THE UNIVERSITY OF STRATHCLYDE

Operations and Maintenance Modelling for the Future Generation of Offshore Wind Energy

A thesis submitted for the degree of Doctor of Philosophy

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Is olc an ghaoth nach séideann do dhuine éigin

- It’s a bad wind that doesn’t blow good for somebody

DECLARATION

Abstract

In today's fluctuating economic climate, reducing the cost of energy remains a critical objective in the development and deployment of renewable technologies. Offshore wind, as a leading source of large-scale renewable power, must continually improve its cost efficiency to remain competitive. One of the most significant areas of cost reduction potential lies in Operations and Maintenance (O&M), which can account for a substantial portion of the total lifecycle cost of offshore wind farms. Over the past two decades, a wide range of strategies and modelling approaches have emerged to optimise O&M planning and execution. This thesis contributes to this evolving field by applying and extending O&M modelling techniques to address some of the emerging challenges facing next-generation offshore wind farms.

The work is structured in two parts. Part I builds upon an existing O&M simulation model focused on corrective and scheduled maintenance. Although the foundational model predates this work, it is significantly extended through new functionalities, updated failure data, and novel scenario analyses. The first set of investigations examines how environmental and human factors influence maintenance strategy and long-term costs. Specifically, it explores the impacts of limited daylight, sea ice, and health and safety considerations, such as the feasibility and effectiveness of implementing night shifts. The findings highlight that human and environmental constraints must be integrated into O&M planning: night shifts offer little economic advantage in regions with extended daylight, and while operating in ice-prone waters is feasible, it introduces substantial additional costs due to the need for icebreaking vessels. These trade-offs underscore the importance of context-specific cost-benefit analysis.

Further in Part I, the model is applied to assess the operational implications of turbine upscaling. The first phase evaluates the performance of larger 10 MW turbines using failure rates derived from smaller, well-established turbine classes. The second phase introduces newly collated failure rate data from literature for 15 MW turbines and explores the impact of different drivetrain configurations across various site conditions. Results show that drivetrain performance is not universally transferable across turbine sizes. For example, medium-speed geared turbines, previously seen as less favourable in other studies, performed comparably to direct-drive turbines in milder metocean conditions, owing to improved reliability and reduced turbine downtime. These findings emphasise the importance of selecting drivetrain technologies based on site-specific conditions, rather than simply extrapolating from existing small-turbine trends. The analysis also reveals a persistent gap in publicly available failure rate data for next-generation turbines, limiting the precision of O&M modelling in this area.

Part II introduces a novel O&M model that incorporates opportunistic maintenance, a strategy that leverages curtailment periods and internal triggers within the wind farm to reduce operational costs. This new model expands the capability of traditional O&M tools by allowing maintenance planners to capitalise on underutilised windows for intervention. Through a series of case studies and sensitivity analyses, the model is benchmarked against conventional approaches. Results demonstrate that the opportunistic strategy can significantly reduce costs when curtailment is sufficiently frequent and teams are prepared to respond flexibly. However, in low-curtailment scenarios, the marginal gains may not justify the added complexity. Sensitivity analysis further identifies uncertainty in failure distributions as a key source of variability in model outcomes, reinforcing the importance of accurate, turbine-specific reliability data.

The thesis concludes by synthesising the insights from both modelling approaches and providing actionable recommendations for developers, planners, and researchers working to optimise O&M strategies for future offshore wind farms. It also outlines key directions for future research, particularly in improving failure data availability and enhancing the adaptability of maintenance models to real-world operational dynamics.

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List of Abbreviations

Acronym	Description	Acronym	Description
O&M	Operations and Maintenance	LCOE	Levelised Cost of Energy
CfD	Contracts for Difference	OW	Offshore Wind
NHPP	Non-Homogenous Poisson Process	CTV	Crew Transfer Vessel
SOV	Service Operating Vessel	HLV	Heavy Lift Vessel
JUV	Jack Up Vessel	FSV	Field Specialist Vessel
IARC	International Agency for Research on Cancer	SWD	Shift Work Disorder
USA	United States of America	OPEX	Operational Expenditure
AEP	Annual Energy Production	NREL	National Renewable Energy Laboratory
IMO	International Maritime Organisation	PC	Polar Class
RIO	Risk Index Outcome	NEMO	Nucleus for European Modelling of the Ocean
ECMWF	European Centre for Medium-Range Weather Forecasts	HAWT	Horizontal Axis Wind Turbine
VAWT	Vertical Axis Wind Turbine	CAWT	Counter Axis Wind Turbine
DFIG	Doubly Fed Induction Generator	PMG	Permanent Magnet Generator
SCIG	Squirrel Cage Induction Generator	GWEC	Global Wind Energy Council
EU	European Union	GOWA	Global Offshore Wind Alliance
CAPEX	Capital Expenditure	SWH	Significant Wave Height
DD	Direct Drive	MS	Medium Speed

Acronym	Description	Acronym	Description
NS	North Sea	RUL	Remaining Useful Life
SCADA	Supervisory Control and Data Acquisition	CMS	Condition Monitoring Systems
SHM	Structural Health Monitoring	FMEA	Failure Mode and Effects Analysis
SPARTA	System Performance, Availability and Reliability Trend Analysis	BoP	Balance of Plant
CM	Corrective Maintenance	PM	Preventive Maintenance
PdM	Predictive Maintenance	CBM	Condition Based Monitoring
MPI	Maintenance Priority Index	EV	Electric Vehicle
MTTF	Mean Time to Failure	KPI	Key Performance Indicator
BAV	Bid Acceptance Volume	BMU	Balancing Mechanism Unit
MEL	Maximum Export Limit		

Nomenclature

Symbol	Description	Symbol	Description
$\bar{x}$	Mean (average)	σ	Standard deviation
C	Ice Concentration	RV	Risk Value
T	Total Period	t	Timestep interval
I	Data collection period	i	Interval for data collection
n	Number of failures	N	Number of turbines in sample
p	Index for turbine	j	Index for component
L	Lifetime of wind farm	λ	Failure rate per turbine per year
P	Number of turbines	J	Number of components
C_{elec}	Electricity price	u_r	Measured wind speed
h_{swh}	Significant wave height	α	Roughness index
z_r	Measurement height	z_{nac}	Nacelle height
P_{rating}	Wind turbine rating	u_{cut-in}	Cut-in speed
u_{rated}	Rated speed	$u_{cut-out}$	Cut-out speed
$\%_{curtail}$	Curtailed capacity percentage	λ_s	Scale parameter
β	Shape parameter	t_{repair}	Repair time
$t_{replace}$	Replacement time	C_{repair}	Repair cost
$C_{replace}$	Replacement cost	H_{CTV}	CTV wave height limit
w_{CTV}	CTV wind speed limit	H_{SOV}	SOV wave height limit
w_{SOV}	SOV wind speed limit	v_{CTV}	CTV average speed
C_{CTV}	CTV daily charter rate	C_{SOV}	SOV daily charter rate

Symbol	Description	Symbol	Description
C_{JackUp}	Jack-up charter rate	t_{mob}	Jack-up mobilisation duration
C_{mob}	Jack-up mobilisation rate	$C_{technician}$	Technician salary
N_{tech}	Technician pool	$R_{curtail}$	Curtailment reimbursement
G	Energy generation	$G_{curtail}$	Lost generation (curtailment)
G_{down}	Lost generation (downtime)	t_a	Start of maintenance trip
t_b	End of maintenance trip	$C_{maintenance}$	Maintenance trip cost
$C_{transport}$	Transport cost	E_{total}	Total possible energy
E_{prod}	Actual produced energy	C_{staff}	Staff cost
$C_{lostrevenue}$	Lost revenue cost	A_E	Energy-based availability
A_t	Time-based availability	$TA_{new,ij}$	New component age
$TA_{old,ij}$	Old component age	q	Maintenance quality ratio
ρ	Fuel consumption	ϵ	Travel hours
K	Status of turbine	x	Failure threshold

Chapter 1

Introduction

The escalating global climate crisis has led countries around the world to commit to significant reductions in greenhouse gas emissions and to transition towards more sustainable energy sources. One of the most promising and widely adopted forms of renewable energy is wind power. Wind energy can be harnessed in two primary environments: onshore and offshore. Onshore wind farms benefit from relatively easy access, allowing for simpler and more cost-effective operation and maintenance (O&M) activities, including routine inspections and part replacements.

In comparison, offshore wind energy presents unique logistical and technical challenges. Offshore turbines are located in remote and often harsh marine environments, where access is limited by weather conditions and distance. Maintenance operations typically require specialised vessels, trained personnel, and complex planning, all of which significantly increase both the time and cost involved. As a result, O&M activities account for a substantial proportion, approximately 20 to 30 per cent, of an offshore wind farm's total lifecycle costs [1, 2, 3].

Unlike capital expenditures, which are largely fixed at the outset of a project, O&M costs can be optimised and reduced over time through technological improvements, predictive maintenance strategies, and more efficient logistical planning. Since O&M costs represent a significant share of overall expenses, they play a critical role in determining the levelised cost of energy (LCOE) for offshore wind projects.

Maintaining a competitive LCOE is essential if offshore wind is to remain an attractive option compared to other energy sources, including fossil fuels. If the cost of offshore wind energy remains significantly higher than that of other renewable or non-renewable alternatives, it may struggle to attract investment and widespread adoption. This not only affects the commercial viability of projects, but also places a financial burden on national economies, as the cost of electricity is ultimately borne by businesses and end-users. Therefore, reducing O&M costs as much as is feasibly possible is essential to ensuring that offshore wind remains a competitive and socially acceptable contributor to a low-carbon energy future.

Given the uncertainty and complexity introduced by these emerging offshore wind scenarios, modelling has become an essential tool for planning, optimisation, and risk reduction. O&M models, in particular, offer a framework for evaluating various maintenance strategies, technology choices, and logistical constraints under a wide range of future scenarios. This thesis uses modelling not only to understand current challenges but also to anticipate those on the horizon. It argues that, in order to maintain offshore wind as a viable and competitive energy source, O&M models must be both responsive to current realities and capable of adapting to the future evolution of wind farm design, technology, and deployment locations.

O&M research aims to reduce the magnitude of the operational proportion of the LCOE through developing new maintenance strategies, improving the reliability of wind turbine components, and advancing the technology used to monitor those components. Despite recent advances in O&M practices, the rapid evolution of offshore wind technologies and deployment environments requires ongoing adaptation and innovation in maintenance strategies. In this thesis, the changing landscape is referred to generally as "the future generation of offshore wind", covering a broad range of expected changes in the offshore wind industry set to occur in the next couple of decades, as the 2050 Net Zero target approaches. Some of these expected changes include: new site locations around the globe, accessibility issues, drive train technology, turbine size, distance from shore, and alternative turbine designs [4].

As these changes are not present at the moment, it can be difficult to predict what effect they might have, if any, on the operations and maintenance of offshore wind sites. One way of preparing for the changes to come in the offshore wind industry is through modelling techniques. Over the past two decades, O&M modelling has become a well-established area of research.

Operations and maintenance (O&M) modelling has become an essential aspect of offshore wind energy planning and optimisation, due to the significant share of costs and performance implications it holds over the operational lifespan of a wind farm. In the early stages of offshore wind development, particularly during the 1990s and early 2000s, O&M strategies were largely adapted from onshore practices. These early models were limited in scope, relying on basic cost estimations and fixed schedules, often reactive in nature due to the lack of detailed performance data and limited understanding of offshore-specific challenges.

As offshore wind farms have increased in size, complexity, and distance from shore, the need for tailored, accurate, and dynamic O&M models has become increasingly apparent. From the 2010s onward, modelling efforts have evolved to incorporate probabilistic elements, logistics simulations, weather constraints, and failure rate distributions. This allowed stakeholders to move beyond simple cost predictions towards optimisation of vessel deployment, technician planning, and spare parts management. The shift towards data-informed planning laid the groundwork for proactive and condition-based maintenance strategies [5].

However, as the offshore wind sector continues to evolve, existing models risk becoming outdated if not continually updated to reflect new technologies, turbine sizes, maintenance philosophies, and operational contexts. The deployment of larger turbines (e.g. 10 MW and beyond), floating wind technology, and new access methods has introduced a set of logistical and technical challenges that earlier models were never designed to handle. Furthermore, the industry's increasing reliance on digital tools, such as condition monitoring systems, machine learning, and digital twins, requires models that can incorporate real-time data and support adaptive decision-making [6].

This thesis is situated within that evolving landscape. It addresses the need to ensure O&M models remain relevant and effective by focusing on two complementary approaches. First, an existing O&M model is enhanced with new functionality to improve its adaptability for modern offshore wind scenarios in new environmental site conditions. It is further utilised to model updated reliability data for larger scale turbines. Second, a novel O&M model is developed, incorporating a new maintenance strategy that reflects recent trends in predictive maintenance and logistical innovation. Together, these contributions demonstrate how models must not only be technically sound but also responsive to the rapidly shifting demands of offshore wind deployment.

By continuously developing and adapting O&M models, the industry can better manage risks, reduce costs, and support the long-term competitiveness of offshore wind. This ongoing evolution is essential if offshore wind is to play a leading role in achieving net-zero targets and ensuring a resilient, low-carbon energy future.

1.1 Overview of O&M Modelling

There are several O&M tools used within industry and academia. Table 1.1 gives an overview of some of the prominent simulation tools from the last 15 years, and their simulation approaches. These tools aim to quantify the trade-offs between availability, reliability, and cost, helping operators to optimise both preventive and corrective maintenance strategies.

Effective O&M strategies aim to balance multiple trade-offs, primarily between maximising turbine availability, minimising costs, and reducing operational risks. 'Optimal' O&M is therefore not a single fixed point but rather a balance that depends on project-specific priorities such as budget constraints, risk tolerance, and technical feasibility.

To support decision-making, a variety of O&M modelling tools have been developed, ranging from simplified deterministic calculators to sophisticated stochastic simulators. Many commercial tools, such as O2M GH, Maros DNV, and SIMLOX, utilise Monte Carlo simulation techniques to capture uncertainties in failure rates, weather windows, and repair durations. Monte Carlo approaches are valuable for their ability to provide probabilistic insights into asset availability and cost variability, but they can require significant computational resources and detailed input data. Conversely, deterministic or analytical models offer faster evaluations but may oversimplify the complex, stochastic nature of offshore operations.

Failure modelling is a fundamental aspect of these tools. A common assumption is that failures follow certain probabilistic distributions, notably the exponential or Weibull distributions. The Weibull distribution, in particular, is useful for representing the 'bathtub curve' phenomenon observed in many engineering systems, as seen in Figure 1.1. This curve describes how failure rates typically evolve over time: starting high during early 'infant mortality' periods due to manufacturing defects or installation issues, stabilising at a low rate during the useful life of components, and finally rising again as wear-out and ageing effects dominate. Incorporating the bathtub curve into O&M models enables more realistic predictions of failure behaviour and informs maintenance scheduling strategies.

However, the Weibull distribution also has some limitations. It requires accurate and sufficient failure data to reliably estimate its parameters, which can be challenging in offshore wind where failures may be infrequent or poorly documented. Additionally, the model assumes that failure behaviour can be neatly categorised into the three phases of the bathtub curve, which may not capture all real-world complexities such as sudden failures due to unforeseen external factors or interacting failure modes. Furthermore, Weibull-based models often assume that failure processes are independent and identically distributed, potentially oversimplifying scenarios where environmental conditions or operational stresses vary dynamically over time.

To address these challenges, other modelling techniques are also employed. For example, Markov models are used to capture system states and transitions over time, particularly when dependencies exist between different failure modes or repair actions [7]. Condition-based maintenance (CBM) models incorporate real-time sensor data and degradation processes to predict failures more dynamically, allowing maintenance to be scheduled based on the actual health of components rather than fixed intervals [8]. Bayesian methods have also gained prominence due to their ability to combine prior knowledge with observed data, enabling continuous updating of failure probabilities and more robust uncertainty quantification, especially useful in contexts with limited or evolving failure data [9, 10]. Additionally, agent-based models and hybrid approaches combine stochastic simulation with system-level interactions to better represent the complex operational environment of offshore wind farms [11, 12]. Each of these approaches has its own advantages and drawbacks, and the choice often depends on data availability, computational resources, and the specific objectives of the modelling exercise.

Understanding these fundamental concepts and the characteristics of existing O&M modelling tools is essential to contextualise further analysis and optimisation efforts. By carefully selecting appropriate modelling approaches and recognising their trade-offs, operators can improve maintenance planning, reduce downtime, and ultimately enhance the financial viability of offshore wind projects.

1.1.1 Applications

O&M cost models play a critical role across the lifecycle of offshore wind projects. While traditionally used to estimate operational costs, their application extends far beyond this function. A robust and well-calibrated O&M model supports financial, strategic, and technical decision-making from early-stage development through to operation.

In the context of CfD auctions, O&M models are essential for informing realistic and competitive strike price bids. Since CfD bids are legally binding over a 15 or 20 year period, un-

Table 1.1: Overview of some pre-existing O&M models and their simulation and failure modelling approaches

Name	Use	Year	Ref	Simulation Type	Failure Modelling
O2M GH	Commercial	2007	[13]	Monte Carlo	Exponential (component-level)
ECN O&M	Commercial	2007	[14]	Deterministic (+ @Risk)	Fixed failure rates (no stochastic events)
Maros DNV	Commercial	2010	[13]	Monte Carlo + Discrete Event	Probabilistic (supports Weibull, exponential)
SIMLOX	Commercial	2010	[15]	Discrete Event + Monte Carlo	Weibull, exponential, detailed reliability data
Strath OW O&M Model	Academic	2013	[16]	Monte Carlo	Weibull, exponential, empirical
NOWIcob	Commercial	2013	[17]	Monte Carlo	Exponential (supports Weibull)
Shoreline	Commercial	2014	[18]	Agent-Based + Stochastic Scenario Simulation	Exponential, Weibull
ECN O&M Access	Commercial	2017	[19]	Monte Carlo-style scenario simulation	Time-based failure rates, weather-aware
Rinaldi et al.	Academic	2018	[20]	Monte Carlo + Agent-Based	Weibull + SCADA/load-based fatigue
Santos et al.	Academic	2018	[21]	Monte Carlo	Weibull + degradation models
ROMEO	Academic	2022	[22]	Monte Carlo + Hybrid	Exponential, Weibull, CBM integration

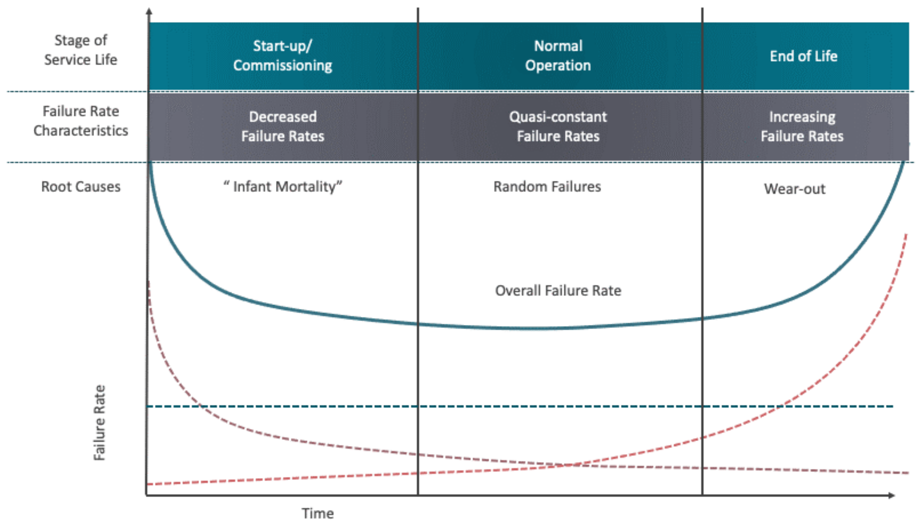

Figure 1.1: Bathtub curve for reliability engineering. Taken from [23]

derestimating future O&M costs could lead to severe financial exposure. Accurate modelling of operational expenditure, turbine availability, weather-related access constraints, and downtime enables developers to refine their revenue forecasts and bid confidently while maintaining financial robustness.

At financial close, investors, lenders, and insurers rely on detailed O&M forecasts to assess project viability. O&M models directly feed into Levelised Cost of Energy (LCOE) calculations and are used to conduct sensitivity analyses and stress testing. These models help validate cost assumptions, benchmark performance against industry standards, and support due diligence activities during investment or divestment transactions.

In addition to financial structuring, O&M models are used to:

- Understand the breakdown of operational costs, enabling high-cost areas to be targeted for reduction.
- Provide year-by-year estimates of OPEX and turbine availability to capture annual and seasonal variability.
- Optimise long-term logistical strategies, such as choosing between Service Operation Vessels (SOVs) and Crew Transfer Vessels (CTVs), or planning staff and vessel utilisation to reduce downtime.
- Benchmark asset availability and expected energy production under different maintenance regimes.
- Assess the value of new technologies or innovative maintenance strategies by modifying key input parameters.
- Evaluate the impact of different met-ocean conditions on accessibility and O&M costs, supporting procurement or strategy decisions in challenging environments.

In summary, O&M models are not only analytical tools for technical optimisation but are also central to the commercial and financial planning of offshore wind projects. Their use in CfD bidding and financial close highlights the need for reliable, scenario-flexible modelling to support long-term investment decisions.

The first part of the thesis is utilising the Strath OW O&M Model, which is further described in the next section.

1.1.2 Overview of Strath OW O&M Model

The following section is an outline of the baseline model used in Part I of the thesis. Amendments are made to the model for Chapter 2, and are described within that chapter.

The O&M modelling tool used in this work is the industrially benchmarked Strath OW O&M model, originally developed by Dinwoodie et al. as part of a thesis project at the University of Strathclyde and validated against three other cost modelling tools [24, 16]. Since then, it has been further refined and widely utilised by Strathclyde researchers [25, 26, 27, 28]. A schematic representation of the model is provided in Figure 1.2.

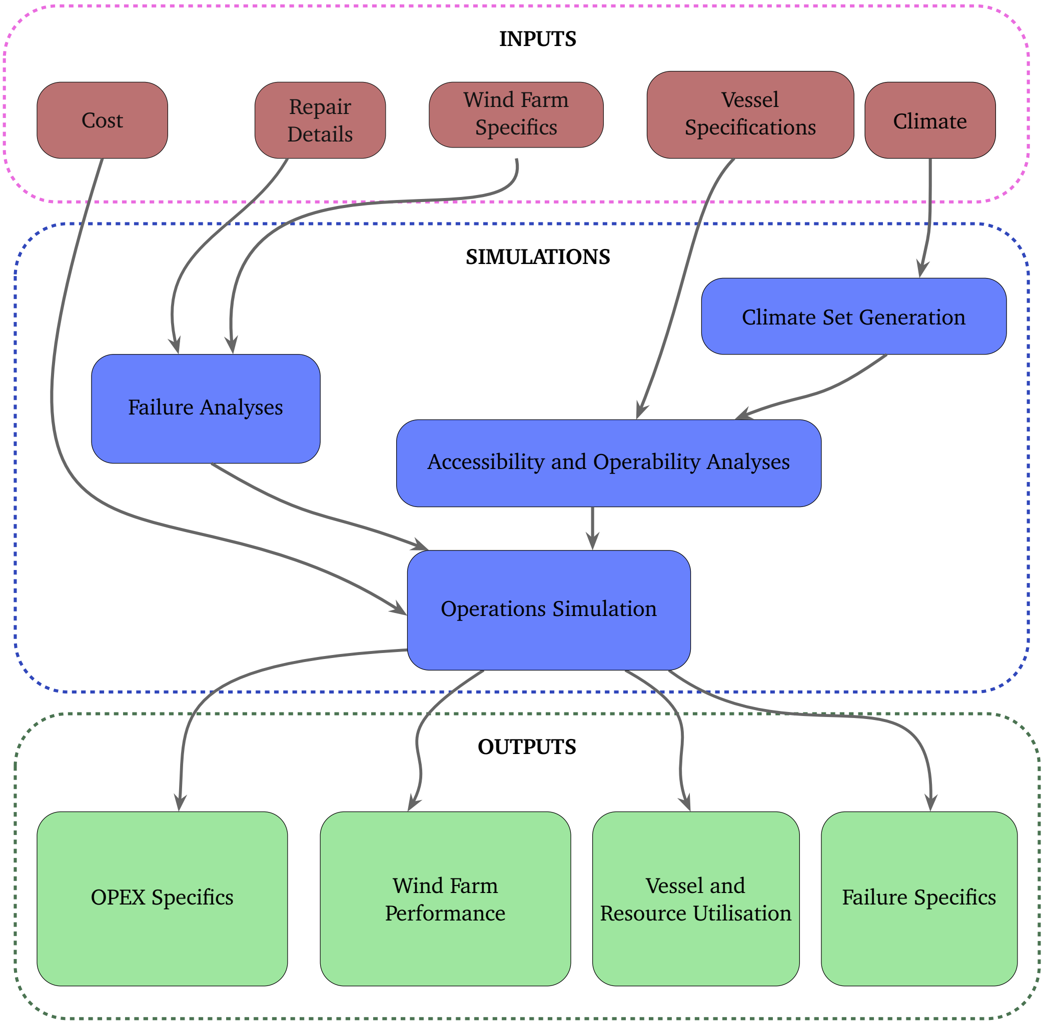

Figure 1.2: A schematic diagram depicting the Strath OW O&M tool and its basic principles of operation.

Strath OW O&M employs a time-domain Monte Carlo simulation approach, allowing for a probabilistic assessment of offshore wind operations. The model consists of five core input modules: climate, vessel specifications and fleet configuration, wind farm and turbine parameters, cost, and failure characteristics. A key focus of the model is the detailed analysis of the O&M fleet, with the ability to assess vessel deployment, resource constraints, and cost implications under varying operational scenarios. It has been validated for its intended use [24] and has been used to assist with commercial operational projects.

The model comprises of three main simulations that filter into the main operations simulations: climate modelling, turbine failure modelling, and resource and cost modelling. Climate conditions, including significant wave height and wind speed, are derived from user-provided historical datasets and simulated using a multivariate autoregressive model, ensuring realistic time-series representation while maintaining seasonal trends. These values determine accessibility for maintenance tasks and influence energy production and losses.

Wind turbine failures are modelled using a Markov Chain Monte Carlo simulation, with failures generated throughout the time series. A Non-Homogeneous Poisson Process (NHPP) determines failure probabilities, incorporating a user-defined hazard rate and failure severity. These failures directly impact maintenance requirements, wind farm availability, and lost energy production.

Maintenance and repair tasks are carried out based on predefined operational strategies, with repairs initiated when failures occur, provided the necessary resources, including vessels, technicians, and spare parts, are available. Vessel deployment is subject to weather constraints, ensuring operations adhere to significant wave height and wind speed limits. If technicians are engaged in other repairs or vessels are unable to operate due to adverse weather, maintenance is delayed until conditions permit. The model estimates maintenance costs based on vessel hire, repair expenses, and lost revenue due to turbine downtime.

Once each shift is simulated, the model records turbine availability, resource utilisation, and maintenance activity. This process repeats over the specified wind farm lifetime, with the number of simulations set by the user to ensure convergence of availability estimates across multiple runs. Model outputs include key performance indicators such as availability, power production, and failure occurrences, alongside cost estimates covering revenue, lost production costs, vessel and staff expenses, and spare part costs. Additionally, vessel-specific data, such as Crew Transfer Vessel (CTV) utilisation and Jack-Up Vessel (JUV) charters, are reported.

The repair costs (C_r) are the sum of the costs for each component and associated failure mode. These are based on the average number of yearly failures simulated for each subsystem multiplied by the cost to repair the component multiplied by the lifetime of the wind farm and the number of turbines in the farm. The transport costs (C_t) are the sum of the costs for vessels used on the wind farm. These costs include charter rates, mobilisation rates, and fuel consumption based on the calculated utilisation of the vessel within the simulation. The lost revenue costs (C_{lr}) are the calculated wholesale value of lost electricity revenue as a result of turbine downtime over the wind farm lifetime. The staff costs (C_s) are the sum of technician costs based on the salary for permanent technicians and the total pool of technicians available throughout the lifetime of the windfarm. The fixed costs (C_f) are the sum of any port or insurance costs for the wind farm during it's lifetime.

The cost outputs from the model are characterised by 'Total OPEX' and 'Direct OPEX' which categorises the operational expenditures. 'Total OPEX' refers to the total operational expenditures of the wind farm including repair costs, transport costs, staff costs, fixed costs and lost revenue costs. 'Direct OPEX' considers all of these operational expenditures apart from lost revenue. These two terms are utilised throughout the thesis when discusses modelling outputs.

1.2 Thesis Overview

This thesis addresses these gaps through a two-part investigation. Part I builds on a pre-existing O&M simulation model but introduces significant novel contributions by expanding its capability, input assumptions, and scope of analysis. Part II presents a newly developed opportunistic maintenance model designed to leverage curtailment windows and improve scheduling efficiency.

1.2.1 Part I: Extending and Enhancing Conventional O&M Modelling

The first part of this thesis comprises of three chapters that aim to refine and extend conventional O&M frameworks. Though the foundational model used in this section existed prior to this research, it has been modified to include new environmental constraints, updated failure data, and scenario specific configurations, offering new insights into the behaviour of offshore wind systems under a wider set of conditions.

Chapter 1 explores the impact of environmental constraints, asking: "How does the presence of sea ice impact the power production, operational costs, and maintenance strategies of offshore wind farms in ice-prone regions?" and "What is the impact of daylight limitations on offshore wind farm O&M costs, particularly in contrasting latitudes such as the North Sea and regions closer to the equator?" This chapter also discusses whether introducing a night shift is a worthwhile addition to the maintenance strategy or if the impact on technician health and safety outweighs the costs saved.

Chapter 2 shifts the focus to future turbine design, posing the question: "Can the OPEX of future generation offshore wind turbines be reduced through turbine upscaling, and what component reliability and site-specific conditions are required to achieve this?" Here, the model is adapted to simulate next-generation 10 MW turbines, offering new insights into the trade-offs between size, reliability, and environmental context.

Chapter 3 builds on recent advancements in failure data and system design, asking: "By utilising new failure rate estimates, how do drive train configuration, failure rate variability, repair duration, and accessibility constraints influence the operations and maintenance costs of 15 MW offshore wind turbines?" This analysis brings together updated reliability inputs and detailed component-specific behaviours to evaluate the cost implications of alternative drivetrain architectures.

Together, these chapters extend the capabilities of the baseline model while delivering original contributions in terms of both methodology and applied insights. They demonstrate that even within existing modelling frameworks, meaningful improvements can be achieved through better input data, refined assumptions, and scenario-specific exploration.

1.2.2 Part II: Developing an Opportunistic Maintenance Strategy

The second part of the thesis introduces a new O&M model that embraces the concept of opportunistic maintenance, a strategy that uses naturally occurring events (such as curtailment periods or concurrent maintenance tasks) to optimise scheduling and reduce costs.

Chapter 4 formulates the core research question of this section: "Can utilising curtailment periods as triggers for opportunistic maintenance reduce the total operational costs and increase efficiency in offshore wind farm maintenance strategies compared to traditional and alternative opportunistic approaches?" The chapter introduces a new modelling approach that integrates preventive, corrective, and opportunity-based maintenance, simulating how these interact with logistical constraints and wind farm operations.

Chapter 5 applies the model to multiple case studies, validating its performance and benchmarking it against traditional methods. This chapter tests the robustness and adaptability of the model across different site conditions and operational scenarios.

1.2.3 Summary

In combination, the two parts of this thesis present a coherent progression from refinement of established models to the development of new, adaptive strategies for offshore wind O&M. The work contributes to the literature not only through technical enhancements and improved failure modelling but also by addressing real-world operational opportunities currently underexplored in both academic and industry practice.

By grounding each chapter in a specific research question and integrating modelling improvements with practical relevance, the thesis aims to advance the understanding of how offshore wind farms can be maintained more efficiently, reliably, and economically in a changing energy landscape.

Maintenance strategies are an important tool to continue to develop as offshore wind moves into a new generation of wind farms. Transport costs, supply chain bottlenecks, and large component repairs are all growing concerns for the industry. To counteract these changes, maintenance strategies are developed to optimise the practices of the wind farm and keep unexpected costs at a minimal level. These strategies have developed over the years as technology has matured.

1.3 Research Question

Accounting for these new challenges in O&M for offshore wind, the concern must focus on how to predict and prepare for the future. Using effective modelling, these problems can be investigated and solutions can be drawn. The research question of this thesis is therefore:

"*How do we address future O&M challenges for offshore wind through modelling techniques and analysis?*"

This main research question is answered in each chapter of the thesis through subsets of research questions, which are outlined throughout each section. The structure of the thesis contains the introduction chapter followed by two distinct parts, that contain relevant chapters within them. Part I contains chapters of work that utilise the Strath OW O&M Model to conduct the research, whereas Part II contains work that was conducted using a model that was developed during the thesis that focuses on opportunistic maintenance. Each chapter reviews the current literature surrounding a defined operational challenge that faces offshore wind currently or will face in the future. The review is followed by a detailed methodology that outlines the structure of the analysis and the modelling inputs required. This is followed by the results of the analysis, a discussion surrounding the modelling outputs and the implications these have on offshore wind practices followed by a summary of the analysis.

1.4 Contribution to Knowledge

The novelty in this thesis is rooted in the upcoming challenges that the offshore wind industry is yet to experience in terms of operations and maintenance, but based on current trends, point towards these issues undoubtedly needing answered in the coming years.

Firstly, the location of offshore wind farms is no longer constrained to only Northern Europe and China. Globally, there is in an increased interest and investment into renewable energy, and specifically offshore wind energy. The thesis outlines several of these new locations and analyses possible maintenance challenges and opportunities that may arise. These include:

- Determining the effect location has on the benefits of implementing a night shift strategy by modelling locations with different amounts of daylight hours.
- An investigation into the impact of sea ice on the operations and maintenance of offshore wind farms in colder climates by developing additional functionality into an operations and maintenance model to include sea ice accessibility constraints and ice breaking vessel selection.
- Comparative analysis on the performance of different drive train configurations for larger rated turbines in different locations with varying levels of accessibility.

Secondly, the thesis provides two pieces of research that centre around the future failure rates of larger offshore wind turbines, considering both 10 MW and 15 MW turbines. Currently, there is a large amount of uncertainty surrounding the reliability of larger offshore wind turbines which will have a direct impact on the viability of offshore wind farms going forward.

Carrying out these analyses for the first time provides both industry and research further insight into the operations of larger turbines. The novelty in the work is as follows:

- Completes analysis to determine at what failure rates a larger rated turbine has the same operational costs as a 3 MW turbine, considering drive train type and location.
- Reviews literature for larger rated turbines surrounding their estimated failure rates and collates failure rate to perform O&M modelling for larger turbines.
- Analyses the impact of drive train type on operations and maintenance cost for large rated turbines.
- Completes multiple sensitivity analyses for larger turbines to determine the range of operational costs that could be expected in the future with these larger turbines.

Finally, as wind farms grow in size and complexity, efficient maintenance strategies are imperative for lower operational costs. The research creates an O&M model that employs a novel maintenance strategy. The work contributes novelty by:

- Implementing a strategy that utilises an external opportunity from the wind farm, namely curtailment, to complete preventive maintenance on turbine component in order to reduce operational costs.
- Providing a cost benefit framework that determines if maintenance is cost effective for the wind farm developer.
- Examining case studies to validate if the strategy is effective in reducing cost by comparing it to two other maintenance strategies, along with sensitivity analyses surrounding the most influential inputs to the wind farm.

1.5 Publications

1.5.1 Peer Reviewed Journal Articles Published:

The following journal publications are featured in the thesis throuhgout the chapters. Chapter 2 contains the analysis carried out in [1]. Chapter 3 is connected to the work completed in [2]. Chapter 4 and Chapter 5 are linked to the work carried out in [4].

[1] Donnelly, O., Carroll, J., & Howland, M. (2024). Analysing the cost impact of failure rates for the next generation of offshore wind turbines. Wind Energy, 27(7), 695-710. https://doi.org/10.1002/we.2907

[2] Donnelly, O., Anderson, F., & Carroll, J. (2024). Operation and maintenance cost comparison between 15 MW direct-drive and medium-speed offshore wind turbines. Wind Energy Science, 9(6), 1345-1362. https://doi.org/10.5194/wes-9-1345-2024

[3] Lochhead, R., Donnelly, O., & Carroll, J. (2024). System-level offshore wind energy and hydrogen generation availability and operations and maintenance costs. Wind, 4(2), 135-154. https://doi.org/10.3390/wind4020007

[4] Donnelly, O., & Carroll, J. (2025). The silver lining: utilising curtailment in offshore wind as an opportunity for operation and maintenance. Ocean Engineering, 330, Article 121190. Advance online publication. https://doi.org/10.1016/j.oceaneng.2025.121190

1.5.2 Peer Reviewed Conference Proceedings Published or Under Review:

These two conference proceeding publications form the basis of Chapter 1 in the thesis, centering around accessibility.

[1] Donnelly, O., & Carroll, J. (2024). Daylight considerations for offshore wind operations and maintenance. Journal of Physics: Conference Series, 2875(1), Article 012018. https://doi.org/10.1088/1742-6596/2875/1/012018

[2] Donnelly, O., Chou, E., & Carroll, J. (2025). The effect of sea ice on offshore wind farm operation and maintenance. Submitted to IOP Journal of Physics: Conference Series 2025.

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Part I

Strathclyde OW O&M Model

Chapter 2

Accessibility Challenges

The following chapter outlines challenges that the offshore wind industry faces in terms of site accessibility, with a focus on site location, weather window opportunities, personnel health and safety, and vessel capabilities. Using operations and maintenance modelling, this chapter investigates the impact accessibility may have on the future generation of offshore wind farms.

2.1 Accessibility Background

Accessibility, in this work, is a metric that indicates the ability of personnel or equipment to transfer to an offshore wind site via a maintenance vessel or transportation mode. It is a key determining factor on the availability of the wind farm. If the wind farm is not accessible, the ability to keep a wind turbine in operating condition at all times is lessened and downtime may occur. Access to an offshore wind site may be limited for multiple reasons such as, weather conditions, insufficient maintenance windows, daylight limitations or vessel capabilities [1]. These limitations all stem from the choice of site location. The distance from shore, met ocean conditions, the amount of daylight throughout the year are all subject to variation dependent on where the wind farm is located. With the influx of offshore wind projects being planned globally to ensure renewable energy targets are met, the number of site locations are increasing and thus posing a question: "*What impact will there be on site accessibility in these new locations?*"

Table 2.1: Vessel characteristics for offshore wind [2, 3, 4, 5]

Vessel Type	Accessibility Limits	Mobilisation Required	Technician Capacity	Repair Type	Estimated Daily Charter Cost
CTV	1.5-2m, 12 m/s	No	12-16	Minor Repair	£2,000
SOV	3-5m, 15 m/s	No	50-100	Minor/Major Repair	£30,000
JUV	Lifting Cap.12.5 m/s	Yes	<300	Major Replacement	£100,000-250,000
HLV	Lifting Cap. 12.5 m/s	Yes	150-750	Major Replacement	£150,000-350,000
Helicopter	25 m/s	No	6	Minor Repair	/

2.1.1 Offshore Wind Vessels

The offshore wind industry currently employs a range of vessels to support maintenance activities. For bottom-fixed wind farms, the most commonly utilised vessel types include Crew Transfer Vessels (CTVs), Service Operation Vessels (SOVs), Jack-Up Vessels (JUVs), Heavy Lift Vessels (HLVs), and Field Specialist Vessels (FSVs). Additionally, helicopters are occasionally used to conduct smaller-scale maintenance operations; however, their deployment is typically dictated by the operational strategy of the individual wind farm.

The key characteristics of these offshore vessels are summarised in Table 2.1. Due to the high capital cost associated with purchasing offshore wind vessels and a generally limited supply chain, it is standard practice to charter them on an as-needed basis. Estimated charter rates for CTVs and SOVs are sourced from [2]. The charter costs for larger vessels such as JUVs and HLVs can vary significantly depending on factors including seasonal demand and vessel capabilities. Approximate cost ranges for these vessels have therefore been compiled from multiple sources [3, 4, 5], although these figures remain subject to market fluctuations. No reliable cost estimates were found for helicopter chartering in the context of offshore wind; however, as helicopters are rarely used for maintenance, due to limitations in technician capacity and equipment transportation, they are excluded from the analysis presented in this thesis.

Each vessel type serves a distinct role in the maintenance process, generally determined by the nature and severity of the required repair. Following the categorisation proposed in previous research [6], maintenance activities are divided into minor repairs, major repairs, and major replacements. CTVs are predominantly employed for day-to-day operations and minor repairs. These vessels offer several advantages, including short efficient transfers, the ability to carry approximately 12 technicians, and relatively low charter costs. They are also readily available and do not require mobilisation prior to deployment.

As an alternative, SOVs offer increased capacity and operational capabilities. Typically equipped with onboard accommodation for around 60 personnel, SOVs can remain on site for extended periods and support both minor and major repair activities. However, this functionality comes at a higher cost, and technicians are required to remain offshore for the duration of their deployment. Furthermore, SOVs are capable of operating in more challenging sea states, with wave height limits generally between 3 to 5 metres, whereas CTVs are limited to conditions between 1.5 to 2 metres.

All vessels are constrained by metocean conditions, particularly significant wave height and wind speed. While CTVs and SOVs are limited in terms of safe transfer conditions, larger vessels such as JUVs and HLVs are mainly restricted by wind speed, which impacts the ability to perform lifting operations with cranes. Accessibility thresholds referenced in Table 2.1 are based on data presented in [7]. A summary of these limits and their impact on operations is illustrated in Figure 2.1.

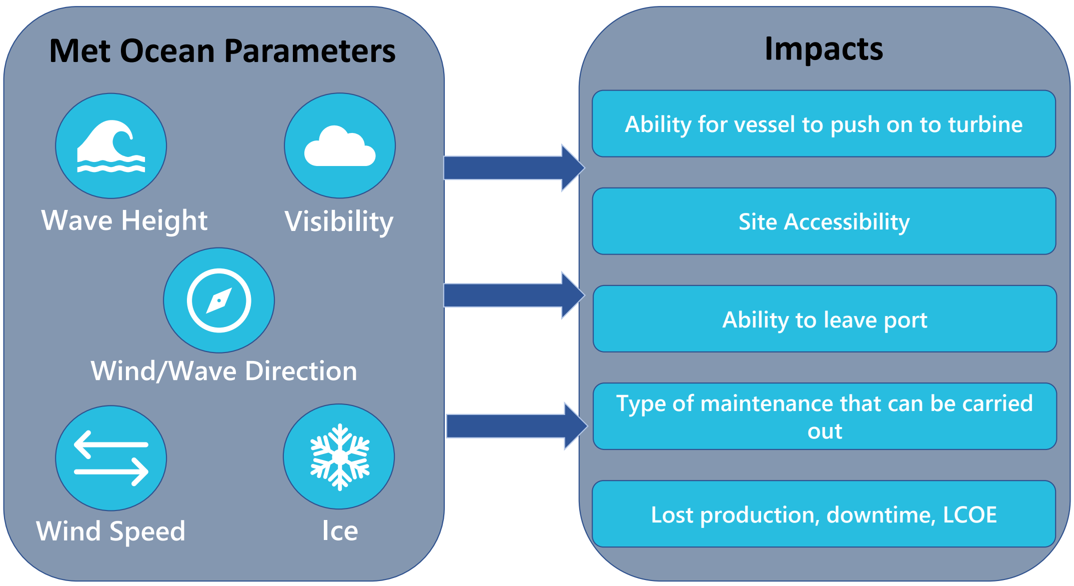

Figure 2.1: Met ocean parameters and the subsequent impact they have on offshore wind operations

In addition to the commonly cited metocean conditions, several less frequently considered parameters also influence offshore maintenance. These include wind and wave direction, which can impair a vessel's ability to safely dock or "push on" to a turbine. The presence of sea ice, often overlooked, can also restrict maintenance activity. Low visibility not only hampers helicopter transfer operations but may also affect the general execution of maintenance tasks, especially during periods of reduced daylight. The impact of all of these parameters can directly effect the ability to leave the port, reach the site, complete a safe transfer of personnel onto a turbine or complete the maintenance task required. The KPI's that metocean parameters can impact are downtime, power production, LCOE and availability.

When metocean conditions exceed predetermined thresholds, typically defined within maintenance contracts, vessels cannot be deployed until a suitable weather window becomes available. Marine coordinators, responsible for operational oversight at wind farm sites, receive daily reports on forecasted metocean conditions. It is their duty to assess whether conditions are within acceptable limits to allow maintenance to proceed safely. This decision-making process is critical to reducing operational costs and mitigating risk. Attempting maintenance under adverse conditions may endanger personnel, result in failed transfers, and increase overall costs due to aborted missions. Conversely, failing to act during favourable conditions may prolong turbine downtime, leading to lost production and missed revenue opportunities.

With current trends indicating that future offshore wind farms will be located further from shore and constructed on a larger scale, concerns regarding accessibility are becoming more prominent. Increased distance from shore typically corresponds with harsher environmental conditions and extended weather windows, which must accommodate transit time to and from site, as well as the duration of the maintenance task itself. Consequently, longer travel distances often equate to reduced accessibility, longer downtimes, and increased financial losses due to unplanned outages.

