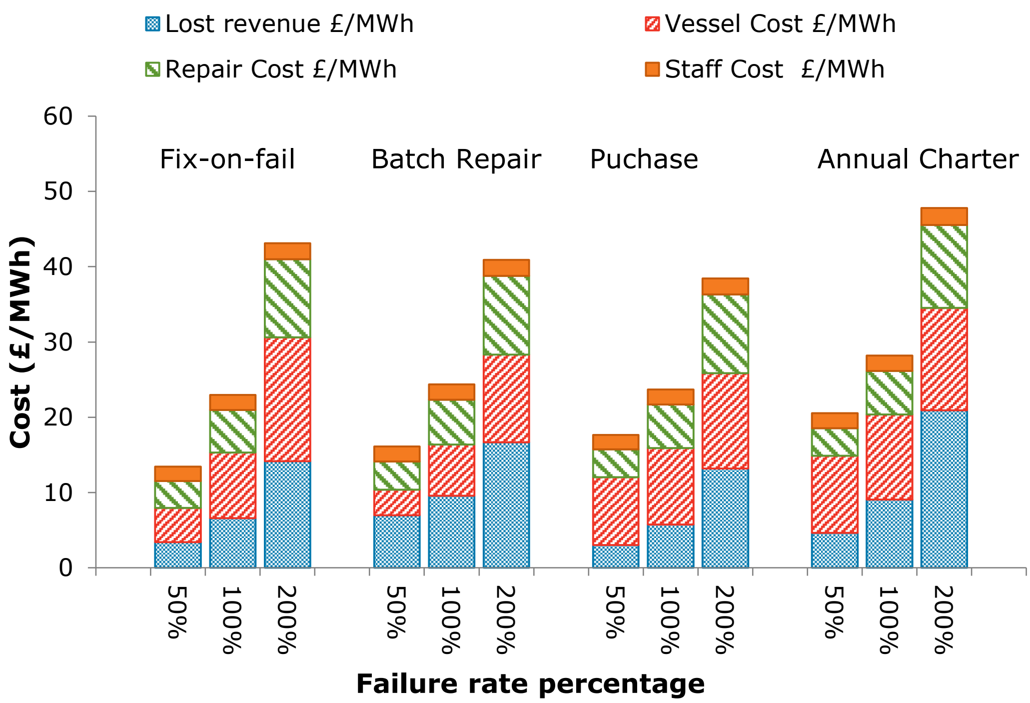


Figure 6.4: Breakdown of cost component and sensitivity to failures of operating strategies

For the baseline failure performance, the reactive fix-on-fail and batch strategies as well as purchase strategy are within 5% of each other, with the fix-on-fail OPEX costs marginally lowest. The fix-on-fail approach is most favourable when failure rates are lower than currently predicted with the batch and purchase strategies costing 17% and 24% more respectively. Scrutinising the reduced failure rate scenario, it can be observed that the batch repair approach costs are driven by lost revenue whereas purchase costs principally comprise of vessel costs, the costs are distributed evenly when adopting the fix-on-fail approach. When the failure rate is greater than predicted, the order of preference is reversed with purchase becoming optimum followed by batch repair and fix-on-fail which are 6% and 11% more expensive. The principal cost driver for the increase in fix-on-fail OPEX are vessel costs - identifying the high cost associated with repeatedly chartering specialist vessels from the spot market. The annual charter strategy is 20%-30% more expensive under all scenarios and on a cost optimal approach would not be considered. However, the operational strategy an operator would choose to adopt may be driven by a number of objectives which are considered in Section 6.4.

Considering the general conclusions from this analysis, the fix-on-fail strategy is demonstrated to be a cost effective approach when failure rates are low or for small wind farms. In addition, this approach is highly flexible with no up-front costs and the ability to move to a different strategy with no penalty. If the vessel market becomes saturated and vessel day rates fall then adopting a fix-on-fail approach will allow an operator to take advantage of this situation. If there is scarcity of vessels and day rates increase, it remains possible to adopt an annual charter type approach or commission a vessel for the remainder of the wind farm life. Finally, the approach benefits from spreading costs evenly between direct vessel costs and lost revenue. However, when failure rates are observed to be high the vessel costs associated with this strategy increase rapidly. Relying on the spot market for chartering vessels also exposes operators to volatile mobilisation times and costs which introduce a higher degree of uncertainty than other strategies.

The strengths of the batch repair strategy are consistent with the fix-on-fail approach with the added benefit of reducing exposure to the fluctuations of vessel market price and in particular the high costs associated with vessel mobilisation. Countering this is the added complexity of determining the optimum batch number to adopt. There is a risk of adopting the wrong value which may change dynamically and is dependent on operational experience. In addition, there is a potential for individual turbines remaining in a failed state for an unacceptable duration. If a strict batch approach is adopted then opportunities to perform maintenance in spring and summer months when accessibility is increased may be missed, resulting in poorer overall availability. The increased exposure to lost revenue results in this approach becoming less favourable than fix-on-fail and purchase strategies if the value of electricity increases, exposing operators to significant external risk.

Purchasing a heavy lift vessel adds a significant capital investment cost at the early stages of a project and may require the establishment of a vessel operations division which is outside the existing structure of a wind farm developer and operator. In addition, if the failures observed are significantly lower than those predicted, the purchase strategy is more expensive than others and cannot readily be changed. Countering these drawbacks, the purchase approach is the most robust strategy to minimising OPEX when failure rates are high and allow the highest availability to be achieved, minimising lost revenue. It should also be noted that the financial penalty from overestimating failure rate and adopting a purchase strategy is less than that from underestimating failures and relying on the spot market. This makes the purchase strategy the most risk averse strategy if the initial financial cost can be tolerated. There is also the possibility of sub-leasing the vessel if it is under used which mitigates some of the previously identified risk but this may be infeasible and is not considered in this study. Alternatively, a lifetime charter with an external vessel operator will provide the protection from increased failures without the high CAPEX and infrastructure cost although the total lifetime vessel costs will increase under this scenario.

The annual charter strategy displays some favourable characteristics; principally the consistent vessel costs irrespective of failure behaviour allow accurate vessel cost estimation. A guaranteed contractual price covering the life of the wind farm would also be favourable as it offers protection from increases in the spot market and the length of the contract may allow reduction in the day rate currently assumed. In addition, as offshore maintenance practice improves, the required duration of repairs will decrease while accessibility will improve with future vessel designs. This will reduce the lost revenue, particularly if failure rate increases. However, with the predicted failure rate performance, the inflexible nature of fixed contracts results in poor availability performance. This could be overcome by chartering vessels from the spot market but this negates the perceived strengths of the strategy. As a greater understanding of the influence of climate and maintenance procedures is developed through operational experience the uncertainty associated with annual charter will decrease and it may become viable.

6.4 Late life failure scenarios and mitigation strategies

The failure behaviour of onshore turbines has been explored in detail and investigations into identifying the properties of the early life hazard rate of wind turbines has been performed [6.11]. However, due to the relative immaturity of the industry there is a lack of data from wind turbines in the later stages of design life; the data has not yet been generated. This is a particular concern for developers and operators of offshore wind farms as unlike early life, this region of the wind farm operation is not covered by the warranty period. There is therefore a critical need to explore the consequences of increased late life failure. The expected late life performance of wind turbines can be informed by the failure characteristics of classical electrical and mechanical components. Figure 6.5 shows classical late life failure behaviour for electrical and mechanical systems, exhibiting different late life trends [6.12].

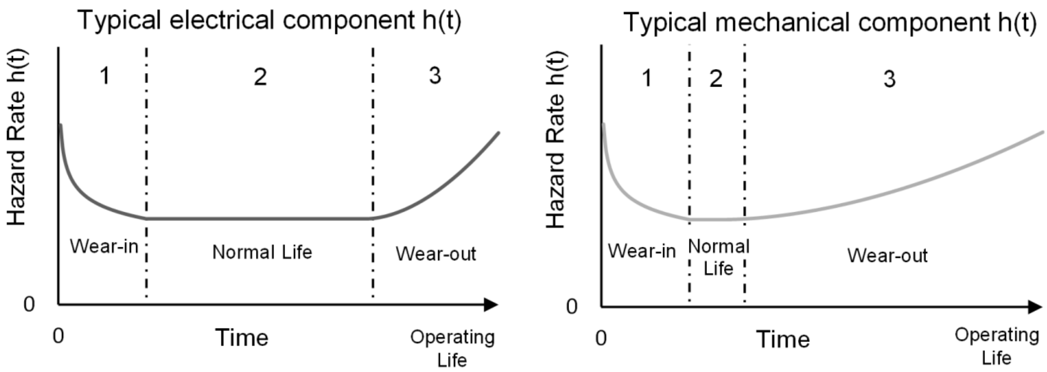


Figure 6.5: Hazard rate profiles of electrical and mechanical components

In both cases, the late life hazard rate is typically observed to double or treble from the ‘normal life’ hazard rate. In electrical components the wear out period follows an extended normal life period before a wear out period with a sharply increasing hazard rate is observed in the last third to quarter of the design life. In contrast, the normal life observed in mechanical components is typically very short and a more prolonged, gradually increasing hazard rate wear out period is observed. In the case where the final observed hazard rate has been reached following the two alternative profiles, the total observed failures over the lifetime duration following the mechanical failure behaviour will be greater.

Wind turbines have been assumed to follow the electrical component bathtub curve [6.4, 6.11]. However, the complex nature of the modern wind turbine means that this is unlikely to be observed for several of the large mechanical components such as the gear box, bearing and blades. One large area of uncertainty associated with the bathtub curve model is the influence of maintenance actions on the population hazard rate. In particular, major retrofits, addition of improved monitoring or more rigorous scheduled maintenance regimes may delay or remove the occurrence of wear-out. All of these actions have an associated cost to implement. While the impact of these actions is uncertain and cannot currently be quantified; the modelling approach and analysis in this study can determine the financial case for such maintenance actions. As a greater understanding of the lifetime failure behaviour is observed in operational offshore wind farms this will allow the optimal operating decisions to be made.