Improving accessibility remains a priority area within operations and maintenance, with ongoing efforts focused on enhancing weather forecasting accuracy, optimising route planning, and developing turbine designs that are more conducive to efficient maintenance. Floating offshore wind turbines offer a notable advantage in this regard, as they can be towed to port for servicing. Once brought ashore, accessibility and weather window considerations are effectively eliminated. However, for fixed-bottom wind turbines, optimising accessibility remains essential to controlling operational expenditures.

In addition to cost reduction, strict adherence to health and safety regulations is imperative to safeguard the wellbeing of both personnel and the public. Achieving a balance between cost efficiency and safety is often described as a trade-off. Two key accessibility challenges identified in this study are the limitations posed by restricted daylight hours and the presence of sea ice. These challenges are examined in greater detail in the subsequent sections of this chapter.

2.2 Operations considering daylight limitations

2.2.1 Benefits of night shift

One proposal to increase accessibility is to increase the amount of time available to access the wind turbines. In other words, by introducing night shift work alongside normal day to day operations, the amount of time available to access the site would increase, and in turn decrease the downtime experienced by the wind farm, improving the overall time based availability. For site locations that experience periods of high inaccessibility, harsh met-ocean conditions, high fault occurrence or a restricted amount of daylight, a night shift may be a favourable maintenance strategy to improve operational efficiency.

Night shift work is common practice in other offshore operations such as oil and gas, and has been adapted by certain offshore wind farms, but it is not yet clear how beneficial this practice is and if there are any potential drawbacks. Operations with night shift for oil and gas usually involve offshore accommodation for workers who will stay offshore for a period of 7 days or longer. In offshore wind, SOVs are commonly used for this practice although it is dependent on the distance the wind farm is from shore and the nature of the maintenance required.

The potential benefits of night shift work in offshore wind is rarely researched, however there have been a few outputs to date that delve into the topic. Firstly, Dalgic et al. [8], explores the impact of night shifts on O&M costs and time based availability. Dalgic uses the Strathclyde OW O&M tool to simulate different configurations of Crew Transfer Vessels (CTVs) during day and night shifts, concluding that the lowest O&M cost was achieved when 4 CTVs were used in both a day and night shift. A maintenance optimisation model found that the most cost efficient maintenance strategy was when technicians were available 24 hours a day, 7 days a week, that implies the utilisation of a night shift or at the least a rotating shift for the technicians. Availability was improved by 1% when switching from 12 hour shifts to 24 hour operations. A business case study estimates using expert elicitation that the use of technicians in day and night shifts could result in 1.8 million euros being saved every year [9].

A more in depth analysis into night shift benefits was found in Anderson's thesis, that attempts to quantify the benefit of employing a night shift into the maintenance strategy, by using a real operational database to train a Bayesian hierarchical model. A baseline scenario found that night shift work increases time based availability by 0.64% annually [10, 11]. It is important to note that Anderson's thesis provided multiple case studies for wind farms of different sizes and the cost savings varied depending on the size of the farm.

While operational costs and availability are crucial KPI's to assess the viability of a maintenance strategy, it is also vital that the health and safety risks of working at night are considered. The aforementioned studies acknowledge in their work that there are potential safety risks but are primarily focused on operational costs and time based availability, emphasising the lack of literature on health and safety considerations in offshore wind compared to the oil and gas industry.

2.2.2 Health and Safety for Night Shift Work

One of the concerns for implementing night shift work in offshore wind is the impact on technician welfare. Currently, there are no known studies that assess the health of technicians who take part in offshore wind farm night shift rotations but many studies have been conducted on workers who are night shift technicians for oil and gas rigs. The nature of the work carried out is not necessarily transferable but the work environment and operating through the night are similar and so it is important to address concerns found in an adjacent industry.

Firstly, adapting from day time operations to night time operations involves a disruption to the circadian rhythm of the body. Circadian rhythm refers to the sleep and wake cycle of the body that spans roughly 24 hours and regulates sleeping patterns to allow the body to operate optimally throughout the day. Disruption to the body's circadian rhythm is not favourable as it may cause drowsiness, fatigue or even insomnia [12]. Applying this to working patterns offshore therefore needs to be handled with care. Regulatory framework often states that night shift work is rotational, meaning a technician will work several days on a night shift and then several days on a normal day shift. These shift patterns allows the body to adjust to the new sleeping pattern without sudden changes back and forth from different shifts. It is recommended that shift workers, who work at night, work the same shift pattern for at least 7 days in a row [13]. However, research has shown that it takes 5 to 6 days for a worker to adapt to working night shift, therefore the worker may not be working optimally during the shifts. Further studies have found that a disruption to circadian rhythm along with working for over 48 hours a week for onshore workers leads to an increase risk in road accidents [14]. Quantifying the productivity of workers on night shift is not an easy task but the adjustment to a new working pattern may have effects on the ability to perform tasks to the usual standard of a day time worker. Worryingly, there are further studies that link serious health conditions to night shift workers in offshore oil and gas. According to one study, completed on a group of Norwegian petroleum workers, there is an increased hazard of rollover shift workers, who have worked for over 19.5 years, getting aggressive prostate cancer due to the impact of circadian rhythm disruption. Night shift work has been classified as a probable human carcinogen, according to The International Agency for Research on Cancer (IARC)[15].

Shift work disorder (SWD) effects roughly one third of night shift workers. SWD results in at least one month where an individual will incur day time sleepiness or insomnia as a result of shift work. An investigation, conducted on Iranian oil rigs, found that SWD had a considerable impact on depression, insomnia and sleepiness [16]. Although, several studies found detrimental effects from night shift work, there are also several that report minimal effects. Two drill ships in Mexico were the basis of one study that found workers who only carried out night shift had a decreased mental fatigue to those that swing between day and night shift [17]. This study points towards the advice of regulatory framework in oil and gas that recommends a reduction of changing between shift types where possible.

The disruption to sleep causing fatigue is another concern of offshore work, as it could lead to lapses in judgement causing accidents that harm workers or damage equipment. Working under fatigue or stress may lead to a lower productivity level, leading to longer times to complete maintenance tasks which may cause a drop-in time-based availability and increase lost revenue costs.

Another risk identified for night shift work is the lower visibility occurring at night. G+ standards, applied to over 100 operational wind farms, emphasise precautions for restricted visibility in small offshore vessels [18]. Transferring from vessels to the wind turbines involves a higher risk if there is not sufficient light for the technicians.

Although literature specific to offshore wind health and safety is limited in comparison to oil and gas, there have been several studies that investigate some health and safety concerns. Technician welfare is considered in studies, like the SPOWTT project [19], that aims at optimising transit safety and productivity. Another study [20], employs machine learning to factor in technician welfare when making dispatch decisions based on sea sickness indicators. A physical demand study compares offshore and onshore technicians, concluding that offshore wind work demands more physically but not excessively compared to other blue-collar jobs [21]. A German based case study, investigates the sleep quality of offshore wind workers who have spent at least four weeks offshore. It was found that the sleep quality for the workers was worse offshore than it would be onshore, but that there was no link between rotating shifts and poorer sleep quality [22].

A review of health and safety practices for offshore wind found that injury rates are four times higher in offshore wind than in oil and gas [23]. The lack of specific regulatory framework for offshore wind may cause additional challenges for night shift work that are not found in the oil and gas literature, and therefore further analysis is required.

2.2.3 Research question

This study explores the impact of daylight limitations on offshore wind farm O&M costs, with a focus on varying site locations. Specifically, it investigates how O&M costs are affected by daylight duration differences, particularly between the North Sea and locations closer to the equator. Additionally, the study assesses whether the introduction of a night shift to the wind farm alleviates O&M costs and to what extent. Consequently, raising the question, if there is a reduction in operational costs, is that reduction worth the increased risk to the health and safety of the offshore wind personnel.

The motivation behind this research is twofold. Firstly, the expansion of offshore wind energy has meant that new locations and sites in development have not yet had extensive research done on their operations and maintenance for the simple reason that the projects are still at early stages. Secondly, the study addresses a gap in existing literature by specifically examining daylight limitations in Australia and the East Coast of the USA. Previous research on night shift work has focused on the North Sea and oil and gas industry practices, but none have conducted a comparative study on daylight hours and visibility across sites.

2.2.4 Methodology

The following section details the methodology utilised to determine the effects of daylight limitations. Firstly, the origin and nature of the data used will be discussed and then the site specifics for each of the locations. The Strath OW O&M model is given a brief overview in terms of it's specific functionality for this piece of analysis and the justification for the input values chosen for the simulations.

2.2.4.1 Climate data and site location

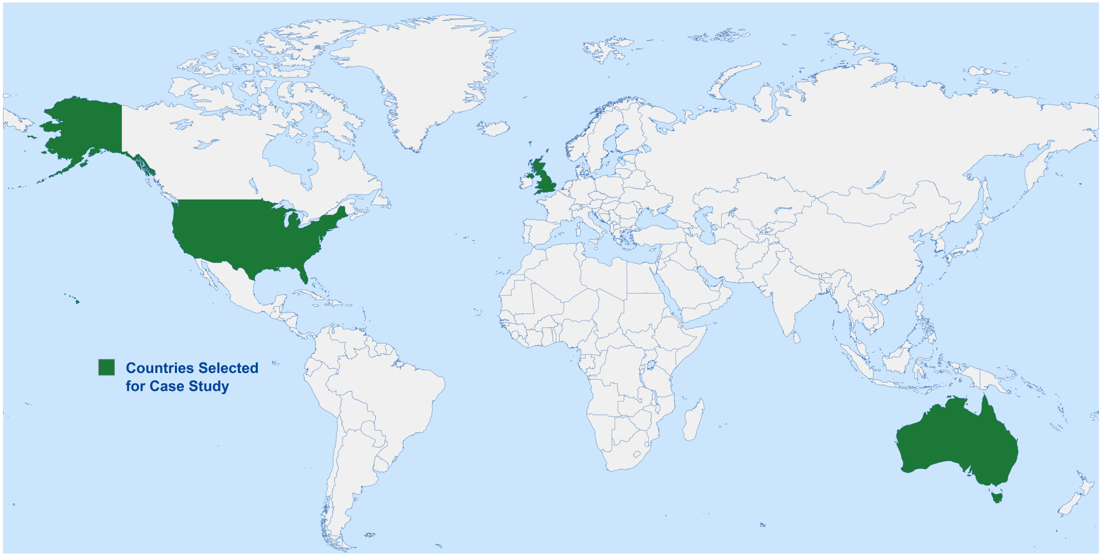

Figure 2.2: Diagram of the site locations selected across the globe, the countries highlighted in green are those chosen for the case studies.

As outlined in Figure 1.2, a critical input for the model is climate data, specifically wind speed and significant wave height, both of which are essential for evaluating the accessibility of a selected offshore wind farm. Wind speed data is used to generate time-series simulations at both sea level and hub height. These simulations influence key operational factors, including vessel transit feasibility and energy production estimates, which are central to overall O&M cost calculations. Significant wave height is a primary determinant of vessel transfer limits, directly affecting maintenance scheduling and accessibility to offshore structures.

This study examines three case study locations: the North Sea, the East Coast of the United States, and Darwin, Australia. The North Sea, characterised by strong wind speeds and shallow waters, utilises wind and wave data from the FINO database, spanning a six-year period [24].

As previously mentioned in the thesis objectives, the North Sea is a well established zone for offshore wind development, with a considerable amount of operations and maintenance analysis focused to this region. The night shift research previously completed by [25] and [11] also focusses in this area, so it has been selected as a baseline comparison to previous work. The second site, off the East Coast of the U.S., relies on data from the Martha's Vineyard Coastal Observatory [26], covering an 18-month period. The East coast of the USA is currently under development for multiple offshore wind farms coupled with the variation in latitude from that of the North Sea, making it a relevant choice for the analysis.

The third location, Darwin, Australia, was included despite not being a primary offshore wind development site. Australia has shown growing interest in offshore wind projects, particularly in Victoria and New South Wales. Darwin was selected due to the presence of existing oil and gas port infrastructure, which could be repurposed for offshore wind operations. Large vessel ports are a shared requirement between the offshore wind and oil and gas industries, making Darwin a suitable candidate for evaluation. While alternative Australian locations with established port facilities exist, Darwin's proximity to the equator provides an additional factor of interest. The study aims to assess the impact of daylight availability on O&M costs, requiring site selections at varying latitudes to analyse how daylight duration influences operations.

Climate data for Darwin is sourced from the ERA5 reanalysis database [27]. The selected site is located 50 km offshore to maintain consistency with the other case study locations. The dataset includes hourly wind speed measurements at 10 m and 100 m heights, along with significant wave height records, covering a four-year period.

Figure 2.2 provides an overview of the selected countries for each case study. Within each country, a specific offshore site has been identified, and simulations have been conducted to evaluate the implications of operations and maintenance costs across different geographic and climatic conditions.

Figure 2.3 illustrates the variation in daylight hours across the three locations by depicting the average monthly daylight duration at each site throughout the year. Darwin consistently experiences daylight ranging from 11 to 13 hours per day, while the United States site exhibits a range of 9 to 15 hours per day. The North Sea demonstrates the greatest variability, with daylight hours fluctuating between 7 and 17 hours per day throughout the year.

The accessibility of these sites is directly influenced by the climatic conditions of each loca-

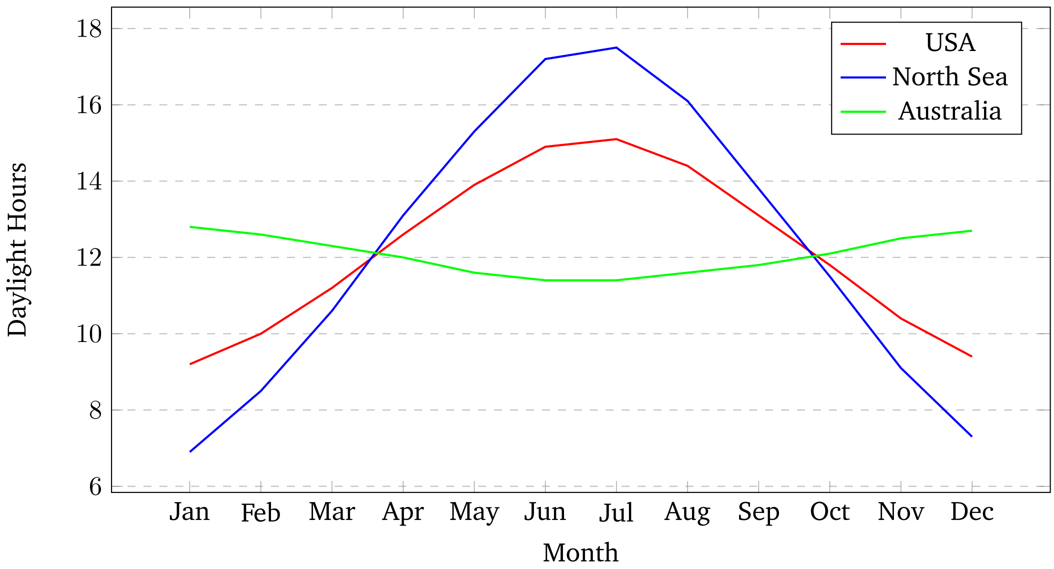

Figure 2.3: Daylight hours over a yearly period for the USA, North Sea and Australia wind farm site locations

tion. To assess this, the daily average wind speed and significant wave height for each site have been calculated and are presented in Figure 2.4 and Figure 2.5. Notably, the United States site experiences highly variable wind speeds and wave heights throughout the year, whereas the Australian site generally encounters lower wind speeds and wave heights.

2.2.4.2 Model Inputs

The inputs to the model outlined in Table 2.2 and Table 2.3 are kept constant across the three case studies to allow for comparisons to be drawn regarding the effect of daylight limitations. The general inputs for the wind farm are displayed in Table 2.2. The number of simulations is set to 100 resulting in 0.022% convergence for the time based availability output. The wind farm lifetime is set to 20 years, a conservative value based off the industry estimate that wind farm lifetime may be extended to 25-30 years [28]. Due to limited publicly available failure data, the failure rates, number of technicians required and component repair times are taken from [29]. Based on the source for the failure rates, the turbine used is a 3 MW direct drive wind turbine. The wind farm has three main maintenance vessels, namely a CTV, SOV and Jack Up vessel. The night shift work will use a CTV Catamaran boat to complete minor repairs on the turbines. The boat has a capacity for 6 technicians. It is assumed the wind farm has 5 CTVs in the fleet and that there is the same amount available for both the day shift and night

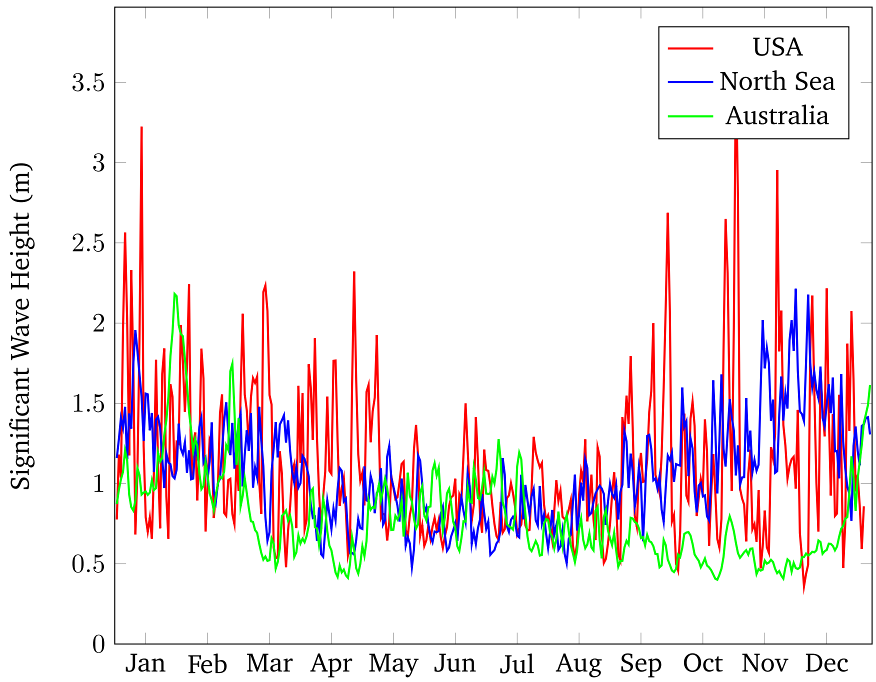

Figure 2.4: Daily average significant wave heights for USA, North Sea and Australia wind farm sites

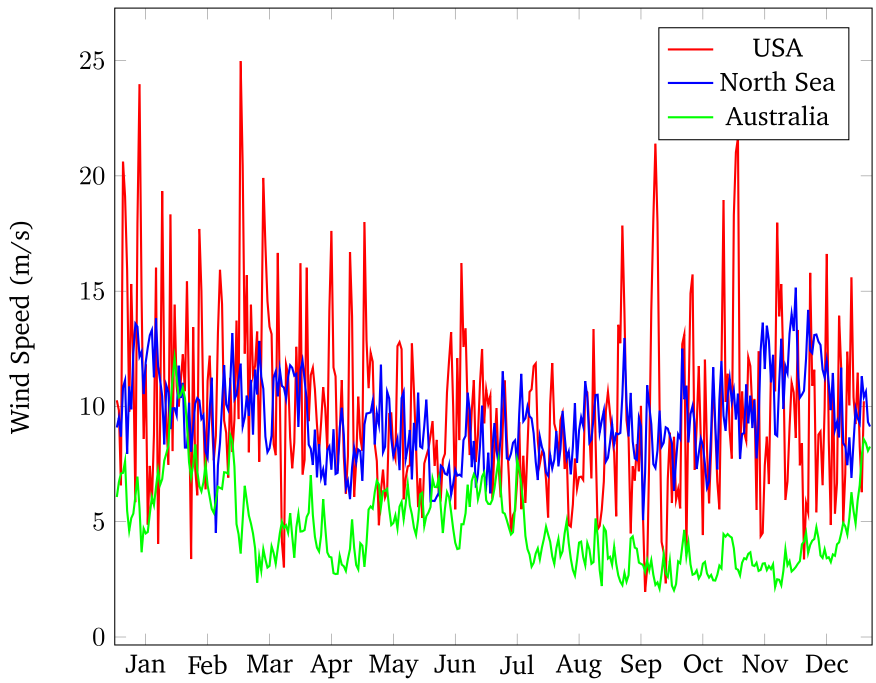

Figure 2.5: Daily average wind speeds for USA, North Sea and Australia wind farm sites

shift. Subsection 2.2.5.5 conducts a sensitivity analysis around the assumption on the number of CTV vessels in the fleet performing night shift work. Transport inputs are outlined in Table

2.3 and are based on vessel specifications. Charter rates and mobilisation times are obtained from previous literature [25]. Note that the JUV also has a lifting capacity limit of 12 m/s.

Table 2.2: Wind farm inputs for each simulation

Inputs	Unit	Value
Number of Wind Turbines	**-**	100
Number of Simulations	**-**	100
Distance from Port	**km**	50
Wind Farm Lifetime	**Yrs**	20
Turbine Power Rating	**MW**	3

Table 2.3: Transport inputs for each simulation [8, 30]

Inputs	Unit	CTV	SOV	JUV
Wave Height Limit	**(m)**	1.5	3	2.5
Wind Speed Limit	**(m/s)**	12	15	36
Fuel Consumption	**(m^3/hr)**	0.24	0.3	0.55
Charter Rate	**(£)**	1980	30,000	360,000
Mobilisation Time	**(days)**	N/A	N/A	60

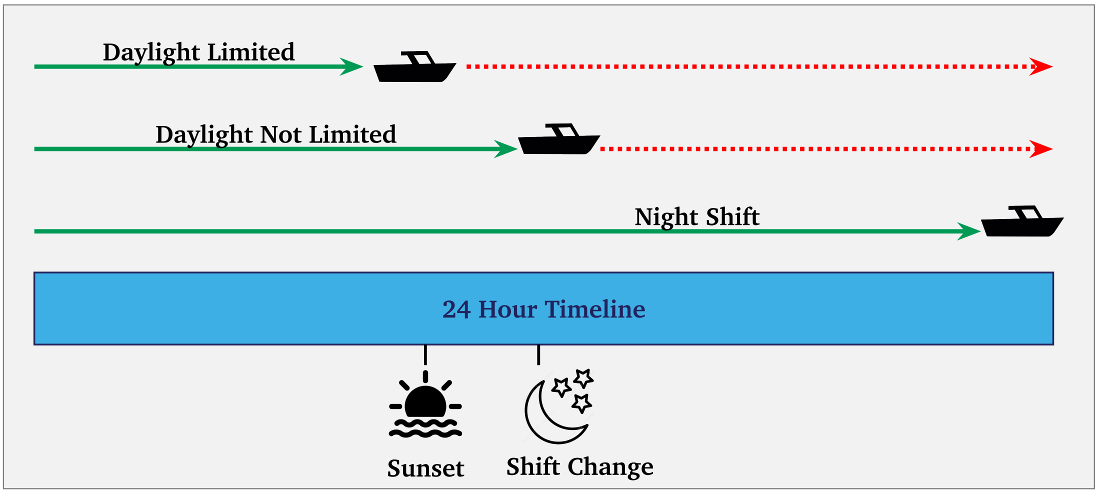

Figure 2.6: Schematic diagram overviewing the daylight maintenance strategies available in the model

The variables changed across the sites will be the climate data, coordinates of the wind farm, the port and the local offset, which is utilised to calculate the amount of daylight hours available throughout the year. Within the site case studies, the input that is varied is daylight limitation. Figure 2.6 presents a schematic diagram for the three different daylight scenarios that the model can simulate.

- **'Daylight Limited'**: regardless of how long is left of the 12 hour shift (8am-8pm), if it is dark then maintenance cannot be carried out
- **'Daylight Not Limited'**: the 8am-8pm shift is carried out regardless of visibility but there is no night shift work
- **'Night Shift'**: the 8am-8pm shift is carried out followed by another 12 hour shift in which night technicians and night CTV's are used

The measure of when daylight is limited and maintenance cannot be carried out is based on the model calculating the sunrise and sunset times of a specified location at a specific period in the year, it accounts for one extra hour of daylight to allow 30 minutes for sunset or 'dusk' and 30 minutes for sunrise or 'dawn'. The code also captures the +1 hour summer time between 'last Sunday of March 01:00:00' and 'last Sunday of October 01:00:00'. The maintenance decision also takes into account the length of the maintenance activity required, the time taken to reach the turbine and the time to transfer from the vessel to the turbine. If the sun sets before the full maintenance task can be completed then the task must wait until the next available weather window, daylight dependent.

If either of the first two options are selected for the simulations then the vessel inputs required are all for day time vessels with associated technicians. If the last option is chosen then inputs must include the number of vessels on the night shift and how many technicians are available. All other inputs to the model are held constant across the different sites so the analysis will only focus on the impact daylight has on the O&M costs.

2.2.4.3 Assumptions and limitations

One of the main assumptions for the analysis is that night shift workers receive the same compensation as those working during the day. However, in practical scenarios, the wages of technicians are not uniform and depend on multiple factors, including the worker's level of experience, the specific nature of the tasks performed, and the time of day at which the work takes place. The assumption of equal pay across all shifts is a simplification intended to maintain a conservative cost estimation. In these simulations, a salary of £40,000 per year was selected, based on industry estimates for technicians working in similar operational roles. The expected outcome of increasing the pay for a night shift technician would be an increased staff cost for the scenarios with night shift.

The turbine model utilised throughout the simulations remains consistent across all locations and is not specifically adapted to the climate of each site. In real-world applications, turbines are often designed to accommodate the environmental conditions of their respective locations. For instance, in Australia and the USA, site-specific turbine modifications are likely to be implemented to enhance performance in varying climates. The lack of such adjustments in this study means that total energy production estimates may be subject to either underestimation or overestimation, depending on local conditions.

To reduce variability in operational cost projections, a fixed electricity price was applied across all scenarios. In reality, electricity prices fluctuate over time due to market dynamics, regulatory changes, and regional supply-demand variations. While this simplification allows for more controlled comparisons, it does not capture the full economic complexity of energy markets.

Another limitation of this study is the restricted availability of field data for failure rates of larger wind turbines. Due to this constraint, the analysis is based on a smaller 3 MW turbine for which complete failure data is available. This choice ensures greater reliability in failure rate predictions but may not fully represent the behaviour of larger-scale turbines in real-world applications.

Finally, metocean data, which encompasses meteorological and oceanographic conditions, is sourced separately for each location to reflect site-specific environmental characteristics. While this approach is essential for accurately individualising case studies, it introduces additional variability in the results. Factors such as local wind speeds, sea states, and daylight duration influence turbine performance and contribute to differences in energy yield across locations.

2.2.5 Results and discussion

2.2.5.1 North Sea

The North Sea data was simulated for three different operational scenarios. Figure 2.7 presents both the direct and total operational expeditures (OPEX) for each scenario. A key observation is that the total OPEX for the scenario where daylight is a limiting factor is more than double the OPEX of the other two scenarios. When examining the direct costs across the three maintenance strategies, they remain relatively close in range, suggesting that the primary driver of high total OPEX costs in the 'Daylight Limited' scenario is the impact of lost revenue. This is further illustrated in the cost breakdown shown in Figure 2.8. Beyond differences in lost revenue, it is observed that repair costs remain comparable across all scenarios, while staff costs are higher for night shift operations, and transport costs are highest in the 'Daylight Limited' case. The elevated transport costs associated with the 'Daylight Limited' scenario could be attributed to maintenance activities not being completed during available daylight hours, necessitating additional vessel charters to return to the site for further maintenance the following day.

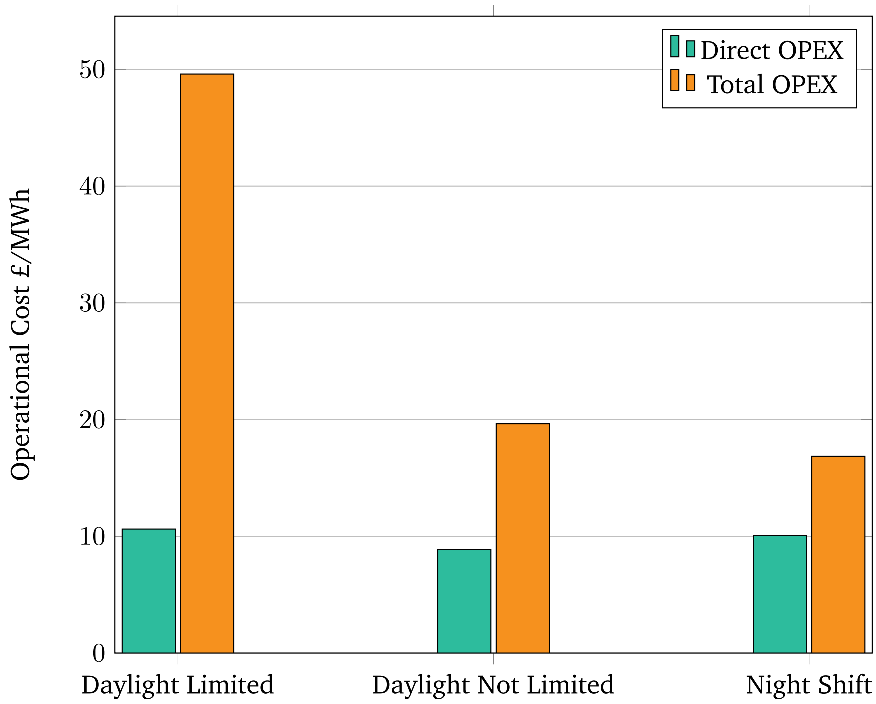

Figure 2.7: Cost overview for North Sea simulations

Lost revenue costs are primarily driven by prolonged turbine downtime, where delayed maintenance prevents turbines from returning to operational status and generating power. In

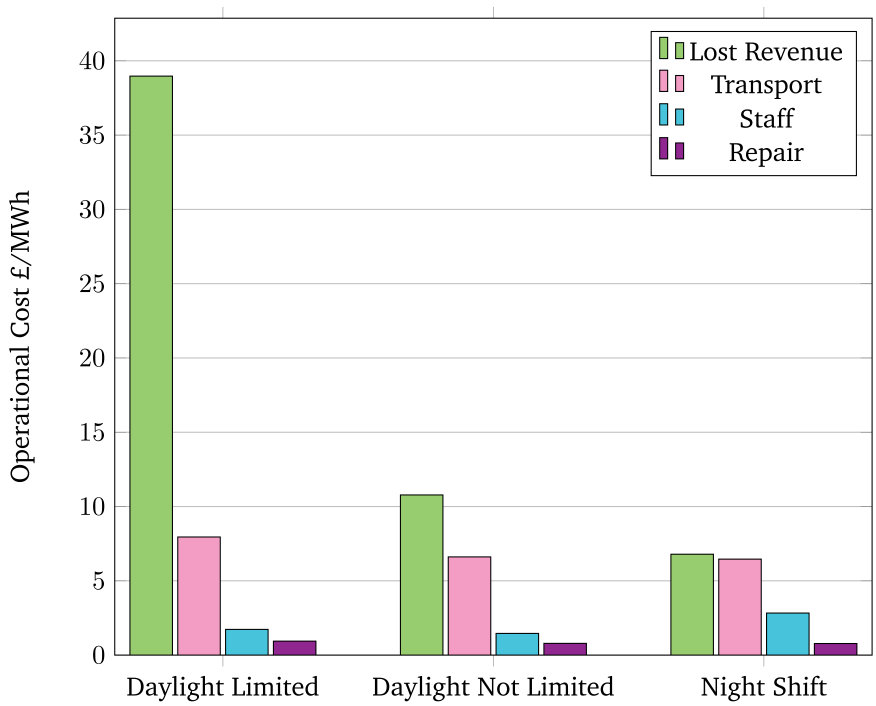

Figure 2.8: Cost breakdown for North Sea simulations

the 'Daylight Limited' scenario, the restricted availability of suitable weather windows for crew transfers significantly reduces accessibility for maintenance teams. This constraint is particularly pronounced in the North Sea, where adverse metocean conditions frequently limit opportunities for maintenance operations, further compounding revenue losses.

In contrast, the 'Night Shift' strategy results in the lowest OPEX, as it enables maintenance activities to be conducted during extended operational windows. By allowing repairs to take place outside of daylight hours, this approach minimises turbine downtime and mitigates the financial impact of lost power generation.

A comparison between the 'Daylight Not Limited' and 'Night Shift' cost breakdowns highlights that the primary differences arise in lost revenue costs and staffing expenses, while repair and transport costs remain largely consistent across both scenarios. For the North Sea in particular, the ability of the maintenance team to operate during designated daytime shift hours (08:00–20:00), irrespective of sunset times, significantly reduces overall costs in comparison to the 'Limited Daylight' scenario. As a result, the expenditure associated with 'Daylight Not Limited' is much closer to the lower operational costs observed in the 'Night Shift' simulation.

2.2.5.2 USA

The same methodology was applied to the simulations for the US site, with cost results presented in Figure 2.9. As with the North Sea, the highest Total OPEX occur in the 'Daylight Limited' scenario. However, the difference in costs between scenarios is noticeably smaller in comparison.

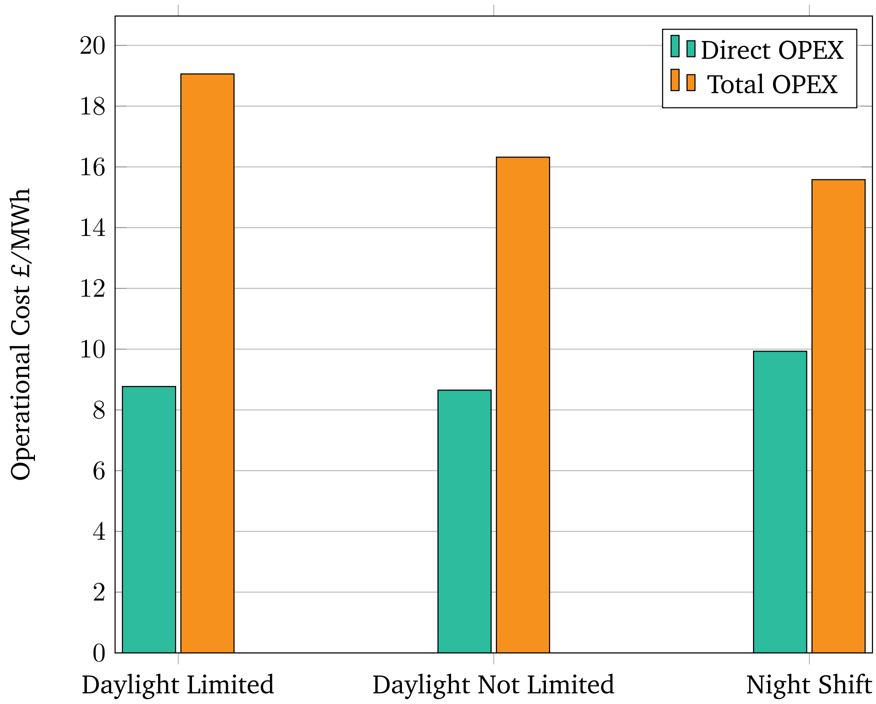

Figure 2.9: Cost overview for East Coast US simulations

At this site, the cost difference between the 'Daylight Not Limited' strategy and the 'Daylight Limited' strategy is smaller than that observed in the North Sea. This suggests that the US site benefits from improved accessibility, which may be attributed to more favourable metocean conditions, extended daylight hours, or a combination of both factors. As illustrated in Figure 2.3, the US site experiences a greater number of daylight hours throughout the year compared to the North Sea. Consequently, the impact of daylight constraints on maintenance accessibility is reduced, leading to a smaller difference in operational costs between the 'Daylight Limited' and 'Daylight Not Limited' scenarios. The maintenance team is less frequently restricted by sunset occurring before the standard shift ends at 20:00, thereby ensuring that more planned maintenance activities can be completed within daytime working hours.

Furthermore, the difference in Total OPEX between the 'Daylight Not Limited' and 'Night

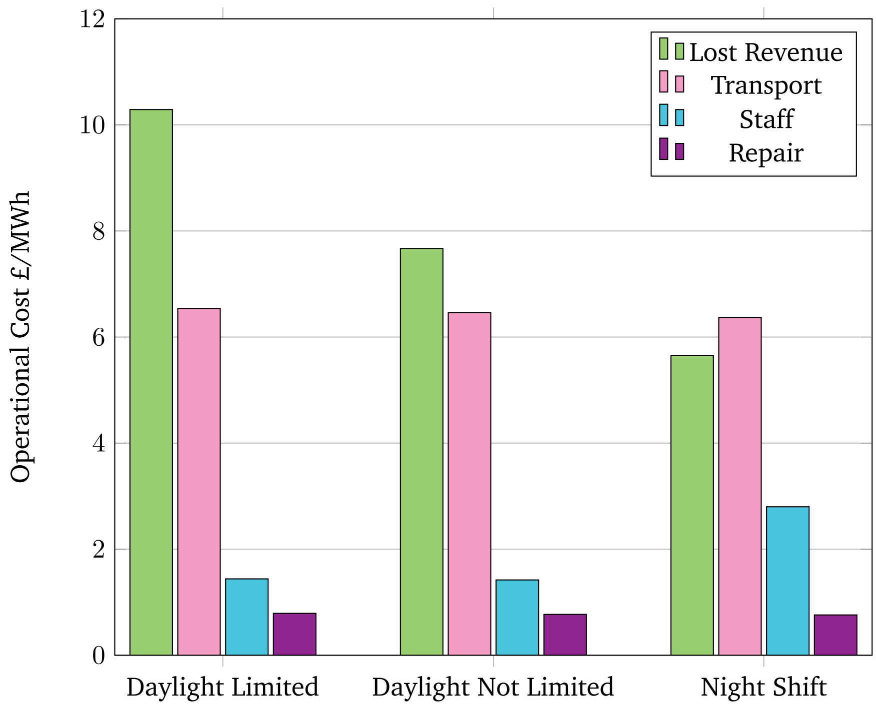

Figure 2.10: Cost breakdown for East Coast US simulations

Shift' strategies in the US is relatively small, suggesting that the incremental increase in daylight hours at this site reduces the financial benefits of implementing a night shift strategy. Supporting this, the Direct OPEX for the 'Night Shift' strategy is the highest among the three operational strategies, although the margin of difference remains relatively modest. This is primarily due to increased staff costs, as evidenced in Figure 2.10, which provides a detailed breakdown of cost components for the US scenarios.

Despite the higher Direct OPEX, the 'Night Shift' strategy remains the most cost-effective overall, based on Total OPEX, as the significantly reduced lost revenue component offsets the increased staffing expenses. The extended maintenance windows provided by this approach allow for more repairs, minimising turbine downtime and improving energy generation efficiency. Conversely, the 'Daylight Limited' scenario results in the highest Total OPEX, with lost revenue once again serving as the dominant cost driver due to restricted maintenance opportunities.

While the difference in costs between the 'Night Shift' and 'Daylight Limited' scenarios remains substantial, it is noticeably smaller than that observed for the North Sea wind farm.

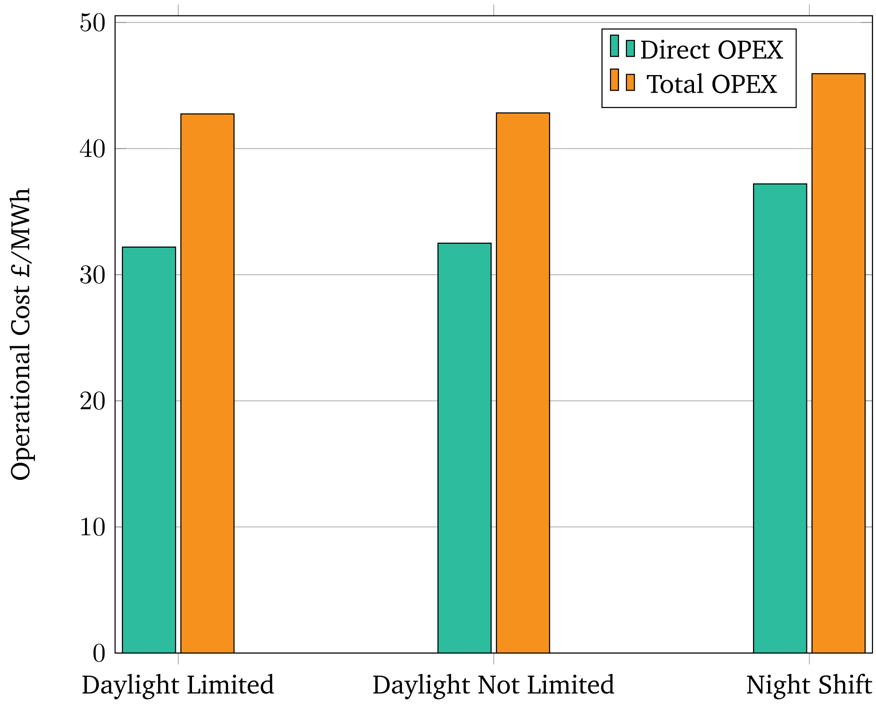

Figure 2.11: Cost overview for Darwin, Australia simulations

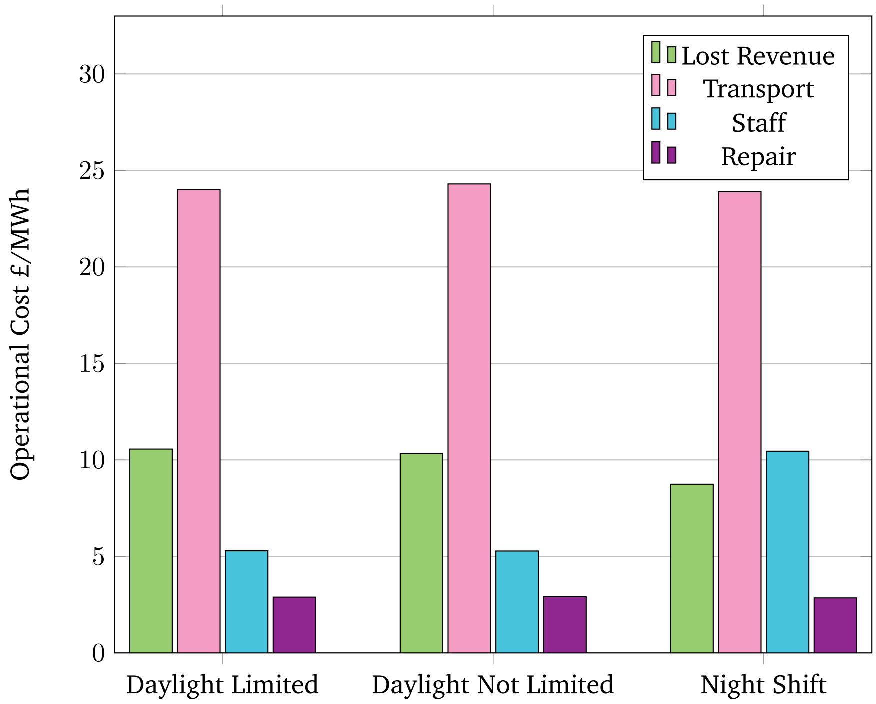

Figure 2.12: Cost breakdown for Darwin simulations

2.2.5.3 Australia

Figures 2.11 and 2.12 present the results for the Australian case study. At this location, both Total and Direct OPEX are significantly higher than those observed in the North Sea site and the US site. This is primarily due to the lower wind resource, with an average wind speed of only 3.84 m/s throughout the wind farm's operational lifetime, based on 100 simulations. The lower wind speeds result in significantly reduced energy production, leading to an inflated OPEX when measured in £/MWh. While the absolute differences in OPEX across the three sites are substantial, the primary focus of this analysis is on the relative differences between operational strategies rather than the inherent cost disparities between locations.

The 'Night Shift' strategy incurs the highest Total and Direct OPEX at this site, indicating that, unlike the previous case studies, lost revenue is not the primary driver of costs. Instead, other operational factors, particularly transport and staffing expenses, play a more significant role in determining overall expenditure.

A closer examination of Figure 2.12 reveals that transport costs constitute a considerable proportion of total expenditure. While absolute transport costs are similar across all sites, the cost per megawatt hour (£/MWh) of electricity produced in Darwin is notably higher due to the lower power generation, resulting in the costs for the site appearing significantly higher than the other scenarios. The transport costs being the main contributer is more of an indication of the large reduction in lost revenue costs for the Australian site. Further analysing the cost breakdown, lost revenue costs are lowest in the 'Night Shift' scenario, indicating that accessibility for maintenance is improved when operations extend beyond standard daylight hours. The 'Daylight Limited' scenario incurs the highest lost revenue costs, but the 'Daylight Not Limited' scenario exhibits very similar total costs. This suggests that the site benefits from high accessibility, likely due to a combination of calmer metocean conditions, resulting from lower wind speeds in the region, and an extended number of daylight hours. The minimal cost difference between these two scenarios indicates that daylight hours are sufficiently long to prevent significant restrictions on an 8 AM–8 PM maintenance shift, thereby reducing the necessity for night-time operations.