The late life failure behaviour has been investigated under several scenarios to explore the overall impact on OPEX cost and potential mitigation strategies. The scenarios and associated assumptions are described in Table 6.2. In all cases, the early life wear in failures are not considered as these have fallen under the warranty period and therefore will have a lesser impact on the long term OPEX costs for developers and operators.

Table 6.2: Late life failure scenarios

Scenario (Number)	Scenario description
Baseline (1)	Baseline scenario where no late life failure is observed. This is the previously assumed failure scenario and provides a benchmark with which to determine the impact of late life failures and the financial benefit of mitigation strategies
Electrical wear-out x2 (2) and x3 (3)	Electrical bathtub curve wear out behaviour takes place over the final quarter of the wind farm life time. This is investigated at a final hazard rate equal to double and triple the normal hazard rate.
Mechanical wear-out x2 (4) and x3 (5)	Mechanical bathtub curve wear out behaviour takes place from one third of the wind farm life time. This is investigated at a final hazard rate equal to double and triple the normal hazard rate.
Electrical x3, minor failures only without (6) and with mitigation strategy (7)	The failure behaviour associated with electrical failures principally relates to minor wind turbine failures that can be performed without the need for specialist heavy lift vessel. Therefore the increased late life failure is applied only to crew transfer failures, in order to mitigate this failure behaviour, increased vessel and maintenance staff are available at all times.
Mechanical x3, major failures only without (8) and with mitigation strategy (9)	The failure behaviour associated with mechanical failures principally relates to major wind turbine failures that require a heavy lift vessel. Therefore, the increased late life failure is applied only to major failures, in order to mitigate this failure behaviour, a heavy lift vessel is purchased and available throughout the duration of the wind farm life.

The resulting £/kWh lifetime OPEX costs of the specified scenarios and the corresponding availabilities are shown in Figure 6.6. The breakdowns of lifetime costs are shown in Figure 6.7. From Figure 6.6 and Figure 6.7, it can be observed that increased late life hazard rate has the potential to significantly increase the lifetime OPEX costs for offshore wind farms as well as influence the key cost drivers that need to be controlled. The most severe scenario is represented by the mechanical failure behaviour in scenarios 4 and 5 leading to OPEX costs increases of 150% and 325%, with large increases in lost revenue, vessel and repair costs. The increased costs under electrical bathtub failure behaviour results are principally driven by an increase in lost revenue as the total increase in failure occurrences are less, despite reaching the same final hazard rate.

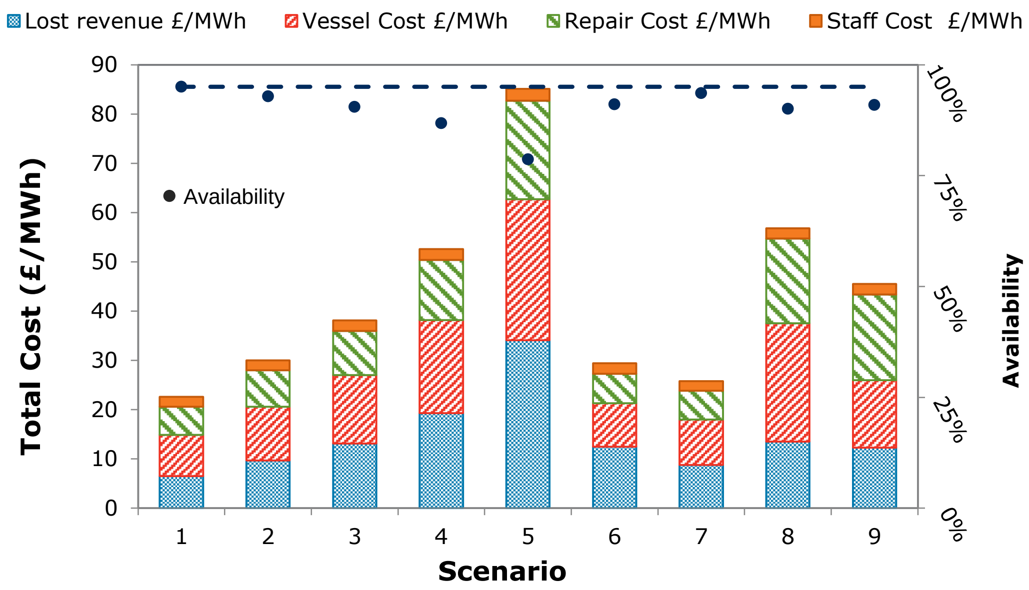


Figure 6.6: Lifetime cost and availability under different failure scenarios

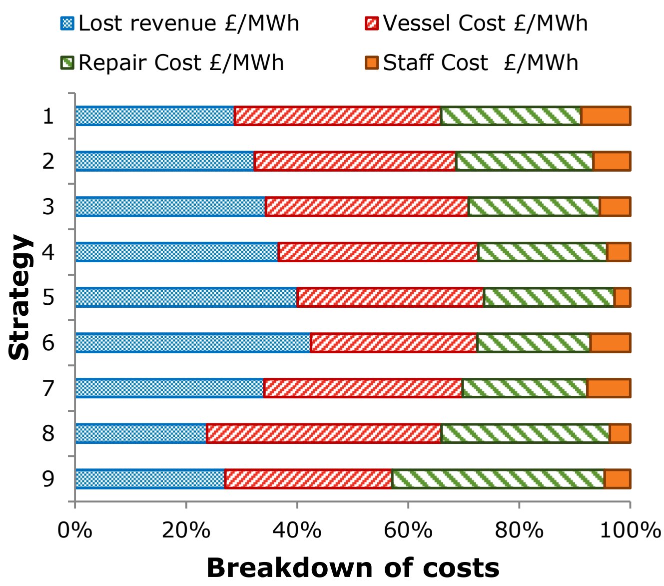


Figure 6.7: Lifetime cost breakdown under different scenarios

The influence of minor and major failures driving lost revenue can be identified by comparing scenarios (3) and (6) and also (5) and (8) which represent the extreme failure scenarios applied to both failure types and minor only (6) and major only (8). Large number of small failures increase lost revenue and critically reduce availability leading to a dramatic increase in £/kWh costs. Major failures have a lower impact on lost revenue and availability but high direct vessel and failure costs. Mitigating the impact of increased minor failures can be cost effectively achieved by increasing the number of vessels and maintenance staff available shown in scenarios (6) and (7) where the reduction in lost revenue and increased availability is greater than the additional costs incurred.

Considering scenarios (8) and (9), the adoption of a purchase strategy reduces the impact of increased major failures. Increased lost revenue and vessel costs are limited but remain significant and the large cost associated with repairs become unacceptable. Therefore, understanding the state of components and failure mechanisms that result in major repair and replacements are vital to controlling lifetime maintenance costs. There is a strong business case for active condition monitoring, inspection and preventative maintenance on these components. The specific value of such action and acceptable expenditure will depend on the configuration of the wind farm involved and could be determined using the prescribed modelling approach for an operational or planned wind farm.

The impact of turbine size and configuration, discounting rates and external price drivers have the potential to impact on optimum vessel strategy. In addition, over the course of a wind farm life cycle, different operational strategies may present the optimal solution. Very large future wind farms may require non-conventional operational strategies such as offshore bases or mother-ships that were considered in Section 5.7 These topics have been identified as key areas of research to be considered in future work.

6.5 Decision support modelling

A limitation associated with the detailed simulation modelling approach developed and utilized in this thesis, is that a single configuration of resources or operational strategy is chosen and the cost of that strategy is calculated over a specified time period. This approach is not able to capture that in practice, resourcing and strategy decisions are dynamic, may change during the wind farm life cycle and should be optimised at a global operator level rather than at a site level. In addition, the model described thus far is a steady state model, representing a static maintenance approach without considering how uncertainties evolve over time. Strategic aspects of large scale projects with long durations, which may be influenced by performance across several sites are unlikely to operate in this manner. Such projects are typically naturally structured and as such there are a number of decision points in the lifecycle. This provides flexibility that allows decision makers to take advantage of changing circumstances, new operational opportunities or avoid losses as uncertainties become realised.

There are a wide range of decision support methodologies that exist in the field of asset management which attempt to capture this dynamic behaviour. It was necessary to identify a decision support methodology that is capable of using the detailed results output from the developed engineering model. The objective is to quantify the impact of decision making and improve the understanding of key uncertainties. In addition, it is desirable to establish the financial benefit associated with reducing uncertainty or controlling uncertainty so that it can be calculated. In collaboration with colleagues from the University of Strathclyde department of Management Science, decision trees informed by Bayesian Belief Networks were identified as a suitable approach.

6.5.1 Decision Trees and Bayesian Belief Networks

Where a project has flexibility to change at different points in the life cycle it is referred to as a "real" option. Decision trees allow analysis that once a decision has been taken, this can narrow or expand the range of decisions available to a decision maker in the future. An additional output of the modelling approach allows quantification of the value of perfect information and control of variables; i.e. to determine how much it would be worth to reduce the uncertainty of a given variable and to reduce the uncertainty and specify the value that the variable takes in the future scenarios.

In order to develop the decision tree and consequently capture the real options available in the life cycle of the wind farm and to optimize decision making throughout, Bayesian Belief Networks (BBNs) are used. BBNs enable the modelling of high-level uncertainty variables in the problem; more specifically, to model high-dimensional probability distributions [6.13]. A BBN is a Directed Acyclic Graph (DAG), which comprises of nodes and arrows (edges). These can be used to create graphical representations of dependencies, typically in the form of influence diagrams. In this case, round nodes represent random variables (continuous or discrete), square nodes represent decision or utility nodes, and the arrows imply direct dependencies between the linked variables. For example, where we have two nodes X and Y with an arrow from X to Y, it implies that Y is conditional on Y. The full joint distribution for this is then $p(x,y) = p(x)p(y/x)$. The strength of the dependency can be estimated by decision makers and is represented in the BBN through the conditional probabilities. To evaluate the BBN, an equivalent decision tree can readily be constructed and standard dynamic programming can be used to solve the decision tree [6.13].

BBNs also provide the framework to update the dependencies as additional data becomes available; this allows the refinement of expert judgement with evidence during the lifetime of a project. For example, in the context of a wind farm, the reliability performance during the warranty period can inform the predicted failure behaviour of normal life operation by updating the beliefs to reflect this. It is then possible to change or modify operating decisions based on this evidence.

As previously identified in the case of influence diagrams, BBNs use graphical representations to qualitatively structure the decision making problem. Decision trees can then be directly created from influence diagrams and then used to show that once a decision has been taken, this can narrow or expand the portfolio of decisions available to a decision maker in the future. By identifying the different utility, minimising costs in the examples performed in this chapter, associated with each decision and random outcome, the decisions that optimize the utility can be selected. A detailed description of BBN theory and development of decision trees, are presented in [6.14], [6.15] and [6.16].

BBNs can be expanded to assess the optimal decision for multiple sites with a large number of uncertainties and decision points. In the context of offshore wind, the major uncertainties associated with life time cost of energy have been previously identified as failure behaviour and external costs. The number of decision points in practice will be determined by flexibility associated with contracts and working practices. In order to demonstrate the applicability and benefit of decision support methodology in this context a case study has been carried out. For this thesis, the creation of BBN influence diagrams was performed using Dynamic Programming Language (DPL) software developed by Syncopation. This allows decision trees to be automatically generated. The cost nodes were populated based on simulation results from the previously developed OPEX model and the decision support analysis could then be accomplished using DPL.

6.5.2 Informing decision support models via simulation

Decision support models allow uncertainties to be considered by assigning probabilities to different potential strategies. These probabilities are typically informed by expert opinion or by detailed operational experience. For some scenarios, the consequences of observing different scenarios will be known. When this isn't the case the cost and performance associated with different scenarios can also be defined through the use of operating history or by expert opinion. However, this approach can only be applied where suitable operating expertise or knowledge of the system exists to allow performance and costs under new scenarios to be inferred directly.

The immature nature of the offshore wind industry together with lack of transparency in operating performance necessitates that it is therefore necessary to inform decision support models using a detailed operating simulation. This is particularly true when considering scenarios with extreme operating conditions or novel scenarios. As operating experience is established, simulation models may still be required to understand what is contributing to observed performance in order to inform hypothetical future scenarios. The use of the detailed simulation model described in the early chapters of this thesis is therefore currently vital in order to facilitate the use of decision support models at this time. By establishing the benefit and a methodology to the industry from these tools it is hoped they will be widely adopted and in the future being informed by simulations, operational history and learnt expert opinion.

6.5.3 Offshore wind case study

The simplest scenario that can be considered is that where there are two decision points and a single uncertainty. In this example three different operational strategies can be adopted at each decision point, fix-on-fail (FoF), batch repair and purchase. Unless stated, the wind farm scenario used for this case study is consistent with that described in Section 6.2. Initially, the only uncertainty considered is failure rate of major subsystems which can have a value of 0.05, 0.2 or 0.4. An initial strategy must be adopted without knowing what the failure rate will be and a late life strategy can be adopted for the second half of the wind farm based on the early life performance. The BBN, graphically represented as an influence diagram for this scenario is shown in Figure 6.8.

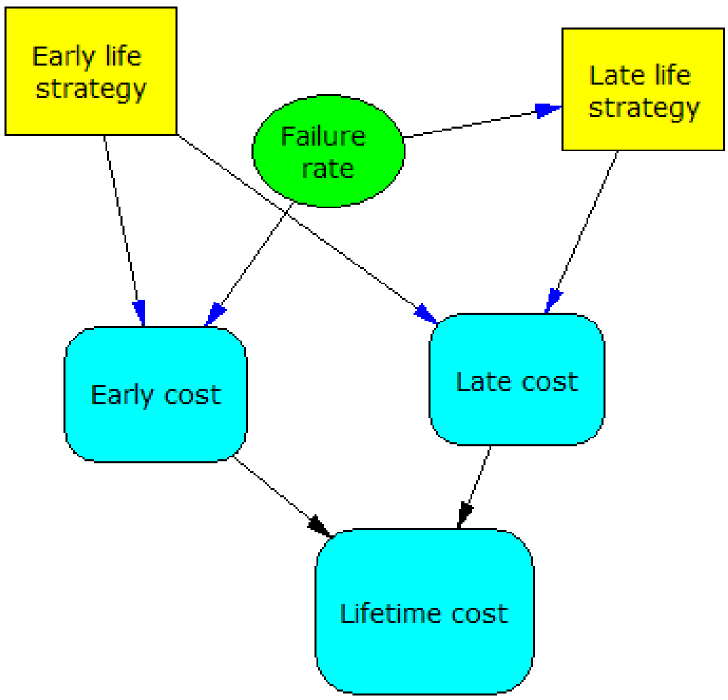


Figure 6.8: Simplistic influence diagram

In Figure 6.8 square nodes represent decisions, oval nodes represent uncertain quantities and square nodes with rounded corners represent value variables. Arrows show that the value taken by the node at the start of the arrow has a direct influence on the value taken by the node at the end of the arrow. Early cost is influenced by failure rate and the early strategy adopted. The late strategy is influenced by the observed failure rate, i.e. the strategy chosen takes into account the learning that has taken place in the early years of operation and changes to the operating performance. From that second strategy, a cost for the remaining life of the wind farm is determined. Finally, the total cost is the sum of the early cost and the late cost. This modelling approach allows the operator to capture the learning that will take place in the early period of operation and identify how the optimal strategy may change over time. The distribution of costs over all the different scenarios for the optimal strategy can be estimated.

The final step necessary before such analysis can be carried out is to provide likelihoods, or beliefs, of different failure scenarios being observed. These values must initially be determined using expert judgement or be based on historical data. As operational experience is gained these assumptions can be refined and the benefit of this reduction in uncertainty can be quantified. Initially, the only uncertainty considered is failure rate but in the expanded analysis, the external cost drivers of electricity price and vessel market are considered. The different uncertainty values and probability of occurrence are shown in Table 6.3. For the simplest case the resulting policy summary and policy tree are shown in Figure 6.9 and Figure 6.10. One assumption in this case study is that late life strategy is not constrained by early strategy. In this scenario, there is a cost associated with changing to/from a purchase strategy, gain/loss of CAPEX discounted by 5% per year until the decision point, but the flexibility to make this strategy change exists. This could be constrained so that the available late life decisions are limited by early life choices.

Table 6.3: Uncertainty values and likelihoods

Uncertainty	Low Value / Probability	Nominal Value / Probability	High Value / Probability
Failure rate of subsystem requiring specialist vessel	0.05 / P(0.2)	0.2 / P(0.7)	0.4 / P(0.1)
Electricity value	55 (£/kWh) / P(0.35)	120 (£/kWh) / P(0.6)	150 (£/kWh) / P(0.05)
Vessel costs	Half current / P(0.3)	Current market / P(0.5)	Double current / P(0.2)

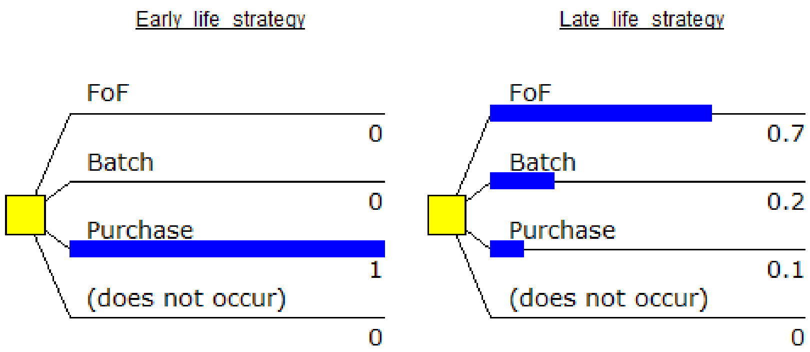


Figure 6.9: Simple scenario policy summary

Considering Figure 6.9, it can be seen that the optimal early strategy choice is to purchase a vessel. The most likely optimal late life strategy to adopt is FoF. In order to understand this result it is necessary to examine the full policy tree with expected values shown in Figure 6.10. Expected lifetime cost values, shown in millions of pounds, are determined based on the calculated values on the right hand side of the policy tree, weighted by the likelihood of reaching each branch. Working backwards to each decision point the strategy that is expected to return the lowest cost can be identified as the optimal decision. In this simple case, a purchase is always the preferable early strategy. Batch, FoF and Purchase are then the optimal late strategy depending on whether low, nominal or high failure rates have been observed respectively prior to making the late strategy decision.