Transport and repair costs exhibit minimal variation across scenarios, reinforcing the notion that these expenditures remain largely independent of maintenance scheduling. The most notable cost variation occurs in staff expenses, which are approximately double in the 'Night Shift' scenario compared to daylight shifts. This increase is driven by the larger number of technicians required for night-time maintenance operations and is a consistent trend across all sites. However, in Darwin, the financial impact of higher staff costs is more pronounced due to the lower overall energy production, amplifying the cost per unit of electricity generated.

To mitigate these financial challenges, optimising wind farm placement should be a key consideration for wind farm developers. Relocating the wind farm closer to shore would reduce transport expenses, which constitute a major cost contributor for the selected wind farm site. While the distance from shore was held constant across all locations to facilitate direct comparisons, in real-world wind farm development, proximity to shore would typically be optimised to minimise logistical costs. This highlights the importance of site selection in offshore wind projects, where balancing accessibility, resource availability, and transport logistics is essential for achieving cost-effective operations.

2.2.5.4 Comparison

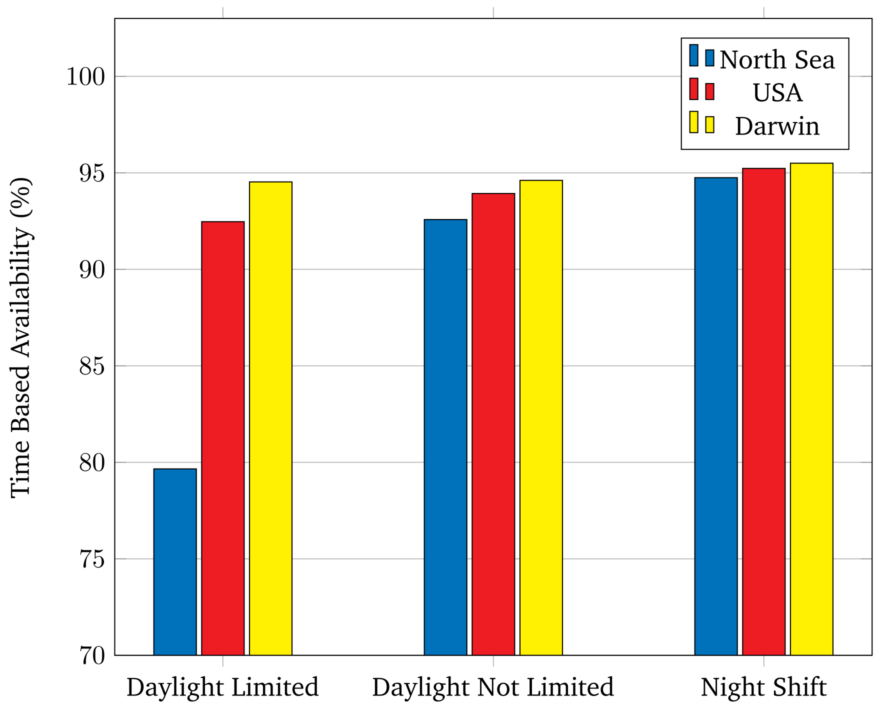

Figure 2.13: Time based availability comparison

To compare the three site locations, there needs to be a focus on the relative difference in costs across operational scenarios, rather than determining the best overall site based on absolute operational costs. Figures 2.13 and 2.14 illustrate the time-based availability and power production of each location. The North Sea wind farm exhibits the lowest time-based availability, particularly in the 'Daylight Limited' scenario, where availability drops to 79%. This results in substantial lost revenue costs. In contrast, Darwin has the highest time-based availability, but its power production remains significantly lower due to its weak wind resource and relatively calm climate. Figure 2.15 depicts the overall relative difference in costs between

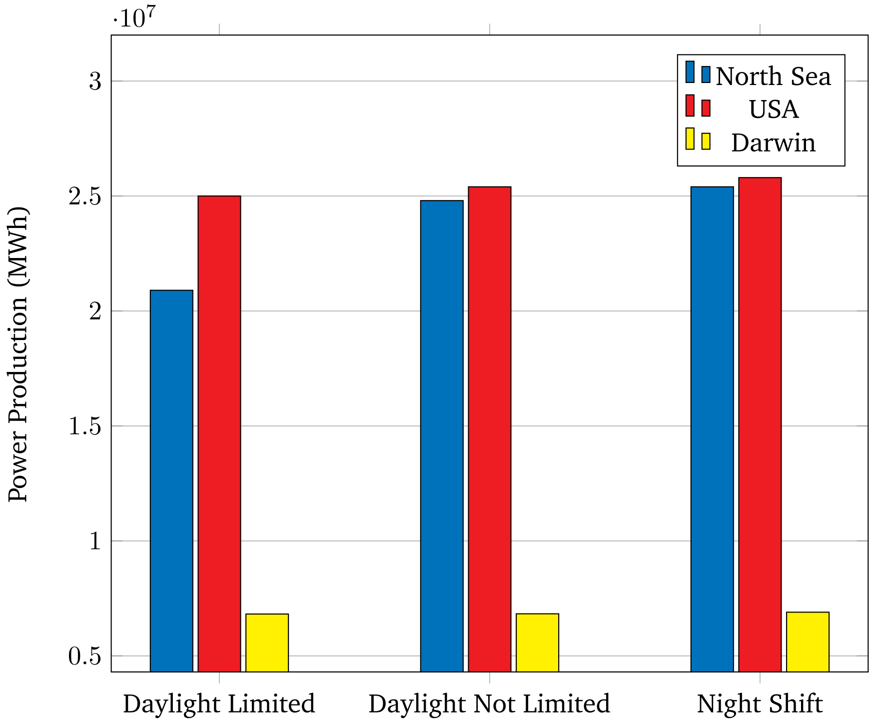

Figure 2.14: Power production comparison

locations, calculated by determining the absolute difference in costs between the 'Night Shift' and 'Daylight Limited' scenarios. The North Sea demonstrates the largest relative difference in Total OPEX, approximately ten times greater than those observed in the US and Australia sites. The large relative difference between strategies indicates that because the daylight hours have the biggest limitation on the North Sea, maintenance strategies involving night shift work would be the most beneficial for this location. However, in terms of direct costs, Darwin exhibits the greatest relative difference, predominantly due to high staff costs. The impact of technician numbers during the night shift on Total OPEX is explored further in Subsection 2.2.5.5. One of the main conclusions from these findings is that implementing a night shift strategy in Darwin would be counterproductive, as the high staff costs outweigh the potential reduction in lost

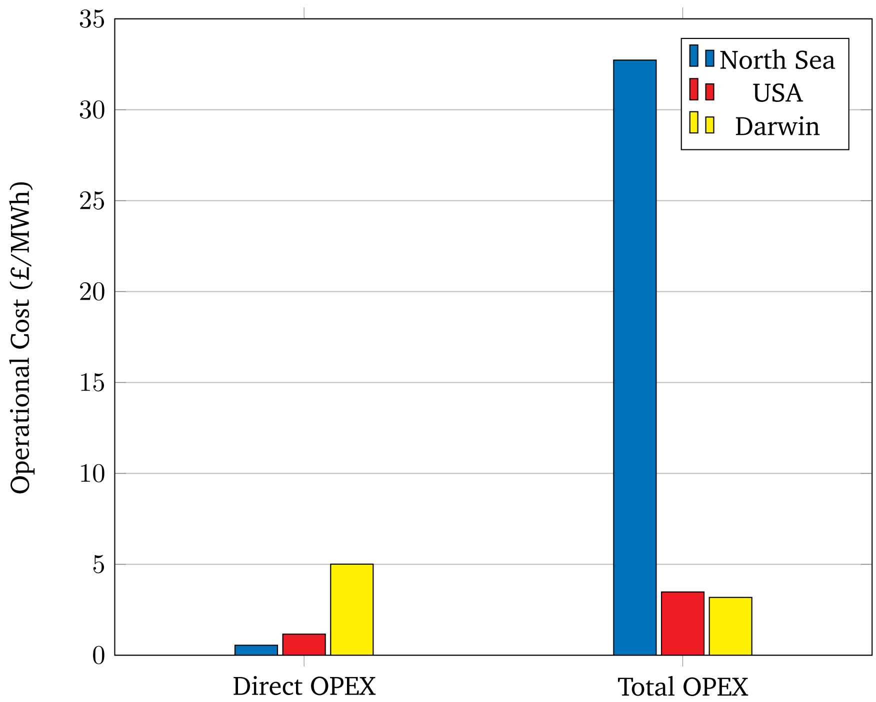

Figure 2.15: Relative difference in costs between daylight limited scenario and night shift scenario for the three site locations

revenue costs.

2.2.5.5 Impact of Vessel Fleet

In these simulations, the number of technicians was assumed to remain constant between day and night shifts to ensure a consistent basis for comparison across operational strategies. However, the results from the Australian case study highlight that staff costs are a major driver of the increased operational expenditure associated with the 'Night Shift' strategy. This finding underscores the importance of resource allocation in offshore wind maintenance, where balancing personnel availability with cost effectiveness is a key challenge. To further assess the impact of available resources, including the number of vessels and technicians deployed, a sensitivity analysis was conducted, with results presented in Figures 2.16 and 2.17.

The red line in both graphs represents the baseline cost of a day shift scenario at the Darwin wind farm, assuming a standard deployment of five crew transfer vessels (CTVs), each carrying six technicians. These vessel and technician allocations were maintained consistently across all locations for both the 'Daylight Limited' and 'Daylight Not Limited' scenarios to facilitate a controlled comparison. The results indicate that when two to five CTVs are deployed at night,

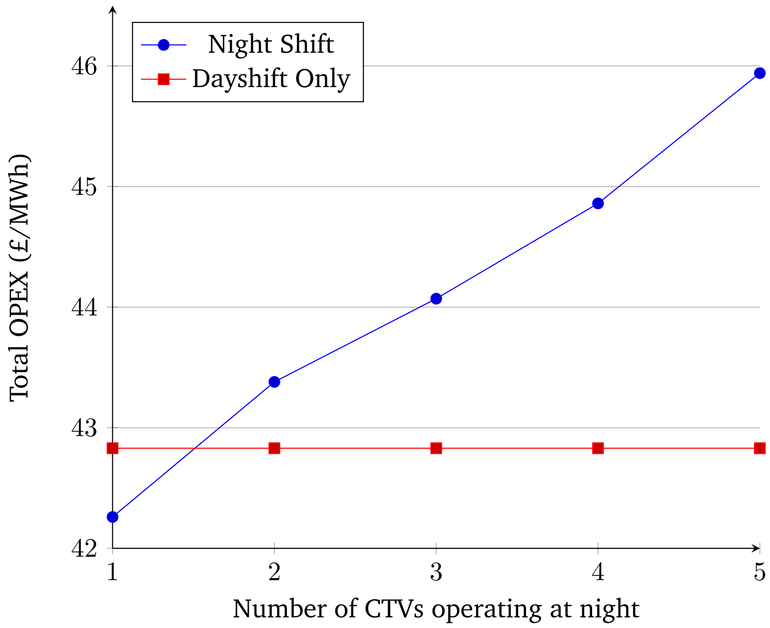

Figure 2.16: Analysing the impact the number of boats used for night shift operation has on the total operational cost for the Darwin case study compared to a day time only maintenance strategy

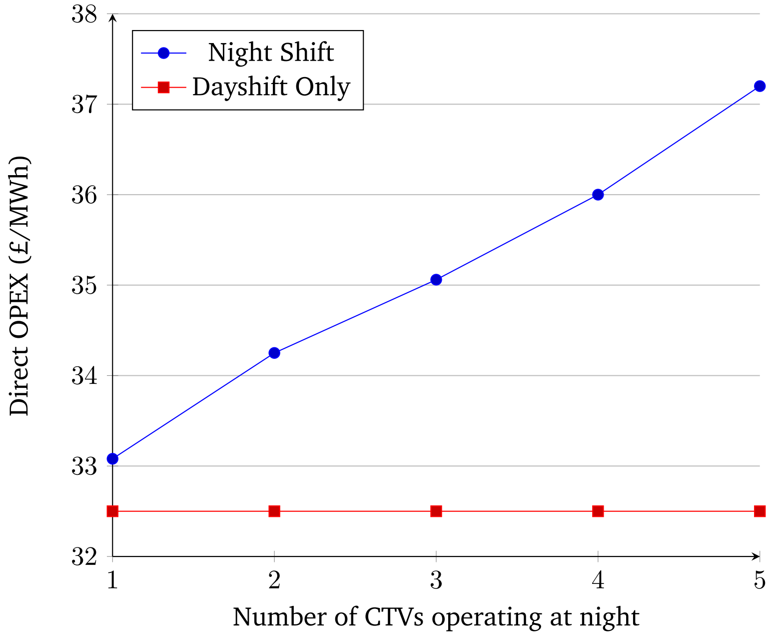

Figure 2.17: Analysing the impact the number of boats used for night shift operation has on the direct operational cost for the Darwin case study compared to a day time only maintenance strategy

total costs for a combined day and night shift exceed those of a strictly day-shift operation. This suggests that the additional expenditure associated with night-time maintenance, including increased staffing costs, logistical complexities and the potential risk to health and safety for the technicians, outweighs the financial benefits of reduced turbine downtime in certain cases.

However, an important exception is observed when only a single CTV is utilised during night time operations. Under this configuration, the 'Night Shift' strategy becomes cost-effective, as the reduction in lost revenue offsets the incremental increase in staffing and vessel related expenses. This finding suggests that while night shifts can provide financial advantages by enhancing maintenance flexibility and minimising turbine downtime, these benefits are highly dependent on the scale of resource deployment. Excessive staffing or vessel allocation at night leads to diminishing returns, making it critical to optimise resource distribution based on site specific accessibility constraints and maintenance requirements.

Further reinforcing this conclusion, 'Direct OPEX' remains consistently higher in night shift simulations across all configurations. This is primarily due to elevated staff costs, which scale directly with the number of technicians required to maintain continuous 24-hour operations. Unlike transport and repair expenditures, which exhibit relatively stable trends across different scenarios, staff costs remain the dominant factor driving overall expenditure. This finding highlights the need for strategic workforce planning in offshore wind maintenance, as well as the potential for alternative solutions, such as increased automation, remote monitoring, or improved predictive maintenance strategies, to help mitigate the financial burden associated with extended operational shifts.

These results reinforce the necessity of tailoring operational strategies to site specific conditions. While night shift operations may be advantageous in high-wind, high-revenue environments where minimising downtime is critical, their cost effectiveness diminishes in locations like Darwin, where lower wind speeds result in reduced energy production. Consequently, an optimised approach to vessel and technician deployment, accounting for local wind resources, accessibility conditions, and economic trade-offs, is essential for maximising the financial viability of offshore wind farms.

2.2.6 Summary of analysis on daylight limitations

The analysis delves into the influence of daylight limitations on offshore wind O&M costs across three global wind farm sites. Employing three maintenance strategies: 'Daylight Limited', 'Daylight Not Limited' and 'Night Shift', the study evaluates their economic viability. Notably, the North Sea site exhibited a £32.74/MWh reduction in costs under the 'Night Shift' strategy compared to the 'Daylight Limited' scenario. Conversely, the US site saw a £3.48/MWh reduction, while the Darwin site experienced a £3.19/MWh increase in costs with the night shift. The variance in results highlights the critical role of location and daylight hours in determining the need for night shift maintenance. Furthermore, the study highlights possible health and safety risks associated with night shift work and its impact on technician welfare, a domain largely unexplored compared to the more extensively studied oil and gas industry. Quantifying and analysing these health and safety risks is often difficult due to the qualitative nature of the data collected and the issues with accurate data collection, however, it is an extremely critical part of ensuring offshore wind maintenance continues to improve in the future generation. The work emphasises the necessity of conducting a case-by-case cost-benefit analysis when considering the implementation of a night shift. O&M operators must carefully weigh the potential reduction in costs against the increased health and safety risks associated with night shift, including fatigue and reduced visibility. The decision-making process should involve evaluating mitigation strategies to address declining technician welfare and increased safety risks during night shifts. The industry's development depends on the well-being of its workforce, necessitating ongoing efforts to enhance safety measures and address welfare concerns for both day and night shift operations in offshore wind. Further investigation into site-specific weather patterns, seasonal variability, and logistical factors influencing maintenance accessibility could provide deeper insights into the cost effectiveness of different operational strategies across varying geographical locations but it is clear that there is no 'one size fits all' approach when it comes to operations at night.

2.3 Operations during icy conditions

2.3.1 The role of ice in offshore wind

Areas planning for offshore wind deployment, that are located in harsher climates, need to also consider the impact icy conditions will have on the wind turbines and operations of the wind farm. Several research papers have investigated the offshore operation of wind turbines in cold climates. One of the first review papers identified that the largest impacts on offshore wind farms in these climates are blade icing and sea ice [31]. Blade icing affects several areas of the wind turbine's performance including, aerodynamics, loads, the control system, and material properties. Ice throws are also of concern when operating in icy conditions at an offshore site as they have the potential to pose serious threats to operating personnel at the wind farm. As a result, research is focused on mitigating these risks by reducing the amount of icing on the blades and by putting regulatory framework in place for operating personnel [32, 33, 34, 35]. On top of the health and safety risk associated with blade icing, in the long-term, it can reduce annual energy production (AEP) and lifespan of the wind turbine [36]. Additionally, icy conditions on platforms and access points can create significant health and safety concerns for maintenance crews, increasing the risk of slips, falls, and other accidents. Previous research has explored these risks, including studies on ice accumulation, ice-related safety hazards, and the potential damage caused by ice breaking against turbine structures [37].

Turbines in cold climates may suffer from lower reliability rates. Condensation and freezing moisture can develop on internal electronics and cause damage [38]. Icing of sensors can cause damage, and send incorrect wind speed and direction information to controllers, leading to yaw and pitch misalignment. Even high-density cold air has caused greater loading than expected on rotors, resulting in more fatigue and generator overheating. To the author's knowledge there is no broad study that has produced data on the reliability of turbines in cold climates, likely due to the lack of operational wind farms currently in significantly ice prone regions. Another critical concern in icy environments is ice scouring, which can endanger subsea power cables [39]. The movement of ice across the seabed can lead to physical damage, increasing the risk of cable failure and disrupting power transmission.

Most wind turbines are designed to operate in temperatures as low as -10°C. However, for offshore wind farms located in extreme cold climates, adapting designs to withstand lower temperatures is essential. Despite the limited availability of turbines specifically engineered for such conditions, some manufacturers provide specialised cold-weather models. These adaptations are particularly important from a maintenance perspective, as they mititgate against potential failures and downtime caused directly from the environtmental conditions. Without appropriate design modifications, offshore wind farms in cold regions may experience increased maintenance requirements and a reduction in availability.

To enhance the performance and longevity of offshore wind components in cold environments, several design adaptations and mitigation strategies have been proposed in the literature [40, 41, 42]. These include using materials and lubricants engineered for sub-zero conditions, incorporating heated and sealed nacelles, and implementing advanced control systems to optimise turbine performance in freezing temperatures. Ice detection systems, anti-icing coatings, and active de-icing mechanisms can also mitigate ice accumulation and reduce structural stress. By integrating these measures, offshore wind farms can improve reliability and minimise the operational challenges associated with extreme cold. However, many of these ideas are not yet commercialised and are in testing stages.

Despite these studies, there is limited research on how sea ice, specifically, influences the long-term operation and maintenance of offshore wind farms. Factors such as ice movement, pressure ridges, and seasonal ice changes may affect the accessibility of turbines, the stability of foundations, and the effectiveness of existing maintenance strategies. It has been recorded that ice loads that collide with the turbine's tower or foundation may result in increased fatigue in the support structures if there are successive ice vibrations [43]. From a structural perspective, measures have already been implemented to mitigate the impact of sea ice on wind turbines in colder climates. When wind turbines are installed in shallow waters or near shorelines, the surrounding sea ice can become fixed in place, a phenomenon distinct from drifting ice, which exerts both static and dynamic forces on the turbine structure. These forces can be substantial, necessitating the development of specialised designs to effectively distribute the contact area between the sea ice and the turbine tower. Modelling of these structural interactions is carried out in one study, based in the Great Lakes in Northern America, to determine the interactions between the offshore turbine with ice sheets as well as the impact the ice has on the soil at the structures foundations [44]. It is found that using a conical structure for the turbine foundations increases structural stability for the turbine and reduces ice sheet impacts.

A study titled 'Ice Risk Analysis for Floating Wind Turbines, Offshore Newfoundland and Labrador' discusses the structural risks a floating wind farm powering oil platforms off the coast of Newfoundland, Canada would face [45]. The study analysed the probability of icebergs, sea ice, and blade icing impacting the turbines, along with the resulting loads caused by the first two. It is determined that iceberg management, the lassoing and dragging away of icebergs from site, was unlikely to be needed, assuming that the structure and moorings are designed for the 50-year iceberg load. The study does not mention maintenance or accessing the turbines through sea ice.

Furthermore, advanced simulation tools have been developed to model ice-structure interactions. The OpenFAST program, designed by the National Renewable Energy Laboratory (NREL), features two ice modules, IceDyn and IceFloe, which simulate ice loads on offshore structures. However, these models are currently limited to fixed-bottom offshore wind turbines and do not account for the dynamic challenges associated with floating structures [46]. The presence of sea ice poses significant challenges to wind turbine operations, particularly for floating wind technology. Ice movement can interfere with mooring lines, causing instability and affecting the buoyancy of floating structures. Semi-submersible and barge-based floating wind turbine designs, for instance, have demonstrated poor interactions with ice [47].

A notable example of a mitagation strategy is in the design approach used at the Tahkoluoto wind farm off the coast of Finland. Tahkoluoto serves as one of the primary case studies for this analysis, being one of the only operational wind farms that experiences sea ice annually. The wind farm's turbine foundations incorporate a conical section at the water level, strategically designed to ensure that incoming ice will break upwards, thereby preventing direct lateral forces from being applied to the structure. Anticipating significant ice impacts, the designers implemented a wall thickness for the conical section that is three times greater than that of the rest of the foundation, providing enhanced protection against potential ice stresses. The stress exerted by sea ice on turbine structures is influenced by various factors, including the type of ice, its mechanical properties, the extent of contact between the ice and the structure, the shape of the turbine's foundation, and the direction and speed of ice movement.

Although structural impacts are accounted for, it remains uncertain what effect sea ice has on the accessibility of wind farms. The review by Battisti et al. notes that installation windows may be shorter, site data communications can be hampered, and accessibility can be reduced by winter storms or vessels may not be equipped to operate in thick ice [31]. The G+, a global offshore wind health and safety organisation, produces a variety of guides outlining best practices for the offshore wind industry but they have no literature on the topic of sea ice. The advice is to avoid transfer from vessel to ice covered ladders and to use grip tape on railings when frosty, but these are both caused by sea spray rather than sea ice [18]. The topic of decreased accessibility due to sea ice often pertains to passage through the Arctic sea or Antarctic ocean, rather than any areas that have or will have offshore wind development [48, 49]. Understanding this is crucial for ensuring the reliable and efficient operation of offshore wind farms in icy environments, particularly given the growing global interest in establishing offshore wind sites in new locations.

2.3.1.1 Operations with sea ice

Sea ice is defined as frozen seawater that forms at temperatures below -1.8°C [50]. Sea ice differs from icebergs, which are made from fresh water and have broken off glaciers. In deep waters, sea ice formation typically requires the top 100 metres of seawater to be at freezing point. In shallower waters near the shore, sea ice can form when the seabed temperature drops below freezing. Ice near the shore generally forms earlier and melts later, and when it freezes to the seabed, it is referred to as "landed fast ice." Sea ice is typically characterised by its thickness, age, and concentration. Ice thickens with the time it spends in freezing conditions, resulting in "new ice" being the thinnest, "first-year ice" being relatively thin, "second-year ice" being thicker, and "multi-year ice" being the thickest. Ice thickness is usually classified into bins, such as 15-30 cm or 120-200 cm. The second key characteristic of sea ice is its concentration, which refers to the fraction of the sea area covered by ice, ranging from 0% to 100%. Furthermore, multiple ice formations can coexist in the same area, complicating the measurement and assessment of sea ice. For example, an area might be 50% covered by 15-30 cm ice and 50% by 30-50 cm ice. The most common areas of sea ice are in the Arctic and Antarctic but sea ice from the north can extend as far south as 50°N. The Bohai Sea, located below this latitude, is the southernmost oceanic basin in the northern hemisphere to experience sea ice, due to the Eurasian winter monsoon causing ice formation [51, 52]. Figure 2.18 shows 50°N latitude as a dashed red line. The countries highlighted in green and blue stripes are countries that have experience with sea

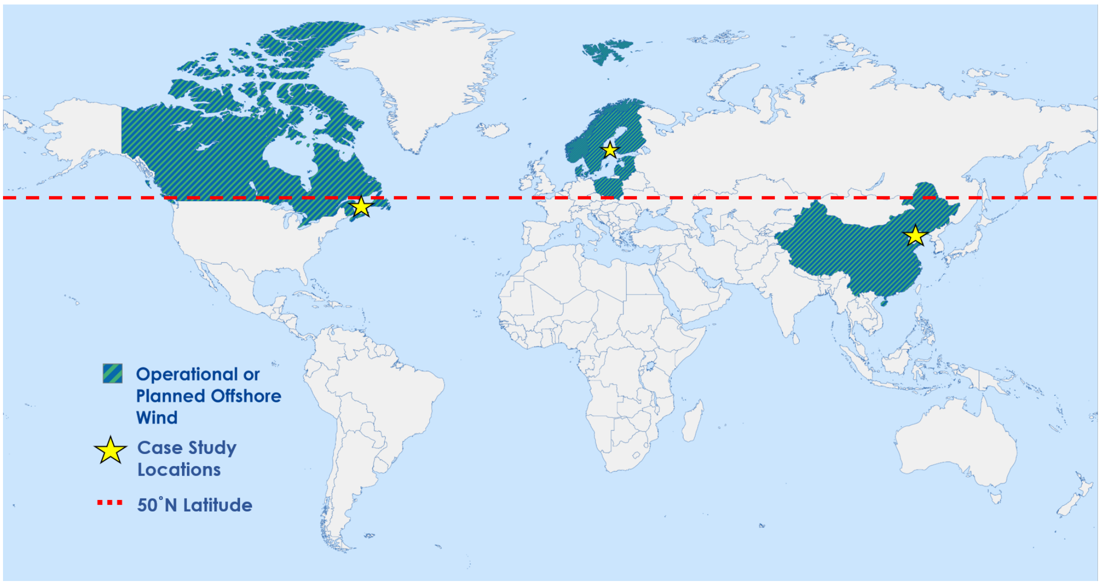

Figure 2.18: Map detailing countries with planned or operational offshore wind farms that are affected by sea ice. The yellow stars on the map indicate the locations of the three case studies chosen for this research. The red dashed line indicates the 50 degrees north latitude, sea ice is typically found north of this latitude.

ice that have offshore wind development, either with operational or planned wind farms. Many countries bordering the Baltic Sea, which can develop sea ice, are planning or operating wind farms. In particular, Finland, who have 65GW of offshore wind farms planned, have most of their offshore waters in the Gulf of Bothnia which develops sea ice every year. As a result of the planned offshore wind development in the Baltic Sea, historical sea ice data has been assessed to determine the variation of ice conditions and how these will impact offshore wind turbines structures [53]. Resource mapping for offshore wind has been briefly outlined for Nova Scotia by Aeger Insights who highlighted the North and East regions may face issues with sea ice throughout the winter making operations more challenging [54]. The potential for offshore wind development in the Great Lakes has been explored in several studies to assess the viability of offshore wind projects, however, there are several political and environmental barriers to do so. Additionally, freshwater ice, that is present in the Great Lakes, is harder and more brittle than sea ice, presenting unique engineering challenges. Freshwater is the key factor in choosing Nova Scotia over the Great Lakes for the case study, as sea ice is not present in the latter. The three stars in Figure 2.18 indicate the case studies that will be focused on in this study, namely the Finnish wind farm, Tahkoluoto, in the Baltic Sea, the Xingcheng development zone in the Bohai Sea and the Nova Scotia region in Canada. The sea ice in these regions is discussed further in Section 2.3.3.2.

Table 2.4: Winter Risk Value lookup table by the International Maritime Organization, determining vessel operation risk based on ice thickness and ice class. Lower values indicate increased risk.

Polar Ship Category	Ice Class	Ice Thickness (cm)											
		Ice Free	0-10	10-15	15-30	30-50	50-70	70-95	95-120	120-200	200-250	250-300	300+
A	PC1	3	3	3	3	2	2	2	2	2	2	1	1
	PC2	3	3	3	3	2	2	2	2	2	1	1	0
	PC3	3	3	3	3	2	2	2	2	2	1	0	-1
	PC4	3	3	3	3	2	2	2	2	1	0	-1	-2
	PC5	3	3	3	3	2	2	1	1	0	-1	-2	-2
B	PC6	3	2	2	2	2	1	1	0	-1	-2	-3	-3
	PC7	3	2	2	2	1	1	0	0	-1	-2	-3	-3
C	IAA	3	2	2	2	2	1	0	-1	-2	-3	-4	-4
	IA	3	2	2	2	1	0	-1	-2	-3	-4	-5	-5
	IB	3	2	2	1	0	-1	-2	-3	-4	-5	-6	-6
	IC	3	2	1	0	-1	-2	-3	-4	-5	-6	-7	-8
	No Ice Class	3	1	0	-1	-2	-3	-4	-5	-6	-7	-8	-8

For vessels travelling in areas where ice may be present, the International Maritime Organisation (IMO) recommends evaluating risk based on the ice class of the vessel being used and the ice regime that is encountered in the area. Table 2.4 outlines the Winter Risk Values associated with each ice thickness category and the ice class of the vessel. Polar ship classes are in order of decreasing ice class, with PC1 as the highest ice class and no ice class being the lowest. The colour associated with the number indicates the level of risk, with red indicating a larger risk. Using this table, the risk index outcome can be calculated using the following equation:

$$RIO = \sum_{t=1}^{T} (C_t \times RV_t) \tag{2.1}$$

where RIO is the Risk Index Outcome, n is the number of areas with varying ice concentration, C is the concentration of the ice in the area, RV is the risk value chosen from the Table 2.4. Once a value for the RIO is calculated, Table 2.5 can be used to determine if a vessel should be sent out for operations. If there is an elevated operational risk, IMO recommends reducing the speed of the vessel or being accompanied by an ice breaker. To date, there are no ice breaking vessels in operation for offshore wind but there are several plans to build specialised vessels. For example, Aker Arctic are in the design stages to develop a Service Operating Vessel (SOV), with ice class PC6, for use in offshore wind [55]. The company estimate that the construction cost for this vessel will be roughly 5-10% more expensive than an open water vessel. SAL Heavy Life are currently constructing a vessel, according to The Royal Insitute of Naval Architect's, that will act as a heavy lift vessel, with ice class IA [56].

Table 2.5: Risk Index Outcome values and the corresponding recommendations for operation for vessels depending on it's ice class

Risk Index Outcome (RIO)	Ice Class $\leq$ PC7	Ice Class < PC7
0 $\leq$ RIO	**Normal Operation**	**Normal Operation**
10 $\leq$ RIO<0	**Elevated Operational Risk**	**Do not operate**
RIO $\leq$ -10	**Do not operate**	**Do not operate**

2.3.2 Research Question

The research undertaken in this study is novel to the offshore wind sector, as there is a distinct lack of available literature that addresses the potential impacts of sea ice on offshore wind operations. This study aims to fill this gap by investigating, through modelling, whether sea ice significantly affects power production and operational costs in regions prone to ice formation. Specifically, it explores how the presence of sea ice might influence wind turbine performance, including potential ice-related downtime due to low accessibility to the site. The study assesses whether the presence of sea ice leads to increased maintenance costs, the need for specialised equipment, or delays in operation due to ice-related issues. Further, it investigates the most effective maintenance approaches, by looking at the use of different ice-breaking vessels to access the different case study sites. Given the growing interest in offshore wind development in regions with cold and icy conditions, this study is highly relevant for future wind farm developers. It will provide valuable insights into the planning, design, and operational strategies that should be considered when establishing wind farms in areas vulnerable to sea ice. Despite anticipated changes in sea ice coverage due to climate change, the research remains vital for both the near-term and long-term success of offshore wind farms operating in ice-prone environments. The research question for this piece of analysis is therefore:

"How does the presence of sea ice impact the power production, operational costs, and maintenance strategies of offshore wind farms in ice-prone regions?"

2.3.3 Methodology

2.3.3.1 Model Adaptation

To incorporate sea ice accessibility into the model, modifications were made to account for vessel classification and ice conditions. Users are required to specify the ice class of all vessels used within the wind farm, selecting from the 12 ice classes listed in Table 2.4, which range from no ice class to PC1. Once a vessel's ice class is defined, its winter risk value is determined on an hourly basis by cross-referencing the current ice thickness with its classification, as detailed in Table 2.4. The ice concentration at that specific hour is then used to calculate the Risk Index Outcome (RIO) using Equation 2.1. A key model constraint dictates that if the RIO is negative, the vessel is unable to travel and must delay maintenance activities until the RIO returns to a positive value, provided that no other accessibility constraints are exceeded.

Additional functionality has been introduced to allow for the seasonal chartering of ice-breaking SOVs. This option was implemented based on the assumption that ice-breaking vessels incur significantly higher chartering costs than standard SOVs. To optimise operational expenditure, the model user can choose to charter ice-breaking vessels only during periods when sea ice is expected to obstruct access, and return to using standard vessels throughout the rest of the year. The seasonal chartering has only been applied to SOV operations, as it is the only vessel that a cost for chartering could be estimated, based on the current vessels in use in the industry.

Key model outputs relevant to this analysis include Total OPEX in £/MWh, power production in MWh, time-based availability as a percentage, and Direct OPEX in £/MWh. A further output enables users to assess the number of days when maintenance was required but could not be carried out due to sea ice, referred to as inaccessible days. These are defined as periods when vessel access to the wind farm was prevented by sea ice, directly impacting maintenance operations.

This study primarily focuses on wind farm availability and accessibility, as these are critical factors in assessing operational feasibility in ice-affected regions. While operational costs are examined in Section 2.3.4.3 within the context of the Nova Scotia case study, the lack of publicly available cost data for ice-breaking vessels presents a challenge in accurately modelling financial implications. As a result, a brief cost analysis was conducted for the Nova Scotia site, due to it's input climate data, further discussed in the following section.

2.3.3.2 Climate Data

The minimum requirement for the model is a year of hourly climate data in a time series. It requires wind speed, both for accessibility limits and also to estimate energy production of the wind farm. Other required accessibility limits are significant wave height and wave period. For this research, the model was adapted to consider sea ice as an additional accessibility limit. Similar to the other climate inputs, a time series of hourly measurements was required for the ice thickness, in metres, and ice concentration, in % of area covered. Based on the ice thickness and ice concentration, an additional accessibility metric, based on sea ice, decides on the vessels ability to perform maintenance on the wind farm. The input climate data at each location for the wind speed and significant wave height meaurements comes from the ERA 5 Reanalysis Hourly Data [27].

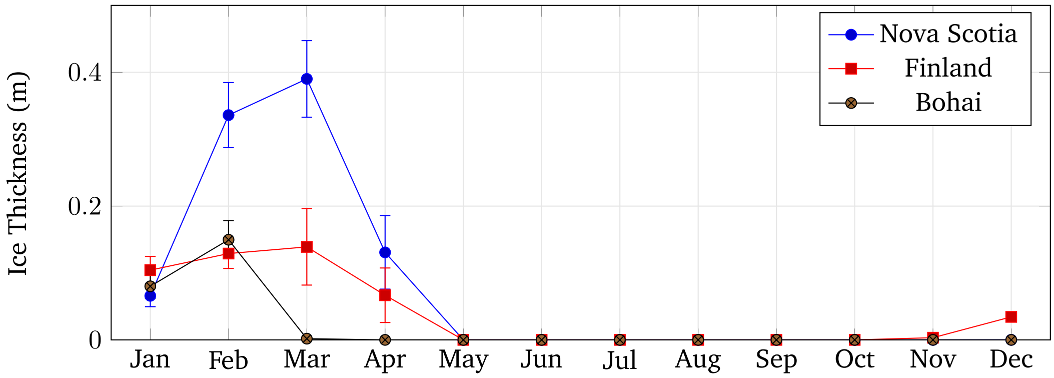

Figure 2.19: Monthly average and associated standard deviation of ice thickness of the sea ice in the three case study locations over the 20 year simulation period

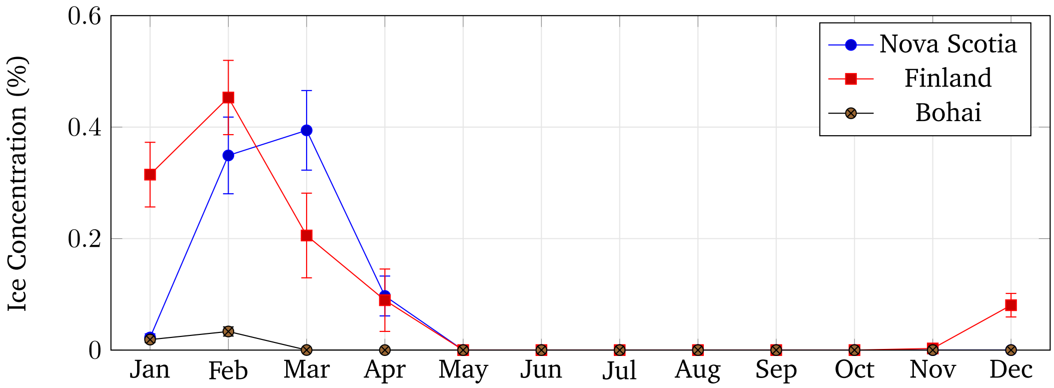

Figure 2.20: Monthly average and associated standard deviation of ice concentration of the sea ice in the three case study locations over the 20 year simulation period

Sea ice data availability within the selected databases is intermittent, leading to the necessity of using non-consecutive years as model inputs. For each case study, a total of eight years of sea ice data was acquired. Given the significant variability of sea ice conditions, the discontinuous nature of the dataset introduces potential uncertainties into the model results. The extent to which this affects the accuracy of the analysis remains uncertain but may bare some weight on the results.

For the Baltic Sea case study, high-resolution sea ice data was sourced from the Baltic Sea Physics Reanalysis provided by the Copernicus Marine Service [57]. This dataset is generated using the NEMO (Nucleus for European Modelling of the Ocean) ice-ocean model, which incorporates thermodynamic processes such as heat exchange, brine entrapment, and sea ice thickness evolution. The reanalysis is driven by observational data assimilation, enhancing its representation of real-world ice conditions. For the Bohai Sea and Nova Scotia case studies, global sea ice data was retrieved from the Global Ocean Ensemble Physics Reanalysis product via the Copernicus Marine Service [58]. More specifically, the ORAS5 reanalysis from the European Centre for Medium-Range Weather Forecasts (ECMWF) was used. ORAS5 is an ocean model that assimilates satellite and in situ observations to produce a consistent representation of global ocean conditions, including sea ice parameters. This dataset provides daily sea ice concentration and thickness estimates, which were subsequently interpolated to align with the hourly resolution of the wind and wave simulation model. Given the daily resolution of the ice data, a key assumption in the model is that if sea ice is recorded at any point during the day, it is considered present for the full 24-hour period. While this may introduce minor inaccuracies, particularly in highly dynamic ice regions, it is a necessary simplification for model consistency.

To compare the seasonal sea ice characteristics across the three case study locations, Figure 2.19 and Figure 2.20 illustrate the monthly mean sea ice thickness and concentration over the simulated 20-year operational period of the wind farm. Standard deviation error bars are included to indicate variability across the dataset. A general trend is observed across all three locations, with peak sea ice conditions occurring during the winter months. However, there are distinct regional differences. Bohai Sea experiences sea ice exclusively in January and February, with complete melting occurring by March. Nova Scotia exhibits a later peak, with the highest sea ice thickness and concentration recorded in March, and sea ice persisting from February to April. Finland has the longest duration of sea ice presence, spanning December to

April. However, the ice is generally thinner and less concentrated than in Nova Scotia. These variations highlight the importance of considering regional ice dynamics when assessing the impact of sea ice on offshore wind operations. While monthly averages provide insight into general trends, they do not capture individual ice events or extreme conditions that may have operational significance. For example, extreme levels of sea ice were present in one year of the data set for the Gulf of Bothnia, therefore, this extreme ice year could skew results.

2.3.3.3 Assumptions and limitations in the model

Determining winter risk values usually is a weighted sum of the different risk values in an area, as there are often differences in the ice regime. Due to the lower fidelity data for the sea ice, the model assumes that the ice studied in the area will have the same thickness when in reality different ice topologies may exist. A negative RIO in the range of 0 to -10 means that for a vessel with class PC7 or higher travel is possible but at a reduced speed. Currently, there are no vessels of this ice class being utilised at wind farms so the model assumes any negative value will result in a no travel decision. The investigation into potential operational costs is limited by the lack of available data surrounding charter costs of ice breaking vessels. There are currently no ice breaking vessels in operation in offshore wind, with available charter cost data therefore an estimation is made to provide some insight into the benefit of utilising these vessels. The estimation is based on the construction cost of the Aker Arctic ice breaking SOV, with polar class PC6, being 5-10% more expensive than a standard SOV, therefore the assumption is that the charter cost will also be increased by this amount. The assumption carries a high level of uncertainty and the given estimate may not apply to all classes of ice breaking vessel. The level of ice breaking may result in higher classes of vessel having much higher charter rates but that is so far unknown in the industry. Furthermore, the ice breaking vessel can be seasonally chartered for a specficied period of the year. However, these chartership periods do not consider the high demand there would likely be for the limited number of ice breaking vessels during the winter months and the subsequent bottle necks that may occur.

2.3.4 Results and discussion

Three distinct case studies are investigated through simulation to assess the operational and economic implications of ice-class vessel deployment for offshore wind maintenance. The selected locations include the Baltic Sea (Finland), the Bohai Sea (China), and Nova Scotia (Canada).

For the Baltic and Bohai Sea case studies, Crew Transfer Vessels (CTVs) form the basis of the maintenance strategy. This selection is justified by the relatively short distance from shore, approximately 15 kilometres in both cases. Moreover, as CTVs are primarily responsible for day-to-day maintenance activities, their frequent deployment makes them particularly susceptible to disruptions caused by sea ice. To investigate the impact of ice on operations, CTV fleets of varying polar classes are modelled across these two sites.

In contrast, a Service Operation Vessel (SOV)-based strategy is employed for the Nova Scotia case study. This choice is primarily driven by the charter cost estimate for an SOV that is currently under construction. Additionally, the wind farm's location is considerably farther from shore than those in the other two case studies, necessitating a vessel with greater endurance and onboard accommodation capabilities. Nova Scotia also experiences the most severe sea ice conditions of the three sites, further justifying the use of a larger, more capable vessel for year-round maintenance. To ensure statistical reliability and consistency in the results, each vessel-ice class configuration is simulated 100 times per location. All simulations are conducted over a wind farm operational lifetime of 20 years. The simulated wind farm in Finland is based on the real-world Tahkoluoto offshore wind farm, comprising 10 wind turbines, each with a rated capacity of 4.2 MW. The fabricated wind farms for the Bohai Sea and Nova Scotia case studies are modelled with 25 turbines each, also rated at 4.2 MW. To maintain consistency across the comparative analysis, all cost, transport, and repair parameters are held constant across the three sites for each polar class scenario.

Finally, a sensitivity analysis is conducted on the impact of seasonal chartership of an ice breaking vessel alongside a non ice breaking vessel versus utilising the same ice breaking vessel throughout the year. The results of the sensitivity analysis will reveal the importance of vessel selection for offshore wind sites experiencing sea ice.