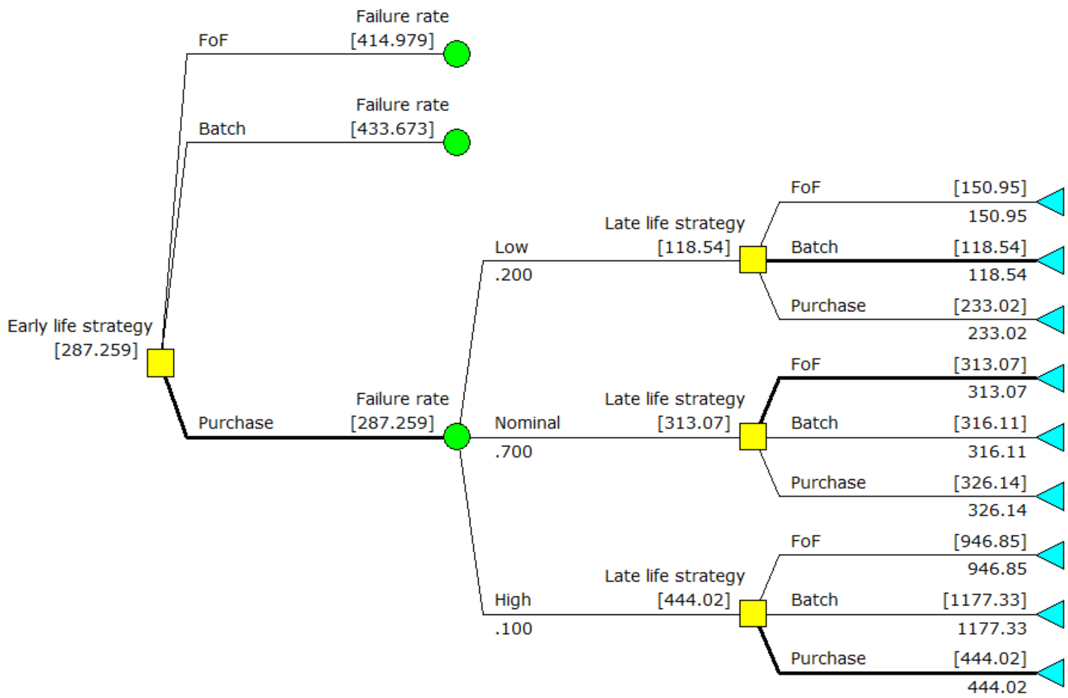


Figure 6.10: Simple scenario policy tree

Expanding this problem to a more realistic scenario where there are three uncertainties and three decision points the influence diagram, decision tree and resulting policy summary are shown in Figure 6.11, Figure 6.12 and Figure 6.13. The construction of the BBN and resulting decision tree follows the same logic and can be readily derived by expanding the simple case study. The interpretation of the policy summary is also consistent with the simpler example. However, as additional uncertainties and decisions are built into the model the policy tree rapidly expands and it becomes impractical to analyse visually. It is therefore more beneficial to represent the modelling output as a risk profile. A risk profile displays the cumulative likelihood of observing different branches at the end of the policy tree and provides the range of lifetime cost values for the project. The risk profile for the multi uncertainty and operator decision BBN is shown in Figure 6.14.

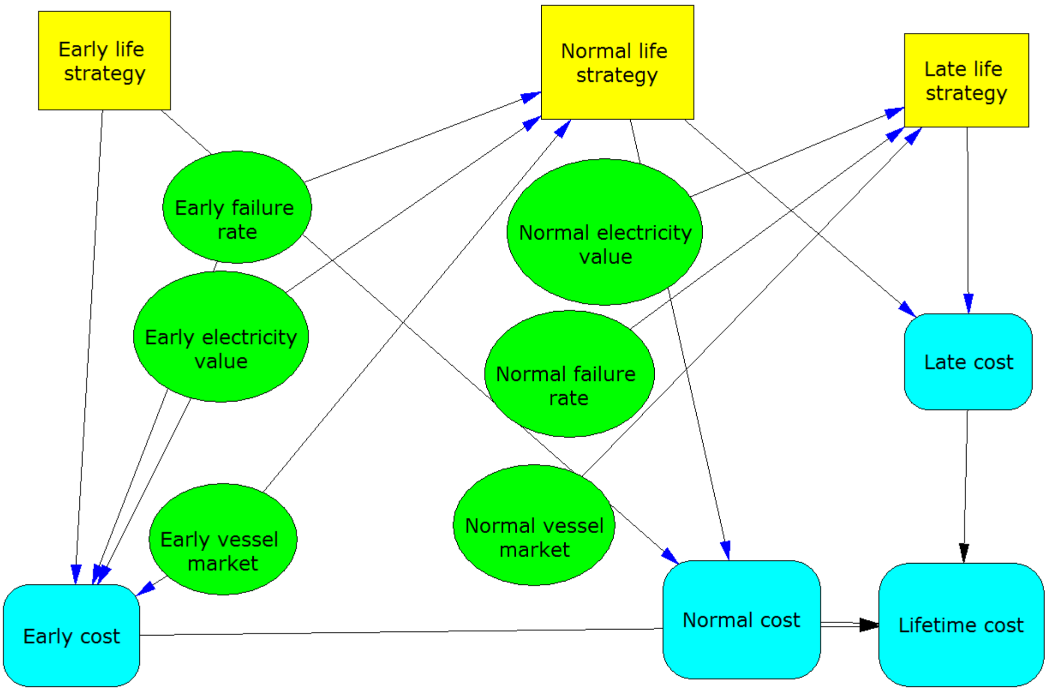


Figure 6.11: Multi uncertainty and decision point influence diagram

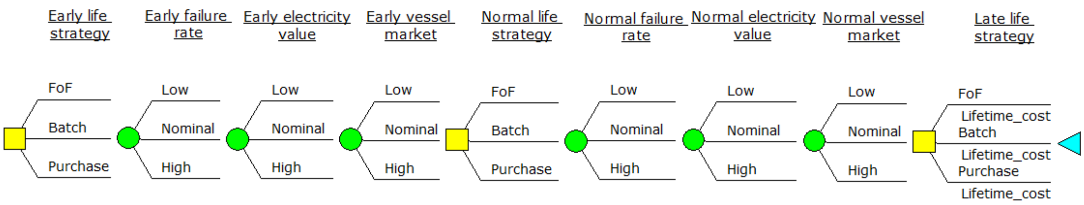


Figure 6.12: Multi uncertainty and decision point decision tree

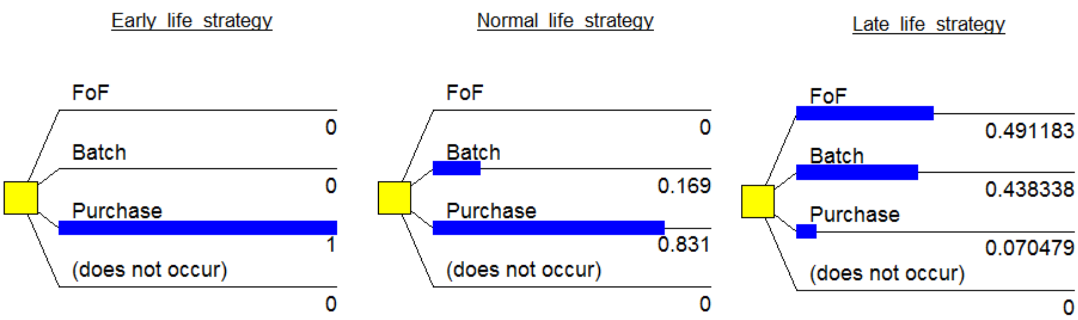


Figure 6.13: Multi uncertainty and decision point policy summary

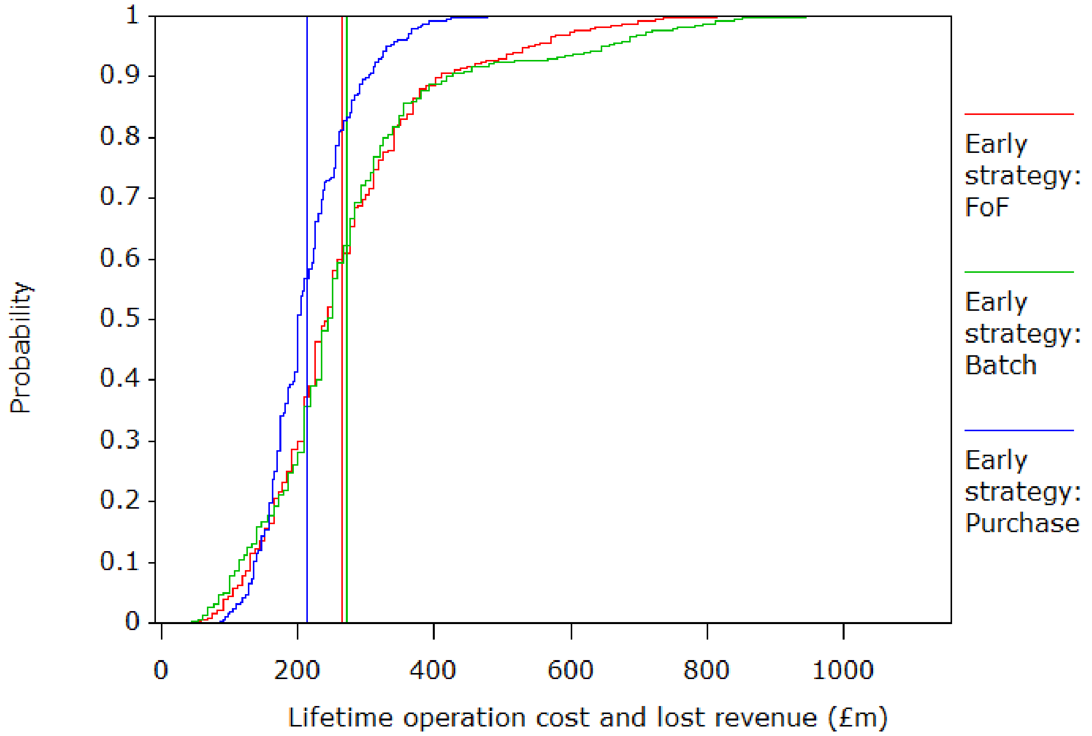


Figure 6.14: Multi uncertainty and decision point risk profile

Figure 6.14 shows the risk profiles for the BBN in Figure 6.11. In this example, the expected outcomes (vertical lines) and the probability of different operational costs associated with adopting each early strategy is shown. The lowest expected value in the modelled scenario arises from adopting an early purchase strategy. In addition, the range of possible costs observed for this strategy is significantly lower than the others and therefore can be considered the most risk averse approach. However, the lowest possible life time costs are achieved by adopting a batch strategy. The probability of achieving lower costs having adopted a batch strategy is approximately 20%. In this example, the large increase in costs associated with choosing a FoF or Batch strategy mean that only the most risk inclined operator would adopt them.

The greater insight into the range and likelihood of project costs provided by this type of analysis has a significant benefit in reducing overall project risk and improves long term budgeting.

There is an additional benefit associated with the presented decision support methodology. By manipulating the decision tree and moving the uncertainty node as far up the tree as possible it is possible to quantify the benefit of being able fully understand or control the uncertainty. The results of this analysis are shown in Figure 6.15 where perfect information is shown in yellow and the impact of controlling the variable shown in red.

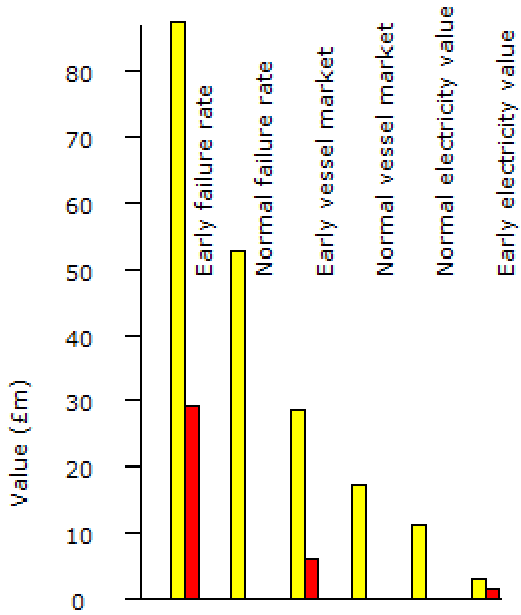


Figure 6.15: Multi uncertainty and decision value of information and control

From this analysis, it can be seen that the most significant benefits are associated with perfectly knowing the failure performance of the wind turbine. Knowing how the early failure rate is going to perform has a value of £87.1M while controlling it has a value of £29.4M. It should be noted that it is possible for the value of information to be zero. This means that knowing the performance in advance may change the absolute value of the maintenance strategy, but it has no effect on the decision making process.

The value of control is calculated by turning uncertainty nodes into decision nodes each time they appear on the decision tree. The value of controlling failure rates has less benefit with regards to the decision making process as there is greater risk and cost penalty associated with decision choices than the uncertainty in this scenario. A more detailed analysis of the value of perfect information is presented in [6.17].

The additional information gained by the combination of the developed operational cost model with decision making analysis is of significant benefit to the offshore wind industry. For developers and operators the principle benefit of this analysis is to be able to quantify the uncertainty associated with wind farm projects and the degree to which they can control related cost risks. This analysis enables the optimal operating strategy to be selected in order to minimise the lifetime operating cost and determine the subsequent range of costs having adopted those strategies. As well as an improved financial understanding this puts them in a significantly stronger contractual negotiating position when assessing which turbines to purchase and with regard to maintenance contracts. For example, in the case study the operator may be willing pay more for wind turbines from an OEM who is willing to take the performance risk (perfect information) or with proven failure performance (uncertainty control). The value they should be willing to pay for such improvements can be taken directly from Figure 6.15. From an OEM perspective the cost benefit analysis of design improvements such as more advanced condition monitoring can be rigorously explored using the described methodology. Extensions to the methodology are described in Section 6.6.

6.6 Further decision support modelling

The methodology can readily be expanded to consider the influence between projects, illustrated in the following scenario. An owner and developer is deciding on a vessel operation strategy for a wind farm that is about to move from the development to operation stage or exiting warranty period. They are currently uncertain about the failure performance of the wind farm and the vessel market is subject to high price uncertainty. They are also developing another wind farm which is scheduled to be commissioned as the early life period of the existing wind farm ends. As a result, the operator will learn about the failure performance from Site A, prior to Site B being complete and will gain a greater understanding of the vessel market. For simplicity, assume that the failure performance and vessel market costs observed at Site A will definitely be consistent with those observed at Site B. The influence diagram for this scenario is illustrated in Figure 6.16.

The BBN can then be solved in the same manner as before. In this way, it is possible to obtain added value from existing projects. Where external uncertainties such as the vessel market price on new projects can be influenced by existing projects, the modelling approach provides a framework to quantify this relationship. One limitation of BBNs is that they are static models that represent the joint probability distribution at a fixed point or interval of time. When considering the evolution of uncertainty during the life cycle it is necessary to consider how decisions change over time as information is gathered. In order to capture time related dependencies, it is required to use an explicit representation of time in a BBN.

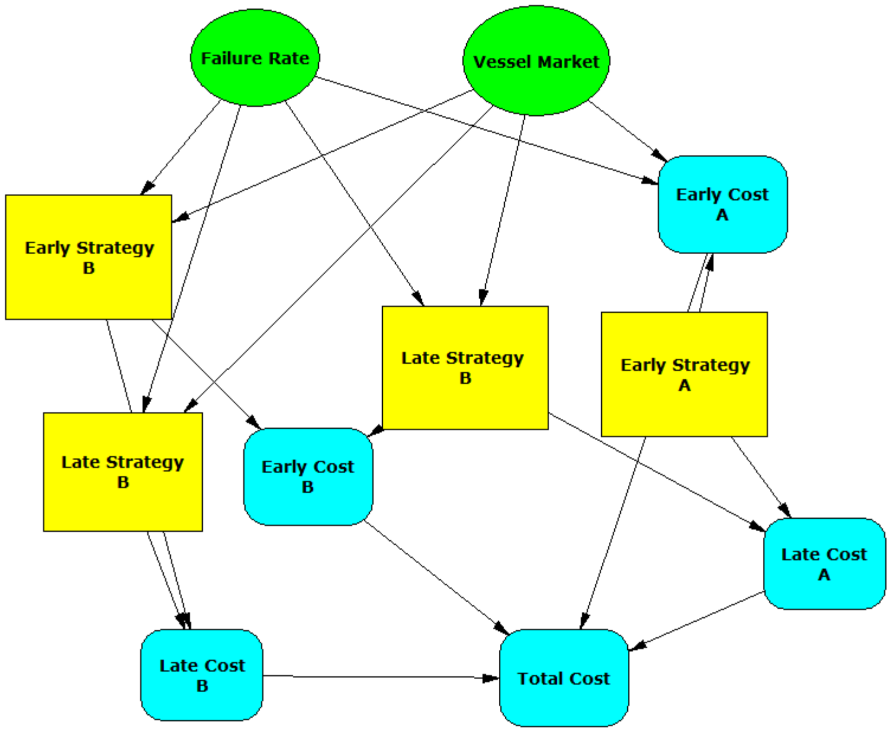


Figure 6.16: Multi site influence diagram

Dynamic Bayesian Belief Networks (DBBNs) are a further development of the decision making methodology and have potential to provide further understanding of uncertainty in the context of the wider offshore wind industry. DBNNs extend BBNs to allow for dynamic reasoning when changes occur over the time. DBBNs can represent the evolution of a system over time by interconnecting static BBNs over slices in time. Specifically, DBBNs allow the variables to be represented at multiple instants of time using the same network structure. Time is divided into successive time instants and a random variable represented by a node, is associated with each time instant. By generating a BBN for a specific time instant then repeating the same structure for all other time instants, the DBBN model is generated. Arrows between variables at different time instants represent temporal dependencies [6.18].

This application of DBBNs has been investigated for the general case of planning for offshore wind [6.19] and specific cases of offshore wind turbine gearbox maintenance [6.20]. However, there is a need to fully specify the full range of variables that will influence the industry going forward. Applying DBBN approach in conjunction with the detailed OPEX modelling approach developed throughout of this thesis, it will be possible to reduce uncertainty associated with temporal aspects of the offshore wind industry.

The importance of heavy lift operational strategies to the overall OPEX costs of offshore wind has been explored in this chapter. It has been identified that as wind farms increase in size it will be necessary to adopt unconventional strategies unless failure rates can be significantly reduced. Building on the work of Chapter 5, the uncertainty associated with late life failure performance of wind turbines has also been considered for minor and major failures. This analysis has highlighted the considerable uncertainty that is currently associated with offshore wind. The developed OPEX model has been used in conjunction with decision support models in order to quantify the impact of this uncertainty and reduce the associated risk. This offers industry, in particular developers and operators the potential to better manage costs and make strategic decisions on the basis of reasoned, considered models. Reducing the uncertainty prevalent in most areas of offshore wind development, which as has been extensively discussed throughout this thesis, remains a key barrier to widespread development of the industry. Until a large quantity of operational experience has been achieved, this modelling approach provides the most effective solution to this challenge.

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Chapter 7

Conclusion and future work

This thesis has presented a methodology for developing a comprehensive OPEX cost model and decision support framework for offshore wind. Using the developed models, the key influences on lifetime cost of energy have been identified and the sensitivity of overall operational performance and costs to their values has been quantified.

This concluding chapter provides a summary of this work, identifying key results and identifying the key contributions to knowledge that have been achieved. In addition, areas of future work that can build on the work or that are required in order to maximise the impact of this thesis are identified and are discussed in detail. Finally, a brief outlook of the industry recognising key challenges and opportunities and how the work in this thesis can contribute to the offshore wind industry is carried out.