2.3.4.1 Baltic Sea

The wind farm Tahkoluoto, an operational wind farm that experiences sea ice frequently, was simulated for the twelve ice classes for CTV operation. The results of the simulations are presented in Figure 2.21. Time based availability is plotted alongside the average number of

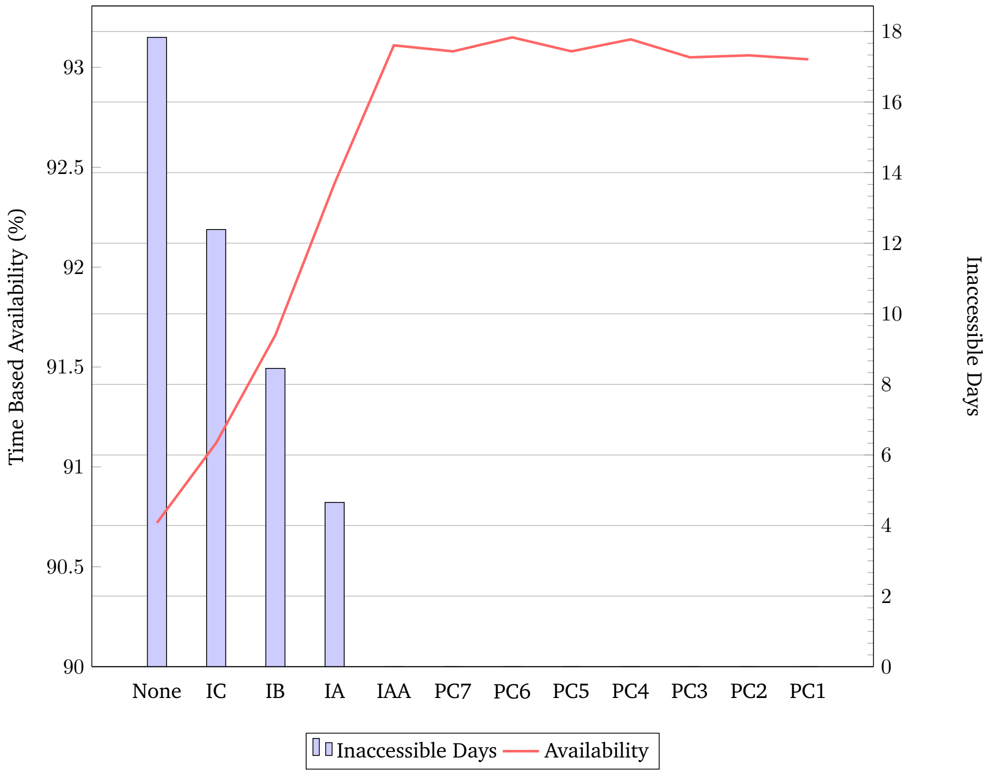

Figure 2.21: Inaccessibility days and the time based availability for the Tahkoluoto offshore wind farm in the Baltic Sea case study site for simulations utilising various classes of ice breaking vessels

inaccessible days per year of operation based on the ice vessel selected. The availability ranges from 90.72%, where there is no ice breaking ability on the vessel, to a maximum availability of 93.15% when PC6 is the class of ice breaking, an overall increase of 2.43%. The increase of availability when increasing polar class is due to the improved accessibility of the site, meaning the downtime of the turbines is reduced. Availability reaches a plateau at polar class IAA, coinciding with the inaccessible days reaching an average of zero days per year, as expected. Inability to access the wind farm only poses issues for vessel classes lower than IAA with the highest amount of inaccessible days being 17.83 when no ice class is assigned to the CTVs.

2.3.4.2 Bohai Sea

Similarly, the results of the simulations for the wind farm in the Bohai Sea off the coast of China are presented in Figure 2.22. Time based availability increases from 93.58% with no ice class to 94.33% with polar class PC7. The overall increase in availability is 0.75%, a lower improvement than seen in the Tahkoluoto simulations. The smaller change in availability is

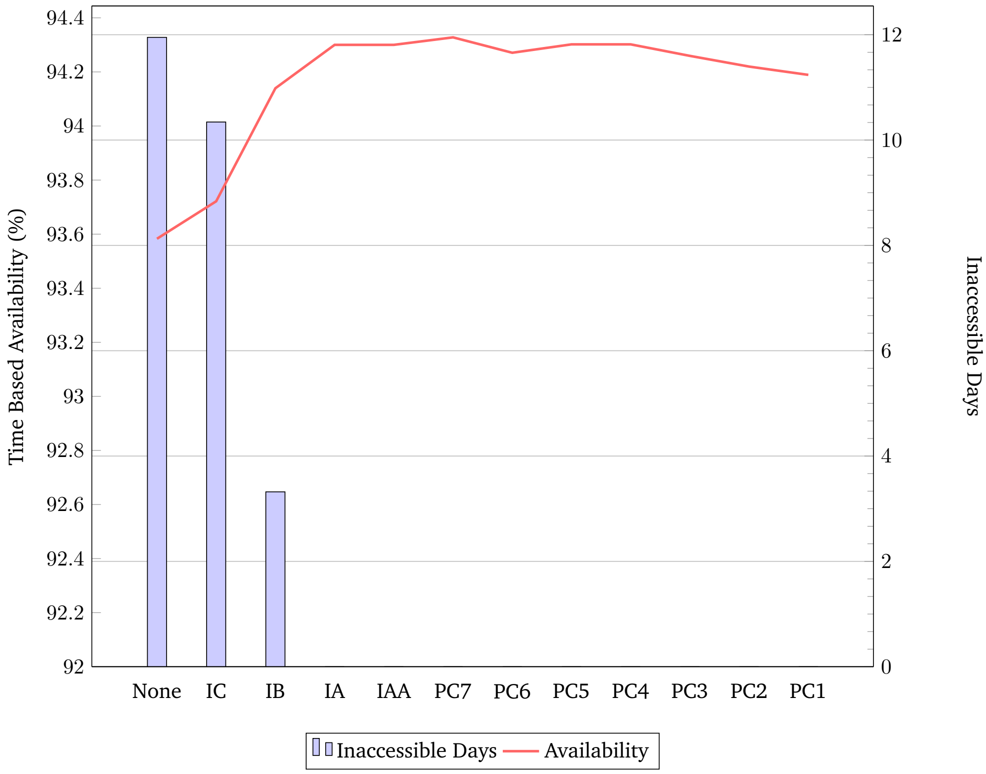

Figure 2.22: Inaccessibility days and the time based availability for the offshore wind farm in the Bohai Sea case study site for simulations utilising various classes of ice breaking vessels.

attributed to the levels of sea ice throughout the year being lower than the other two locations, therefore accessibility is less of an issue, decreasing the downtime of the turbines. Similar to Tahkoluoto, there is a plateau of availability once there are no inaccessible days due to ice. Inaccessibility days are limited to the simulations of no ice class, ice class IC and ice class IB, ranging from 11.95 days to 3.32 days.

2.3.4.3 Nova Scotia

For the Nova Scotia simulation, adjustments were made to the inputs of the simulation. The focus of this case study was to not only look at the availability and inaccessible days as seen previously but to also investigate potential operational costs associated with ice breaking vessels. Aker Arctic estimated that the construction cost for a PC6 ice breaking vessel will have an increase of 5-10% compared to normal vessels. That increase is applied as a rough estimate of the increase in daily charter rates for ice breaking SOVs. As a result, the Nova Scotia case study uses an SOV strategy as opposed to a CTV strategy. The availability results from the simulations

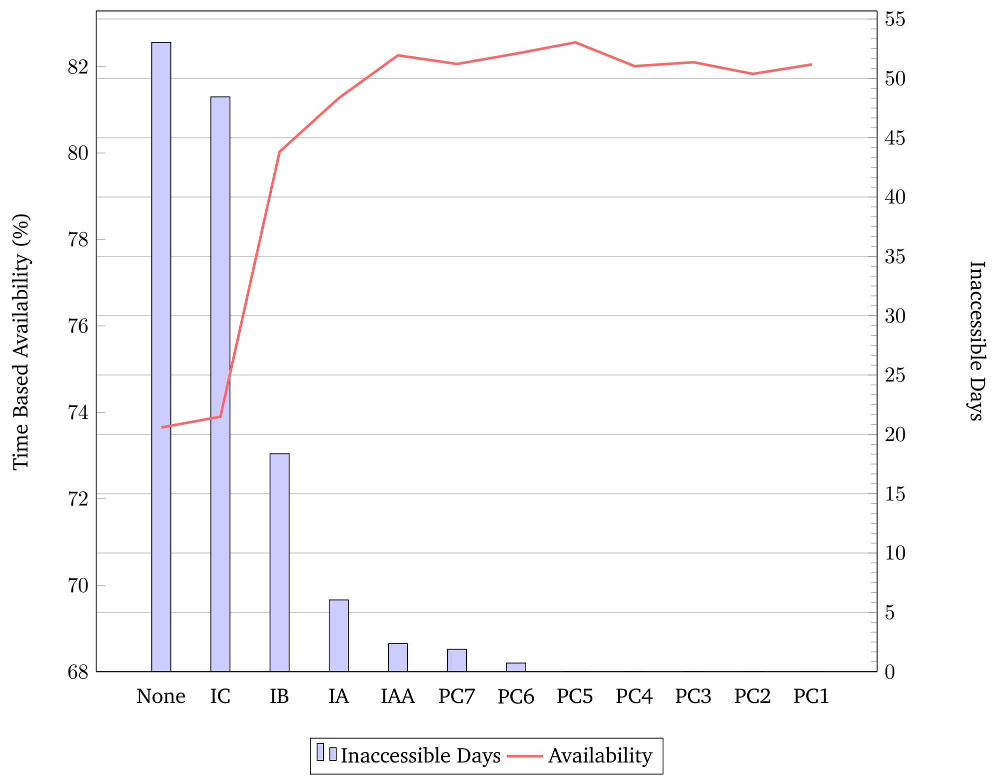

Figure 2.23: Inaccessibility days and the time based availability for the offshore wind farm in the Nova Scotia case study site for simulations utilising various classes of ice breaking vessels

for Nova Scotia can be seen in Figure 2.23. The graph is similar to Figures 2.21 and 2.22. Figure 2.24 outlines the total operational costs and the proportion of the costs that come from transport expenditures. Operational costs are highest for the simulations of no ice class and polar class IC, at around £93 /MWh. Costs then drop to £78 /MWh for class IB and slowly start to plateau for the remaining polar classes. In correspondence with the costs, the inaccessible days peak at 53 days when no ice class is used for the vessels, 48 days for class IC and then a significant drop to 18 days when the IB class is used. Availability for the wind farm ranges from 74% up to 83%, an increase of almost 10%. The large availability increase and larger amount of inaccessible days for the wind farm is due to the sea ice data for Nova Scotia spanning three months of the year with combined higher average thickness and concentration than the other two sites. Inaccessibility to the site increases potential downtime for turbines that have broken, not only decreasing the availability but also increasing lost revenue costs. The increase in lost revenue costs is apparent in Figure 2.24, where operational costs are higher for the ice classes that experience more inaccessible days. For the SOV strategy, the chartering period of the ice

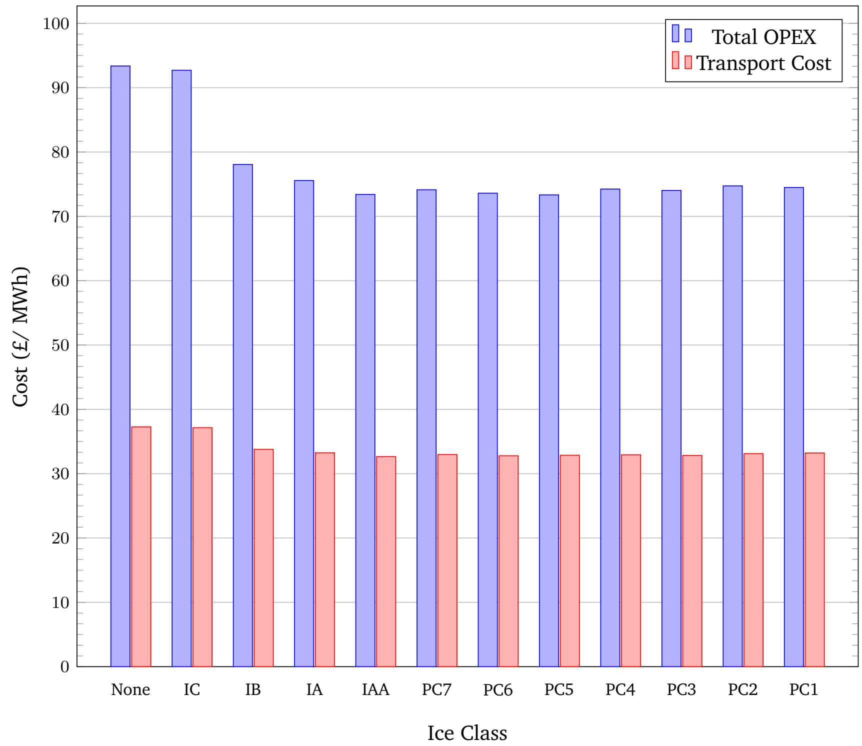

Figure 2.24: Total OPEX and transport costs for the offshore wind farm in the Nova Scotia case study site for simulations utilising various classes of ice breaking vessels

vessel can be selected. To understand the impact of seasonal chartering of specialist ice vessels, a sensitivity analysis is conducted where the months the ice breaking vessel is utilised is varied. The results are presented in Figure 2.25. The figure illustrates the OPEX savings associated with deploying an ice breaking SOV in comparison to the scenario where no ice vessels are used in Nova Scotia. This was done by varying charter durations starting in January. Each column represents a different end month for the ice breaking charter, for example, "Jan" indicates one month of ice class usage, followed by 11 months with a standard SOV; "Apr" reflects four months of ice class usage, then standard SOVs thereafter.

Over a 20-year period, the absolute cost of SOVs are lowest when no ice breaking vessel is used, due to the lower charter rate. However, the data shows that targeted deployment of ice breaking SOVs can yield significant total OPEX savings. Savings are minimal when the ice breaking vessel is used only through January or February, but increase substantially for charters extending through March and peak savings are seen in April. This aligns with ice conditions in Nova Scotia, where ice is typically present from January to April.

Beyond April, OPEX savings decline due to the higher cost of chartering ice class vessels

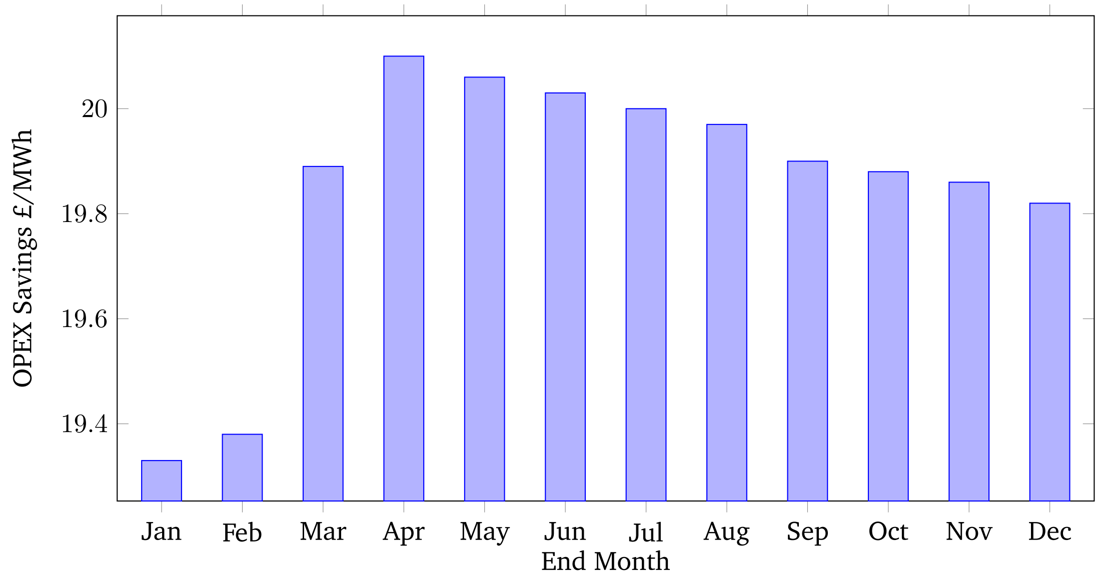

Figure 2.25: OPEX savings based on number of months an icebreaking SOV chartership is used before reverting to standard SOV chartership. All charter agreements start in January in this case. End month indicates that the chartership for the ice vessel finishes at the end date of that month.

during ice free months, providing no operational advantage. These results indicate that there is value in the seasonal chartering strategies, that can result in optimising OPEX for offshore wind farms in ice prone regions.

The simulations for each site have shown that the impact of sea ice is variable depending on the concentration, thickness and duration of the ice throughout the year. The choice of ice breaking vessel is pertinent to the key performance indicators of a wind farm with sea ice, as poor selection could be detrimental in two ways. On one hand, choosing a vessel with too low an ice breaking capability may result in reduced accessibility, increased operational costs and a reduction in time based availability, as the vessel is not capable of breaking through the ice. On the other hand, choosing a high ice breaking class may result in overspending if a lower ice class is capable of accessing the site at all times. In reality, wind farm developers need to treat each wind farm location as an individual case that requires investigation, rather than a one fits all approach for operations and maintenance linked with sea ice.

2.3.5 Summary of Analysis

The impact of sea ice is variable depending on offshore wind farm location. Sea ice can impact accessibility of maintenance vessels thereby having a subsequent impact on availability, power production, and operational costs of a wind farm. Currently in literature, this impact is unexplored, despite the growth of offshore wind projects in areas that experience sea ice during the year. This research adapts an operations and maintenance model to account for the effects of sea ice on maintenance activities for offshore wind. Alongside the traditional accessibility metrics, wave height and wind speed, a sea ice metric is included in the model based on the IMO's guidance for sea ice. Vessels with varying ice breaking capabilities are input into the model and simulated for three different site locations; Finland, China and Canada. Results showed that availability can be improved when using vessels with a higher ice breaking ability, with greatest improvement found for the Canadian site at 10% increase when compared to a vessel with no ice breaking capabilities. Operational costs for the Canadian site also were lowered when ice breaking vessels were utilised, due to the reduction in the lost revenue costs. It was found for all site locations that there is a point where increasing the ice breaking class of the vessel is no longer providing additional benefits and key performance indicators begin to plateau. The point this occurs is different for each location and is dependent on the sea ice thickness and concentration. To further expand this work, an investigation into the reliability of the turbines in cold climates would provide further insight into the operations and maintenance necessary for these offshore wind sites.

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Chapter 3

Determining Cost

This chapter evaluates the impact the future generation of offshore wind may have on the operational costs for an offshore wind farm. There is an uncertainty in the offshore wind industry surrounding future failure rates of the next generation of offshore wind turbines, so in this chapter, multiple scenarios are simulated, using known failure rates for smaller turbines, to address this uncertainty. More specifically, using operations and maintenance modelling, this chapter looks at how operational costs may differ, depending on turbine configuration, turbine size and the location of the site. In order to assess the impact on operational costs for future offshore wind turbines, the current trends in offshore wind energy must first be identified.

3.1 Review of Turbine Design, Siting and Size

3.1.1 New Design Concepts

One significant development that is already reshaping the offshore wind industry is the emergence of novel wind turbine designs. Traditionally, commercial offshore wind turbines have been bottom-fixed, horizontal-axis wind turbines (HAWTs) featuring a single rotor with three blades. This configuration has dominated the industry for decades due to its proven performance and maturity. However, there is a growing impetus to explore alternative configurations in order to enhance various aspects of turbine performance.

There is increasing consensus among industry stakeholders that the scalability of bottom-fixed turbines is approaching practical and economic limits. While a definitive upper boundary has not been formally established, the upscaling of these turbines introduces several challenges.

These include operational and maintenance (O&M) difficulties, limitations in manufacturing capacity, logistical constraints, and significant cost implications associated with transporting, installing, and servicing larger turbine components [1, 2].

To address these challenges, a range of novel turbine concepts are being developed, each aiming to improve different facets of turbine performance. These improvements may include enhanced system redundancy, alternative material choices, optimised aerodynamics, streamlined maintenance procedures, and increased turbine availability. Among these novel approaches, floating wind turbines represent the most commercially advanced alternative to bottom-fixed designs. The key advantage of floating systems lies in their mobility, specifically, their deployment in deeper waters, further from shore, where wind resource is often higher. However, in deeper water, metocean conditions tend to be harsher resulting in weather windows needing to be longer which can effect accessibility. Vessels such as JUVs are unsuitable in very deep waters so O&M strategies need to take these factors into consideration. The tow to port maintenance strategy has the potential to significantly reduce operational costs by minimising downtime, avoiding the logistical complexities of offshore maintenance, and enabling repairs in controlled, port-side environments. Despite these advantages, early demonstrations of tow-to-shore operations, namely Kincardine wind farm in Scotland, experienced longer than anticipated downtimes, due to the distance the turbine had to be towed to reach a suitable port, raising questions about the practical viability and efficiency of these systems in large-scale deployment if supply chains are not addressed sufficiently [3].

Other emerging concepts include Vertical Axis Wind Turbines (VAWTs) have demonstrated varying levels of success, but failed to reach large scale commericial viability. There are multirotor turbine designs that utilise multiple small rotors to improve redundancy by reducing global failure of the turbine and also avoid the large loadings seen with traditional rotors. There are also more experimental designs such as Counter-Rotating Wind Turbines (CAWTs), the X-Rotor design, and other Dual rotor wind turbine designs [4, 5, 6]. These latter designs are largely at the conceptual or early prototype stage and remain primarily within the academic and research domain. Nevertheless, they present opportunities to address specific shortcomings of conventional designs, particularly in the context of operations and maintenance. Many of these alternatives offer inherent design features that could improve ease of access, modularity, and overall availability [7, 8, 9].

Figure 3.1 illustrates the number of academic publications related to several of the aforementioned novel turbine design concepts over the past ten years. The data, sourced using the Web of Science search engine, may contain some inconsistencies due to keyword matching limitations. However, the overarching trend is evident: floating wind has emerged as the most prominent novel concept, with a trajectory that reflects increasing commercial interest and research activity. In contrast, other novel designs remain in their infancy, with limited industry uptake and a greater reliance on academic exploration.

The growing volume of literature surrounding floating wind also reflects the unresolved challenges in the industry as some of the first commericial floating offshore wind farms begin deployment. Although the concept of towing turbines to shore offers a promising route to reduce operational expenditure, practical implementation has thus far revealed significant complexities regarding port availability and extended weather windows.

Until these issues are resolved and alternative designs can demonstrate comparable reliability and cost-effectiveness, bottom-fixed HAWT turbines are likely to remain one of the dominant design choices in the offshore wind sector. This raises the question, *'What is the turbine size limit for bottom fixed wind turbines?'*

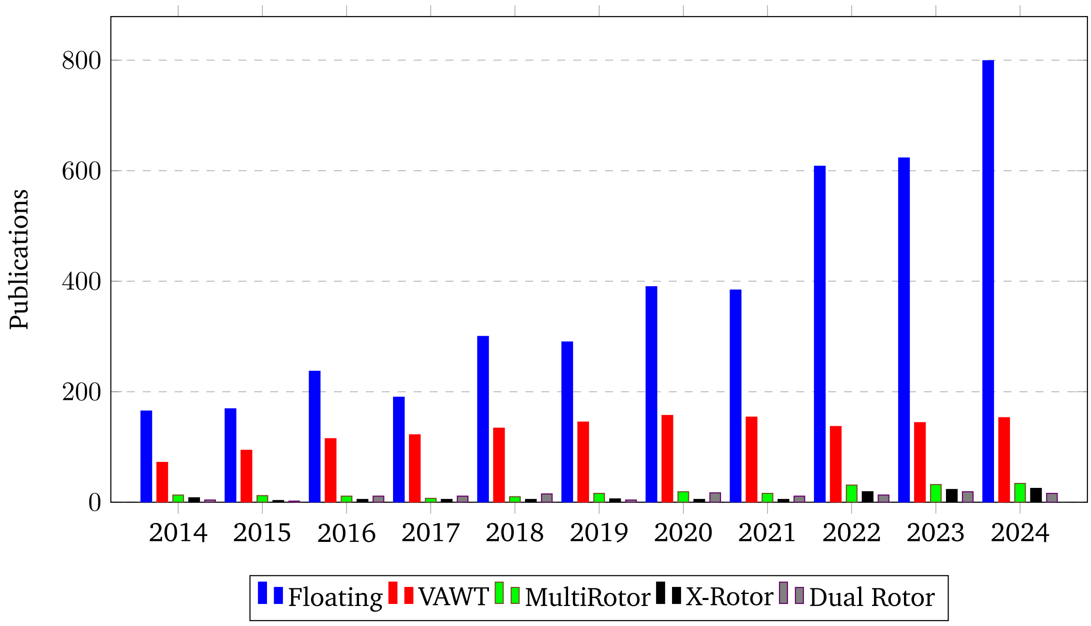

Figure 3.1: Number of research papers published regarding novel wind turbine concepts over the last decade (Based on Web of Science search engine [10] analysis completed by the author)

3.1.2 Turbine Size

The first offshore wind farm started operation in 1991 and had wind turbines with a power rating of 450 kW each [11]. Since then, the power rating and size of turbines has grown, with the industry in a constant competition to develop the next biggest turbine. Swiftly after it was announced that planning was in place to deploy a 15 MW turbine, the developer Minyang announced the production of a 22 MW turbine with a rotor diameter of 310 metres within the next decade [12, 13]. There are indicators that this turbine size will become an industry standard, as turbine manufacturers continue to upscale their testing and manufacturing facilities. Figure 3.2 is a schematic diagram to outline the change of turbine size as the power rating of the turbine increases from 3 MW to 20 MW. The benefit of upscaling the power rating of the wind turbines is the increase in the annual energy yield. The 15 MW turbine is predicted to increase the annual energy production by 45% compared to the previous 11 MW model [12]. In 2016, Wiser at al.[14] carried out an expert elicitation survey regarding the future costs of offshore wind, considering the increase in turbine size. The survey was completed by 163 wind experts and results estimated a 9% reduction in operational expenditures (OPEX) for an 11 MW turbine fixed bottom case. The drawbacks, as mentioned by the study, is that expert elicitation can only predict the future based on opinions but the reality may differ from these results.

Due to lack of experience with larger turbines, the problem facing the industry is the unknown and as a result, research is focused on predicting the cost associated with wind farms at this scale. There are studies that indicate that bigger is not necessarily better, in terms of continued LCOE reduction and increased energy yield. A study by DNV found that, for different wind turbine configurations, the LCOE differs only slightly between 12 MW-20 MW turbines [15]. It was found that turbines with lower capacity (12-15 MW) and high specific power density (400-450W/m^2) are the most cost-effective. DNV predicts that the new generation of offshore wind turbines will retain a turbine rating between 20-24 MW and not continue to grow in size but instead the optimisation of offshore wind will focus on maintenance and other technological advanacements to the current designs with a standardisation achieved. Furthermore, a study by Barter et al.[16] comes to a similar conclusion in their work, which looks at different generator technologies for 15 MW to 25 MW turbines. Although this study holds the O&M costs at a constant, the study does indicate a plateau in the LCOE with increased turbine ratings. This could be driven by the fact LCOE also takes into account materials cost, current markets and location specifics not just the power rating of the turbine. Another study that models multiple turbine designs found a marginal change in LCOE when upscaling the turbines, concluding that upscaling may not always be beneficial and should be weighed against the possible logistical challenges that larger turbines have [17].

Developers are competitively increasing the power rating and size for the next generation of wind turbines but the question of how operations and maintenance will change needs to be raised. With larger components, there may be issues with increased usage of larger vessels that are more costly and have limited availability, a possible increase in technicians required, longer repair times and, importantly, larger costs incurred from downtime. Furthermore, the blades of these turbines will be much larger and therefore the loads imposed on the turbine structure will be substantial, that could lead to increased failures and required maintenance [18]. Hofmann and Sperstad [19] ask the question 'Will 10 MW Wind Turbines Bring Down the Operation and Maintenance Cost of Offshore Wind Farms?' and using a O&M modelling tool simulate scenarios for two 5 MW turbines versus one 10 MW turbine. They conclude that the answer to this question will be entirely dependent on the failure rates of these larger turbines and the maintenance duration for tasks. The study does not provide specific inputs for the component failure rates but does vary the 10 MW inputs through sensitivity analysis while holding a 5 MW turbine baseline scenario. The study also only looks at one location and turbine type.

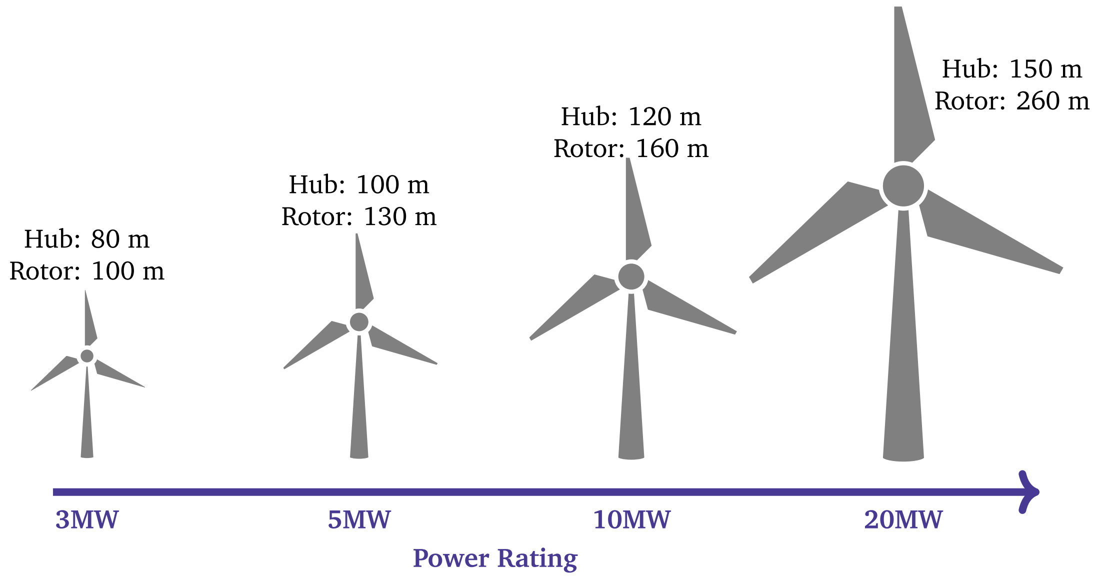

Figure 3.2: Progression of turbine rating and size of bottom fixed offshore wind turbines

3.1.3 Turbine Configurations

There are various types of drivetrain configurations currently in operation for offshore wind turbines, with key differences in the use of gearboxes, generators, and power converters. Historically, many turbines adopted a three-stage gearbox paired with a doubly fed induction generator (DFIG) and a partially rated power converter. Although this configuration was popular with developers due to its maturity and cost-effectiveness, the industry is increasingly moving away from DFIG systems. This shift is largely driven by the higher efficiency of permanent magnet generators (PMGs), which are becoming the preferred choice, provided the cost of magnets remains stable [20].

The gearbox, a critical nacelle component, converts the turbine's high-torque, low-speed rotation into low-torque, high-speed input suitable for the generator. However, offshore environments are subject to harsher and more variable conditions than onshore sites, including large waves and high speed turbulent winds. These factors contribute to increased mechanical stress on the gearbox. Studies have shown that gearboxes suffer from relatively low reliability, with faults often resulting in significant downtime [21, 22, 23]. Offshore turbine downtime is more costly than onshore due to restricted site accessibility, as repairs frequently require specialised vessels and favourable weather conditions [24]. Moreover, the gearbox is one of the most expensive components to replace, often necessitating a HLV for major replacements [25].

To address these reliability issues, direct-drive configurations have gained popularity in offshore applications. These systems eliminate the gearbox entirely by directly connecting the rotor to the generator, thereby removing a major point of mechanical failure [26]. However, this configuration requires larger, heavier, and more expensive generators capable of handling high torque loads. PMGs, which can be deployed with or without a gearbox, are commonly paired with fully rated converters. Over the past decade, direct-drive and medium-speed PMG configurations have emerged as the dominant drivetrain solutions in offshore wind [27].

While other drivetrain configurations continue to be explored and developed, most remain at an early stage and have not yet been deployed commercially at scale. Therefore, these alternative designs are not considered within the scope of this study [24].

Carroll et al. [25] conducted a comparative study of offshore wind turbines using different drivetrain configurations, focusing on O&M costs. The configurations studied were among the most widely used offshore turbine types at the time and included:

1. A three-stage gearbox with a doubly-fed induction generator (DFIG) and a partially-rated converter.

2. A three-stage gearbox with a permanent magnet synchronous generator (PMSG) and a fully-rated converter.

3. A two-stage (medium-speed) gearbox with a PMSG and a fully-rated converter.

4. A direct-drive turbine with a PMSG and a fully-rated converter.

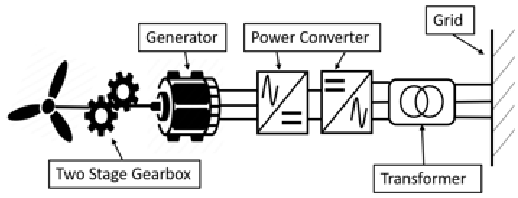

Figure 3.3: Drivetrain configurations for two offshore turbines. The left configuration shows a two-stage permanent magnet generator with a fully rated converter. The right configuration is the direct drive turbine with a permanent magnet generator and fully rated converter.

The results indicated that the direct-drive configuration had the highest availability and lowest O&M costs, followed by the medium-speed configuration, the three-stage PMSG, and finally the DFIG setup. The analysis found that lower O&M costs significantly contributed to a reduced LCOE for direct-drive and medium-speed turbines [28]. This trend is reflected in broader industry developments, with a shift away from high-speed drivetrains towards medium-speed and low-speed machines. Figure 3.3 shows the two drivetrain configurations from [28] that will be the focus of this study, as they are the current industry focus for future turbines.

Figure 3.4, based on the Global Wind Energy Council (GWEC)'s 2022 report [29], shows the evolution of drivetrain market share from 2016 to 2021 in both Europe and China. Europe has moved from an approximately equal share between squirrel cage induction generators (SCIG) and direct-drive PMGs to a near equal split between medium-speed and direct-drive PMGs. In China, while low- and medium-speed systems have gained ground, about a third of the market continues to use high-speed configurations. These trends suggest that the industry's focus is no longer on the merits of high-speed, medium-speed, and low-speed systems broadly, but rather on determining which of the two remaining contenders, medium-speed or direct-drive, will become dominant.

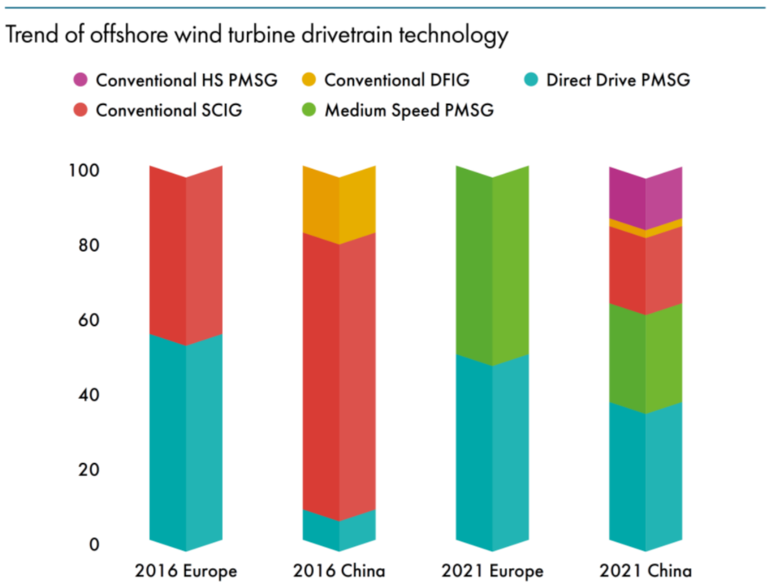

Figure 3.4: Offshore wind market share in Europe and China according to the GWEC's Global Offshore Wind Report 2022 [29].

Vandekaa et al. [30], developed a methodology to evaluate which configuration has the greatest potential for success. The study concluded that, as of 2020, both medium-speed and direct-drive systems remain viable contenders. The key criteria influencing future success include energy cost and system reliability, with other relevant factors such as brand reputation, total energy yield, pricing strategy, access to critical resources, supply chain capabilities, and long-term manufacturer commitment.

The ongoing shift towards direct-drive technology coincides with a move to higher turbine power ratings, as previously discussed in Section 3.1.2. This raises a key question regarding whether operational data from older turbine designs can reliably inform expectations for newer, larger machines. This issue is explored by [31], who conducted a meta-analysis of legacy data applied to modern direct-drive systems. They found that, even for components assumed to be comparable across different turbine designs, there were significant differences in stop rates and downtime durations.

Jenkins et al. [32] provide estimated availability and O&M costs for next-generation (15 MW) turbines using the drivetrain configurations illustrated in Figure 3.3. Their analysis, based on structured expert elicitation detailed in [33], suggests that medium-speed turbines may result in lower costs for major component replacements compared to direct-drive systems. This finding contrasts with Carroll et al. [25], and is attributed to the lower component costs of the medium-speed generator and gearbox in comparison to the more expensive direct-drive generator.

3.1.4 Location

Over the past decade, the offshore wind energy sector has experienced remarkable growth, both in terms of installed capacity and the number of operational wind farms. As already mentioned, this expansion reflects a global shift towards renewable energy sources as part of broader efforts to address climate change and transition away from fossil fuels.

Figure 3.5 illustrates the global distribution of operational offshore wind farms as of 2015, using data sourced from Carbon Brief. At that time, a substantial concentration of offshore wind activity was evident in Northern Europe, particularly among countries bordering the North Sea. This region emerged as a focal point for offshore wind development due to a combination of favourable conditions, including consistent wind patterns, relatively shallow waters conducive to fixed-bottom turbine installations, strong political and financial support for renewable energy, and the presence of a well-established offshore oil and gas industry that provided transferable expertise and infrastructure. Beyond these geographical advantages, a series of strategic policy incentives and collaborative efforts, particularly spearheaded by the European Union (EU), have been instrumental in transforming the North Sea into a hub for offshore wind energy. While offshore wind activity was largely centred in Europe during this period, the map also indicates limited development in other regions, such as China, where a small number of projects had begun to emerge, albeit on a significantly smaller scale. By 2025, the landscape of offshore wind energy has transformed considerably, as depicted in Figure 3.6. The data, derived from the Global Wind Power Tracker, captures the current state of offshore wind development, encompassing both fixed-bottom and floating turbine technologies. In this updated map, green markers denote operational wind farms, while red, orange, and yellow markers represent announced, pre-construction, and under-construction projects, respectively. Northern Europe continues to serve as a global hub for offshore wind, maintaining its leadership position through the expansion of existing farms and the announcement of new projects. However, there is also a noticeable diversification in geographical engagement. Offshore wind initiatives have spread across other parts of Europe, including the Atlantic and Mediterranean coasts, indicat-

Figure 3.5: 2015 offshore wind operational farms worldwide according to data taken from Carbon Brief [34].

ing a broader continental investment in offshore wind. Many of these projects are driven by the development of floating offshore wind due to deeper waters surrounding these areas. One of the most striking developments is the rapid acceleration of offshore wind projects in China. From its smaller developments in 2015, China has emerged as one of the global leaders in the offshore wind sector, driven by ambitious national energy goals and significant public and private investment. Furthermore, the map reveals a significant interest from other regions of the world that had little or no offshore wind presence a decade earlier. In particular, North America, South America, Northeast Asia, Southeast Asia, and Australia have all announced potential offshore wind projects in recent years. Although not all proposed developments will necessarily reach operational status, the sheer volume of announced and pre-construction projects demonstrates a clear and growing international commitment to offshore wind as a viable and scalable solution for future energy needs.

3.1.4.1 Drivers and Challenges

In the early 2000s, EU member states began promoting renewable energy through national policies. Denmark and Germany introduced feed-in tariffs to reduce investment risk, while the UK used mechanisms like the Renewables Obligation and Contracts for Difference to drive off-

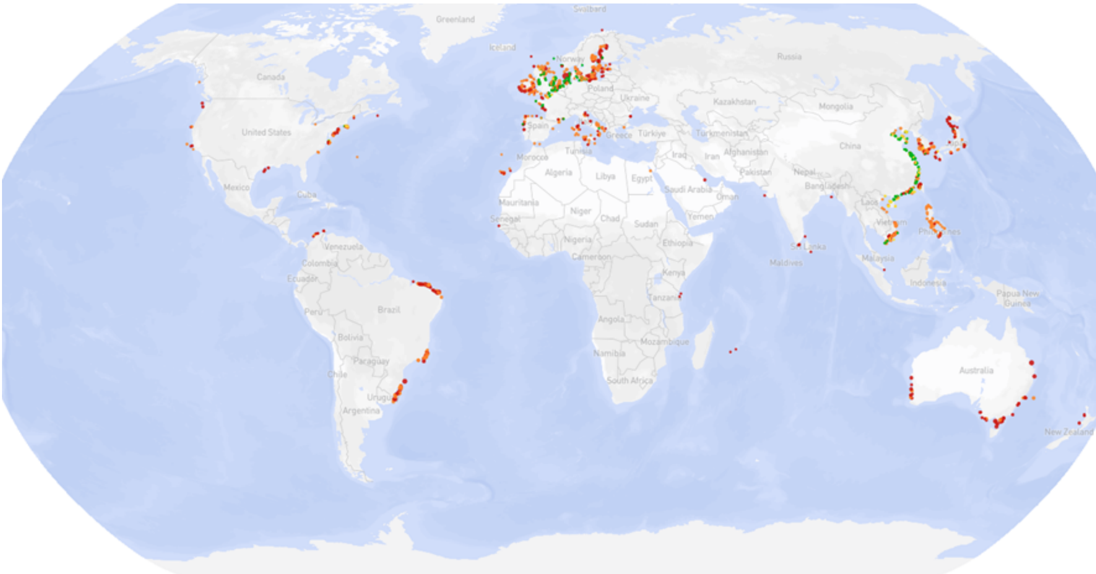

Figure 3.6: 2025 offshore wind farms including operational, announced, construction and pre-construction stages according to Global Wind Power Tracker, Global Energy Monitor, February 2025 release [35].

shore wind development [36, 37]. Recognising the need for coordination, the EU set binding renewable targets with the 2009 Renewable Energy Directive, requiring national action plans and investments in technologies like offshore wind. To strengthen regional cooperation, the North Seas Countries' Offshore Grid Initiative (2010) and later the North Seas Energy Cooperation (2016) aimed to integrate offshore grids, standardise regulations, and support cross-border energy trade [38]. The EU has provided critical funding through programs like the Connecting Europe Facility and advanced research via Horizon 2020 and Horizon Europe, boosting innovation in turbine technology and infrastructure. Overall, a mix of national incentives and EU-driven collaboration has positioned the North Sea as a global leader in offshore wind energy. However, to continue the growth in these established areas, there are a number of roadblocks that still need to be rectified or addressed.

One emerging challenge is the correlation of wind power output due to the geographic clustering of future wind farm sites in the North Sea. When multiple wind farms are located too closely, they experience similar weather patterns, resulting in low variability in power generation. This can lead to grid congestion, price volatility, and a lack of diversification in energy supply. To mitigate these risks, it is crucial that North Sea bordering countries coordinate site selection collaboratively, rather than planning projects in isolation [39]. Grid connections remain a major bottleneck across much of Europe. As more wind farms come online, grid infrastructure has not kept pace, leading to increased curtailment, where excess wind energy is wasted because it can't be transmitted or used. This limits the full potential of wind power. To address this, efforts are underway to develop alternative energy storage solutions that can capture surplus wind energy and release it when demand is higher. Interconnectors between countries also offer a critical solution, enabling the transfer of excess electricity across borders to areas where it's needed, helping to balance supply and demand more effectively and reduce curtailment.

Although there are many challenges regarding the future operations for areas with an established offshore wind industry, the North Sea benefits from lessons learned and can rely on the experience of offshore wind developers to address issues and overcome hurdles for development. The same cannot be said for countries that are dipping their toes into offshore wind for the first time.

Barriers and challenges for offshore wind can be broken down into technical, economic, political and social. For offshore wind to be successful in new global locations, these challenges must be considered. A case study for floating offshore wind in South Africa discusses how the geography for floating offshore wind, in terms of wind resource and water depth, and the country's need for better electricity supply are two main drivers of offshore wind projects. Furthermore, the case study indicates that, in terms of infrastructure, there are suitable port facilities for installation and grid connections. However, there a several barriers such as lack of skilled workforce, supply chain and social acceptance that will hinder the development of offshore wind in the country [40].

Many countries face challenges surrounding regulatory framework that is not specfic to offshore wind structures or lacks clear guidelines for extreme events. Australia, for example, faces a lack of standard practices for offshore wind, where it may not be suitable to adapt frameworks from other countries in Europe or the USA. The country faces tropical cyclones and other extreme met ocean conditions, so instead needs a unique set of practices that fit to the country [41].

COP27 was the catalyst for nine new countries signing up to the Global Offshore Wind Alliance (GOWA), pledging to escalate and support plans for offshore wind [42]. Many of the countries in the GOWA, such as the UK, already have large commercial offshore wind farms but others, such as the USA, do not. The growth in the size of turbines has been a natural progression for European developers, starting with smaller rated turbines and as experience in the field has developed, the technology has advanced to a much larger scale. With the USA developing their offshore wind sector later, they have the opportunity of entering at the larger turbine stage, avoiding the smaller rated turbines, if it is profitable to do so.

A comparative review in 2019 looked at the development of offshore wind in Europe, China and the USA and the different challenges faced by each [43]. It states that the USA has a well developed onshore wind sector yet has struggled to mirror this progress in the offshore sector despite having high potential in terms of the wind resource. Economic incentives have fallen short of the mark also. There is currently no mandatory legislation regarding purchase agreements with grid operators as of 2023. A recent assessment completed in 2023, describes the current projections outlined by the Biden administration to install 30 GW of offshore wind by 2030 and the reality of trying to achieve that [44]. The paper highlights issues with licensing and states that it currently takes 5 years to go through the process of putting a bid in for a project and receiving approval. Site locations on the Atlantic coast tend to be near major cities but this has lead to issues regarding public support, leading to lengthy project times. Political uncertainty with the Trump administration has left offshore wind in a difficult position with many investors unsure if investing in new projects is worth the risk. Regardless of challenges facing the US, there is still a strong push for offshore wind to become more integral in the US energy make up. Figure 3.7 shows a map of offshore projects in the USA as of 2023. The planned sites in blue, are the vast majority of projects on this diagram with only five projects either being approved, under construction or operational. The black circle indicates Martha's Vineyard Coastal Observatory, the location for the climate data utilised in this thesis for US case studies.

Each offshore wind farm site has vastly different climate characteristics, with associated advantages and disadvantages. Consequently, location is a variable that will substantially impact the operations and maintenance of a wind farm and ultimately, the overall cost. Factors to consider when evaluating a location include wind resource, sea conditions, distance from shore, grid connection, seabed foundations and many more. One way to address the introduction of multiple locations with different geographical characteristics is by creating turbines that are site specific. There are multiple papers that delve into this concept using different

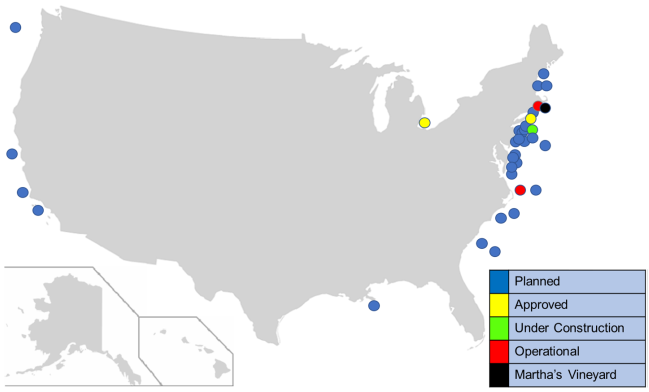

Figure 3.7: Map of offshore wind farms in the USA ranging from planning stages to fully operational. Black circle indicates Martha's Vineyard Coastal Observatory, the location that the climate data for the US site is sourced. Data sourced from [45], up to date as of 2023.

optimisation methods [46, 47]. Tailored turbine designs could improve maintenance efficiency and reduce operational costs by minimising downtime. However, due to higher upfront costs and lack of standardisation, site-specific designs are not yet industry standard, meaning current O&M strategies must adapt to a diverse range of conditions using the tools and methods already available.

3.1.5 Research Question

There has been limited investigation into the operations and maintenance costs in the USA for large offshore wind turbines and the performance of different drive train configurations in this climate. Research from Shields et al. investigates the impact of LCOE from upsizing turbines and plant size using a site location along the East Coast of the USA [48] . The paper succeeds in determining the benefit of using larger turbines and larger wind farms at the chosen site but does not go into depth regarding specific turbine configurations and how this affects the operations and maintenance costs. It highlights one of the key assumptions in the paper is to hold failure rates constant regardless of the size of the turbine. In this analysis, the failure rates will be adjusted for a 10 MW turbine to determine the rates at which a 10 MW will have the same O&M costs as a 3 MW turbine, this allows us to determine what level of reliability a 10 MW turbine needs to obtain to have equal or lower O&M costs compared to early offshore wind turbines of 3 MW. As mentioned before, each site will offer different climate characteristics but this investigation will give a comparative analysis of the two locations which contributes to the originality of this work.

This chapter utilises O&M modelling to conduct an analysis that aims to determine the implications of upscaling offshore wind turbines on the OPEX of the wind farm. While it is widely accepted within the wind energy industry that capital expenditure (CAPEX) per megawatt-hour (MWh) decreases with increasing turbine size, it remains unclear whether the same trend holds true for OPEX. This study addresses that gap by evaluating whether OPEX per MWh decreases as turbines become larger, under the assumption that the reliability of these larger machines is maintained or improved relative to current 3 MW turbines. Furthermore, the research investigates the level of reliability required for next-generation offshore wind turbines to achieve cost parity or savings in O&M compared to existing designs. Additional analyses assess how site location, turbine and drivetrain type, influence the O&M costs of future offshore wind farms. Collectively, these investigations provide a comprehensive evaluation of the key factors influencing the economic viability of next-generation offshore wind technologies. The research question for this chapter is the following:
"Can the OPEX of future generation offshore wind turbines be reduced through turbine upscaling, and what component reliability and site-specific conditions are required to achieve this?"

3.2 Methodology

In this analysis, based on the literature completed, two different locations have been chosen. The first site is in the North Sea off the coast of Germany, where there are multiple operational offshore wind farms, which can be found on TGS 4c offshore wind maps [49]. As mentioned in the previous section, this is an established area for offshore wind and there are projects underway that will utilise larger rated wind turbines. The second site is on the North East Atlantic Coast of the USA, a location where there are many projects in the early planning stages but the area is not yet established in offshore wind and therefore there are many unknowns about the performance of larger turbines in these waters. The overall aim is to assess the suitability of larger rated turbines in both locations and compare O&M costs between turbine sites, types and sizes. Section 3.2.1 discusses the turbine reliability and the justifcation of the wind turbine related inputs in the model. Section 3.2.2 outlines the climate data of both sites selected and the impact that may have on the results.

3.2.1 The Turbine

One important focus in this analysis is turbine reliability. More specifically the number of turbine failures per unit time, known as the failure rate. The classification of failure differs from paper to paper but the grouping used in this research will be failures that require minor repair, major repair and major replacement. Minor and major repairs can be carried out using crew transfer vessels (CTVs), with the minor being less expensive than a major repair. A major replacement refers to a replacement of a component that involves a heavy lift vessel (HLV) to carry out the operation. Major replacements are the most costly out of the three classifications. Note that, these classifications do not use the same cost thresholds as they were originally defined by ReliaWind in 2007 (stated in [50]). Turbines were much smaller in size and components were less expensive so classifications in terms of cost will have increased over time. The failure rates used in this research come from the paper by Carroll et al. [50] which uses this definition in their work. These are in the format of failure rates per turbine per year using the formula:

$$\lambda = \frac{\sum_{i=1}^{I} \sum_{j=1}^{J} \frac{n_{i,j}}{N_i}}{\sum_{i=1}^{I} \frac{T_i}{8760}} \tag{3.1}$$

where λ is the failure rate per turbine per year, T is the total period in hours, N is the number of turbines, n is the number of failures and i represents the intervals for data collection and j represents the sub-assemblies. Carroll et al. [50] found an average failure rate, λ, of 8.3 failures per turbine per year. One of the uncertainties regarding 10 MW turbines are their failure rates. Previous work by Jenkins et al. [51] uses structured expert elicitation methods to determine major replacement rates for 15 MW turbines. Results showed that 15 MW medium speed turbines would be subject to a larger number of major replacements than direct drive. The study was limited to major replacements for 15 MW turbines and does not discuss the major repairs and minor repairs. Chapter 3 aims to collate new failure rates from updated literature and estimate large turbine failure rates but that is not the focus of this chapter.

The aim here is not to predict what these failure rates will be but rather to input known failure rates from smaller rated turbines to see how this impacts the O&M costs. Then after looking at the baseline failure rates, adjust the baseline failure rates through sensitivity analysis to see at what failure rates do a 10 MW turbine and a 3 MW turbine have the same O&M costs in a cost unit per MWh format. It should be noted that the failure rates of the 3 MW turbines are not representative of larger 10 MW turbines. To perform the sensitivity analysis all variables in the simulation are kept the same, apart from the failure rates. The failure rates are increased by 10%, 20% ... up until 100% of their original value and input into the model for individual simulations. Similarly the failure rates were decreased by 10%, 20% ... until a 90% decrease from their original value. Table 3.1 outlines the failure rates taken from Carroll et al. [50] which will be used for both the direct drive and medium speed turbines and the vessel type that is required to complete the maintenance. Note that for the gearbox failure rates the direct drive is set as blank as this component is not present in the configuration. Furthermore, the main bearing failures are encompassed in the rest of turbine failure rates.

Table 3.1: Outlining the baseline failure rates per turbine per year for the wind turbine components of a 3 MW medium speed turbine and 3 MW direct drive turbine [50].

Component	Repair Type	MS	DD	Vessel
	Minor Repair	0.473	0.546	CTV
Generator	Major Repair	0.026	0.030	CTV
	Major Replacement	0.008	0.009	JUV
	Minor Repair	0.538	0.538	CTV
Converter	Major Repair	0.338	0.338	CTV
	Major Replacement	0.077	0.077	SOV
	Minor Repair	0.305	-	CTV
Gearbox	Major Repair	0.030	-	SOV
	Major Replacement	0.042	-	JUV
	Minor Repair	5.76	5.76	CTV
Rest of Turbine	Major Repair	0.686	0.686	CTV
	Major Replacement	0.001	0.001	SOV

The 10 MW turbine represents the ‘next generation’ of offshore wind turbines as, at the time of writing, the average rated power of current operational wind farms is below 10MW, aside from Dogger Bank which has recently deployed 13 MW turbines and Moray West which deployed 15 MW turbines earlier in 2025. Furthermore, Seagreen in Scotland deployed the first 10MW offshore wind turbine in 2021. As mentioned previously, the 3 MW turbine in this study is based on the work by Carroll et al. [25] and will be the baseline for the failure rates.

The outputs from the model for O&M costs are in £/MWh, therefore the power production is required. For the model, information was required regarding the 3 MW turbines and 10 MW turbines for both the direct drive configuration and the medium speed configuration. The 10 MW NREL reference turbine’s power curves were used, one for direct drive and the other for medium speed, as well as turbine characteristics such as hub height, cut in, cut out and rated speeds [52]. The 3 MW turbine inputs come from the work from Carroll et al. [25]. The other turbine specific input was the failure rates for the turbine depending on configuration, which can be seen listed in Table 3.1.

To estimate the repair costs for the 10 MW turbines, a report by BVG and the Crown Estate was used [53]. The report provided values for major replacement costs for turbine components. Any major or minor repair costs for the 10 MW were taken from the 3 MW case and scaled proportionally. Scaling was done by using the ratio of major replacement to major repair and minor repair costs for the 3MW components, then costs were scaled using these ratios to estimate the 10MW turbine major repair and minor repair [50]. The cost inputs for the wind turbine components, based on the repair required, are listed in Table 3.2.

Table 3.2: Outlining the cost inputs in £ for the wind turbine components of a 3 MW direct drive turbine, 3 MW medium speed turbine, 10 MW direct drive turbine, 10 MW medium speed turbine.

Component	Repair Type	3 MW DD(£)	3 MW MS(£)	10 MW DD (£)	10 MW MS(£)
Generator	Minor Repair	875	398	5,253	2,627
	Major Repair	19,573	8,897	117,497	58,749
	Major Replacement	333,174	151,443	2,000,000	1,000,000
Converter	Minor Repair	237	237	788	788
	Major Repair	5,280	5,280	17,600	17,600
	Major Replacement	12,742	12,742	42,473	42,473
Gearbox	Minor Repair	-	97	-	384
	Major Repair	-	2,007	-	7,957
	Major Replacement	-	176,588	-	700,000
RoT	Minor Repair	181	181	602	602
	Major Repair	2,234	2,234	7,445	7,445
	Major Replacement	33,427	33,427	111,422	111,422

Repair time and number of technicians required for repair are held the same for 10 MW as 3 MW, which can be found in [50]. These have been held constant based on the assumption held by experienced members of the offshore wind industry that due to lessons learnt and the modern processes in optimising maintenance through innovation, that holding this constant is a conservative approach. Electricity price has been held constant across all scenarios in this study. While in reality there are multiple electricty markets within the North Sea as well as a different market in the US, that are likely to have different pricing for electricity, the focus here is to obtain a relative difference between scenarios to allow comparisons to be made.

3.2.2 The Site

These are inputs regarding the wind farm that are held fixed across the four different scenarios. Table 3.3 outlines the important variables that were held constant throughout the models. Wind farm lifetime was chosen as 20 years, however it has been indicated in some literature that due to advances in lifetime extension methods this may be extended to 25-30 years. For the purpose of this research, it was only important to keep the value consistent throughout the scenarios, not the value itself and 20 years is in agreement with some early lifetime predictions [54]. As with previous studies in the thesis, each scenario is simulated 100 times to allow convergence in the results. The distance from shore was selected based on the location the climate data was observed for the North Sea and also aligns with the predicted trend that 'next generation' of turbines will be further from shore [55]. The number of turbines is a value in keeping with patterns in industry and for comparison the number of turbines should be kept constant for both turbine sizes, similar to [51].

Table 3.3: Inputs to model which were held constant regardless of location, drive train or turbine size.

Model Input	Value Chosen
Number of Simulations	100
Wind farm lifetime (yrs)	20
Number of turbines	100
Distance from shore (km)	45

As previously mentioned, the two climate data sets come from the North Sea and the East Coast of the USA. The North Sea data set is a 6 year span of FINO data located 45km off the coast of Germany, it includes a complete set of hourly measurements of wind speed, wave period and significant wave height [56]. The wind speed is required for two reasons, firstly to calculate the power production of the wind turbine and secondly the wind at the sea surface to determine accessibility for different vessels. The significant wave height and wave period are also used for accessibility indicators, in particular, significant wave height limits are widely used as the main criterion to authorise maintenance vessels to travel to the wind farm. The data for the East Coast of the US is in the same format but only contains 15 months of recorded data, which was sourced from the Martha's Vineyard Coastal Observatory located in Edgartown, Massachusetts [57]. The model will take these climate inputs and generate a simulated time series of weather over the span of the wind farm lifetime based on the data set provided.

Taking each variable separately, the wind speed, wave period and wave height for both sites can be compared. The mean and standard deviation for the wind speed, wave height and significant wave height are shown in Table 3.4.

Table 3.4: The averages for the three climate variables taken from the North Sea data and US data

Climate Variables	North Sea $\bar{x}$	North Sea σ	US $\bar{x}$	US σ
Wind Speed (m/s)	7.77	3.52	7.81	3.94
Wave Period (s)	5.62	1.33	6.06	1.54
SWH (m)	1.08	0.63	1.13	0.58

The data indicates that the climate characteristics in the US are more variable than in the North Sea. Looking at the wind speeds, the USA experiences higher peaks and lower troughs than the North Sea and this is confirmed by the higher value for the standard deviation of wind speed also. A similar trend can be seen for both the wave period and significant wave height. The standard deviation for the data indicates that the wind speed and wave period vary from the average more than the North Sea, however, the standard deviation is lower for the significant wave height for the US. The length of data being shorter for the USA may lead to limitations as the selection range may include a particularly harsh weather year that does not necessarily align with the locations characteristics over a twenty year period.

Furthermore, Table 3.4 shows the averages over the 20 year life time but accessibility and crew transfer decisions are on a much smaller timescale. The decision to dispatch maintenance is on an hourly basis and requires consecutive hours where the vessel limitations are not breached, known as weather windows. Therefore, average values often do not capture the overall picture when it comes to accessibility. According to the mean and standard deviation it may appear that the US site is more inaccessible, however, the accessibility is actually higher for the US site due to the consecutive weather windows provided to allow maintenance to occur. The North Sea, despite having lower average wind speeds and wave heights, has more frequent, consistent wind speeds and wave heights that breach the limitations assigned to the vessels. Taking the percentage of significant wave height measurements that are 1.5 m or above, the

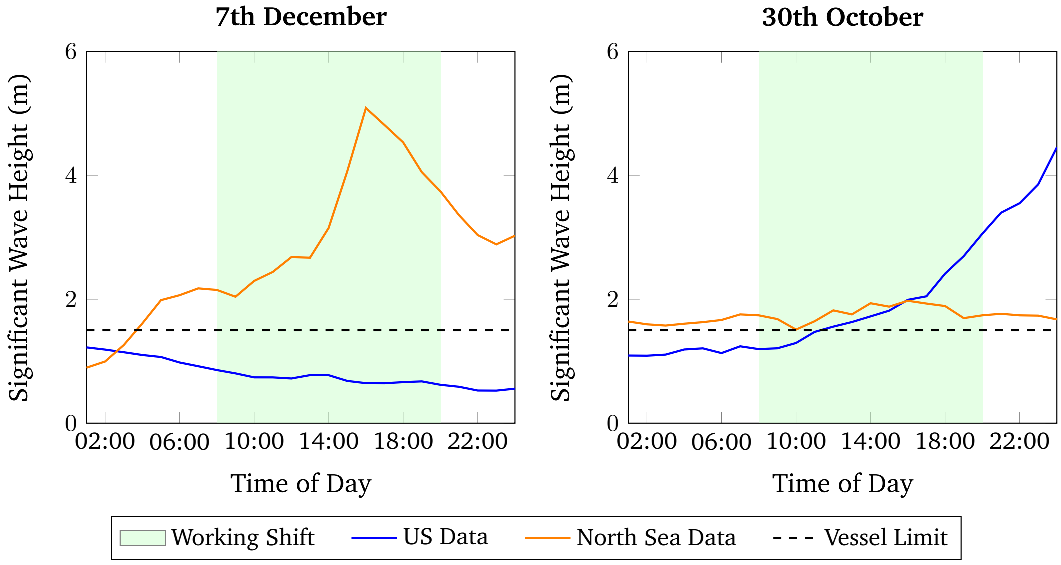

Figure 3.8: Weather window examples for the North Sea and US sites. The left plot shows the significant wave height on the 7th December, where the highest wave height for the North Sea is experienced. The right plot shows the significant wave height on the 30th October, where the highest wave height for the US site is experienced. The green shaded area is to highlight the working shift when crew transfers occur (8am-8pm), the black dashed line represents the significant wave height limit for a CTV.

North Sea breaches the limit 21% of the time whereas the US scenario breaches the limit 18% of the time. Narrowing the data to only values during the working shift (8am to 8pm), the North Sea was found to breach the limit 21.4% of the time, whereas the US breached the limit 19.3% of the time. Though there is a smaller difference between the percentages, the trend is still the same. It was found that there were no occasions where the wind speed breached the vessel limit that did not also have a corresponding significant wave height measurement that exceeded the vessel limit, so these have not been considered here. Figure 3.8 gives some examples of weather windows at both sites. The two dates have been selected as they contain the maximum value significant wave height for both the North Sea (7th December) and the USA (30th October). The green highlighted area of the graph shows the 12 hour shift from 8am to 8pm. Although these are only two examples of weather windows, in both plots in Figure 3.8, the North Sea significant wave height is above the wave height limitation for a CTV (marked on the graph with a black dashed line) throughout the work shift. The US significant wave height is below the CTV limit for the plot depicting the 7th December but on the 30th October plot, when the US experiences the maximum wave height, the limit is breached after 11am. These examples are to illustrate that metocean conditions can be misinterpreted if looking at the overall climate set over a long period of time. Accessibility involves dissecting the data at a smaller scale to understand dispatching decisions.

3.2.2.1 Transport Inputs

Three types of vessels were utilised in this work, the general inputs of these vessels are shown in Table 3.5, which is based on work by Dalgic et al.[58]. The CTV used is a Catamaran, there are 5 of these available with the capacity to carry 6 technicians. The Jack-up strategy is fix on fail with fixed charter and has a mobilisation cost of £1.8 million. In terms of scaling for turbine size, the mobilisation cost for the Jack-up vessel for a 3 MW turbine is £250,000 and the 10 MW turbine is £1,800,000. The difference in mobilisation costs is based on a report by ORE Catapult that suggests that the lifting capacity of the vessel will result in higher O&M costs for larger turbines [59]. The report talks specifically about the heavy lift vessels that would be used in a floating case so using the value stated in their report is a conservative approach for this study. It is reasonable to assume that due to the lack of heavy lift vessels available for charter, the prices are going to increase for these larger turbines.

Table 3.5: Transport inputs to the model which were held constant in all scenarios. Based on work by Dalgic et al.[60]

Input	CTV	SOV	Jack-up
Wave Height Limit (m)	1.5	3	2.5
Wind Speed Limit (m/s)	12	15	36
Charter Rate (£/day)	1980	30,000	360,000
Mobilisation Time (days)	N/A	30	60
Fuel Consumption (m^3/hr)	0.24	0.3	0.55
Operational Speed (knots)	12	12	11

3.2.3 Limitations

There are several unknowns surrounding the operations and maintenance for larger turbines and as a result several assumptions are made throughout the analysis. Cost and failure rates for larger turbines are unknown, for this reason scaling has been used throughout. To address the uncertainty in the inputs for costs, the method for scaling is kept constant across all the scenarios, to allow for comparisons to be made between the different configurations and locations. The main outcome from the work is not the absolute value for OPEX but the change in the OPEX across several simulated scenarios.

Another smaller limitation within the model was identified. The inter transit time between wind turbines for maintenance trips was held constant regardless of the turbine size. In reality, the size of wind farms will undoubtedly increase from 3 MW to 10 MW due to the increased rotor diameters which requires an increase in spacing between turbines to reduce the effect of wake interactions. As a result, the model was updated and functionality was introduced to allow the inter transit time to be modified as a function of the diameter of the rotor, however, the modification resulted in negligible change to the KPI's in the analysis.

The length of climate data for the US site was not favourable and ideally the dataset would have covered a longer period of time. Due to the intermittent nature of the data, there were incomplete periods throughout the year making it difficult to get a sufficient length of unbroken data. This resulted in only 15 months of data being appropriate to use in the study.

3.3 Results and Discussion

The presentation of results within this chapter is organised into three distinct sections. Initially, the outcome for the 10 MW turbine cases at both study locations are detailed. This is subsequently followed by a comparative analysis in the final section. Prior to a discussion of the 10 MW turbine results, it is necessary to establish the baseline scenarios to compare to. Accordingly, for both the North Sea (NS) and US sites, a baseline scenario employing 3 MW turbines was simulated for each drive train configuration.

The outputs generated from the simulations include an overview of O&M costs, alongside an evaluation of turbine availability and power production. The cost analysis specifically examines both Direct and Total OPEX, consistent with the methodologies employed in previous chapters.

The calculated values for total and direct OPEX costs are presented in Table 3.6, that are then utilised in the subsequent sections for comparison with the 10 MW case studies. These findings are consistent with the results reported by [25], which concluded that 3 MW turbines employing a direct drive (DD) configuration exhibit lower Total and Direct OPEX costs compared to those equipped with a medium speed drive train configuration. This trend is evident for the 3 MW turbines at both the North Sea and US locations.

A comparative analysis between the two sites reveals that the total OPEX associated with a 3 MW turbine is significantly lower in the United States than in the North Sea. While the direct OPEX is also reduced at the US site, the disparity between the two locations is less pronounced for this particular cost.

Table 3.6: 3 MW Turbine Results

	Total O&M Costs (£/MWh)	Direct O&M Costs (£/MWh)
North Sea Direct Drive	19.66	8.88
North Sea Medium Speed	26.68	14.34
US Direct Drive	16.30	8.61
US Medium Speed	23.11	14.03

3.3.1 North Sea site

Figure 3.9 illustrates the total OPEX obtained for the 10 MW turbine scenario in the North Sea. The plot corresponds to the direct drive configuration, whereas Figure 3.10 represents the medium speed configuration. In each case, the blue line denotes the O&M costs of the 10 MW turbine as the baseline failure rates are systematically varied from -90% to +100%. The red dashed line indicates the constant baseline total OPEX cost for the 3 MW turbine, as reported in Table 3.6.

For the direct drive configuration, the intersection point, where the total OPEX of the 10 MW turbine scenario equals the total OPEX of the 3 MW turbine scenario, occurs when the failure rates are increased by approximately 20%. In comparison, for the medium speed configuration, this equivalence is reached with only a 10% increase in failure rates. The greater tolerance observed in the direct drive case may be due to the enhanced power production capabilities of the 10 MW turbine, which lowers the total O&M cost per unit of electricity generated.

Moving beyond total OPEX to consider only direct OPEX by excluding the lost revenue contribution, Figure 3.11 and Figure 3.12 presents the direct OPEX for the 10 MW turbines at the North Sea site. For the direct drive configuration, the 10 MW turbine remains more cost effective than the 3 MW case until failure rates reach approximately 70% to 80% of the baseline value. In contrast, for the medium speed configuration, the 10 MW turbine maintains the cost

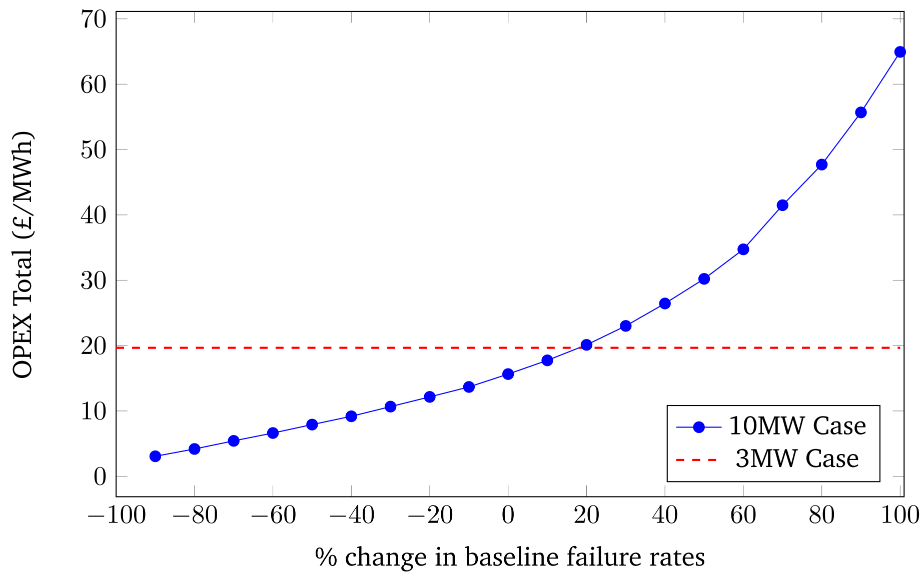

Figure 3.9: NS Total OPEX Costs for direct drive turbines

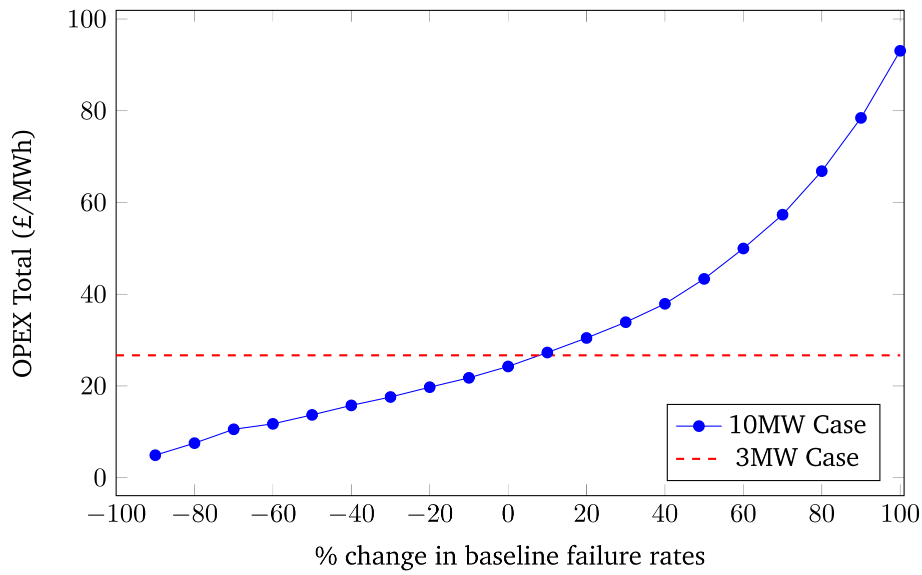

Figure 3.10: NS Total OPEX Costs for medium speed turbines

advantage only until failure rates are increased by approximately 30%, at which point the 3 MW scenario is more cost effective.

These findings are particularly noteworthy for two reasons. Firstly, they reaffirm that the direct drive configuration maintains a cost advantage over the medium speed configuration irrespective of increases in turbine rating at the North Sea site. Secondly, the results highlight that the effect of lost revenue is considerably more pronounced in the direct drive configuration

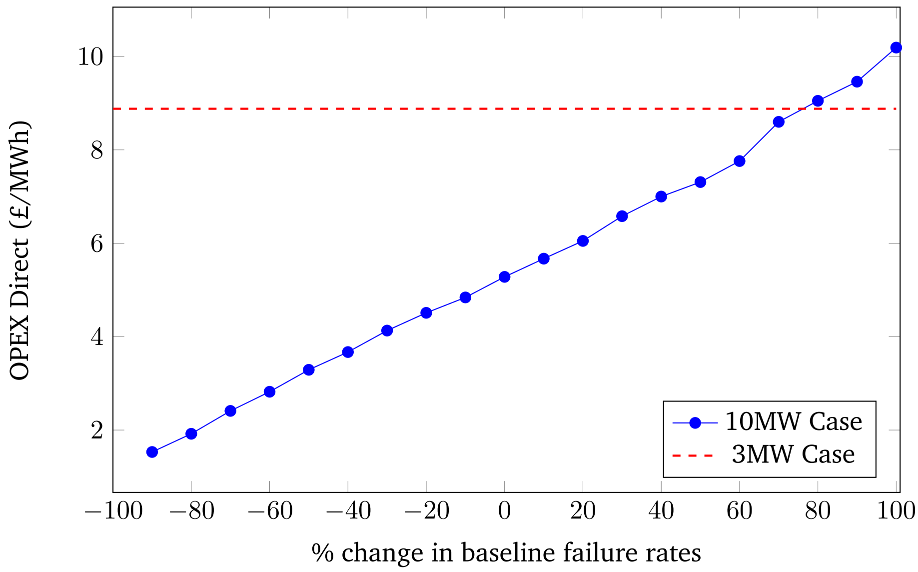

Figure 3.11: NS Direct OPEX Costs for direct drive turbines

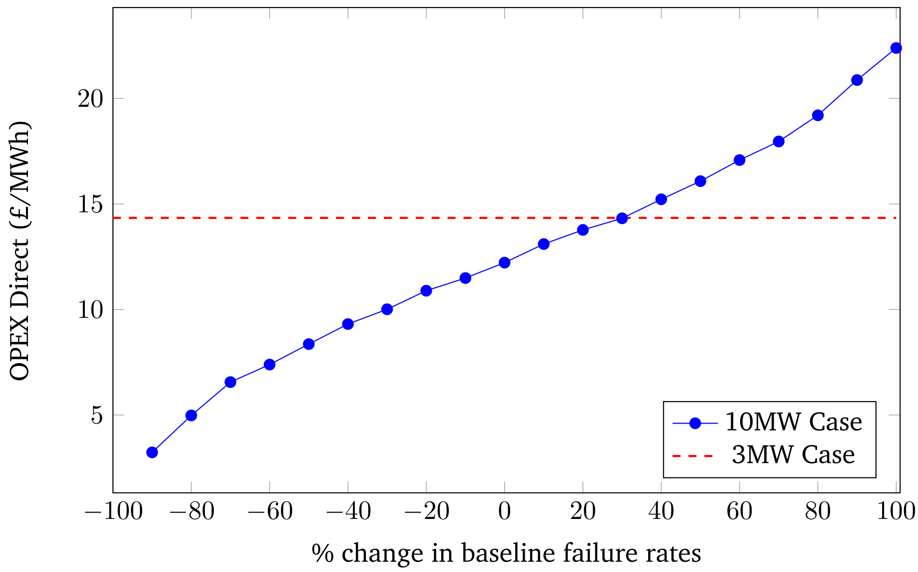

Figure 3.12: NS Direct OPEX Costs for medium speed turbines

than in the medium speed configuration. Specifically, when comparing the percentage change in failure rates and taking the point of intersection where a 10 MW turbine costs the same as a 3 MW turbine, the difference between the total OPEX and direct OPEX is larger for direct drive than for medium speed. The estimated difference for the direct drive configuration is around 55% compared to an estimated 20% for the medium speed configuration. This outlines the heightened sensitivity of direct drive turbines to lost revenue considerations.

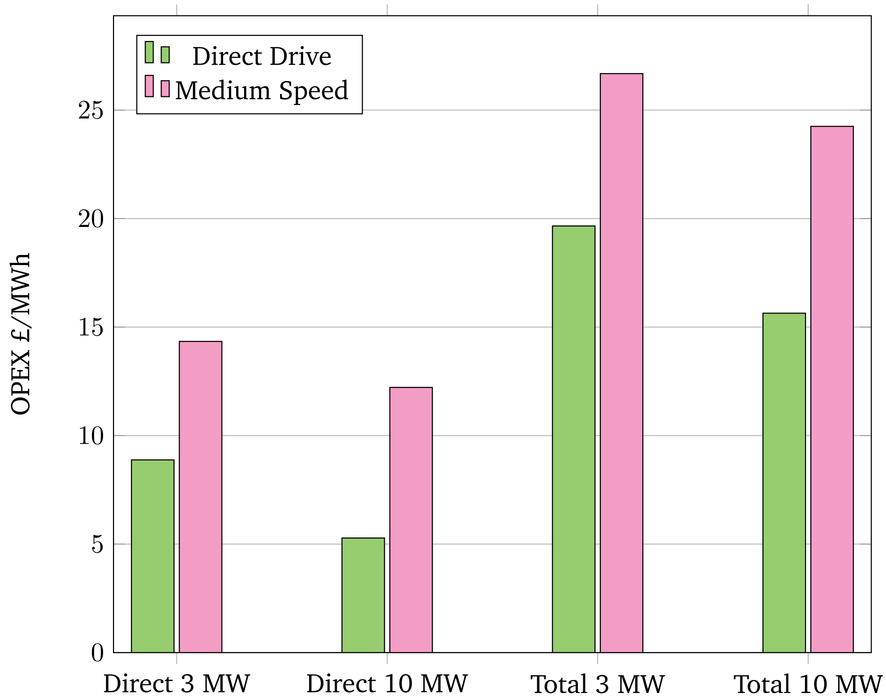

Figure 3.13: Overview of output simulated operational costs of 3 MW and 10 MW wind farms in the North Sea site.

To further explore the impact of turbine rating on O&M costs, Figure 3.13 compares the 3 MW and 10 MW turbines under conditions of identical failure rates, presenting both direct and total OPEX. The relative difference between total and direct OPEX remains broadly consistent between the two turbine sizes. For example, for the direct drive configuration, the difference between total and direct OPEX is £12.34/MWh for the 3 MW turbine and £12.03/MWh for the 10 MW turbine. Thus, in the North Sea, increasing turbine capacity from 3 MW to 10 MW does not markedly alter the relative relationship between direct and total OPEX.

3.3.2 US site

Figure 3.14 shows the total OPEX for the 10 MW direct drive turbine relative to the baseline 3 MW direct drive turbine and Figure 3.15 shows the direct OPEX. In this case, the 10 MW turbine maintains a lower total OPEX until failure rates are increased by approximately 20% to 30%. When baseline failure rates are identical for both turbine sizes, the 10 MW turbine achieves a total OPEX that is £3.42/MWh lower than the 3 MW turbine, corresponding to a 21% reduction in total OPEX.

For the direct drive configuration, the 10 MW turbine is less costly than the 3 MW scenario

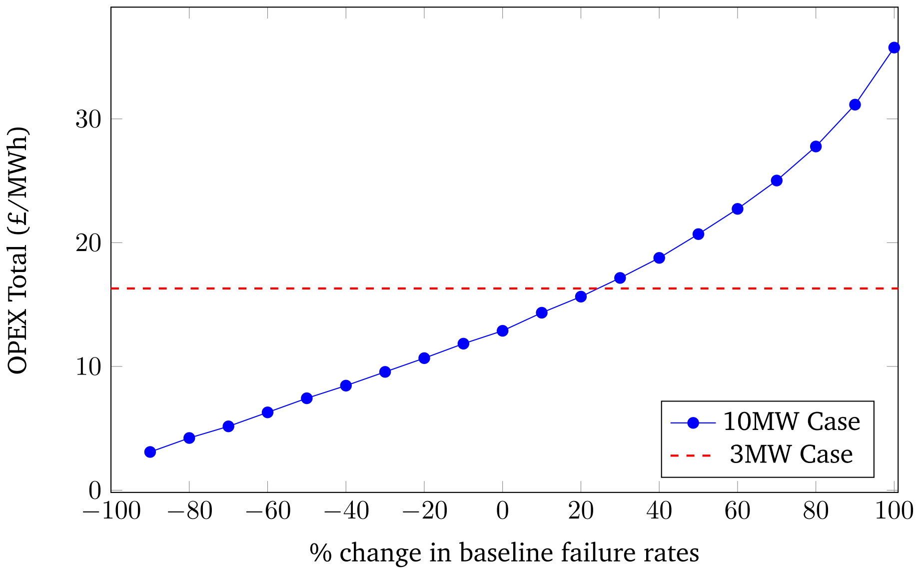

Figure 3.14: US Total OPEX Costs for Direct Drive turbines

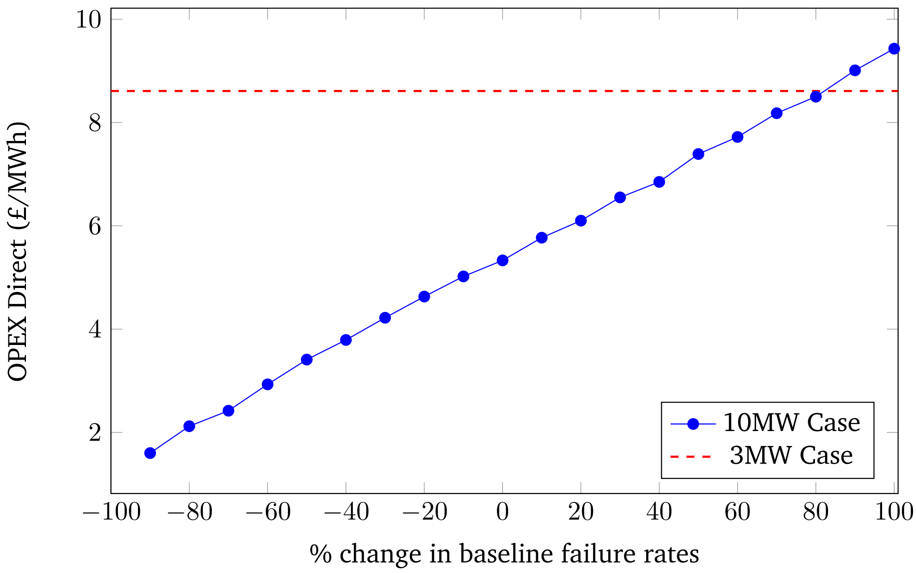

Figure 3.15: US Direct OPEX Costs for Direct Drive turbines

until failure rates exceed approximately 80% of their original baseline value. This finding again suggests that lost revenue plays a significant role in the cost structure of larger turbines, particularly given the substantial power output associated with the 10 MW turbines. Consequently, when only direct costs are considered, the 10 MW turbine offers a marked O&M cost advantage relative to the 3 MW turbine.

When examining the medium speed configuration at the US site, as illustrated in Figure

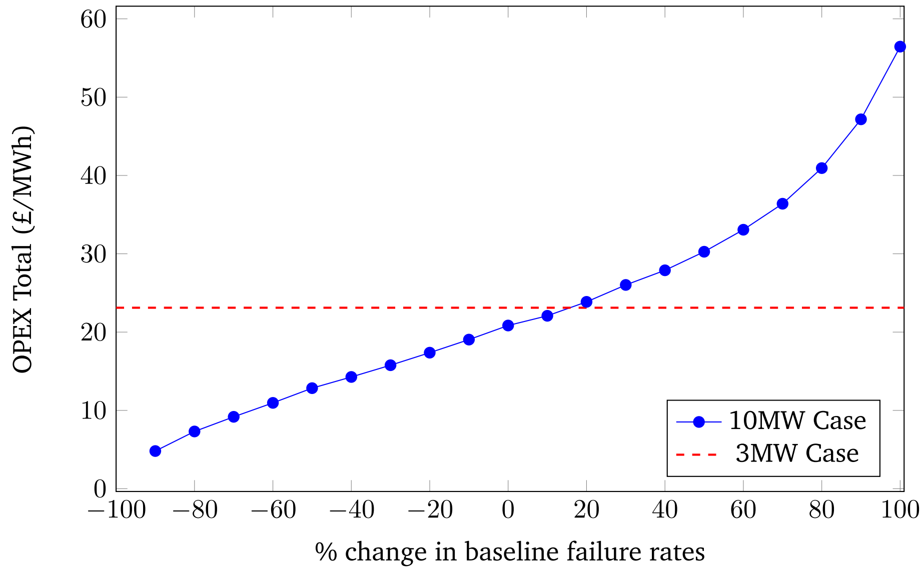

Figure 3.16: US Total OPEX Costs for Medium Speed turbines

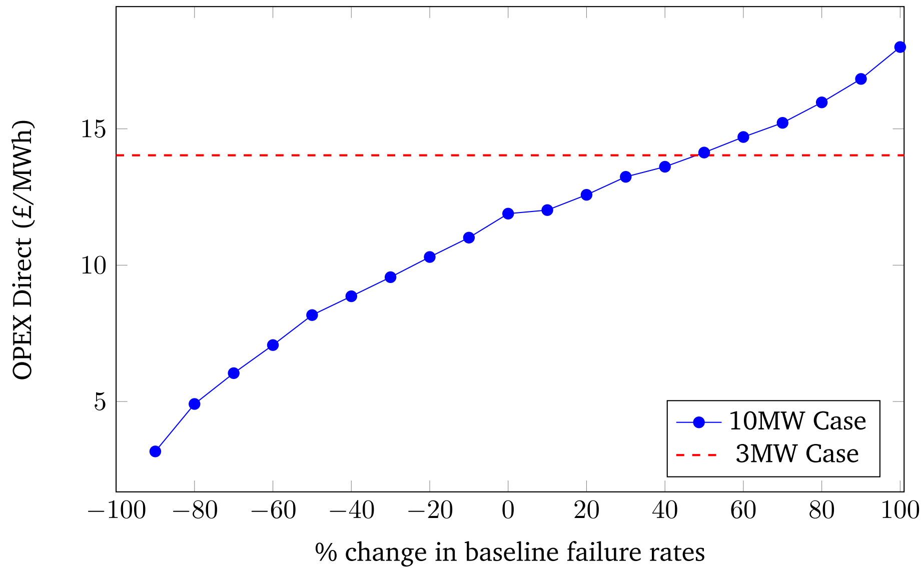

Figure 3.17: US Direct OPEX Costs for Medium Speed turbines

3.16 and Figure 3.17, a different trend emerges. Here, the 10 MW turbine exhibits lower total OPEX compared to the 3 MW turbine until failure rates are increased by only 10% to 20%, a narrower margin than observed for the direct drive configuration. In the case of the medium speed configuration, the 10 MW turbine has lower direct OPEX until failure rates are increased by between 40% to 50% compared to the original values. In line with the observations from the North Sea site, there is a larger gap between the total and direct OPEX for the direct drive configuration than for the medium speed configuration. Thus, the findings for the US site corroborate the earlier conclusion that accounting for lost revenue impacts the direct drive configuration more than the medium speed configuration.

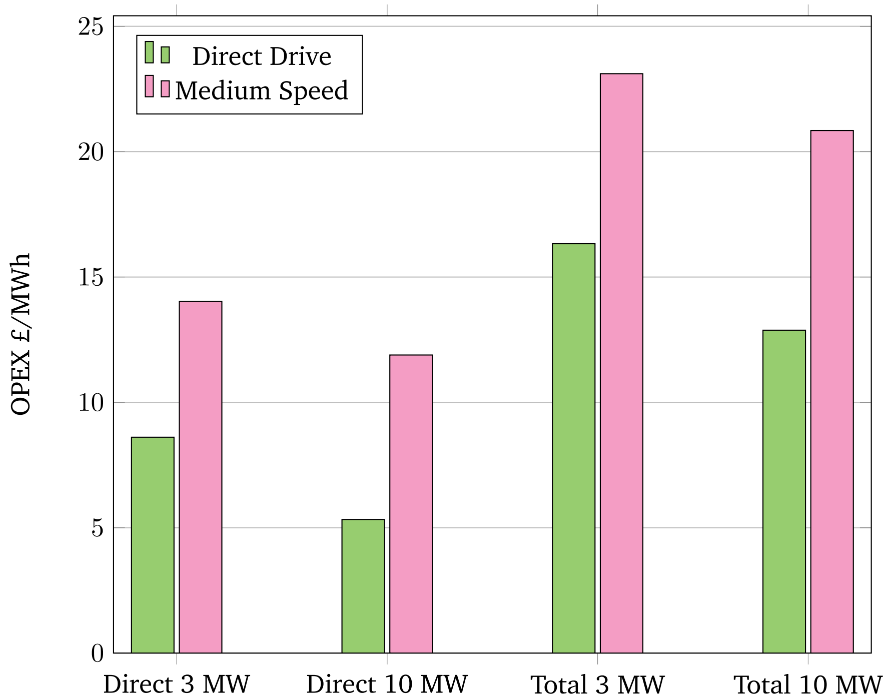

Figure 3.18: Overview of output simulated operational costs of 3 MW and 10 MW wind farms in the US site.

Similarly to the North Sea, Figure 3.18 outlines an overview of the baseline cost comparison between the 3 MW and 10 MW turbines considering the direct and total OPEX. It is again notable that the relationship between the direct and total OPEX remains relatively similar across the 3 MW and 10 MW turbines, indicating that the lost revenue contribution is not impacted by the size of the turbine.