7.1 Summary of conclusions

The first chapter outlined the objective, scope, output and novelty of this thesis. The first objective of this thesis was to specify a modelling methodology to estimate lifetime OPEX costs for offshore wind, including key modelling assumptions. The developed model was then to be used to identify key cost drivers and areas of uncertainty for offshore wind. The final objective specified was to establish a methodology for quantifying the impact of uncertainty. This was to be achieved by building on the OPEX model in order to reduce the risk present in the industry.

Chapter 2 reviewed the state of current pertinent literature and based on this, the key knowledge gaps were identified such as the impact of climate and failure rates on lifetime cost of energy. The large body of work exploring offshore wind O&M, along with more generic areas of asset management, failure and reliability modelling and climate simulation were all considered in detail. Additionally, a series of failure rate data sets were also specified for succeeding analysis in the thesis and for wider future work.

In Chapter 3, the ability to capture the influence of climate, wind turbine performance and operator strategy were specified as the key requirements for an OPEX model in order to accurately capture the operational reality of offshore wind. In addition, a suitable methodology was identified and described in sufficient detail for future researches to adopt that successfully meets the modelling requirements while remaining computationally efficient.

Chapter 4 established the degree to which the offshore environment influences the operating performance of wind farms. A number of issues that arise from adopting the chosen climate methodology in Chapter 3 were examined in the simulation context. The capability of the modelling approach to capture all relevant climate parameters was demonstrated successfully. Having considered the model, additional issues that arise from operating in the harsh offshore environment were identified; the availability and quality of data and the inter-annual variability of climate at a single site are both analysed. This allowed the impact of both on estimated performance to be quantified for the first time.

In Chapter 5, the uncertainty associated with offshore wind was examined in order to identify and separate aleatory and epistemic sources. The consequences of these sources of uncertainty when attempting to validate or verify models was considered in the context of a commercially sensitive industry. In this regard, a combination of using data from operational wind farms where available as well as model to model verification was identified and carried out in order to maximise confidence in the simulation model.

A detailed study of performance and costs was performed in order to identify key performance drivers and provide a greater understanding of what is contributing to operational costs. Based on this investigation, various sensitivity analyses were performed and the key results are highlighted in Section 7.3.2.

The initial analysis of Chapter 6 focused on the different heavy lift vessel strategies that an operator can choose to adopt in the current operating environment. The strengths and weaknesses of adopting each strategy were then identified by considering the direct and indirect operational costs for each strategy over a range of wind farm size and failure rate scenarios. Combining the developed OPEX modelling work, a case study examining the uncertainty of late life failure behaviour was performed.

Using the developed models in Chapters 5 and 6 it was possible to specify a decision support framework for offshore wind which has significant economic benefits. A case study comparing operational strategies was performed in order to demonstrate the decision support methodology and highlight the associated improved understanding of risk. By combining expert opinion with the detailed OPEX model, it was possible to determine the optimal early strategy to adopt, the range and likelihood of experiencing different life time costs and the value associated with perfect information.

7.2 Key contributions to knowledge and results

During the course of this thesis, various new contributions to knowledge have been produced. These consist of methodology and procedural outputs as well as results from analysis. These are briefly highlighted in this section.

7.2.1 Methodology and procedures

This thesis has detailed and rigorously tested a simulation structure that allows the lifetime operational costs of offshore wind to be specified. In particular, a novel Multivariate Auto-Regressive climate simulation model has been developed. In order to do this the key requirements for an offshore wind climate model have been specified as: simulating wind speed, wave height and wave period concurrently while replicating the annual distribution, short term (0-24 hours) correlation and longer term duration windows (24-72 hours); correlation between different climate variables and seasonality. Combined with A Markov Chain Monte Carlo failure simulation model which has previously been applied to engineering systems it was demonstrated that the model is able to accurately simulate offshore wind O&M.

A baseline wind farm has been established in collaboration with other research groups and wind farm operators. This will enable future models to be verified. In addition, the subsequent sensitivity analysis carried out greatly increases confidence in the performance of developed models when applied to hypothetical scenarios.

The first detailed study of operational strategies for heavy lift vessels has been carried out providing valuable new information to the industry. Four current operational strategies considered by operators have been identified and modelled, Fix-on-fail, batch repair, annual charter and purchase. The optimal strategy at a given wind farm will depend on a host of external costs and market conditions which are variable in time. Therefore, it is not possible to construct a definitive set of conditions for when a given strategy should be adopted. However, the analysis demonstrates that it is possible to gain an understanding of what is driving lifetime cost of energy under different operating scenarios using the prescribed methodology. This will allow operators to recognise the consequence of their operating decisions in a new level of detail.

Finally, a decision support methodology that enables the consequences of large uncertainties that are present for offshore wind to be considered and scrutinised has been specified. This was achieved using Decision Trees which are generated from Bayesian Belief Networks, represented by Influence Diagrams. This allows the value of uncertainty knowledge and control to be quantified for a project, guiding financial decisions and reducing risk for the industry.

7.2.2 Analysis results highlights

The Egmond aan Zee wind farm was simulated and strong agreement was shown between model and data. The simulated availability was within 0.5% of the observed availability with seasonality preserved and the relative contributions to downtime from each subsystem replicated.

A number of locations representing current and future wind farms around the UK and in the North Sea were compared. The influence of climate on operational performance was quantified. For the baseline scenario, excluding major replacements, a 5% difference was observed between the site with the calmest and most extreme operational climate. Additionally, the seasonal variation at sites further from shore was shown to be up to 4 times that of near shore, sheltered sites.

It has been shown that increasing accessibility can reduce the variation across sites but there is a marginal benefit beyond 2m Hs in the North Sea. Finally, a direct analysis in order to quantify the influence of wind and wave climate on OPEX costs was performed and is shown again in Figure 7.1. An approximately linear relationship is present between wave heights and operating costs as this only influences accessibility. Considering wind speed which influences power production and accessibility, it was identified that there will be a minimal OPEX value for a given wind farm and vessel configuration.

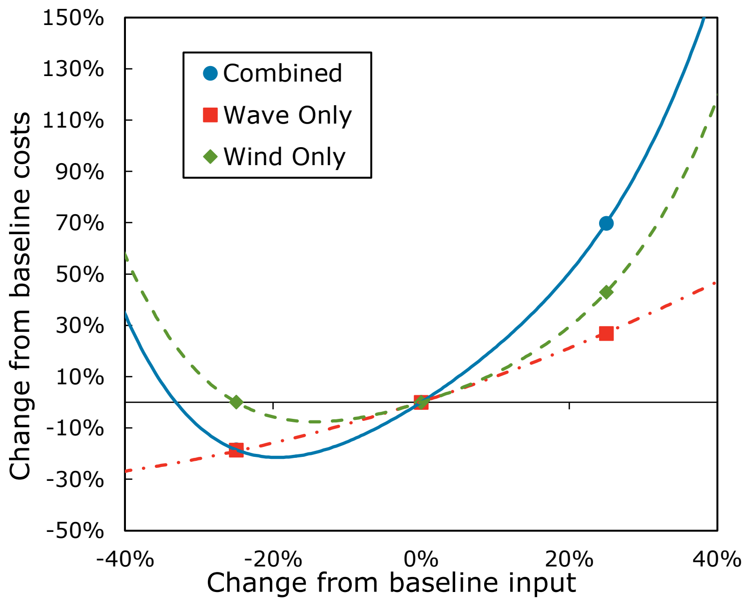


Figure 7.1: Variation of OPEX costs with change in wind and wave climate

The highest modelling sensitivity was observed from failure rate and climate. This emphasizes the urgent need for the industry to improve understanding of how wind turbines are performing in the offshore environment and reaffirms the vital need to build an industry wide failure database and offshore operating practices identified in Chapter 3.

The distance to shore and wind turbine size configuration were both identified as key cost drivers, although they will not impact on operational costs as immediately as failure rate. As wind farms become larger and further from shore, alternative maintenance strategies will become optimal. Detailed analysis results identified:

- Doubling the average size of offshore wind turbines from 5 – 10MW results in a 28% reduction in direct operational costs, if failure rates can be maintained while increasing machine size.
- A mother ship scenario will deliver 4-20% availability improvement, dependent on failure rate profile, when moving 100km from shore while annual variation is minimised under all distance and failure scenarios.
- Considering the baseline scenario the use of a helicopter in addition to CTVs ranges from 1.5 – 9.9% and increasing revenue by up to £100m over the lifetime of a project as the wind farm moves 100km from shore. A clear economic case for when to use a helicopter can therefore be made using the developed model.

When considering external costs that do not impact on operational performance, the largest external cost driver has been identified as electricity price followed by jack-up vessel costs. Jack-up vessel costs were therefore identified as the key external cost driver that operators have the ability to influence.

A study of late life failure behaviour addressed the uncertainty surrounding the late life performance of large turbines. This established that for minor failures, it is possible and cost effective to mitigate increased failures with additional resources. For major failures requiring specialist vessels it is not possible to increase resources in a similar manner. As a result, the lifetime charter/purchase strategy was identified as the most robust strategy to adopt to mitigate the costs associated with late life failures.

Finally, it was demonstrated that as wind farms increase in size, the conventional approach of going to the spot market when a failure is observed no longer represents the optimal strategy; a batch or lifetime charter option become preferable. The specific cross over point will vary significantly depending on the operating environment, wind turbine performance and localised costs of resources. Under current market and operating performance conditions, there is an economic case for adopting unconventional strategies at wind farms with more than 60 turbines. The cost reduction in heavy lift operations for larger wind farms has been shown to be up to 50%. Importantly, the modelling methodology developed allows the key cost influences to be considered for a given site with the current operational cost values to determine the most appropriate scenario in the development stage and the degree to which improvements can be made during the operating life time of the wind farm. Critically, the value of key financial choices at the development and operations stage will be significantly more informed by quantifying the uncertainty in a project which is not understood using traditional modelling approaches alone.