3.3.3 Comparison

Figure 3.19 presents a comparative analysis of the North Sea and US sites for both direct drive and medium speed drive train configurations, considering total and direct OPEX costs for the 10 MW turbine. At baseline failure rates, it is evident that the differences in O&M costs between the two configurations are broadly similar across the two locations, both in terms of total and direct OPEX. However, a divergence emerges as failure rates are progressively increased. In particular, the gap in OPEX between direct drive and medium speed configurations widens more rapidly in the North Sea than at the US site. To highlight this divergence, the plot Figure 3.20 shows how the total OPEX changes with increased failure rates for the four scenarios.

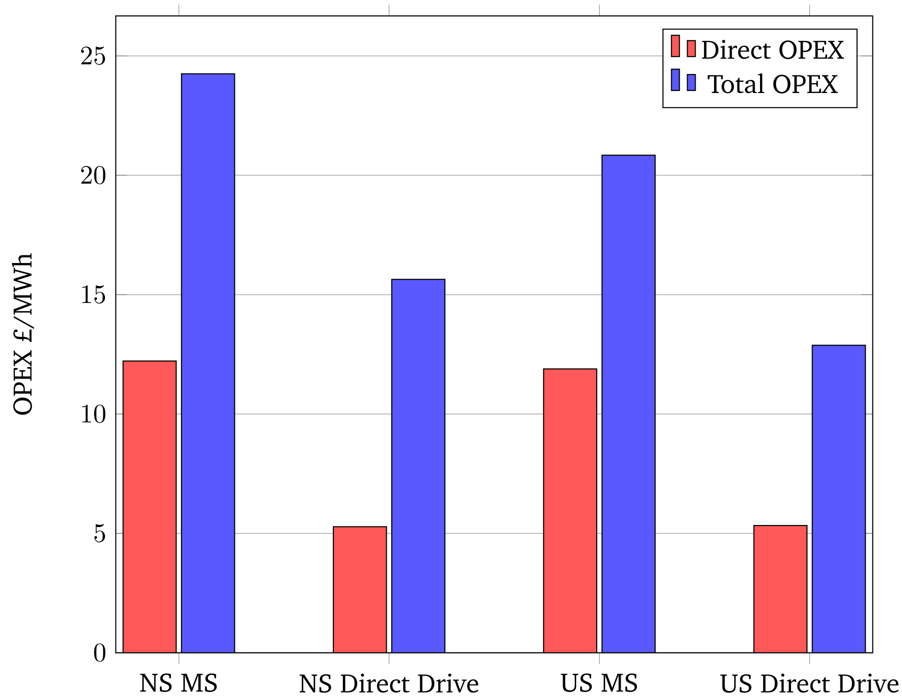

Figure 3.19: Cost overview of OPEX for both site locations for the 10 MW turbine simulations

This suggests that if 10 MW turbines experience higher failure rates than anticipated, the US site may offer a more favourable environment for the deployment of a medium speed configuration compared to the North Sea. One underlying reason for this could be attributed to differences in transport and maintenance logistics. In the case of medium speed turbines, maintenance interventions often require the use of heavy lift vessels, significantly elevating transport costs. The US site, benefiting from greater accessibility and reduced downtime, may be better positioned to manage these increased logistical demands more cost effectively than the North Sea, where harsher and less predictable weather conditions prevail.

The changes in OPEX based on the varying failure rate implies that sites with limited access windows and higher weather-related downtime, such as the North Sea, stand to benefit more from investing in high-reliability turbine models, even if this entails higher initial CAPEX. A more reliable turbine reduces the frequency and cost of unplanned maintenance, helping to mitigate OPEX and revenue losses over the project lifetime. In contrast, at sites like the US location, where accessibility is higher and repair operations are less constrained by weather,

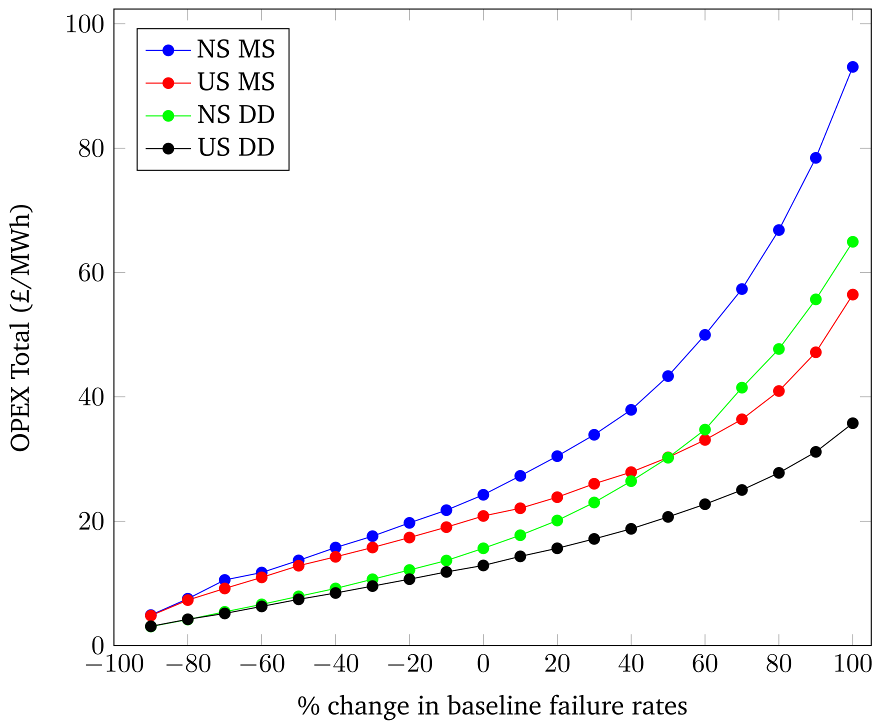

Figure 3.20: Impact of changing failure rates on the total OPEX for selected case studies.

a project may tolerate a lower-reliability (and therefore often cheaper) turbine model, as the associated increases in OPEX are less severe.

These trade-offs underscore the importance of considering the site-specific balance between CAPEX and OPEX. From a financial perspective, the cost of a project is sensitive to how costs are distributed over time. Higher CAPEX spent upfront on reliability may be justified in high-OPEX-risk environments if discounted future maintenance savings exceed the initial investment. Conversely, in lower-risk sites, the discounting of future OPEX reduces its financial weight, making lower-CAPEX turbines more attractive despite higher ongoing maintenance costs. Therefore, the impact of failure rates on OPEX, when viewed through the lens of accessibility, turbine reliability, and discounting,can help determine the optimal turbine selection strategy for each site.

Climate data from Table 3.4 initially suggested that accessibility should be greater in the North Sea, owing to the lower average wind speeds, significant wave heights, and wave periods. However, this assumption proves to be more complex in practice. While the average meteorological conditions may favour the North Sea, the operational windows for maintenance interventions are influenced not only by average conditions but also by variability, extremes, and seasonal patterns. As discussed in Section 3.2.2, the US site had higher percentage of time when access to site was possible for maintenance.

Furthermore, when comparing total OPEX, it is clear that the 10 MW turbines operating at the US site demonstrate lower costs than the equivalent North Sea turbines. This trend persists even when lost revenue costs are included, implying that the US site is a more economically viable location for larger turbines from a total OPEX perspective. When considering only direct OPEX (excluding lost revenue), the difference between the two sites narrows significantly. In fact, for the direct drive configuration, the US site even exhibits a marginally higher direct OPEX compared to the North Sea. These findings underscore the significant impact that lost revenue has on total OPEX and emphasise the critical role of turbine availability in offshore operations.

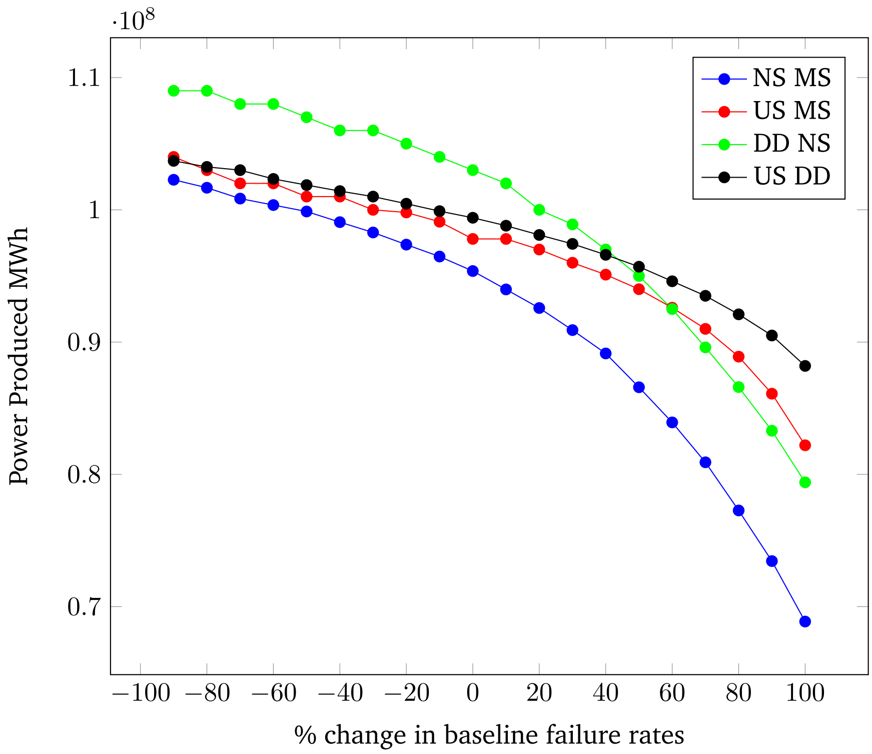

Figure 3.21: Power produced comparison for sensitivity analysis

Interestingly, despite harsher climate conditions on average, the North Sea site achieves higher power production across all failure rate scenarios, as shown in Figure 3.21. This apparent contradiction can be explained by the turbine selection used for the model. The 10 MW turbines were not optimised for site-specific wind conditions and were designed with a fixed rated speed of 12 m/s. Given the greater variability in wind speeds at the US site, the selected turbines were less able to capitalise on the wind resource, whereas the North Sea site benefited from wind conditions that more closely matched the turbine's rated speed. Analysis of wind conditions below the rated speed (0–12 m/s) revealed that the North Sea experiences higher average wind speeds in this operational range compared to the US, further explaining the higher overall power production observed.

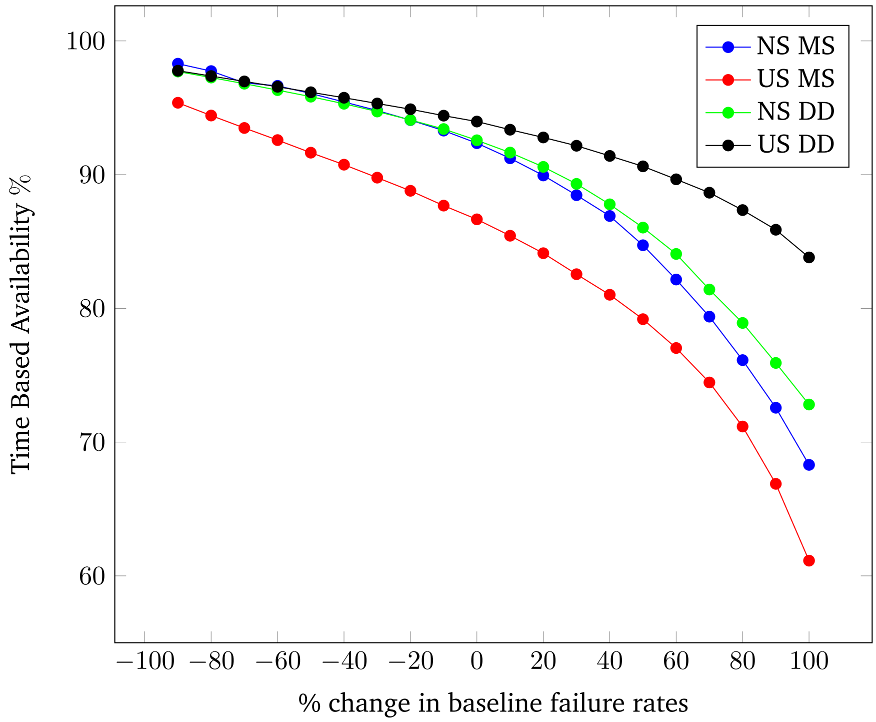

Figure 3.22: Availability Comparison for sensitivity analysis

These results collectively highlight the importance of minimising downtime in large turbine deployments. As turbine ratings increase, profitability becomes more reliant on high availability and consistent power production. If met-ocean conditions regularly exceed operational limits for maintenance vessels, delays in repair activities can significantly compromise turbine availability and, consequently, overall project costs. This effect is particularly visible in Figure 3.22, where the availability of the North Sea turbines declines more rapidly with increasing failure rates compared to the US turbines.

Further insight into the OPEX is given by a cost breakdown in Figure 3.23, which details the individual contributions to total OPEX across the four scenarios. For the medium speed configuration at the US site, transport costs represent the largest share of total OPEX, contrasting with the other three scenarios where lost revenue dominates. The increased transport costs for the

US medium speed turbine are primarily due to the frequent need for heavy lift vessels associated with gearbox and generator maintenance. Nevertheless, the calmer met-ocean conditions at the US site likely reduce downtime, thereby partially mitigating the elevated transport costs by minimising lost revenue.

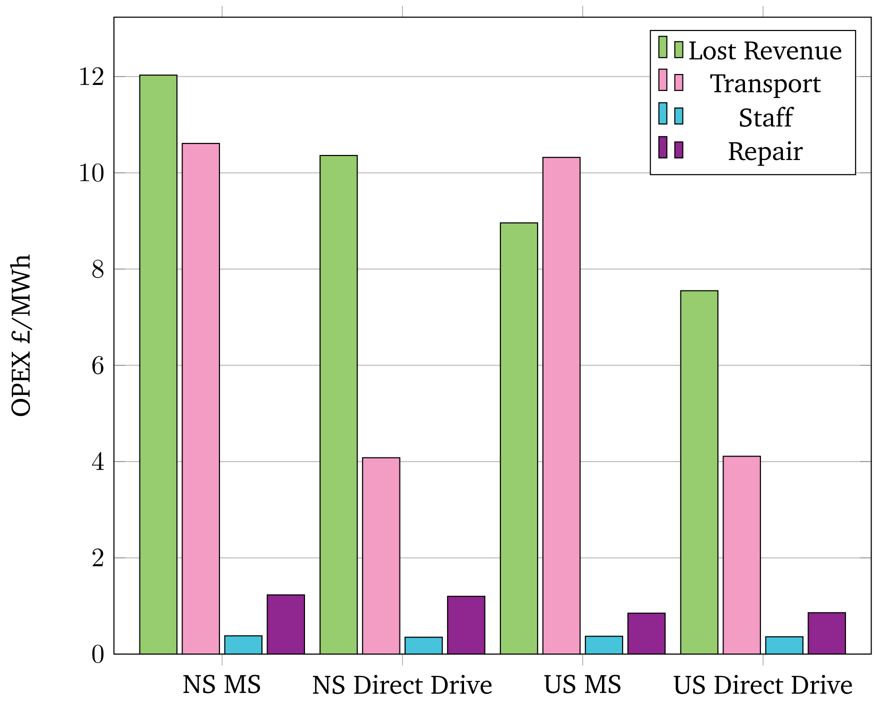

Figure 3.23: Cost breakdown for selected sites for 10 MW simulations.

Overall, the largest contributor to the cost differential between direct drive and medium speed configurations is the transport cost associated with the medium speed design. Heavy lift vessel mobilisation represents a significant expense, and its frequent utilisation in medium speed turbines substantially increases both direct and total OPEX. The comparison between the North Sea and US sites reinforces the critical influence of site-specific factors, particularly accessibility and climate, on the operational and maintenance economics of large offshore wind turbines.

3.4 Summary of Analysis

The aim of this research was to determine if a larger 10 MW turbine would have a lower operation and maintenance cost than a 3 MW turbine when the failure rates were held the same. Based on the two sites analysed, results found that when the same baseline failure rates are used for a 3 MW turbine and a 10 MW turbine with the same location and same configuration, the 10 MW turbine will be lower in cost in terms of both direct OPEX and total OPEX. This was held true for both the North Sea site and the US site.

The paper also reaffirmed results from previous work that found direct drive turbines to have lower total OPEX than a medium speed turbine for both 3 MW and the larger 10 MW turbine in both locations. The main driver for this difference in cost came from high transport costs from the increase usage of a heavy lift vessel for the medium speed drive train. For the North Sea, the direct drive configuration for a 10 MW turbine would have lower or equal O&M cost to a 3 MW turbine until failure rates were increased by 18%. The medium speed configuration 10 MW turbine was found to have lower or equal O&M costs to a 3 MW turbine until failure rates were increased by 8%. For the US, the direct drive configuration for a 10 MW turbine would have lower or equal O&M cost to a 3 MW turbine until failure rates were increased by 24%. The medium speed configuration 10 MW turbine was found to have lower or equal O&M costs to a 3 MW turbine until failure rates were increased by 16%.

One of the biggest drivers for the lower total OPEX in the 10 MW turbine is larger power production, so having increased periods of downtime is even more detrimental to the wind farm with larger turbines than smaller turbines. The North Sea site produced lower total OPEX for the direct drive 10 MW turbine in comparison to the medium speed 10 MW turbine. Despite this, the US site resulted in the least expensive total OPEX for the direct drive 10 MW turbine. This was contributed to the fact that lost revenue costs in the North Sea were much higher as a result of higher power production but lower availability. Increasing the failure rates for the 10 MW turbine for North Sea and US also highlighted the differences in the total and direct OPEX stemming from increases in lost revenue. Based on the sites analysed, results indicated that the two stage drive train configuration for a 10 MW turbine may be more suited to the US site than the North Sea site. Increased availability in the US compared to the North Sea resulted in lower lost revenue costs for the medium speed configuration which combats the high transport costs due to the requirement of heavy lift vessels for the gearbox.

The observed differences between direct drive and medium speed configurations are particularly significant. Direct drive turbines exhibit a greater tolerance to increased failure rates before total OPEX exceed those of the smaller 3 MW turbines, but are also shown to be more heavily impacted by lost revenue associated with downtime. This highlights an important trade-off inherent in turbine design: while direct drives may offer simpler mechanical systems and reduced baseline failure risks, the economic penalties for reduced availability become more severe as turbine output capacity increases. Thus, based on the results shown, any degradation in reliability would disproportionately affect direct drive configurations in larger turbines, particularly in high-energy offshore environments.

The findings from the North Sea and US analyses provide important insights into the operational cost dynamics associated with scaling offshore wind turbines to higher ratings, specifically from 3 MW to 10 MW. Overall, the results demonstrate that larger turbines can yield substantial reductions in both total and direct OPEX under baseline failure conditions. However, this advantage is highly sensitive to increases in component failure rates, underscoring the importance of maintaining high reliability as turbine sizes scale.

Furthermore, site-specific factors appear to modulate the sensitivity of total and direct OPEX. Although general trends were consistent across the North Sea and US sites, notable differences in the cost margins and failure rate tolerances suggest that environmental conditions, logistical accessibility, maintenance infrastructure, and regional energy markets could significantly influence the economic performance of scaled turbine deployments. These observations point towards the necessity of integrated site-specific techno-economic assessments when planning future offshore wind projects.

It should also be acknowledged that the modelling approach used in this analysis, while comprehensive, is subject to certain limitations. For instance, the assumption of uniform failure rate adjustments across all components may oversimplify the complex interdependencies present in actual turbine systems, where some components (e.g., blades, generators) may exhibit different scaling behaviours. Additionally, the baseline cost data and failure rates were assumed to be static across locations, despite known regional variations in supply chain costs, technician availability, and vessel mobilisation expenses. These simplifications, while necessary for comparative purposes, suggest that absolute cost estimates should be interpreted with caution, and that the primary value of this analysis lies in the comparative trends rather than in absolute predictions.

Finally, the results reinforce the strategic importance of reliability engineering and proactive maintenance strategies as turbine capacities continue to grow. Innovations in predictive maintenance, remote monitoring, and design for maintainability are likely to be central in safeguarding the economic competitiveness of larger offshore turbines. To extend this analysis further in future, a better understanding of the failure categories that contribute most to the cost deltas would be valuable. A study of specific minor repair, major repair and major replacement contributions to cost may shed further light on the areas of operations and maintenance that need addressed for these larger turbines. Another point arising from this work is the contribution from the converter to the total O&M costs. The lost revenue costs being consistently high points to the converter being a large contributor. Additionally, as mentioned, the optimisation of a turbine based on the site location is another suggestion for further work as it would potentially provide a fairer comparison between sites.

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Chapter 4

Determining Failure Rates

Following Chapter 3, where the aim was to determine potential operational costs by varying known failure rates of smaller turbines, in this chapter, updated failure rates for larger turbines are acquired and collated to determine more accurate operational costs. There is a gap of knowledge surrounding generator and drive train technology in terms of reliability, diagnostics and prognostics. Previous research with old reliability data sets has provided insights into the operations and maintenance costs for smaller rated turbines with different drive train configurations, and the previous chapter has given some insight into the potential operational costs if those same failure rates were accurate for larger 10 MW turbines. Collating and utilising newer failure data for the prominent drive train configurations used in larger rated turbines will provide an understanding of the possible operations and maintenance costs for future wind farms, that are currently being developed. Modelling operations and maintenance for new wind farm sites allows comparisons to be made between drive train configurations in terms of availability, power production and total maintenance costs. Reducing unplanned downtime for turbines has potential to reduce the cost of generating offshore electricity by roughly 10 % [1].

4.1 Review of Failures in Offshore Wind

4.1.1 Failure Detection, Prognosis and Data Availability

Understanding and classifying failure mechanisms within wind turbines is fundamental to improving their operational reliability and minimising unplanned downtime, particularly in offshore environments, where maintenance logistics are significantly more complex and costly.

Efficient identification of faults is essential for enabling strategic maintenance planning and ensuring the economic viability of offshore wind farms. Failure detection and prediction techniques provide operators with the opportunity to shift from reactive to preventative maintenance strategies, ultimately reducing operational expenditure and extending the service life of critical components.

Accurate failure prediction relies on two key elements: the ability to detect abnormal behaviour in turbine components, and a robust understanding of common fault modes within specific subsystems. Prognostics plays a crucial role in this process, offering estimates of a component's remaining useful life (RUL) and the probability of failure within a given time horizon. These insights allow maintenance teams to make informed decisions regarding inspection intervals, spare parts logistics, and long-term operational planning.

To support effective fault detection and prognosis, continuous monitoring of turbine performance is required. This is typically achieved through systems such as Supervisory Control and Data Acquisition (SCADA), Condition Monitoring Systems (CMS), and Structural Health Monitoring (SHM). A range of methodologies are employed to analyse this data and identify emerging faults. These include simple threshold-based techniques, data-driven approaches such as machine learning algorithms, and more recent developments such as digital twins, which are virtual replicas of physical assets that leverage physics-informed models to simulate system behaviour under varying conditions.

All of these methods share a common objective: to reduce the incidence of costly corrective maintenance by enabling earlier intervention during fault development. However, their effectiveness is highly dependent on the availability and quality of operational data. Accurate, high-resolution datasets are required to train predictive models and calibrate simulations, yet obtaining such data can be challenging. Barriers include the proprietary nature of SCADA and CMS data (often controlled by turbine manufacturers), inconsistent data formats across different turbine models or wind farms, and the presence of missing, noisy, or low-frequency data that may hinder accurate diagnosis. Furthermore, the scarcity of labelled failure data, particularly for rare but critical faults, presents a significant obstacle to the development of robust prognostic systems.

A detailed breakdown of failure modes in key wind turbine subsystems is provided in [2]. In the offshore context, these failures are often exacerbated by harsh environmental conditions not encountered onshore. Offshore turbines are particularly vulnerable to salt-induced corrosion, biofouling, and fatigue that is induced by combined wind and wave loading. The dynamic and less predictable nature of the marine environment further complicates structural and mechanical integrity management, reinforcing the importance of accurate fault detection and prognostic methodologies tailored to offshore conditions.

The definition of "failure" varies across the literature, often leading to inconsistencies in both classification and data interpretation. A 2017 review notes the critical need for a consistent taxonomy across studies and initiatives, highlighting that many datasets either lack transparency or rely on outdated technologies, particularly for offshore wind turbines [3]. This issue is compounded by the fact that prominent initiatives do not offer a clear definition of failure, limiting the reliability of comparative analyses.

Failures in wind turbines are often categorised by component or subsystem, with literature highlighting trends in failure types specific to each. A Danish turbine study revealed that approximately 60% of failures for turbines above 1.5 MW can be attributed to seven key systems: the electrical control system, gearbox, generator, yaw system, hydraulic system, grid interface, and blades [4]. Other studies identify pitch systems, converters, generators, and yaw mechanisms as critical during the early operational phase, commonly referred to as the "infant mortality" period, while the gearbox, drive train, and rotor tend to dominate failure statistics over the full lifecycle of the turbine.

Although the gearbox does not exhibit the highest frequency of failure, it is one of the most time-intensive and costly to repair, making it a critical contributor to turbine downtime. This aligns with the 20/80 Pareto principle as applied to wind turbines: 20% of component failures result in over 80% of lost availability. Notably, direct-drive (DD) turbines, which eliminate the gearbox, show increased failures in generators and converters due to the higher mechanical stresses borne by these components [5].

Failure Mode and Effects Analysis (FMEA) remains the most widely adopted methodology for identifying and evaluating failure modes within wind turbine systems. This involves breaking down the turbine into its major subsystems, such as the drivetrain, electrical system, control system, and support structures, and systematically assessing failure modes for each. The consequences of these failures are then evaluated with respect to safety, operational impact, and repair costs. A number of studies have developed breakdowns and diagrams to aid in this process [2], though some sources, such as the 2015 review mentioned, may be outdated and should be supplemented with more recent analyses.

Despite advances in SCADA systems, the availability and granularity of failure data remains limited, particularly for offshore turbines. Many models and decision-making tools must therefore rely on assumptions, which often diverge from operational realities [6]. This lack of reliable data hinders the development of accurate predictive models, especially when compounded by the fact that much of the existing failure data is derived from older, onshore turbines ranging from 300 kW to 3 MW, rendering it only partially relevant for modern offshore applications.

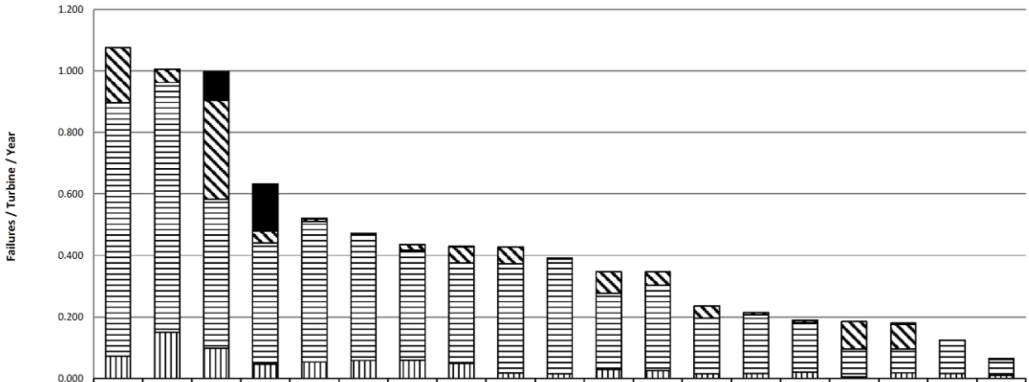
In terms of risk, the implications of turbine failures are disproportionately large for small-scale offshore projects. A recent study indicates that for projects with fewer turbines, the financial risks posed by poor reliability are significantly magnified, making failure prediction and detection essential for securing investor confidence [7]. This further underscores the necessity for robust failure analysis and transparent data-sharing practices within the wind industry.

In summary, while considerable progress has been made in identifying and categorising wind turbine failures, the field continues to be limited by inconsistent definitions, outdated data, and a lack of transparency. To enhance reliability, particularly in offshore applications, a shift towards standardised taxonomies and real-time failure detection, supported by accessible and current datasets, is essential.

4.1.2 Acquiring Updated Reliability Data

One of the most widely referenced datasets for failure rates in offshore wind turbines, previously utilised in Chapter 3, is presented by Carroll et al. [8]. This dataset encompasses failure records for a fleet of 350 offshore wind turbines with rated capacities ranging from 2 to 4 MW. While it provides valuable insights into component reliability and failure trends, it is important to acknowledge that the average size and complexity of offshore wind turbines have increased substantially since the time of data collection. As discussed in the preceding chapter, failure rates may change as turbines scales; larger and more modern turbines may exhibit different operational stresses, design tolerances, and maintenance requirements.

The uncertainty of the estimates in Carroll et al. [1], may be reduced by updated reliability data for offshore wind turbines in the public domain. The data set presented and used in the original comparison of drive-train configurations remains the most comprehensive source



	Pitch / Hyd	Other Components	Generator	Gearbox	Blades	Grease / Oil / Cooling Liq.	Electrical Components	Contactor / Circuit Breaker / Relay	Controls	Safety	Sensors	Pumps/ Motors	Hub	Heaters / Coolers	Yaw System	Tower / Foundation	Power Supply / Converter	Service Items	Transformer
Major Replacement	0.001	0.001	0.095	0.154	0.001	0.000	0.002	0.002	0.001	0.000	0.000	0.000	0.001	0.000	0.001	0.000	0.005	0.000	0.001
Major Repair	0.179	0.042	0.321	0.038	0.010	0.006	0.016	0.054	0.054	0.004	0.070	0.043	0.038	0.007	0.006	0.089	0.081	0.001	0.003
Minor Repair	0.824	0.812	0.485	0.395	0.456	0.407	0.358	0.326	0.355	0.373	0.247	0.278	0.182	0.190	0.162	0.092	0.076	0.108	0.052
No Cost Data	0.072	0.150	0.098	0.046	0.053	0.058	0.059	0.048	0.018	0.015	0.029	0.025	0.014	0.016	0.020	0.004	0.018	0.016	0.009

Figure 4.1: Failure rates for components by Carroll et al.[8].

of reliability figures for offshore wind turbines [8]. Failure rates estimated in the study are summarised in Figure 4.1. The analysis also catalogues repair times, repair costs and number of technicians per repair for the same categories. However, the analysis has two disadvantages: (i) the failure data is becoming out of date with respect to the latest wind turbines and (ii) the availability and O&M rate estimates utilise some transformed data from onshore turbines. Applying updated failure rates may reduce the uncertainty in the failure rate figures of the previous drive-train comparison. The following subsections elaborate on the sources for these updated failure rates.

4.1.2.1 Jenkins

Jenkins et al. estimates replacement rates for major components of next generation turbines using the classical method of structured expert elicitation [9]. Namely, they estimate replacement rates for the gearbox, generator and rotor for 15 MW medium-speed and direct-drive turbines. Both fixed-bottom and floating turbine concepts are considered. While the cited conference paper provides combined replacement rates for these components [9] , the breakdown of replacement rates by component is presented in their PhD thesis [10] . The results of that analysis is shown in Figure 4.2.

Two sets of replacement estimates are provided in [10]. These were obtained using different methods of structural expert elicitation, which is described in more detail in [10]. The

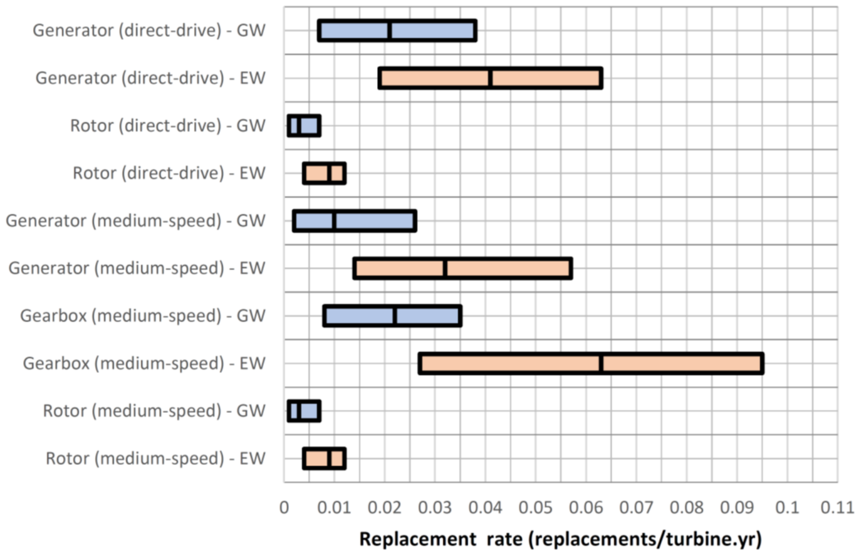


Figure 4.2: Major replacement rates for 15 MW fixed-foundation turbines, as presented in [10]. *EW* stands for *Equal Weighting* and *GW* stands for *Global Weighting*. The 5^{th}, 50^{th} and 95^{th} percentiles are shown for each component/elicitation method. Taken from [10].

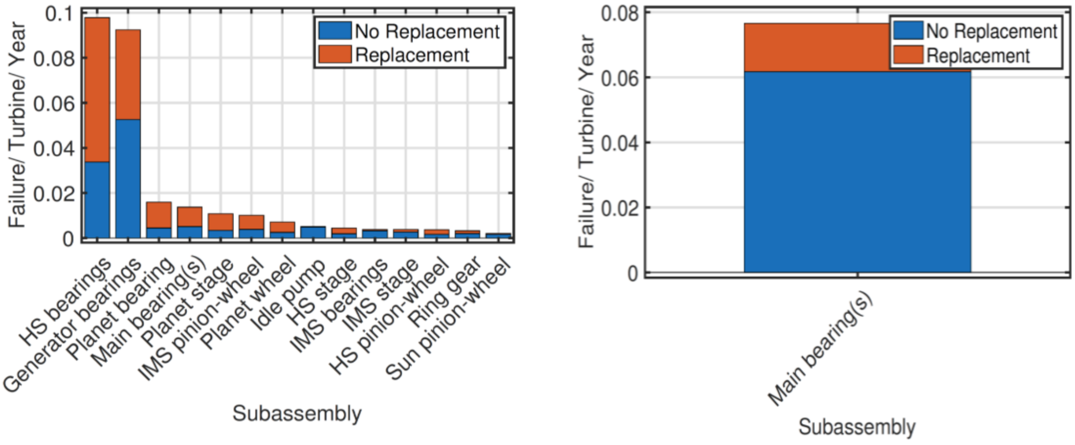
methodology has the benefit of uncertainty quantification, meaning that estimates for the 5^{th}, and 95^{th} percentiles are available for each replacement rate estimate as well as the median. Key take-away points from [10] results are as follows:

1. Comparing the estimated failure rates for next-generation turbines shown in Figure 4.2 to first-generation turbines shown in Figure 4.1; there is a decrease in generator and gearbox major replacements and increase in rotor major replacements. The overall view of the experts used in that study is therefore that of a shifting risk profile. Major drive-train components have been identified as a problem point for first-generation turbines and consequently there has been an effort to increase their reliability.

2. Collectively, medium-speed drive-train components still have a higher replacement rates than direct-drive turbines.

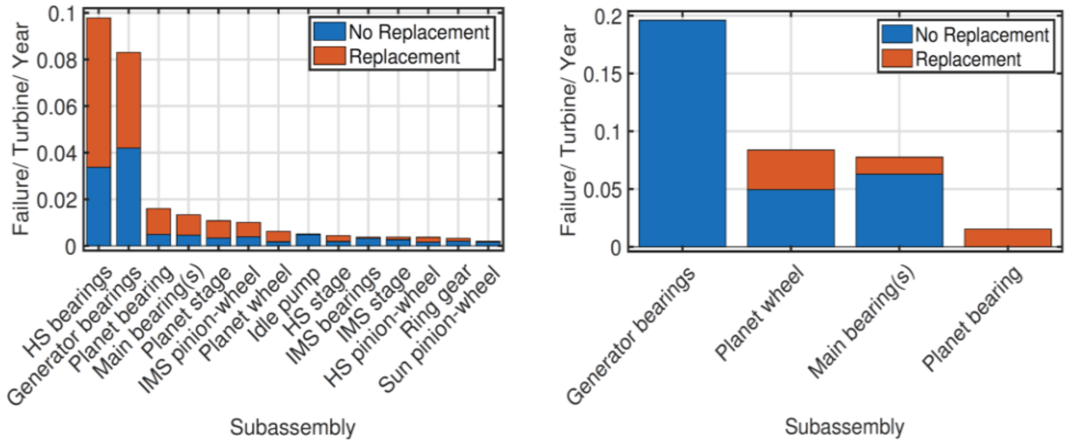
4.1.2.2 Koukoura

Koukoura et al. [11], also includes drive-train failure rate data in their thesis. These are derived from field data. The field data is a population of 1200 offshore wind turbines from over 20 wind farms with a power rating between 2-10MW. It contains a mixture of drive-train configurations



(a) (b)

Figure 4.3: Mechanical drive-train failure rates for (a) geared turbines and (b) direct-drive turbines. Taken from [11].



(a) (b)

Figure 4.4: Mechanical drive-train failure rates for (a) turbines < 5 MW and (b) ≥ 5 MW. Taken from [11].

containing high-speed gearboxes, medium-speed gearboxes and direct-drive machines. They present two sets of partitioned data which might be of use in the following analysis. Namely;

1. they compare failure rates for direct-drive and geared turbines- Figure 4.3;

2. they compare lower power ratings (< 5 MW) to higher power ratings (> 5 MW) - Figure 4.4.

The first point could ostensibly provide failure rate data which could be used directly for an O&M cost comparison. However, the population of geared turbines in that comparison contains a mix of high-speed and medium-speed gearboxes. The second point goes some way to breaking this down; newer, higher capacity turbines are more likely to be medium-speed than high-speed. Figure 4.4b also suggests a medium-speed population of turbines since many of the failure categories associated with a high-speed gearbox have been removed.

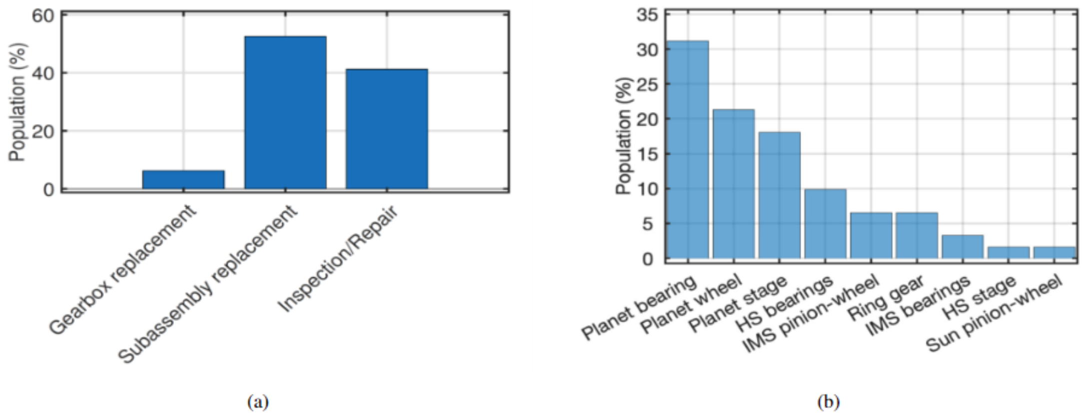


Figure 4.5: (a) Breakdown of gearbox replacements/sub-assembly replacements/repairs and inspections. (b) Breakdown of causes of gearbox replacement [11].

There are some features of Koukoura's failure rate figures that should be kept in mind if they are to be incorporated into the following analysis. First, the failures are mechanical only. For the generator, this effectively restricts the failure modes to the generator bearings. They do not capture failures in the generator fan, cooling system, stator/rotor issues or grease pipes. The gearbox and rotor are mechanical components, so most of the failure modes are captured for those components. Still, issues with the oil/lubrication system for those components are not captured. Second, the reliability statistics in Figures 4.3 and 4.4 are sub-assembly repairs/replacements. Only replacement rates for the gearbox are detailed in the thesis. These are shown in Figure 4.5.

Thirdly, both repair and replacement rates are presented for sub-assemblies. From a cost modelling perspective, this only provides one set of necessary inputs. Using these figures on their own would induce an uncertainty in the repair/replacement times and number of technicians needed for repair. Lastly, replacement and repair rates are presented for the main bearing. The main bearing is another key O&M cost driver in the drive train that was not considered as a separate component by either [1] or [9].

4.1.2.3 SPARTA

The SPARTA (System Performance, Availability and Reliability Trend Analysis) campaign is bench-marking initiative for offshore wind farms in the UK. The 20/21 SPARTA portfolio review contains major component failure rates and forced outages per turbine [12]. Their estimates for major component replacement rates are shown in Figure 4.6.

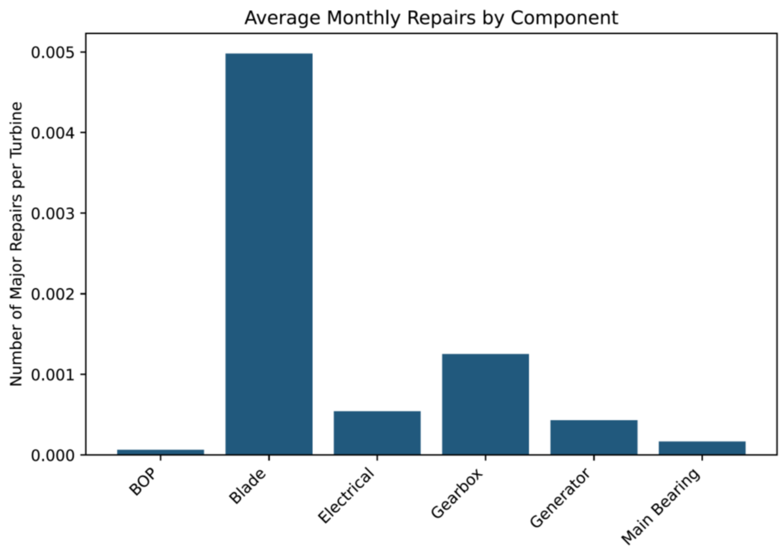


Figure 4.6: Major component replacement rates from the 20/21 SPARTA portfolio review [12].

Again, these figures come with some caveats. Firstly, they represent a mixed population of first generation and current generation turbines which would contain high-speed, medium speed and direct-drive machines. It would also presumably contain a mix of predominantly first-generation DFIGs and current generation PMSGs. Secondly, SPARTA reports component repairs as "*forced outages*". How forced outages relate to repairs or failures in their definition is not clearly defined. As part of that portfolio review they also compare the forced outages of direct drive turbines with geared turbines (grouped by capacity < 3.6 MW and ≥ 3.6 MW). Figure 4.7 shows their results. Here we can see that turbines in the direct drive and ≥ 3.6 MW categories show higher forced outage rates than in the < 3.6 MW category. However, SPARTA note that "*Since these turbines are still young, these failure rates can be expected to decrease in general in the future.*" and that "*more data is required to create strong insights about the differences between direct drive turbines and turbines with gearboxes.*"

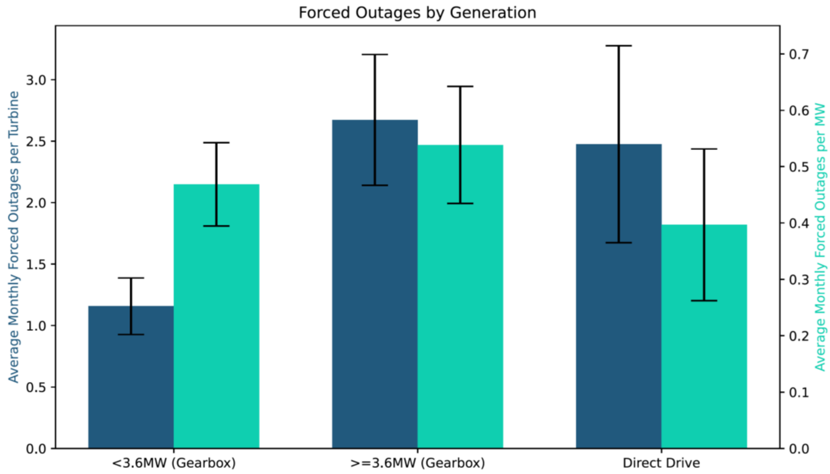


Figure 4.7: Comparison of different wind turbine concepts from the 20/21 SPARTA portfolio review [12].

4.1.2.4 Anderson

Anderson et al. presents reliability data for an offshore wind farm in the UK [13]. The analysed database consists of approximately 800 turbine hours of data. Reliability information is presented in terms of interventions per year in the case of non-corrective works and failures per turbine per year in the case of corrective works. The study also presents mean downtime per maintenance action. Figure 4.8 gives and overview of the contribution of different maintenance types to overall downtime of the turbine. The inner ring shows within that maintenance action the contribution of individual types of maintenance, and the brackets with the values indicate the average number of hours downtime per turbine per year associated with each action. From the corrective interventions, which make up almost half of the maintenance actions, 56% of interventions are minor repair, 26% major repair, 13% are major replacements and the rest is balance of plant (BoP). Figure 4.9 outlines the mean intervention rate for the components that had the longest amount of downtime during replacements that required a JUV. Although these failures make up a small percentage of the overall failures in the wind farm, they account for some of the largest portions of downtime hours. The dashed lines indicate that opportunisitic jobs may have been carried out during this downtime as a chance to allow operators to carry out other maintenance jobs during the replacement.