7.3 Future work

Despite being considered one of the most mature renewable sources of energy, there are a large number of areas where further research opportunities exist. In particular, there are certain areas where further investigation that can directly build on the work in this thesis. Additionally, there are areas where further information has the potential to increase the impact of this work which are discussed in this section.

7.3.1 Research that can build directly on this thesis

The focus of the work in this thesis has been directed at identifying long term cost of energy for offshore wind and strategy decisions that are made at yearly or greater intervals. In order to facilitate this, the operations simulations have been limited to hourly resolution in order to remain computationally practical. As the offshore wind industry matures and sites are developed many of the long term variables considered with the current model will become fixed. At mature sites operating in the post warranty period, there will be an increased focus on variables and decisions that are effected over a shorter time horizon of weeks, days and even within the operating shift. As a result, there is an opportunity to develop a model with greater fidelity in order to focus on the maintenance actions in a single shift as opposed to lifetime strategies.

A high resolution, short term modelling tool could be developed as a separate model to sit alongside the lifetime cost of energy model. Alternatively, the simulation of operational shifts where maintenance actions can be performed can be simulated separately and feed back into the lifetime OPEX model. The latter approach is being carried forward at the University where the operational shift is considered within the larger simulation model. This will allow the impact of climate on operability to be considered in detail as well as simulating a detailed mixed vessel fleet and different access systems to be explored in a greater level of detail although it will come with a computational penalty.

The strategy analysis in this thesis simulated a single individual, well defined strategy for the duration of the wind farm life. Moving between strategies was considered only in the decision support model at discrete times. Fully integrating the operational and decision support models would allow for the consideration of hybrid or dynamic strategies throughout the wind farm life cycle. To do this accurately, the real world constraints on changing strategy that arise from contracts and obtaining resources must be imposed. If this can be achieved, it is conceivable that a decision support model could be developed that uses operational history in order to accurately estimate future OPEX as well as identify optimal strategy and configurations.

One area where the decision support model could be extended has previously been identified in Section 6.6 and relates to using Dynamic Bayesian Belief Networks. This would allow the variable outlook of the offshore wind industry to be considered. For example, uncertainty associated with the number of future wind farms could be examined. This could be in the context of likely impact on external market costs or from the viewpoint of pooled resources across wind farms. This has the potential to significantly reduce the costs associated with vessel operations. In addition, if a single operator has a portfolio of wind farms that are built in different stages DBBNs allow the changing operating conditions to be represented.

7.3.2 Knowledge areas to increase the impact of this thesis

This thesis has identified that the biggest epistemic uncertainty in offshore wind comes from wind turbine failure behaviour. This is currently being addressed by the creation of failure databases and knowledge sharing. Combined with individual operator experience at operational sites, the uncertainty surrounding failure rates will be reduced as the industry matures. However, there is still uncertainty surrounding the underlying failure behaviour drivers and the extent to which operators can influence failure performance through their actions.

In order to create a fully representative OPEX model, the impact of maintenance, effect of climate, benefit of condition monitoring and consequence of retro-fitting need to be better understood. In the context of this work, the hazard function model described in Section 3.2 could readily be replaced with a more sophisticated model. This would allow these currently poorly understood influences to be reflected as additional knowledge of them becomes available. Ultimately this could extend to integrating operational data in order to refine the expected OPEX costs throughout the lifetime of a project.

The focus of reliability in this thesis has been on the wind turbine generator. The methodology is readily extendable to common cause failures such as interconnecting cables or substations that affect the power delivery of multiple wind turbines due to a single failure. Unlike the wind turbine, where there is a historical onshore record with which to inform offshore failure rates, there is currently no publically available failure datasets for these ancillary components of the wind farm. As operational data becomes available, expanding the model to represent these rare, high impact failures will be possible. This will allow their impact on lifetime cost of energy to be quantified and reduce the overall uncertainty associated with offshore wind.

Due to the availability of data and the industry standard of determining vessel access by considering only significant wave height, the operational analysis in this thesis considered only wind speed and significant wave height. The climate model has been demonstrated to be readily extendable to include wave period which has a direct influence on operability of vessels and there are a number of additional weather parameters that influence marine operations. For heavy lift vessels, currents and tides will also impact vessel capability. Helicopter operations are limited by visibility and there may be a limit on turbine transfers associated with icing in colder waters. The influence of these factors will be heavily dependent on the wind farm location and require additional data sets that are less readily available. Nevertheless expanding the offshore climate model to incorporate all climate aspects that could influence offshore wind maintenance would improve the applicability of the developed OPEX model.

Finally, it has been identified in this thesis that weather represents the largest aleatoric uncertainty for offshore wind. The impact on operational and cost performance from inter-annual variation has been considered in this thesis. However, a large additional uncertainty associated with offshore maintenance comes from forecasting accuracy. There is a large body of scientific work in the field of forecasting. In the context of wind energy, this has typically focused on the power systems operations impact from incorrect forecasting. Quantification of the impact and value of accurate forecasting in the context of wind farm maintenance has significant value from the offshore wind perspective.

7.4 Outlook for the industry

Over the duration of this thesis, the offshore wind industry has continued to show strong growth in Europe and in particular in the UK. However, many of the challenges facing the industry that existed when this work started remain and in some instances the outlook for the industry has worsened. A competitive market with various machines in the 6MW and greater size still remains a number of years off. Issues and uncertainty surrounding reliability performance remain and are likely to do so until a larger number of OEMs enter the market or a more diverse range of owners gain significant operational experience. While CAPEX costs have not shown significant reductions, capacity factors and overall cost of energy have shown improved performance indicating there is a clear path to reduced cost of energy.

In the UK, the uncertainty surrounding the electricity market reform has led to a number of wind farms being down scaled or suspended indefinitely. There still remains a large number of projects in the development and planning stage and a political will for offshore wind to contribute significantly to the future energy portfolio of the country. In order for the promise of offshore wind to be realised, developers require confidence that the technology makes economic sense even in the face of future uncertainties.

The methodology developed and analysis in this thesis allows a greater understanding of the key variables that will influence the life time cost of energy going forwards. Where these can be influenced by operators, the value from improving performance can be quantified allowing focused spending. For external drivers that are outside of direct operator control, the modelling framework allows the risk of a project to be quantified to be more accurately captured in project planning or when entering long term contracts. This could result in the delay or cancellation of projects that are not economically viable with the current turbine performance and access solutions. However, this will help identify key developments that are required to secure the industry going forward and ensure innovation is focussed where it will have the greatest impact. The work in this thesis can therefore contribute considerably to improving confidence in the industry in the short term. In the longer term, this thesis can help to define the path for offshore wind to become a mature technology, providing a reliable, cost effective contribution to the energy mix in the future.

Appendix I – Model convergence

The Gelman-Rubin convergence diagnostic operates on the basis that if several independent streams are run, the variance between the streams, B and variance within the streams, W will converge. For *k* parallel streams of length *n*, B and W are calculated for each scalar summary *v* and then compared. With v_{ij} , *i* identifies which chain is being considered and *j* determines the position in the chain. This is expressed mathematically in Eq. (A.1) – Eq. (A.7).