Likewise to those of Jenkins, Koukara & SPARTA, the dataset has some limitations. Firstly, the dataset is only representative of one turbine model at one location, and so is much less

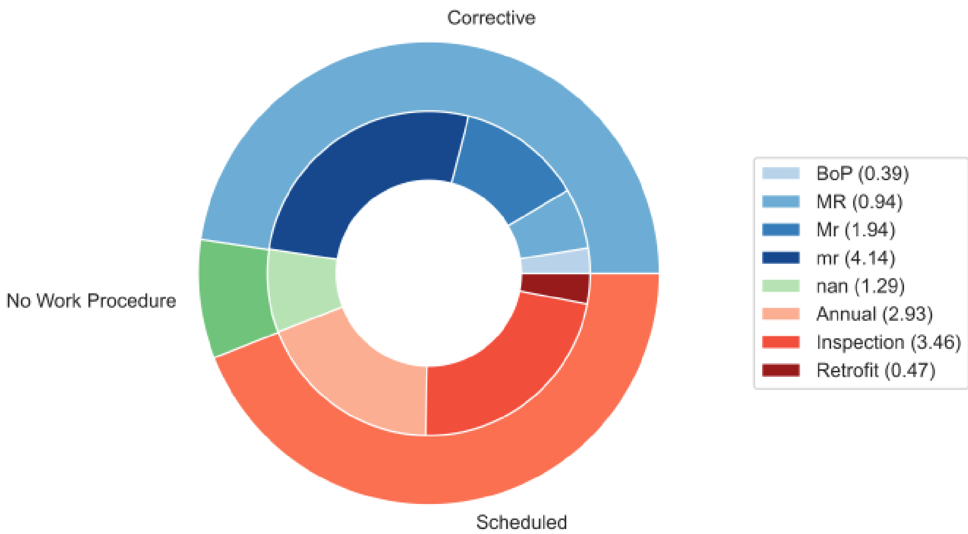


Figure 4.8: Contribution of types of maintenance action to the overall turbine downtime

representative of a generic wind turbine as the other reliability figures. Second, the turbine model which is represented is a high-speed geared machine, so the figures are not directly applicable to the research question of this study. Third, Anderson highlights in his thesis that there are uncertainties in the failure rate figures due to (i) the possibility for different failure definitions and (ii) the possibility for misinterpretation of work orders and alarm codes from the researcher.

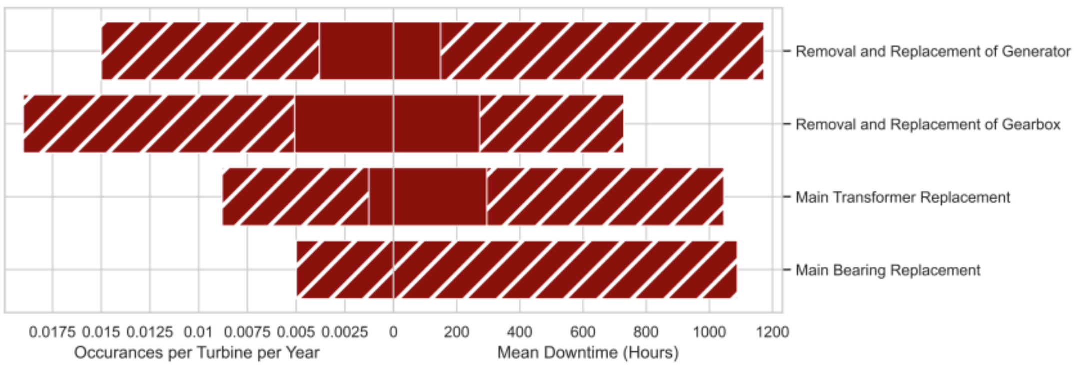


Figure 4.9: Mean intervention rate compared to mean downtime for each turbine focusing on components that have the longest downtime in the data sets according to the work procedures.

4.1.2.5 Summary

This section presents a review of literature surrounding drive-train reliability for wind turbines since the publication by [8] and not included by [14]. These are summarised in Table 4.1. With the aim to complete a cost modelling comparison between direct-drive and medium-speed machines, the key components are (ostensibly) the generator, gearbox and main bearing. The level of detail for future-generation turbines to be taken away for each of these components is summarised below.

1. Gearbox- [10] provides estimates for replacement rates of next generation gearboxes. These estimates present a significant increase in reliability compared to the work of [8]. Referring to Figure 4.7, the annual major replacement rate for gearboxes, as estimated by SPARTA, is approximately 0.015. This is within the uncertainty range presented by [10], and reinforces the trend of improving reliability for wind turbine gearboxes. Improved repair rate estimates for gearboxes might be assumed from [11]. "Improved" is used here to simply say that the failure data is less out of date than those used by [1]. However, the population of turbines making up those figures is young. The failure rates presented therefore might be obfuscated by failures that occur later in the component lifetime, or by more frequent early failures.

2. Generator- Again, [10] provides estimates for replacement rates of next generation generators, for both Direct Drive (DD) and Medium Speed (MS) geared turbines. Similar to the gearbox, there is a reliability improvement over the first generation of wind turbines represented by Figure 4.1. SPARTA's figure of approximately 0.005 is within the uncertainty limits for medium-speed machines, but outwith that of direct-drive machines. Mechanical repair rates for geared turbines can be updated by [11]'s figures for > 5 MW machines. Similar to above, the failure rates represent a young population of turbines.

3. Main bearing- Neither [8] nor [15] present failure figures for main bearings. As summarised by [16], main bearings are often neglected in reliability analyses such as those presented by [8], [17], [18] and [19] either by (i) lumping the main bearing in with the gearbox of (ii) not including it at all [11]. Koukoura provides figures for the main bearing of both direct drive and geared configurations which might be used for cost modelling purposes.

Table 4.1: Summary of the data-tables relevant to a reliability analysis.

O&M Data Type	Information Derived	Disadvantages
Jenkins [15]	• Major replacement rates of next generation generators, gearboxes and rotors from expert elicitation • Median, 5th and 95th percentile estimates • Global and equal weighting methods.	• No main bearing replacements • No Major repair/minor repair rates
Koukoura [11]	• Mechanical repair/replacement rates for drive-train assemblies; • Comparison between geared and direct drive turbine failure rates; • Comparison between sub-5MW and over-5MW failure rates	• No electrical failure rates in the generator; • No repair times/number of repairs; • Young population of direct drive turbines.
SPARTA [12]	• Major replacement rates of the BoP, blade, electrical, gearbox, generator and main bearing components; • Forced outage rates; • Comparison of forced outage rates between direct drive & geared turbines	• No repair rates; • No repair times/ number of technicians; • Young population of direct-drive turbines.
Anderson [13]	• Repair and replacement rates for high-speed geared turbine assemblies; • Major Replacement/Major repair/minor repair categorisation	• Older turbines (not medium speed or direct-drive) • Only data from one wind farm.

Jenkins et al. provides estimates for drive train component replacements based on a structured method for elicitation which incorporates uncertainty quantification [9]. Since replacements are a driver of costs, that study provides a solid base upon which to build the analysis. Koukoura et al. [11] data is useful for building on that base to provide updated reliability estimates for the drive train for offshore turbines which are less out-of-date than those used previously by Carroll et al. [8]. However, those figures will likely still not represent accurately the failure rates of a 15 MW wind turbine. Since they are only mechanical failures, they will also need to be fleshed out by minor failure rates from Anderson et al. [13], the dataset which is least representative of a future 15 MW machine, but nevertheless is still a new source of failure data. In updating the failure rate inputs used for modelling, it is important to ensure consistency in how failures are classified. A common taxonomy, categorising failures into minor repair, major repair, and major replacement, is maintained across the updated data sources, making them suitable for integration and comparative analysis. This classification framework aligns with that employed in the original dataset by Carroll et al. [8], facilitating continuity in failure mode interpretation and enabling a structured approach to reliability modelling. The consistency in categorisation across datasets ensures that variations in failure rates can be attributed more confidently to turbine characteristics or environmental conditions, rather than differences in how faults are defined or recorded.

4.1.3 Research Question

This chapter contributes novel insights to the field by reviewing and synthesising recent literature on failure rate estimates for the latest generation of large offshore wind turbines. It is among the first to collate multiple data sources specific to 15 MW-rated turbines and apply these inputs within an operations and maintenance (O&M) modelling framework. The analysis focuses on several key areas. Firstly, it examines how different drive train types, specifically medium-speed geared and direct drive configurations, affect O&M costs. Secondly, it explores the sensitivity of these costs to variations in failure rate estimates, using both lower and upper bounds derived from the literature. Thirdly, it investigates how changes in repair time for major components influence total O&M expenditure across the different drive train designs. Lastly, the study assesses the impact of maintenance vessel accessibility by adjusting environmental accessibility limits to reflect realistic offshore conditions. These integrated analyses aim to provide a more comprehensive understanding of cost drivers for next-generation offshore wind turbines. The central research question in this chapter is:
"By utilising new failure rate estimates, how do drive train configuration, failure rate variability, repair duration, and accessibility constraints influence the operations and maintenance costs of 15 MW offshore wind turbines?"

4.2 Methodology

To evaluate the performance of large-scale 15 MW wind turbines under a variety of operational conditions, the StrathOW O&M Model is once again employed. In order to assess the impact of updated failure rates, derived from the sources mentioned in the previous section, three representative case studies are selected. These case studies reflect different site characteristics, including accessibility and environmental conditions, and are also representative of locations anticipated to deploy larger turbines in the near future.

In addition to the base case analysis for each of the sites, a series of four sensitivity studies are performed to explore the robustness and implications of the revised failure rates. These sensitivity analyses systematically adjust key operational parameters: major component replacement rates, accessibility metrics, and repair durations. The aim is to quantify how each of these variables influences the overall O&M costs when compared to the baseline scenario.

This comparative approach is intended to highlight the divergence in cost and reliability outcomes when applying updated failure rates tailored to 15 MW turbine platforms, in contrast to older data based primarily on smaller 2–4 MW turbines. As turbine capacity increases, failure modes and maintenance requirements do not necessarily scale linearly. Therefore, this methodology provides insight into whether older reliability assumptions remain valid or if substantial modifications to maintenance planning and cost forecasting are required for modern offshore wind projects.

4.2.1 Reliability Inputs

Failure rates for every component bar the drive train are assumed to be equivalent for geared and direct-drive turbine concepts. These are taken from Carroll et al. [8], excluding the rotor major replacements rate, which is taken from Jenkins et al. [15]. Assumed failure rates for the gearbox, generator and main bearing are summarised in Table 4.2.

4.2.2 Baseline Assumptions and Cost Inputs

For the baseline comparison, repair times and number of technicians are based on the work by [8]. Main bearing replacements and repairs are assumed to take the same time as gearbox replacements and use the same number of technicians.

Replacement costs are taken from BVG Associates' guide to offshore wind farms [20]. Since the original figures represent 10 MW turbines, they are scaled to 15 MW turbines using a linear cost assumption, i.e. all component costs are multiplied by a factor of 1.5.

Repair costs are based on [21] and calculated in a similar manner to [22]. The cost ratios for minor and major repairs relative to full component replacement are derived and then multiplied

Table 4.2: Summary of baseline failure rate inputs.

		Medium-Speed		Direct Drive	
Component	Failure Mode	Failure Rate	Source	Failure Rate	Source
Gearbox	Replacements	0.022	Jenkins	N/A	N/A
	Planet Wheel Repair	0.05	Koukoura	N/A	N/A
	Other Gearbox Minor Repair	0.32	Anderson	N/A	N/A
Generator	Replacements	0.01	Jenkins	0.021	Jenkins
	Generator Bearing Replacement	0	Koukoura	0	Koukoura
	Generator Bearing Repair	0.196	Koukoura	0	Koukoura
	Other Generator Minor Repair	0.22	Anderson	0.22	Anderson
Main Bearing	Replacements	0.009	Koukoura	0.015	Koukoura
	Main Bearing Repair	0.006	Koukoura	0.062	Koukoura

by the cost of a new component to estimate the respective repair costs.

Similarly to [9], a 1.5 GW wind farm comprising 100 × 15 MW wind turbines is used. The farms are assumed to have an operational lifetime of 20 years. Three locations designated as suitable for fixed-bottom developments in the ScotWind leasing process were selected as case studies [23, 24], namely, Bowdun, Caledonia and Machair, as depicted in Figure 4.10.

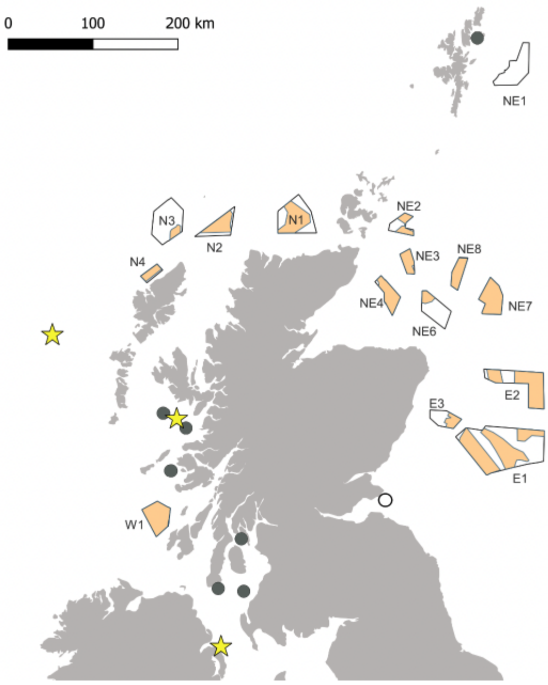


Figure 4.10: Map of ScotWind leasing sites [24]. The three chosen sites, Bowdun, Caledonia and Machair, are identified by the codes E3, NE4 and W1 respectively.

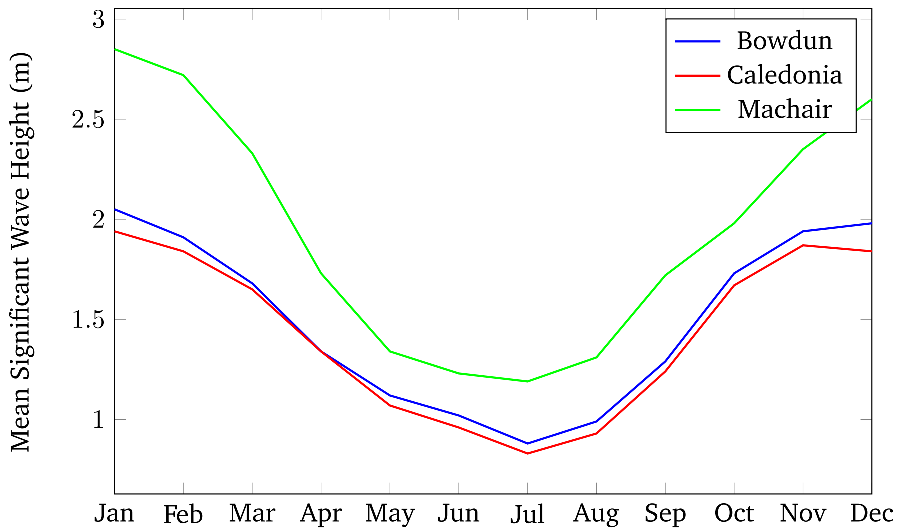


Figure 4.11: Average significant wave height values for three scotwind sites over a 30 year period.

ERA5 reanalysis data for each site was obtained using the online ESOX tool developed by [25], providing 20 years of hourly wind speed (at 100 m height) and significant wave height data. For all sites, the power curve used corresponds to the IEA 15 MW reference turbine from [26], and an electricity price of £40.70/MWh is assumed, based on [27].

A critical site characteristic is accessibility, the proportion of time environmental conditions are within the operational limits required for transferring technicians to turbines. These limits are typically based on wind speed and wave height thresholds. For vessel operations, the commonly applied significant wave height limits are 1.5 m for CTVs and 2.5 m for SOVs. Figure 4.11 presents the monthly average significant wave height for the three sites. Machair exhibits the highest wave heights, potentially reducing accessibility for maintenance activities, whereas Caledonia and Bowdun show lower average values, suggesting more frequent access windows. A similar trend was found for the average wind speed for the three sites also.

The vessel assumptions used in the model are summarised in Table 4.3. A combined SOV–CTV strategy is employed, based on the mothership concept described by [28], in which a service operation vessel equipped with an access mechanism enables the transfer of technicians to turbines. No mooring capability is assumed for these vessels.

Table 4.3: Summary of vessel inputs. Wave height limits are based on work by [29, 30] and charter rates come from [20, 31].

Vessel Type	CTV	SOV	JUV
Number of Vessels	4	1	1
Charter Day Rate (£)	3,000	30,000	360,000
Mobilisation Time (Days)	N/A	N/A	60
Mobilisation Cost (£)	N/A	N/A	2,100,000
Charter Type	Continuous	Continuous	Fix-on-Fail
Charter Length (Days)	Lifetime	Lifetime	60
Wave Height Limit (m)	1.5	2.5	2.5

4.3 Results

The following section presents the results obtained from the simulation of the baseline scenario, which is designed to compare the performance of three distinct wind farm sites under two different drive train configurations. After completing this initial simulation, a series of sensitivity analyses are conducted to determine the susceptibility of cost outputs to several different inputs.

4.3.1 Baseline Comparison Between Direct Drive & Medium-Speed

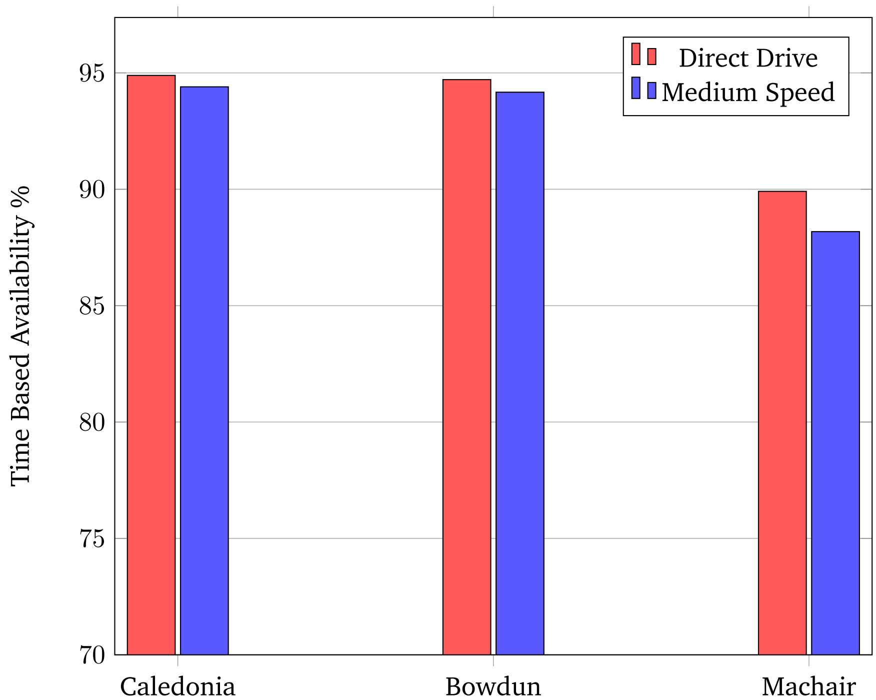


Figure 4.12: Comparison of availability for the three chosen wind farm sites between the two drive train configurations.

The results of the baseline comparison are shown in Figures 4.12, 4.13 and 4.14. Figure 4.12 shows the baseline availability results. For all scenarios, the direct drive has higher availability than the medium-speed concepts. The difference in the absolute percentages of the two configurations is 0.49 %, 0.54 % and 1.73 % for the Bowdun, Caledonia and Machair sites respectively. The delta is notably greater for Machair, the site characterised by lower accessibility than the other two, as seen in Figure 4.11.

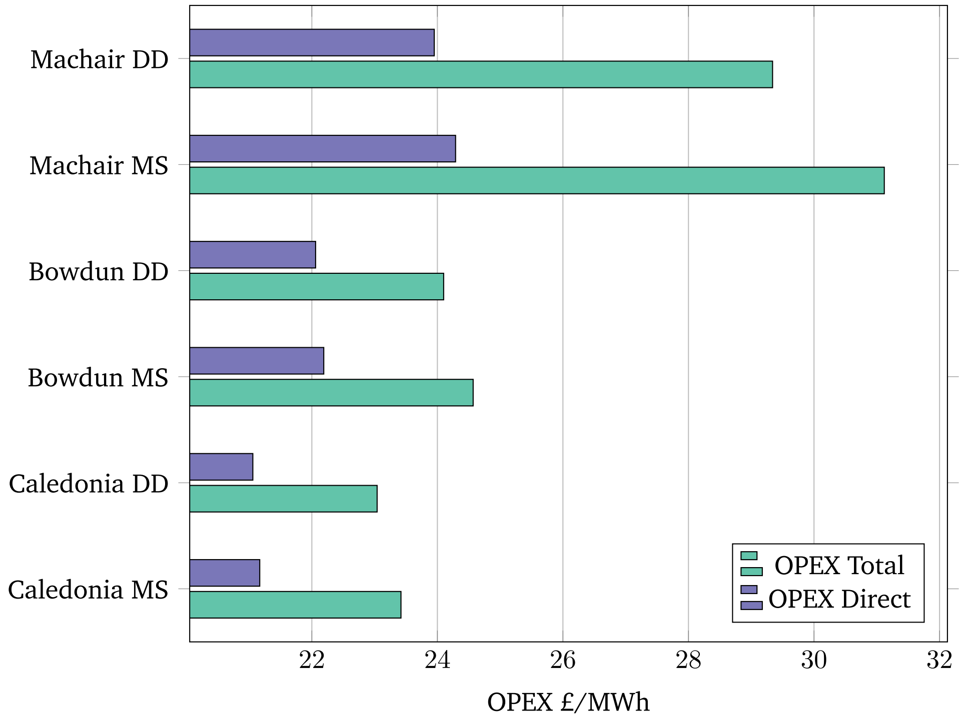


Figure 4.13: Comparison of OPEX costs (direct and total) for chosen wind farm sites and drive train configurations.

Figure 4.13 shows the OPEX overview for the six scenarios and Figure 4.14 gives a breakdown of these costs into the different cost contributors, measured in £/MWh. For all scenarios, the direct drive configuration has lower O&M costs than the medium-speed. Again, the difference is greater for the less-accessible Machair site than the Bowdun and Caledonia sites. The relative percentage difference between the two configurations is around 1.59 %, 1.58 % and 5.78 % for the Bowdun, Caledonia and Machair sites respectively. The cost breakdown across all scenarios reveals that transport costs consistently represent the largest portion of total operational expenditure (OPEX), while staff costs contribute the least, remaining below 2% in all simulations. The most significant variation in cost components is observed in lost revenue,

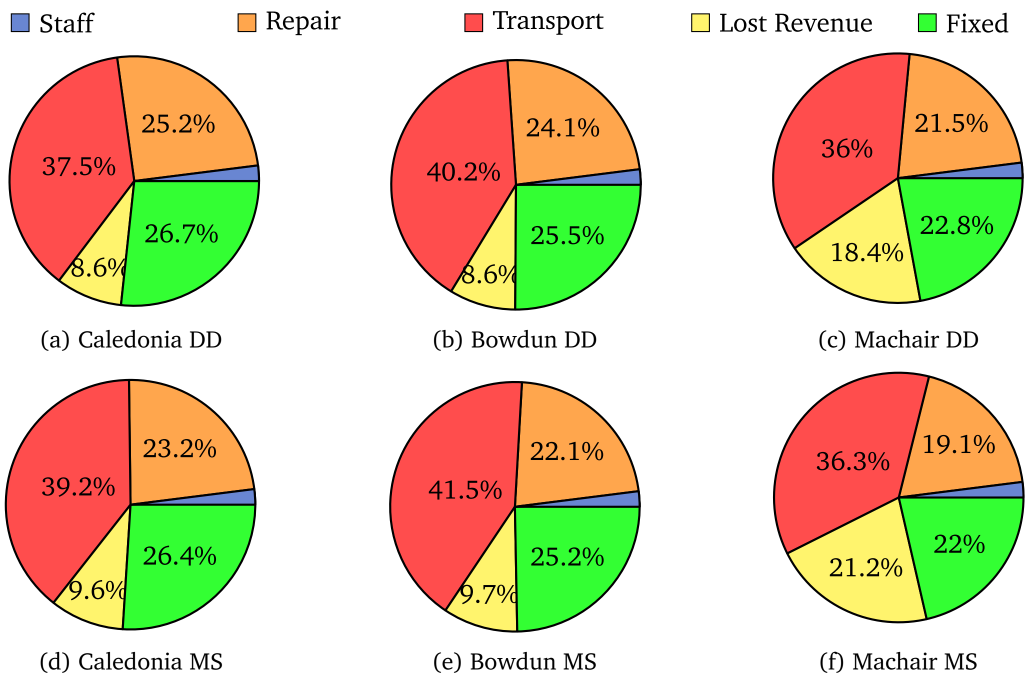


Figure 4.14: Cost breakdown for the medium speed and direct drive simulations

which accounts for less than 10% at the Bowdun and Caledonia sites, but rises to approximately 20% at the Machair site. This variation correlates with site availability figures, as Machair is less accessible, leading to longer downtimes and higher revenue losses. While these results highlight differences between the sites, the more insightful comparison lies in evaluating the performance of the two drive train configurations at each individual site.

Important differences in the cost breakdown between the two configurations are as follows:

1. **Lost Revenue costs**. Opportunity costs are higher for medium-speed turbines than direct-drive turbines. The medium-speed machines are still expected to have (i) higher overall failure rates and (ii) more major replacements than direct drive turbines. The relative difference between the two configurations, in terms of the lost production cost, is higher at the less-accessible Machair site (at around 20 %) compared to the Caledonia and Bowdun sites (at around 13 % each).

2. **Transport costs**. Vessel costs are higher for medium-speed turbines than direct drives. Since there are more major replacements for medium-speed machines, the increased utilisation of JUVs results in higher transport costs.

3. **Repair Costs**. Repair costs are higher for direct-drive turbines compared to medium-speed machines. This is attributable to higher assumed generator costs. According to BVG Associates' guide to an offshore wind farm [20], a direct-drive generator costs twice as much as that of a medium-speed. The cost of replacements and repairs are therefore assumed to be twice as much for direct-drive generators. This extra assumed cost is enough to exceed the repair costs afforded to the gearbox.

4.3.2 Sensitivity of Assumptions

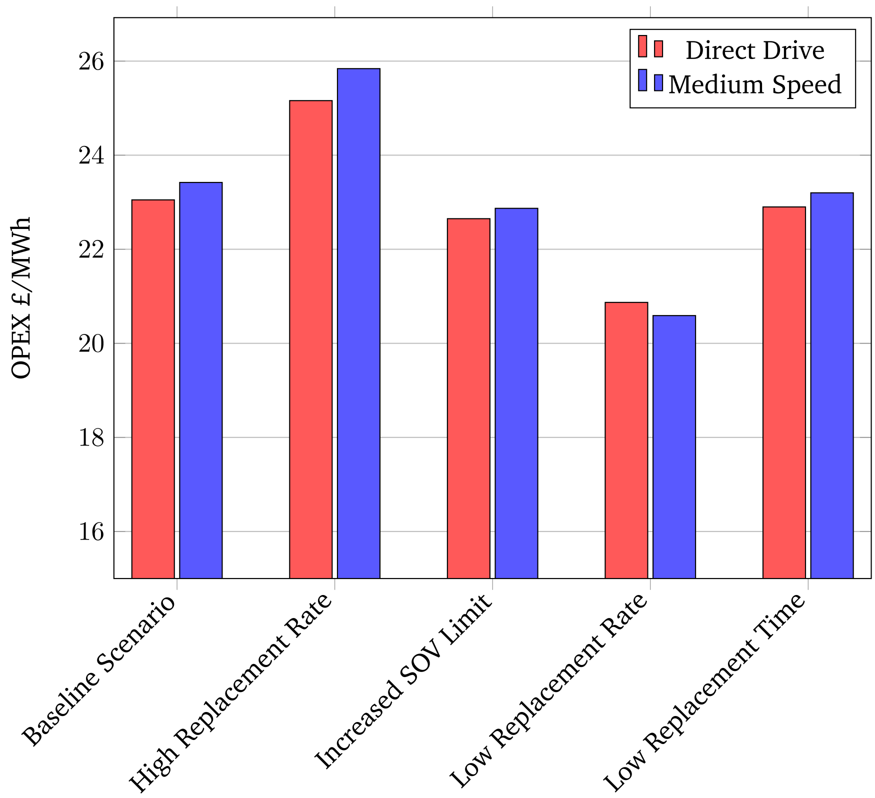


Figure 4.15: Sensitivity analysis results for Caledonia wind farm site. The total O&M costs of the baseline scenario are compared to the total O&M costs for each analysis.

Due to the nature of the inputs used for the model and the various sources utilised to synthesise the baseline scenario, it is important to investigate how sensitive these assumptions are. There are three inputs which were identified for sensitivity analysis: replacement rate, SOV accessibility limits and the replacement times. For the replacement rates, two analyses were completed by using the 5th and 95th percentile estimates from [10], as a low replacement rate

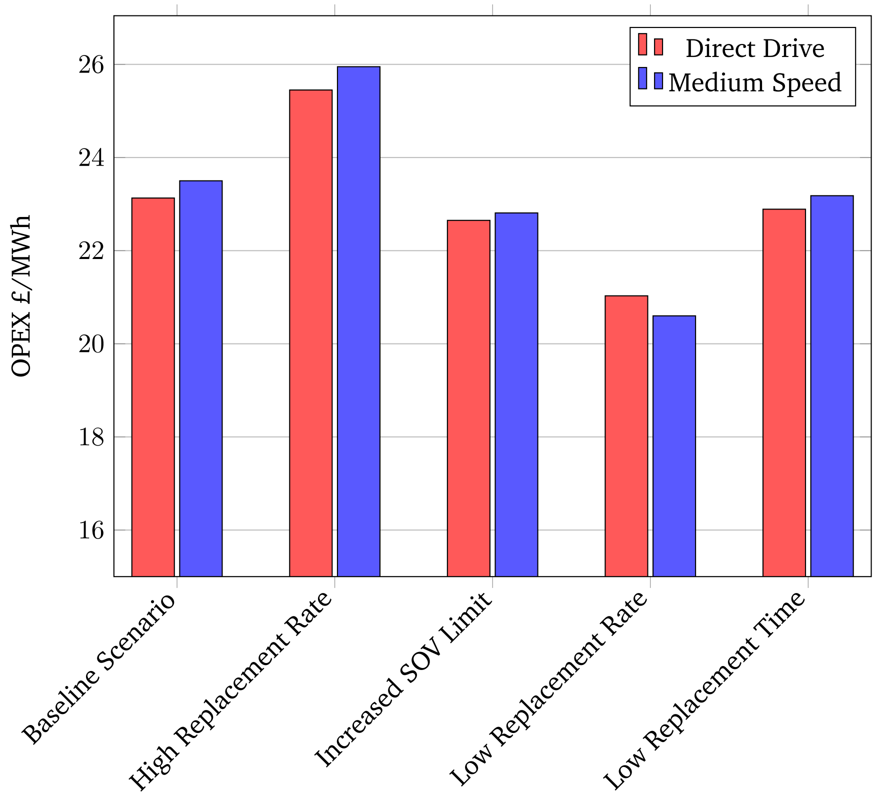


Figure 4.16: Sensitivity analysis results for Bowdun wind farm site. The total O&M costs of the baseline scenario are compared to the total O&M costs for each analysis.

scenario and high replacement rate scenario. These were input into the model for the generator, gearbox and rotor components.

Secondly, the accessibility for the SOV was increased. The Machair site was identified as the least accessible site which, after analysing the baseline scenario, had a clear impact on the overall costs of the wind farm. The SOV wave height limit input was adjusted from 2.5 m to 3.5 m to increase accessibility for maintenance trips.

Additionally, the repair times for the baseline scenario are based off [8], but a study by [31] uses the assumption that major replacements take under 47 hours to complete. Using this assumption, the repair times which exceeded 47 hours in the baseline scenario are set to 47 hours to simulate the lower replacement times. Finally, the repair costs were altered post processing. The repair costs were based on 10 MW turbine costs and scaled linearly by 1.5 times for the 15 MW turbines. In the sensitivity analyses the minor repair costs were scaled down to the original values, as it is not known that minor repairs would continue to increase in cost linearly with the turbine size. However, the results showed that altering the minor repair

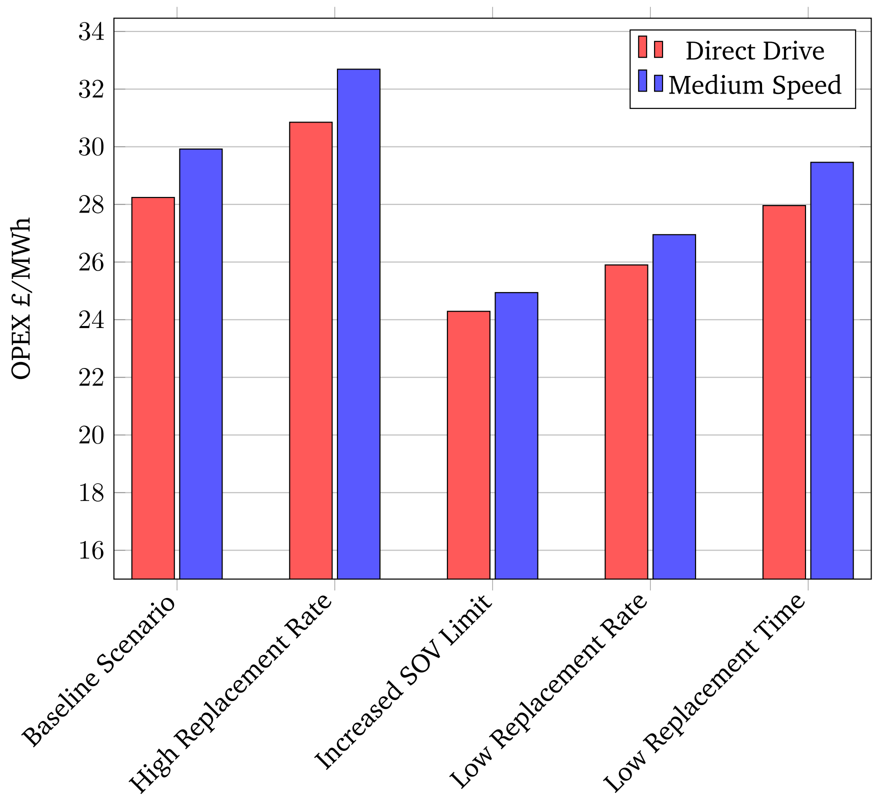


Figure 4.17: Sensitivity analysis results for Machair wind farm site. The total O&M costs of the baseline scenario are compared to the total O&M costs for each analysis.

costs in this manner, resulted in less than a 1 % change in total O&M costs for all sites and the two different configurations. Therefore, it has not been included in the following figures as the change in repair costs was deemed not significant compared to the other factors being studied.

These four sensitivity analyses results are plotted in Figures 4.15, 4.16, 4.17 against the baseline scenario. The figures graph the total O&M costs for each of the wind farm sites. To highlight the change in costs from the baseline scenario, Table 4.4 shows the % change for the three wind farm sites.

One of the main takeaways from Figure 4.15, is that the direct drive is the drive train configuration with lower costs for all cases except for the low replacement rate at the Caledonia wind farm. The same trend is seen for the Bowdun wind farm in Figure 4.16, where direct drive has higher costs than medium speed for the low replacement rate case. Table 4.4 indicates that for the higher replacement rate, the cost difference between the configurations becomes wider, with medium speed costs increasing more than the direct drive costs. Aside from the high replacement rate case, all other scenarios result in the reduction in the cost gap between the medium speed and direct drive case, which, in two scenarios resulted in the direct drive having higher cost than the medium speed. For the Machair site, the high replacement rate resulted in the medium speed still having higher costs than the direct drive as seen in Figure 4.17. However, in Table 4.4, it is clear that the % increase in costs compared to the baseline was 9.26 % for medium speed, only a slightly bigger increase than the 9.23 % for the direct drive.

Table 4.4: The % change in total operational costs from the baseline scenario for all three wind farm sites. Note that 'High Replacement Rate' values are a percentage increase in the operational costs whereas 'Low Replacement Rate','Increased SOV Limit' and 'Low Replacement Time' values are a % decrease in operational costs. 'DD' represents the Direct Drive turbine simulation and 'MS' represents the Medium Speed turbine simulation.

	Caledonia		Machair		Bowdun	
	DD	MS	DD	MS	DD	MS
Baseline Scenario	-	-	-	-	-	-
High Replacement Rate	9.16	10.31	9.23	9.26	10.00	10.43
Low Replacement Rate	9.43	12.09	8.27	9.93	9.07	12.31
Increased SOV Limit	1.72	2.38	14.00	16.64	2.08	2.92
Low Replacement Time	0.63	0.95	0.98	1.53	1.03	1.35

4.3.2.1 High Replacement Rate

In this analysis, the failure rates were increased to the 95th percentile estimate of the baseline scenario failure rates for the major components of the drive train for both configurations. This resulted in higher operational cost for all sites due to the increase on repairs required. Based on Table 4.4, the % increase in costs was relatively similar in all scenarios, between 9-10.5% increase in the operational costs compared to the baseline scenario. The high replacement rates resulted in a larger % increase in total operational costs for medium speed configuration for all three sites. For the Machair site, there was a similar % increase for the total operational costs for both configurations, therefore there was little change to the cost gap between turbines. This could be related to the accessibility issues at the site.

4.3.2.2 Low Replacement Rate

Lowering the failure rate for the major components of each turbine to the 5th percentile estimate from the baseline scenario failure rates resulted in a decrease in operational costs for all sites. The reduction in failures occurring leads to a reduction in downtime, which contributes to lower lost revenue, as well as lower transport costs, repair costs and staff costs. In all cases, there was a significant % reduction in costs compared to the baseline case both for medium speed and direct drive, as seen in Table 4.4. However, the % reduction in costs was larger for the medium speed turbines than the direct drive turbines, resulting in a smaller difference in cost between the configurations compared to the difference seen in the baseline scenario. The reason behind the larger % reduction for medium speed is that the failure rates for medium speed that were lowered also included the gearbox component which is a large source of failure for the turbine. Reducing the failure for this component, significantly reduces the overall cost, whereas the drive train for the direct drive does not have a gearbox and so does not benefit.

4.3.2.3 Increased SOV Limit

From Table 4.4, all scenarios had a reduction in the total operational cost compared to the baseline case when the SOV limit was increased from 2.5 m to 3.5 m. Increasing the accessibility of a site will reduce the lost revenue generated due to longer down times, explaining the reduction in cost seen for this analysis. In particular, the Machair site saw a large % reduction in operational costs which stems from the low accessibility the site had in the baseline scenario, so altering the SOV limit would benefit this site more than the other two site selections. In terms of configurations, the medium speed configuration saw a greater reduction in the total operations costs for all three sites when compared to the direct drive turbine case. Increasing the SOV wave height limit benefits medium speed turbines more as these turbines have higher failure rates and an increased number of major replacements required, due to the additional gearbox component. Therefore, increasing accessibility will reduce a greater amount of downtime for medium speed, that leads to the greater % difference in cost between the baseline scenario and the increased SOV limit scenario. In this analysis, the increased limit for SOV transfers results in a smaller total difference in operational costs between the configurations which narrows the gap between the two drive train types.

4.3.2.4 Low Replacement Time

Setting the maximum replacement time to 47 hours meant a number of components had a reduced time required for replacement. As a result, the operational cost for all sites was lowered when compared to the baseline scenario. The reduction in total operational costs was not as significant as the other sensitivity analyses, indicating that replacement time is not as significant a factor in the operational costs as the failure rates or the accessibility limits of the wind farm. There was, however, a larger % reduction in costs for the medium speed turbines than the direct drive turbines in this analysis. For all sites, the medium speed saw a larger reduction which stems again from the gearbox component. The gearbox replacement time in the baseline scenario is 231 hours, so lowering this time to 47 hours saw a larger reduction in the overall costs than the direct drive which does not avail of the gearbox component.

4.4 Discussion

4.4.1 Limitations of Analysis

Operations and maintenance modelling comes with a level of uncertainty, as with all models they are never a perfect representation of reality. This analysis also holds this uncertainty in certain aspects. Firstly, the reliability figures taken from [11] are based on two different graphs presented in the work, there may be a level of uncertainty in using the two different sources. It is also assumed that these failure rates can be applied to a 15 MW turbine which may not be the case. However, the assumption is that even with a 10 MW power curve the trend between configurations would not differ but the magnitude of the power produced and therefore the magnitude of the costs may change. As seen in Table 4.2, some of the generator failure rates are 0, this may be due to the fact the data is taken from a relatively young population of turbines which have not had failures, adding to the uncertainty of some of the results. The reliability data from Section 4.1.2 is taken from four different sources that may have categorised failure data in slightly different ways. Therefore, there is a possibility that the failure rates for the components for minor repair, major repair and major replacement may have some overlap. With raw data, there is often discrepancies within the work orders and distinguishing between reapir types can often be difficult if maintenance teams do not record logs in a consistent manner. Furthermore, the reliability figures from [13] for the generator and gearbox minor repair and major repair come from high speed geared machines and do not directly translate to direct drive and medium-speed turbines. Other model inputs are based on previous literature and industry knowledge, however, it is important to consider that some of the literature may be considered outdated and therefore the inputs may carry a level of uncertainty. This study assumes that the the only failure rates that change between the two configurations are the gearbox, generator and the main bearing. However, the work done by [14] suggest that this is not the case. The study showed that direct drive turbines had twice as many stops per year compared to the medium speed geared turbine. Further work would involve adjusting some of the direct drive components based on the work done by [14] to see the impact this would have on the cost gap between the configurations.

The model aims to capture the most important aspects of O&M modelling but due to the complex nature of the industry itself, it is impossible to accurately capture the variability of all the different aspects. In this analysis, some of the factors that may not be true to reality are:

1. Electricity prices. A fixed electricity price was assumed in this study for simplicity. However, under the UK's Contracts for Difference (CfD) scheme, many offshore wind farms receive a fixed strike price for electricity over a 15-year contract period. This mechanism protects against wholesale price volatility, effectively fixing revenue during the CfD term. Therefore, while market prices do fluctuate, the assumption of a fixed price is reasonable for CfD-backed projects but may not hold beyond the contract period or for projects without CfD support.

2. Future failure rates. Future failure rates are still unknown, therefore as time progresses the inputs used in this analysis may prove to not match to the operational data of future wind farms.

3. The supply chain. Finally, the supply chain is becoming a growing concern for a lot of wind energy experts who have stated that the expanding industry may not have the resources and vessels to support the growth. Supply chain bottle necks are not captured in this O&M model although this may be an important consideration in reality.

4.4.2 Key Takeaways

In the majority of cases, this study corroborates [21]'s finding that direct drive turbines outperform medium speed turbines in terms of availability and O&M costs. However, considering more recent failure rate estimates for offshore turbines leads to a narrower gap than that presented by [21], where accessibility is good. To summarise, the key findings to take away from this study are:

- The work done by [21] found the difference in availability between configurations, for a site 50 km from shore, to be roughly 0.7 %, with direct drive having the higher availability. The baseline case in this study finds the difference in availability to be 0.49 % and 0.54 % for Bowdun and Caledonia, which are also 50km from shore.
- Previously, in terms of cost, [21] found the absolute % difference in O&M costs for the two configurations to be 29.79 %, with direct drive having lower cost. Whereas, with the updated reliability data used in this analysis, the absolute % difference between the configurations for the baseline comparison were 1.58 %, 1.59 % and 5.78 % for Bowdun, Caledonia and Machair respectively.
- Medium speed turbines incur larger O&M costs if the site suffers from low accessibility, due to the increased amount of major replacements and higher overall failure rates. This was highlighted in this study through the Machair case study site.
- At a certain threshold of improved drive train reliability, there are scenarios where the medium speed turbines have lower operational costs than the direct drive turbines. These lower operational costs are dependent on the accessibility of the site. One way to tackle the higher costs incurred for medium speed turbines at low accessible sites, is by increasing the wave height limit for vessels to allow more transfers to occur. While the results from this analysis paint the medium speed turbines in a more favorable light than previous studies, it is important to note that the direction of industry is to select sites further from shore which tend to have lower accessibility.
- Similarly, if future generation turbines have higher failure rates than expected in equal measures across both drive train configurations, based on the analysis carried on in this study, the operational costs for the medium speed will be higher than the operational costs

of a direct drive turbine and more importantly, that cost gap between the configurations will be larger.

- One factor that did not seem to have as large an impact on the operational costs of a site is the replacement time for major components. Although, lower replacement time did lower costs and lower the cost gap between configurations, it had the least impact on costs when comparing to failure rates and accessibility limits.

Overall, the apparent reduction in cost gap between the two configurations seems to corroborate with the opinion held in industry. Many developers are still investing in two stage medium speed turbines and direct drive turbines which implies an understanding that both turbines are viable options for offshore wind farms. Whether this trend continues, remains to be seen as there is still a large uncertainty surrounding the operation of larger rated turbines for configurations.