$$B = \frac{n}{k-1}\sum_{i=1}^{k}(\bar{v}_{i.} - \bar{v}_{..})^2 \tag{A.1}$$

where

$$v_{i.} = \frac{1}{n}\sum_{j=1}^{n}\bar{v}_{ij} \tag{A.2}$$

and

$$v_{..} = \frac{1}{k}\sum_{i=1}^{k}\bar{v}_{i.} \tag{A.3}$$

$$W = \frac{1}{k}\sum_{i=1}^{k}{s_i}^2 \tag{A.4}$$

where

$$s_i = \frac{1}{n-1}\sum_{j=1}^{n}(\bar{v}_{ij} - \bar{v}_{i.})^2 \tag{A.5}$$

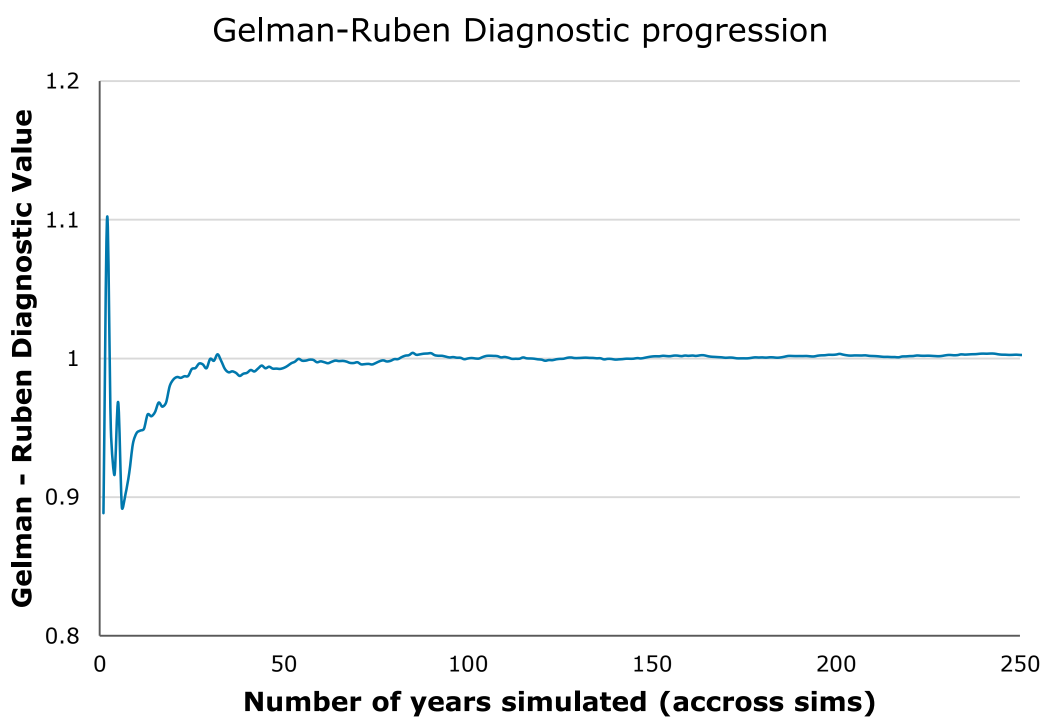
Overall variance of v is therefore

$$\widehat{var}(v) = \frac{n-1}{n}W + \frac{1}{n}B \tag{A.6}$$

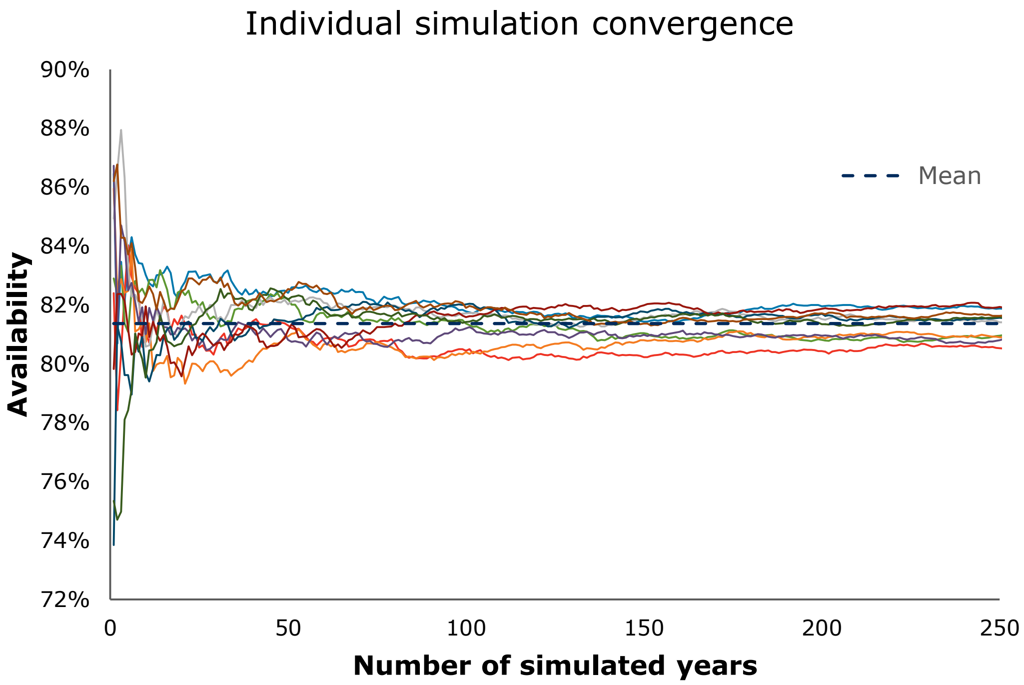
This expression is a conservative estimate of variance; it tends to overestimate the variance. W is the opposite, it under estimates variance. Comparing the two therefore provides a metric, $\hat{r}$ to compare the convergence of the variances to determine if n is large enough. The test statistic is formalised in Eq. (A.6)

$$\sqrt{\hat{R}} = \sqrt{\frac{v\hat{a}r(v)}{W}} \tag{A.7}$$

It is recommended that $\hat{R}$ values are less than 1.01 for convergence. A sample plot showing the convergence from 10 parallel lifetime simulation outputs along with the value of the individual simulation availabilities are shown in Appendix 1 and Appendix 2. It can be seen from comparing across simulations that for this example approximately 150 simulations are required in order for the simulation to be considered converged at a mean availability of 81.17%



Appendix 1: Gelman-Ruben convergence example



Appendix 2: Individual simulation stream convergence

Appendix II – Cost input and model output

Appendix 3: List of model cost inputs

Name of attribute	Description	Unit
Market Electricity Price	Wholesale value of produced power	£
Support Mechanism Value	Value of any support mechanism	£
Support Mechanism Factor	Multiplication factor (current ROCs is 1.5)	£
Staff Cost	The total of staff wages	£
CTV Day Rate	Daily vessel charter rate	£
CTV Fuel Cost	Fuel cost of CTV per litre	£
Fixed CTV Costs	Fixed costs for CTVs per year	£
Helicopter Fuel Cost	Fuel cost of helicopter per litre	£
Fixed Helicopter Cost	Fixed costs for helicopter per year	£
FSV Day Rate	Daily vessel charter rate	£
FSV Mobilisation Cost	Total mobilisation cost for FSV	£
FSV Fuel Cost	Fuel cost of FSV per litre	£
Fixed FSV Costs	Fixed costs for FSV per year	£
Jack-up Day Rate	Daily vessel charter rate	£
Jack-up Mobilisation Cost	Total mobilisation cost for Jack-up	£
Jack-up Fuel Cost	Fuel cost of Jack-up per litre	£
Fixed Jack-up Costs	Fixed costs for Jack-up per year	£
Port and Operations Costs	Total cost of port operations per year	£
Insurance Costs	Total insurance cost per year	£
Scheduled (Repair Costs)	Average cost of single scheduled repair	£
Remote Reset (Repair Costs)	Average cost of single remote reset	£
Minor (Repair Costs)	Average cost of single minor repair	£
Medium (Repair Costs)	Average cost of single medium repair	£
Major (Repair Costs)	Average cost of single major repair	£
Replacement (Repair Costs)	Average cost of single replacement	£

Appendix 4: List of model outputs

Name of output	Description	Unit
Availability	Average availability for each year	%
Availability - no scheduled maintenance	Average availability without scheduled maintenance for each year	%
Availability - OEM	Availability excluding weather and logistics delays which are assumed responsibility of the operator	%
Availability - Power Based	Availability based on power produced compared to theoretical maximum yield	%
Power Produced	Average power produced for each year	kWhr
Lost Power	Average power lost for each year	kWhr
CTV Travel	Average total time of CTV travels for each year	hours
CTV Usage	The usage of CTVs divided by the theoretical maximum usage if the CTV could be used with perfect accessibility	%
Helicopter Travel	Average total time of helicopter travels for each year	hours
FSV Travel	Average total time of FSV travels for each year	hours
FSV Charter	The average number of times a FSV is chartered over the life time of the wind farm.	
FSV Usage	The number of hours the FSV is used divided by the total number of chartered hours.	%
Jack-up Travel	Average total time of Jack-up travels for each year	hours
Jack-up Charter	The average number of times a Jack-Up is chartered over the life time of the wind farm.	
Jack-up Usage	The number of hours the Jack-Up is used divided by the total number of chartered hours.	%
Average Wave height	Average wave height for each year	m
Average Wind Speed	Average wind speed for each year	m/s
Completed Scheduled Maintenance	Percentage of scheduled maintenance tasks that are completed over the duration of the wind farm life	%
Capacity Factor	The ratio of wind farm potential power output over theoretical maximum output if perfect availability and rated wind speeds were observed at the site	
Convergence	A measure of the confidence in the simulation results described in Chapter 3	
Simulation Time	Total time spent for the simulations	seconds
Monthly Av. -Abs	Average availability for each month within the simulation length	%
Monthly Av. - OEM	Average monthly availability based on the definition of OEM availability in 3	%
Monthly Power Produced	Average power produced for each month within the simulation length	kWhr

Monthly Lost Power	Average power lost for each month within the simulation length	kWhr
Failure Rate	The average number of yearly failures simulated for each subsystem. If this number is lower than the annual failure rate value input to the model, it is an indication that there is insufficient resources and times when no turbines are operating are being simulated, hence failures cannot be allocated to turbines.	failure/ year
MTTR	Average mean time to repairs	hours
η	Estimated contribution of subsystem to overall down time of wind turbine.	%

Appendix III – Base case specification

Appendix 5: Base case vessel inputs

Vessel input	Crew Transfer Vessel (CTV)	Field Support Vessel (FSV)	Heavy-Lift Vessel
Number of vessels	3	1	1
Governing weather criteria	Wave	Wave	Wave (movement) / Wind (repair)
Weather criteria	1.5 m	1.5 m	2.0 m / 10.0 m/s
Mobilisation time	0 weeks	3 weeks	2 months
Mobilisation cost	£ 0	£ 0	£ 500 000
Speed of vessel	20 knots	12 knots	11 knots
Technician capacity	12	60	100
Day rate	£1750/day	£9500/day	£150 000/day
Maximum offshore time	1 shift	4 weeks	No limit
Comment	Hired.	Charter period 1 month.	Charter period 1 month.

Appendix 6: Base case failure classification

Failure input	Manual reset	Minor repair	Medium repair	Major repair	Major replace	Service
Repair time	3 hours	7.5 hours	22 hours	26 hours	52 hours	60 hours
Required technicians	2	2	3	4	5	3
Vessel type	CTV	CTV	CTV	FSV	HLV	CTV
Failure rate	7.5	3.0	0.275	0.04	0.08	1
Repair cost	0	£1000	£18 500	£73 500	£334 500	£18 500

Appendix 7: Base case wind farm description

Wind farm description	Value	Comments
Number of turbines	80	
Distance maintenance base to wind park	50 km	
Wind and wave weather data	FINO	Pre-processed wave height and wind speed data.

Appendix 8: Base case technician inputs

Technician inputs	Value	Comments
Technician cost	80 000 £/year	Per person
Number of technicians available	20	
Working shift	12 hours	
Number of daily shifts	1	

Appendix 9: Base case revenue inputs

Revenue inputs	Value
Price of electricity	90 £/MWh
Wind turbine power curve	Based on V90 power curve from [16]
Cut-in and cut-out speeds	3 m/s, 25 m/s