4.5 Summary of Analysis

The primary objective of this chapter was to assess whether conclusions derived from prior reliability studies on smaller turbines could be extrapolated to the emerging generation of larger turbines, specifically those rated at 15 MW. Earlier research had established that direct drive turbines exhibited superior cost-effectiveness and higher availability compared to medium speed geared turbines. To investigate the applicability of these conclusions to larger turbines, the study synthesised new failure rate data for the generator, gearbox, and main bearing, simulating the operations and maintenance of a wind farm featuring 15 MW turbines. Utilising the Strath OW O&M modelling tool, simulations were conducted for three distinct case study wind farm sites, incorporating updated repair costs.

The simulations consistently demonstrated that direct drive turbines, across all three sites, yielded lower operational costs and higher availability in comparison to medium speed turbines. Notably, the cost gap between the two configurations was found to be narrower than in previous studies. Looking back at Chapter 3 there is some indication of this smaller gap between configurations in the previous analysis as well.

Following the establishment of a baseline scenario, sensitivity analyses were conducted to evaluate the influence of various inputs on overall costs. In scenarios with high replacement rates, costs increased by approximately 10%, whereas low replacement rates resulted in a 10% cost decrease for both turbine configurations across all sites. The impact of replacement rate variations was more pronounced on medium speed turbines, widening the cost gap between the two configurations. Accessibility proved critical, with low-accessibility sites favouring direct drive turbines due to their lower failure rates and reduced need for major replacements, minimising downtime.

The study's key takeaway was that, in situations where site accessibility is limited, direct drive turbines prove more economically viable for next-generation 15 MW turbines. However, with good accessibility, the cost gap between direct drive and medium speed configurations is reduced. Moreover, medium speed turbines might have lower operational costs than direct drive turbines if failure rates fall below a specific threshold, as indicated by the 5th percentile estimates from [10]. These findings hold significance for developers planning future wind farms with larger turbines, aiding them in selecting the optimal drive train for specific sites. There should be a continued focus on obtaining reliability data from larger operational turbines to enhance the accuracy of operations and maintenance modelling for offshore turbines. Additionally, obtaining updated failure rates for components beyond the generator, gearbox, and main bearing is suggested for a more comprehensive analysis and informed decision-making in turbine selection.

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Part II

Opportunistic Curtailment Model

Chapter 5

Developing an opportunistic maintenance model

Transport costs, supply chain bottlenecks, and large component repairs are all growing concerns for the industry. To counteract these changes, maintenance strategies are developed to optimise the practices of the wind farm and keep unexpected costs at a minimal level. These strategies have developed over the years as technology has matured. Effective maintenance strategies are critical to ensuring the reliability, efficiency, and long-term viability of offshore wind farms. Traditional maintenance approaches often rely on fixed schedules or reactive interventions, which can lead to either excessive costs or unplanned downtime. In recent years, research has looked closer on opportunistic maintenance, a relatively new strategy for offshore wind that has a broad definition. It aims to carry out maintenance when there is a predefined opportunity, in order to reduce operational costs.

In this chapter, a new opportunity is considered for offshore wind maintenance. There are multiple opportunistic maintenance models that have been developed over recent years, that investigate different factors and outline new opportunities, but, to the author's knowledge, the research has not yet considered all external factors. Curtailment, the deliberate reduction of power output due to grid constraints or market conditions, presents a unique opportunity in the offshore wind context. These periods, often considered economically unfavourable, can be strategically leveraged for maintenance activities to preventively maintain components during times when downtime costs are negligible due to grid payments. However, integrating curtailment into maintenance planning requires validation through modelling to determine it's viability as an opportunity.

This chapter begins by reviewing relevant literature on maintenance strategies in offshore wind, with a focus on corrective, preventive, condition-based and opportunistic approaches. It also examines the role of curtailment in wind power operations and the potential alignment of curtailment events with maintenance windows. Following the literature review, the chapter introduces the proposed opportunistic maintenance model, detailing the methodology used to incorporate curtailment data into maintenance scheduling. The goal is to develop a model that dynamically identifies optimal maintenance opportunities that align with periods of curtailed output, ultimately reducing cost and improving system availability.

5.1 Maintenance Strategies

Over the past century, maintenance strategies have evolved significantly, becoming increasingly efficient and sophisticated in response to technological advancements. Before the Second World War, maintenance was mainly corrective, or reactive, where components would run until failure. At this time, systems were a lot simpler and therefore downtime was not as costly as it is at present day, so there was little need for a formalised strategy. Moving into the 1950's, the idea of preventive maintenance was first formalised by the US Department of Defense, as aviation and military industries wanted to increase system reliability and needed to have a regimented scheduled maintenance plan in place [1]. Throughout the 1960's and 1970's, other industries such as manufacturing began to adopt scheduled maintenance practices to reduce the number of breakdowns in equipment. There was a significant rise in reliability engineering, as well as the practice of Total Productive Maintenance, developed in Japan, a holistic approach to maintain equipment in order to reduce overall costs [2]. The advent of monitoring technology in the 1980's-1990's also brought about the advent of predictive maintenance strategies and condition based maintenance to industry. With vibration analysis and thermal imaging providing information on machine components, maintenance could have a preventive schedule based on real time data. In the turn of the milennium until now, technology has continued to advance, meaning condition based monitioring has become more digitised [3, 4]. Artifical intelligence has created more advanced predictive analytics, digital twins and risk based maintenance. Optimisation tools have also led to opportunistic maintenance and hybrid strategies being favourable options in industry [5].

The continued development of maintenance strategies is essential as, although there has been development in the way systems can be monitored, the systems themselves have become more complex and costly to fix, so strategies need to accommodate for this complexity.

For offshore wind, the shift from reactive maintenance to condition-based monitoring has mirrored the broader industrial trend, but with unique challenges due to the offshore environment. In the early stages of offshore wind development, corrective maintenance was common, largely due to limited operational data and the relatively small scale of early wind farms. However, as turbines have grown in size and farms have moved farther from shore, access constraints, weather dependency, and higher repair costs have driven the adoption of preventive and predictive maintenance strategies.

More recently, digitalisation and remote monitoring systems have enabled more sophisticated condition-based maintenance approaches, including the use of SCADA data, vibration sensors, and machine learning algorithms to detect early signs of failure. At the same time, the growing scale and clustering of offshore assets has opened up new opportunities for opportunistic and fleet-level maintenance, where interventions are bundled based on logistics, weather windows, or vessel availability rather than fixed schedules.

Looking forward, the complexity of offshore wind systems, including floating platforms and hybrid energy hubs, will continue to drive innovation in maintenance. Strategies must evolve not only to improve reliability and reduce costs, but also to integrate with broader operational and energy market considerations.

Table 5.1 gives a summary of the most commonly used offshore wind maintenance strategies. The following subsections discuss the first three maintenance types in more detail along with reference to specific offshore wind implementation, and then Section 5.2 delves into further detail about opportunistic maintenance, the focus of the chapter.

Table 5.1: Overview of the most common maintenance strategies for offshore wind and some of their associated characteristics

Maintenance Type	Maintenance Trigger	Frequency	Initial Cost	Risk	Required Planning
Corrective	Fix on fail	Unpredictable	Low	High	Minimal
Preventive	Time based intervals	Regular	Moderate	Low	Moderate
Predictive/CBM	Data driven	As needed	High	Low	Moderate
Opportunistic	Opportunity dependent	As needed	Moderate	Low	Moderate

5.1.1 Corrrective Maintenance

Corrective maintenance (CM) refers to actions taken after a failure has occurred, aiming to restore equipment to operational condition. Often referred to as a "run-to-failure" strategy, it involves minimal upfront planning and is typically used for non-critical components or systems where unplanned downtime has limited impact. The literature generally acknowledges CM as the simplest and least resource-intensive maintenance approach in the short term, making it attractive in early project phases or in cost-sensitive environments.

However, its limitations are well documented. Corrective maintenance can lead to extended downtimes, higher operational costs, and increased risk of collateral damage if failures propagate to interconnected systems. In industries such as offshore wind or aviation, where access and repair logistics are complex, the reactive nature of CM can result in significant availability losses and cost inefficiencies.

Despite these drawbacks, CM remains a baseline strategy against which other approaches, such as preventive and predictive maintenance, are compared. It also plays a foundational role in hybrid or opportunistic maintenance schemes, where unplanned failures may trigger bundled maintenance actions. As such, while CM is rarely sufficient as a standalone approach in complex systems, it remains an essential component of broader maintenance planning frameworks.

5.1.2 Preventive Maintenance

Preventive maintenance (PM) involves scheduled interventions at predetermined intervals, based on time, usage cycles, or manufacturer recommendations, regardless of the actual condition of the component. The goal is to reduce the likelihood of failure by addressing potential issues before they manifest. This strategy is widely adopted in many industries due to its simplicity and predictability in scheduling and resource allocation.

The literature generally supports PM as a more proactive alternative to corrective maintenance, helping to minimise unplanned downtimes and extend the operational life of assets. However, it can also result in unnecessary maintenance actions, potentially replacing parts that still have usable life, thus increasing material costs and labour demands. Over-maintenance in offshore wind can be costly due to high costs associated with transport to the wind farm site.

Overall, PM strikes a balance between reliability and cost, making it suitable for systems where the risk of failure is moderate, and data availability or monitoring capabilities are limited.

It is also often used in regulatory-driven industries, where routine inspections are mandated regardless of component condition.

5.1.3 Predictive Maintenance

Predictive maintenance (PdM) uses real-time data and condition monitoring to anticipate failures before they occur. By tracking indicators such as vibration, temperature, oil quality, or electrical signals, PdM systems aim to intervene just-in-time, maximising component usage while minimising the risk of failure. Advances in machine learning and sensor technologies have significantly expanded the scope and accuracy of predictive models.

The literature highlights PdM as the most efficient of the traditional maintenance strategies in terms of balancing cost, downtime, and asset health. It enables data-driven decisions, reduces unnecessary interventions, and can improve overall system availability. However, the adoption of PdM faces several barriers, including high upfront investment, the need for robust data infrastructure, and specialised analytics capabilities.

PdM is especially valuable in industries where failures are costly and predictable patterns of degradation can be monitored. While it offers clear long-term benefits, it is often most effective when combined with other strategies, especially in complex operational environments where not all failure modes are predictable such as offshore wind.

5.2 Opportunistic Maintenance

The strategy of opportunistic maintenance was first developed in 1963 for maintaining a single component in a multi component system, with the simple strategy of performing maintenance on other components while repairing a down component [6]. Since 1963, variations of opportunistic maintenance strategies have been adopted in multiple industries such as aviation, manufacturing and power systems. The use of opportunistic maintenance in wind energy was first proposed by Besnard et al. [7] in 2009. Over the last 50 years, the definition of an 'opportunity' has been unclear, and varies from paper to paper. Some literature only considers opportunities that are internal to the wind farm, for example, corrective replacements whereas other literature considers external factors such as weather conditions [8]. In this work, we use the definition that 'an opportunity is a pre-determined event which triggers a decision to perform a predefined set of tasks', which follows the definition used in the work of Mc Morland et al. [9].

5.2.1 Early opportunistic models

Early strategies for opportunistic maintenance in the wind energy sector primarily concentrated on internal factors that could trigger additional maintenance actions. One of the simplest forms of opportunistic maintenance involves leveraging corrective maintenance events to conduct preventive maintenance on other components within the same wind turbine [10]. During a maintenance trip when a component is being replaced, if another component within the same turbine has reached a predetermined level of degradation, preventive maintenance can be performed on that component to extend its lifetime. It is advantageous to complete the preventive maintenance as the repair costs are less expensive than replacing the component if it breaks. If applied to offshore wind, this offers the other advantage of reducing the expensive travel costs associated with transiting to the offshore wind site on separate maintenance trips.

Tian et al. [11] extended this concept by allowing a corrective maintenance action in one turbine to trigger preventive maintenance activities across multiple turbines, provided that the components involved have exceeded the degradation thresholds set by the model. In such models, opportunistic triggers are typically defined based on the age or degradation level of components. When a component reaches its preventive maintenance threshold, the model may schedule maintenance. A multi-threshold approach is presented in [12], where the degree of repair is proportional to the level of degradation: older components receive more extensive maintenance, resulting in a greater reduction in their "effective age." Conversely, components just above the lower threshold undergo minor maintenance with limited age reduction.

In these studies, the act of repairing a component and returning it back to the condition it was when it was new is called perfect maintenance. Imperfect maintenance repairs the component by a certain degree but not back to its initial condition. Often, a Weibull distribution is utilised to simulate the failures of the wind turbine components, however, this requires well-characterised failure distributions, which can be problematic in practice due to the limited availability of empirical failure data.

More sophisticated models replace or augment age-based thresholds with condition-based monitoring (CBM) approaches. In such cases, thresholds are defined in terms of the probability of failure, offering a more dynamic and responsive maintenance framework [13]. For example, Su et al. [14] present a model incorporating both Weibull-distributed component failure times and a condition index, which reflects real-time component health using sensor data. This method provides a more accurate representation of the occurrence of failures as it provides a fuller assessment of component health.

Thresholds also do not need to be set at a fixed value, with dynamic thresholds being utilised in recent studies. A number of papers look at wind speeds to determine these dynamic thresholds [15, 16]. A higher threshold is set during high wind speeds, as it is less favourable to perform maintenance when energy production of the turbines is high. At lower wind speeds, these thresholds are lowered allowing more maintenance to occur during periods of lower production, thereby reducing the lost revenue costs. The most widely used thresholds in literature utilise the reliability, condition or age of the components to determine if maintenance should occur.

5.2.2 Specific offshore wind models

Table 5.2 outlines recent opportunistic maintenance models specific to offshore wind, the type of thresholds utilised in the model, if the opportunity is based on external triggers and if there are met-ocean limits implemented.

In terms of thresholds, the majority of offshore wind opportunistic models have thresholds centered around the age of the components or the reliablility of the components [12, 15, 16, 21, 22, 23, 24, 26, 28, 29, 30]. As previously stated, some models are based on the condition monitoring indicators to determine whether preventive maintneance is required [13, 17, 25]. Luo et al. [21] propose a component health-based framework, using health stages to prioritise maintenance and a Maintenance Priority Index (MPI) to sequence tasks. Although weather is acknowledged in the decision-making process, the model lacks detail on how weather limits or vessel types are explicitly factored into the scheduling process. It also assumes full availability of all required maintenance resources. Li et al. [18] is the only previous model that considers the cost benefit of the maintenance task to determine if opportunistic maintenance should occur. If the cost of conducting opportunistic maintenance is larger than the overall maintenance cost then the maintenance action is deemed inappropriate and does not continue. Li et al.[20] uses a risk based threshold that examines the likiehood of failure within the components to

Table 5.2: Literature for offshore wind opportunistic maintenance strategies

Authors	Thresholds	External Triggers	Met-ocean limits
[12]	Age Based	No	No
[13]	Condition Based	No	No
[17]	Condition Based	No	No
[18]	Cost Based	No	No
[19]	Hybrid	No	No
[20]	Risk Based	No	No
[21]	Reliability Based	No	Yes
[22]	Time Based	No	Yes
[23]	Age Based	No	Yes
[16]	Reliability Based	Weather Conditions	No
[24]	Age Based	Extreme Weather	No
[25]	Condition Based	Weather Conditions	No
[26]	Reliability Based	Joint Wind Farm	No
[27]	No Threshold	Weather Conditions	Yes
[28]	Time Based	Weather Conditions	Yes
[15]	Reliability Based	Weather Conditions	Yes
[29]	Relaibility Based	Weather Conditions	Yes
[30]	Reliability Based	Weather, Cable Failure	Yes
This Study	Age/Cost Based	Curtailment	Yes

detemine a risk priority number for components during inspections. The study focuses on opportunistic maintenance specific for floating wind, considering 26 components of the turbine as well as the floating substructure and its moorings. Consideration into grouping maintenance tasks appears in Xiang et al, who address the problem of resource allocation under dynamic conditions [19]. Their model employs a hybrid threshold approach that not only looks at the reliability of the components but also models the deterioration of the components and uses degradation thesholds to determine maintenance actions. Notably, the paper highlights that literature insufficiently accounts for maintenance resource preparation, such as technician availability and vessel allocation, gaps that their model aims to address.

In contrast to internal opportunities, external triggers remain underutilised in the literature. When external triggers are incorporated, they are most commonly based on weather conditions. Weather conditions is a blanket term used for where the literature has either defined maintenance as occurring during favourable weather or during periods of low energy production for the turbine, both of which involve low wind speeds and/or low wave heights. For instance, [25] propose a model that schedules maintenance during intermittent low wind periods, specifically when wind speeds drop below the turbine's cut-in threshold. In doing so, the maintenance carried out does not effect the downtime costs of the turbine. Equally some literature states that maintenance should be avoided in periods of high winds when energy production is at its highest. These periods may also coincide with inaccessible met ocean conditions, as high wind speeds may be accompanied by inoperable wave heights, compounding this logical strategy.

Tao et al. [26] propose a joint maintenance strategy across two wind farms, where maintenance decisions in one site can trigger opportunities in the other, an example of external interdependence. Si et al. [30] treat cable failures and weather as external triggers, justifying this approach by highlighting the disproportionate financial impact of cable faults, which can account for up to 80% of offshore wind farm losses. During cable failure, the wind turbines will be unable to produce electricity making it a favourable time to carry out any needed repairs. Extreme weather incidents are used to trigger maintenance in the model by Li et al., which is defined separately to the other weather conditions, as it defines the occurence of an extreme weather condition, such as lightning strike or typhoon, as an opportunity. If a wind turbine experiences an extreme weather incident and it requires maintenance, this is an opportunity to carry out other maintenance on other turbines [24].

Several papers touch on market-based external factors. For example, [22] and [28] consider curtailment events and electricity market prices, although they do not formally classify these as triggers for maintenance. Similarly, [16] examines external economic variables but does not define them as maintenance opportunities. McMorland et al. highlights in their review that the lack of consideration of market dynamics is a gap in the literature surrounding external factors for opportunistic maintenance [9].

Met-ocean limits, which define vessel accessibility to offshore sites based on weather conditions and vessel capabilities, are underrepresented in the literature. While some models include these constraints [15, 21, 22, 23, 27, 28, 29, 30], few differentiate between vessel types or provide detailed input modelling. For example, [23] considers wave height and wind speed as accessibility metrics but combines these into one metric which is not specific to different vessels, when, in reality, the decision to dispatch vessels is much more nuanced.

There is a clear lack of integration between external factors and opportunistic maintenance triggers in the existing literature. Many models fail to address offshore-specific constraints, such as transportation logistics, limited weather windows, and resource availability. Furthermore, insufficient attention is given to accessibility metrics, particularly in terms of vessel capabilities and scheduling. Beyond weather conditions, other potential external opportunities, such as market prices, curtailment, or inter-farm coordination, are rarely or never leveraged in existing models.

Finally, many strategies are disconnected from key industry performance indicators, such as lifetime cost, turbine availability, and energy production. Future research should aim to integrate external triggers more systematically, improve resource modelling, and align maintenance strategies with real-world operational KPIs to support more efficient and cost-effective offshore wind farm operation.

5.3 Curtailment

5.3.1 What is curtailment?

Curtailment, in this study, refers to the process of a generator reducing its energy output to an amount less than its actual energy production, usually at the request or benefit of the electricity grid [31, 32]. There are several reasons curtailment may occur, such as operational constraints, weak transmission infrastructure or system balancing challenges. The increase in renewable energy sources means a higher penetration of wind energy into the grid, that can cause issues if the grid is structurally weak. With the rate of new wind farm developments, many transmission networks have not been improved or expanded at a fast enough rate to handle the energy production increase. Curtailment is particularly relevant to wind energy, as wind is a source of variable generation. Variable generation can be hard to integrate into the grid due to the misalignment of supply and demand over a period of time, for example, wind energy might have peak production during the night time, but the demand at night time is often a lot lower. Due to the non-synchronous nature of wind energy generation, there can be problems with frequency control and system stability. High penetrations of non-synchronous generation can cause issues if the non-synchronous generators are unable to provide fast frequency response and synthetic inertia.

Grid instability can be partially solved by curtailment, as high levels of energy production may not match the demand from the end user and issues can arise with voltage control. As a preventive measure, non-synchronous generation can be curtailed or constrained by the required amount. The levels of curtailment for wind energy are increasing as a result, in particular for offshore wind. Curtailment is becoming a concern for national grids that have not got the necessary mechanisms to handle the increased energy production. From 2011 to 2021, the UK has experienced increased levels of curtailment, rising to around 4% of the total electricity generated in 2020, which is predicted to rise in future [33]. Figure 5.1 shows the rise in annual curtailment for the UK over this period. In 2020-2021, Scottish wind represented the vast majority of curtailment and associated costs, with 88% of the total wind curtailment volume. The total cost of wind curtailment for the UK was £507 million in 2021 [34]. Public acceptance of wind energy is key in the approval of future developments and curtailment is seen as a drawback of renewable energy generation. Carbon Tracker, a UK based think tank, non-profit organisation, has predicted that wind curtailment may cost households an additional £150 onto their annual energy bills in 2026, if electrical infrastructure does not improve [35]. Economically, curtailment leads to wasted clean energy, increased reliance on fossil fuels, and

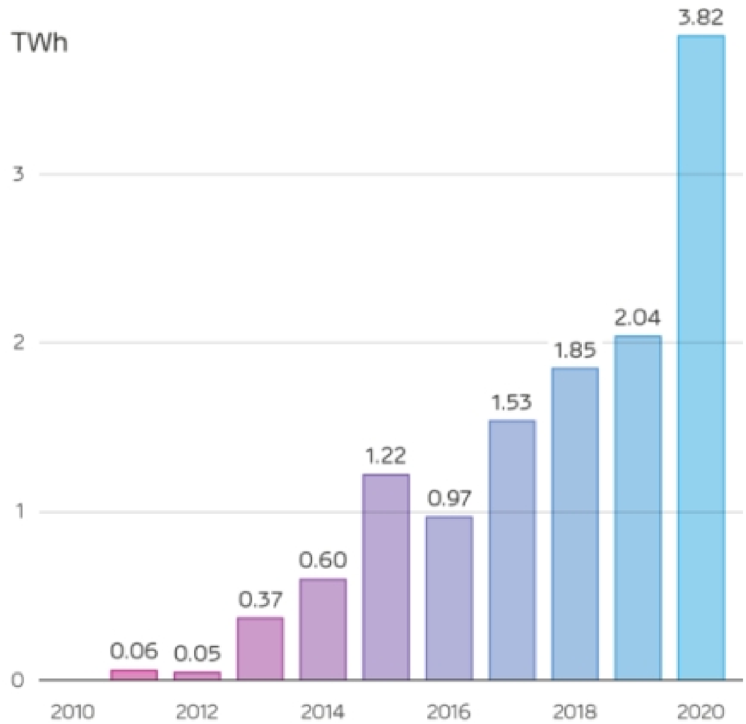

Figure 5.1: Annual curtailment for wind energy in TWh for the UK between 2010 to 2020. Figure sourced from [36].

unnecessary CO_2 emissions [37].

For wind farm operators, curtailment may not be favourable either. Despite the compensation provided by the national grid to curtail the turbines, there may still be disadvantages. The switching off of the turbines involves transitioning between the operational conditions. If this is done frequently, as a result of curtailment, the wind turbine may experience high fatigue loads on the tower and foundations [38]. Furthermore, high penetrations of wind energy also creates a risk of causing cannibalisation and driving down market prices, thereby reducing the compensation received by the wind farms [39].

5.3.2 What are the solutions?

There is a growing body of research exploring solutions to reduce the curtailment of renewable energy, especially as its share in the energy mix increases. These solutions span technological, economic, and behavioural strategies, each suited to different regional and infrastructural contexts. One key area of focus is energy storage, which addresses curtailment by absorbing excess generation and releasing it during periods of low supply. However, storage solutions vary in cost, scalability, and technical feasibility depending on the country or region. Denholm et al. [40] emphasise the importance of understanding the timescales over which storage is needed, as short-duration storage might help with intra-day balancing, whereas long-duration storage is more suitable for addressing seasonal imbalances.

Grid improvements and congestion management are also critical. For example, Germany's current congestion management scheme is projected to become increasingly costly. Schermeyer et al. [41] suggest a shift toward cost-based congestion management mechanisms, which could reduce overall system costs and better integrate renewables into the grid.

Another effective strategy involves increasing electricity consumption during times of high renewable generation, effectively shifting demand to match supply. This can include electric vehicle (EV) charging, water heating using heat pumps, or delay-tolerant tasks such as computation in data centers [42]. However, implementing such demand-side solutions requires the ability to accurately predict when and where curtailment will occur which is a complex challenge due to its intermittent nature. This calls for detailed, high-resolution models of curtailment both temporally and geographically. Yet, as highlighted in [43], gathering sufficient historical data with appropriate sampling frequency remains a complex task, given the uncertainties in user demand, price volatility, and forecasting limitations.

Some researchers have proposed behavioural and incentive-based solutions to shift consumer demand. One approach involves notifying consumers when curtailment is likely, prompting them to adjust their energy usage accordingly. Another model, the "fixed time slot" strategy, assigns consumers periods based on historical curtailment data and encourages energy use during those windows [37]. These demand-shifting solutions have been explored in real-world contexts. For instance, in Jordan, where renewable energy accounts for about 30% of the national mix, a systems-thinking approach was applied to use EVs as distributed storage. With 120,000 EVs in the country, a simulation showed that if 50% of them participated, curtailment could be significantly reduced in the base case scenario [37].

In China, notable progress has been made in recent years, though solutions vary by region. According to Chen et al. [44], the northwest of China has invested heavily in expanding power transmission infrastructure, while the northeast has implemented a peak-shaving auxiliary services market to mitigate curtailment. Li et al. [45] also examine China's broader strategy in balancing economic and technical aspects of curtailment reduction.

The cost of inaction is significant. According to a study by Laimon et al. [37], that focuses on Jordan, between 2.5% and 14% of renewable energy production could be curtailed by 2030, depending on the scenario. This level of curtailment could result in CO_2 emissions equivalent to 2–10% of the country's annual total and impose financial costs of up to $419 million.

Recently, there has been a significant shift in how the UK electricity system is managed, particularly with the introduction of more flexible market mechanisms by UK Power Networks. One such development is the opening of a day-ahead electricity market, which aims to increase participation in grid balancing by a wider range of stakeholders, including non-traditional actors such as electric vehicle (EV) owners and smaller energy producers [46].

The day-ahead market functions by using advanced forecasting models to predict electricity demand and generation patterns approximately 24 hours in advance. These forecasts allow the grid operator to schedule energy production and demand-side services in advance, improving the overall efficiency of the system. For generators, such as offshore wind farms, participation in the day-ahead market provides advance notice of expected curtailment events. This early warning enables operators to proactively adjust their maintenance schedules or production forecasts, potentially aligning downtime with periods of low or curtailed output, thus minimising financial losses.

In addition to this, the UK is also beginning to explore and support the development of secondary markets for curtailment management [47]. These secondary markets occur after the closure of the primary (day ahead) markets and are intended to create financial and operational mechanisms that can reallocate or trade curtailment obligations among participants, with the goal of reducing the total amount of curtailment across the network. For instance, a generator facing curtailment may be able to transfer or offset some of that curtailed output to another party who can absorb it or reduce their own demand accordingly. This adds an extra layer of market-based flexibility to the system and could, in the long term, help to improve the financial viability of intermittent renewable energy sources such as offshore wind.

Ultimately, no single solution will eliminate curtailment. A multi-faceted approach tailored to local infrastructure, market design, and consumer behaviour is needed. Ongoing innovation, data modelling, and policy reform will be crucial in addressing this complex challenge.

5.3.3 Can curtailment be beneficial?

Curtailment, while often seen as a drawback, can actually enhance grid stability and flexibility. Renewable energy sources can adjust output quickly, so curtailing them can help manage periods of excess generation and support system balancing. According to a recent NREL report, wind curtailment, for instance, gives other power plants more time to adjust during supply-demand imbalances and can keep renewables ready to ramp up when needed. Low levels of curtailment (under 3%) are considered a cost-effective way to add flexibility and may be more economical than investing heavily in infrastructure to avoid brief, infrequent curtailments [48]. There are other sources that note the curtailment may be of benefit to the energy sector and the economy as it encourages the development of energy storage devices which may provide system balances in the future and allow for flexible electricity loads [49, 50].

In this chapter, curtailment is used as a silver lining by using periods of curtailment as an external opportunity to complete maintenance. Curtailment periods could offer more frequent opportunity for maintenance action in comparison to waiting for the wind turbine to drop below cut in speed, as seen in previous literature, as often wind farms can be asked to shut off when they are within these operational limits. Based on the assumption that wind farm operators are paid by the grid to curtail their generation output, maintenance is essentially completed in “free downtime”, where there is no lost revenue cost that would be associated with standard maintenance procedures.

5.4 Research Question

There exists a notable gap in the current literature surrounding opportunistic maintenance strategies for offshore wind farms, specifically those that consider external factors beyond low wind speeds as triggers for maintenance. This research aims to address that gap by developing a novel operations and maintenance model that incorporates periods of curtailment, times when wind farms are required to limit production, as potential opportunities to perform preventive maintenance.

The proposed model simulates the lifetime operations of an offshore wind farm, integrating an opportunistic maintenance strategy that works in tandem with traditional internal failure triggers. Key features of the model include:

- Consideration of accessibility constraints, vessel selection, repair types, multiple failure thresholds, resource availability and transit times.
- Simulation of energy production, operational costs, and lost revenue due to downtime.
- A cost-benefit decision-making process to evaluate whether a maintenance trip during a curtailment period is economically justified.

Inspired by the structure of traditional O&M models ([51]) and opportunistic maintenance frameworks ([18]), this model offers a holistic approach that allows for detailed comparisons.

With global curtailment levels on the rise due to increasing grid constraints, this research explores the potential for curtailment to have a silver lining as an operational advantage. It aims to determine whether significant cost savings or efficiency gains can be achieved by scheduling maintenance during curtailment periods. The model is intended as a foundational tool that can be expanded to include other external economic or operational factors, such as market electricity prices, in future work. At the time of writing, the author is unaware of any existing models that specifically use curtailment periods as triggers for opportunistic maintenance in offshore wind farms.

To summarise, this research contributes to the field by:

- Developing a novel O&M model tailored for offshore wind farms.
- Proposing an opportunistic maintenance strategy that utilises curtailment events.

- Introducing an embedded cost-benefit mechanism to reduce unnecessary maintenance.
- Evaluating the full economic impact of this strategy, including operational, transport, repair, and lost revenue costs.

The research question for this chapter can be summarised as:
Can utilising curtailment periods as triggers for opportunistic maintenance reduce the total operational costs and increase efficiency in offshore wind farm maintenance strategies compared to traditional and alternative opportunistic approaches?

5.5 Methodology

In this section, an opportunistic maintenance strategy for an offshore wind farm is proposed, and a model to simulate the operations of the wind farm utilising this strategy is developed. Figure 5.2 gives an overview of the model. The model is set up as a Matlab live script to allow the user to alter any of the inputs for the model and obtain outputs regarding cost, energy production and availability without a requirement to understand the operations simulation itself. The model uses a Monte Carlo simulation and simulates the entire lifetime of the wind farm in hourly intervals.

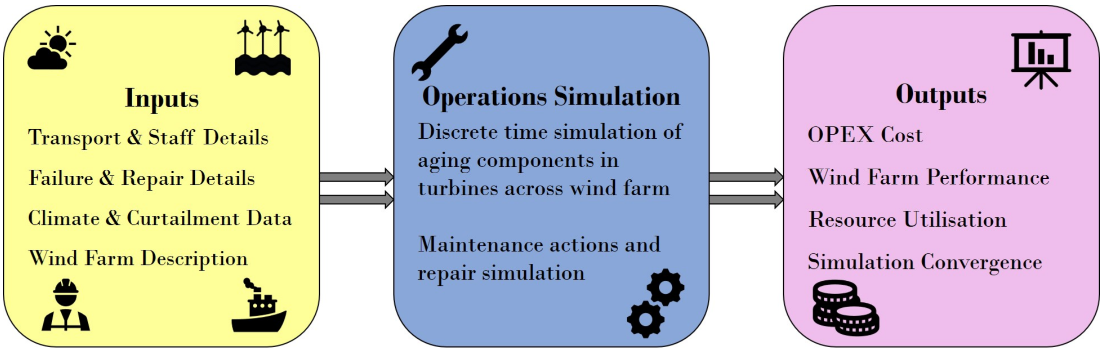

Figure 5.2: Overview of the model outlining the main inputs, the operations simulation and outputs.

The maintenance strategy encompasses both preventive maintenance action and corrective maintenance action, and is outlined as follows:

1. If a component within the wind farm fails, a corrective maintenance strategy is implemented and the component is replaced at the earliest opportunity, with the turbine out of operation until replacement is complete.

2. During a corrective replacement, other components within the turbine can have preventive repair take place if the component age falls between predetermined preventive thresholds.

3. During a period of curtailment, a component in the wind farm that is closest to it's predetermined failure age can be repaired subject to a cost benefit analysis.

The underlying assumption for this maintenance strategy lies with the availability and delivery of curtailment requests from the grid to the operator. The strategy works under the assumption that the curtailment data will be provided to the operator the day ahead of the maintenance in order to allow the maintenance teams enough time to determine if a maintenance trip is worthwhile and organise the logistics of the implementation of that trip. In reality, curtailment can occur unexpectedly or the wind farm operators may struggle to organise maintenance with short notice. This is noted as one of the limitations in the strategy. The model is specified for offshore wind and therefore, needs to address how the accessibility of the wind farm will impact maintenance. Any maintenance that occurs at the wind farm must abide to the accessibility limits of the vessels. If the climate conditions exceed the accessibility limits, maintenance is delayed until a suitable weather window appears. The thresholds chosen in the model are age based thresholds that trigger different degrees of preventive repair dependent on the age of the component in question but also rely on a cost benefit analysis to determine if the maintenance trip is beneficial to the overall wind farm operation. All maintenance actions abide by accessibility limits that are applied to each specific vessel and include both wind speed and wave height restrictions.

5.5.1 Inputs

The model requires the user to input a general description of the offshore wind farm. A wind farm contains P turbines, with J components in each turbine, that are identical throughout the wind farm. It is assumed that a component of the same type, for example a gearbox, has equal repair time and cost as other gearboxes within the wind farm. All component lifetimes, or mean time to failure (MTTF), are modelled with two parameter Weibull distribution with scale and shape parameters β and λ_s. Weibull distribution is chosen as it is a widely applicable method in literature and is flexible to different failure behaviours. Each component has an associated repair time and repair cost as well as a replacement time and cost. The probability density function for a component in the wind farm is given as :

$$f_{pj}(t) = \frac{\beta_{pj}}{\lambda_{s,pj}} \left(\frac{t}{\lambda_{s,pj}}\right)^{\beta_{pj}-1} e^{(-t/\lambda_{s,pj})^{\beta_{pj}}} \tag{5.1}$$

and the MTTF for each component can be found using :

$$MTTF_{pj} = \int_0^\infty t f_{pj}(t) dt \tag{5.2}$$

The degradation of each component will increase as the component ages until it reaches its failure age, at which point it requires replacement. The failure ages for each component are generated randomly by sampling the Weibull distribution based on the scale and shape parameters provided by the user. It is assumed in this analysis that component failure rates are time-invariant. Although the Weibull distribution is used to model failure behaviour, it is applied here with constant parameters across the simulation period and does not capture age-related degradation or early-life defects. This reflects the current limitations in available failure data, which are typically insufficient to robustly model non-constant hazard rates.

In parallel to the hourly lifetime operations, wind speed, wave height and curtailment time series are simulated. Using the input climate data, a time series is generated for the lifetime of the wind farm. The model requires at least one year of hourly wind speed measurements, u_r, and one year of significant wave height, h_{swh}, measurements. If the input data spans only one year but L is greater than a year, it is repeated L times to generate climate for the duration of the wind farm operations. For an input of 2 years and over, if the input data is shorter than L, the model randomly selects years from the input to construct the extended time series. This process ensures that the generated series reflects the variability of the input data while fulfilling the required time span. Wind speed and wave height are used to determine accessibility to the offshore wind site. Wind speed is also required to calculate energy production from the turbines. Using the wind power law as shown in Equation 5.3, nacelle height, z and measurement height, z_r as user inputs, a time series is created for the wind speed at sea level and the wind speed at the turbine nacelle. The model assumes that the two wind speed time series are uniform across the whole wind farm.

$$U(t) = u_r(t) \left(\frac{z}{z_r}\right)^\alpha \tag{5.3}$$

Similarly, the curtailment data is in a time series format. The user can input curtailment data in a hourly or half hourly format. The half hourly format is added as extra functionality for curtailment due to the structure of the electricity market in the UK, where data is provided in half hour measurements known as settlement periods. If the data is given in a half hourly format the model will average the two values within that hour period to allow an hourly time series to run concurrently with the wind speed and wave height. If the user does not have real curtailment data they can enter the time series as one's or zero's for every hour, where one indicates the wind farm is required to curtail and zero indicates operation as usual with no curtailment. Real curtailment data in the form $\%_{curtail}$, which is the % of the active installed capacity to be curtailed, allows the model to estimate the number of turbines that are being switched off during a time period based on the total number of turbines in the farm and the rated power of the turbines. This functionality is based on an assumption that the windfarm operator has the capacity to select which turbines to swtich off during curtailment rather than derating the whole wind farm to the curtailed amount required. The ideal power generation is calculated to determine what the generation would be if there was no downtime, this can then be used for the calculation of the curtailment payment provided by the grid operator. Using this information, more insight can be given regarding Key Performance Indicators (KPI's) such as energy production and availability. The user can decide the power rating of the turbine, P_{rating}, and enter a specific power curve for the model. The power curve must include a power output, $p(u)$, for each wind speed from cut in speed, u_{cut-in}, to cut out speed, $u_{cut-out}$, as well as stating the rated speed, u_{rated}. The calculation for the power produced at time t, $P(t)$, is shown in Equation 5.4. Equation 5.4 is then used to determine an estimate for the energy produced in the total wind farm and to determine lost generation caused by downtime.

$$P(t) = \begin{cases} 0, & u_{cut-in} \leq U(t) \\ U(t)p(u), & u_{cut-in} < U(t) \leq u_{cut-out} \\ 0, & U(t) > u_{cut-out} \end{cases} \tag{5.4}$$

In order to carry out any of the repairs or replacements on the turbines, vessels for transporting the maintenance staff and spare parts to the wind farm are required. The location from the nearest port to the offshore wind farm is needed to determine the transit time for the vessels, with the assumption that the port and wind farm are two points and a chosen vessel is travelling at a constant speed between the two points. The three vessel types that can be selected for repairs and replacements are: Crew Transfer Vessel (CTV), Service Operating Vessel (SOV) and Jack-Up Vessel (JUV). Accessibility limits for each of the vessels need to be specified: a maximum allowable significant wave height and maximum allowable wind speed. The average speed of the vessel is used to estimate the total amount of time in hours that is spent travelling to and from the wind farm, ϵ_v. The vessel fuel consumption, ρ_v, and unit cost of the fuel, C_f, is also required to calculate the total cost of fuel for each vessel as shown in Equation 5.5. All of the vessel costs are assumed to be one off costs which are totalled at the end of the wind farm lifetime. If a vessel is utilised for a maintenance trip they have an associated daily charter cost, C_{CTV}, C_{SOV} and C_{JUV}. For the JUV, a mobilisation period, t_{mob}, is included, due to the variability of the availability of these vessels.

$$C_{\text{fuel}} = \sum_{v=\text{CTV, SOV, JUV}} C_{f,v}\, \rho_v\, \epsilon_v \tag{5.5}$$

There is an associated mobilisation cost for this period, C_{mob}. Along with vessel specifications, the user must select the number of CTV's within the wind farm's fleet and the total number of personnel that can carry out the maintenance at the wind farm. With each vessel the user selects the number of technicians that can transit on the boat safely to the wind turbines as well as selecting the number of technicians required to carry out each maintenance task. For example, if the j^{th} component requires minor repair which needs 4 technicians and a CTV, as long as the CTV technician limit is 4 or greater, then maintenance can be carried out. For each componenet repair type, namely minor repair, major repair and replacement, the vessel required to complete the specific maintenance task must be determined by the user.

Simulation time for the model is dependent on the number of iterations chosen by the user. The higher the number of simulations the greater the convergence achieved in the outputs.

5.5.2 Operations Simulation

Figure 5.3 and Figure 5.4 represent the decision process for maintenance at the wind farm. Figure 5.3 illustrates each time step within the simulation, focusing on the corrective replacement element of the maintenance strategy. The step 'Curtailment Repair Check' is then expanded upon in Figure 5.4. Similarly, in Figure 5.4, the first step is 'Corrective Repair Check' which represents all of the previous steps that have been shown in Figure 5.3. Initially, component lifetimes are generated for each component in the wind farm using a random Weibull distribution function based on the input scale and shape parameters. The component lifetime is equal to the failure age of the component. During each time step, the age of a component increases by one, only if the turbine is operational. If there is component failure, it is assumed that the

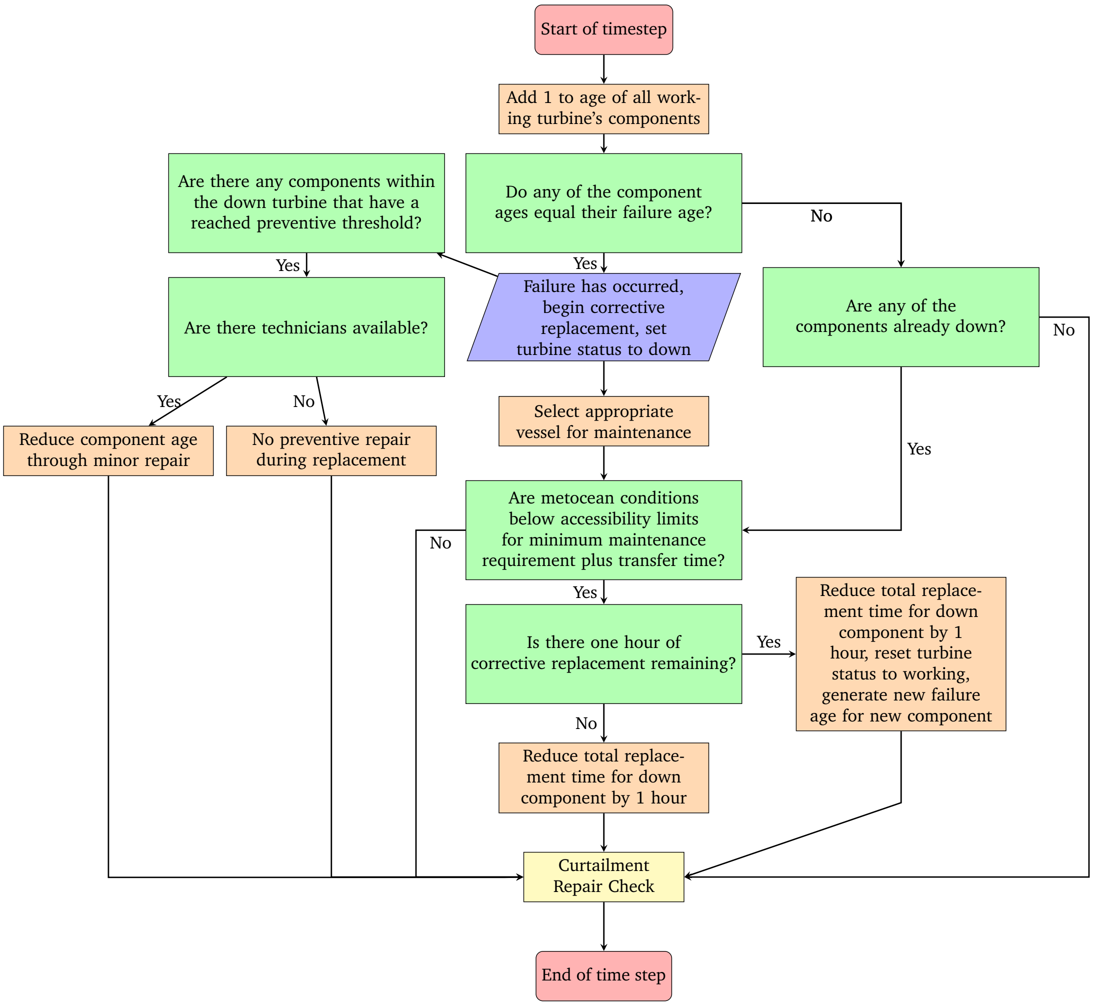

Figure 5.3: Decision flow chart for corrective replacement induced opportunistic maintenance at each timestep in the model simulation

turbine of the failed component does not age during the period of repair or replacement, as the turbine is shut down during maintenance activities. The model continually monitors component ages, checking whether any component's age reaches any the predetermined failure age, indicating the need for replacement. If a corrective replacement is required, an appropriate vessel is allocated for the replacement and the total time for the replacement is set based on the user inputs. Simultaneously, the components in the turbine containing the down component are surveyed to see if any meet the predetermined preventive thresholds. The thresholds are a fraction of the component's failure age and will determine the level of maintenance that will be required. If a component age falls within the range x_1 and x_2 then minor repair will take place. A component age that is above x_1 but below the components failure age will undergo major

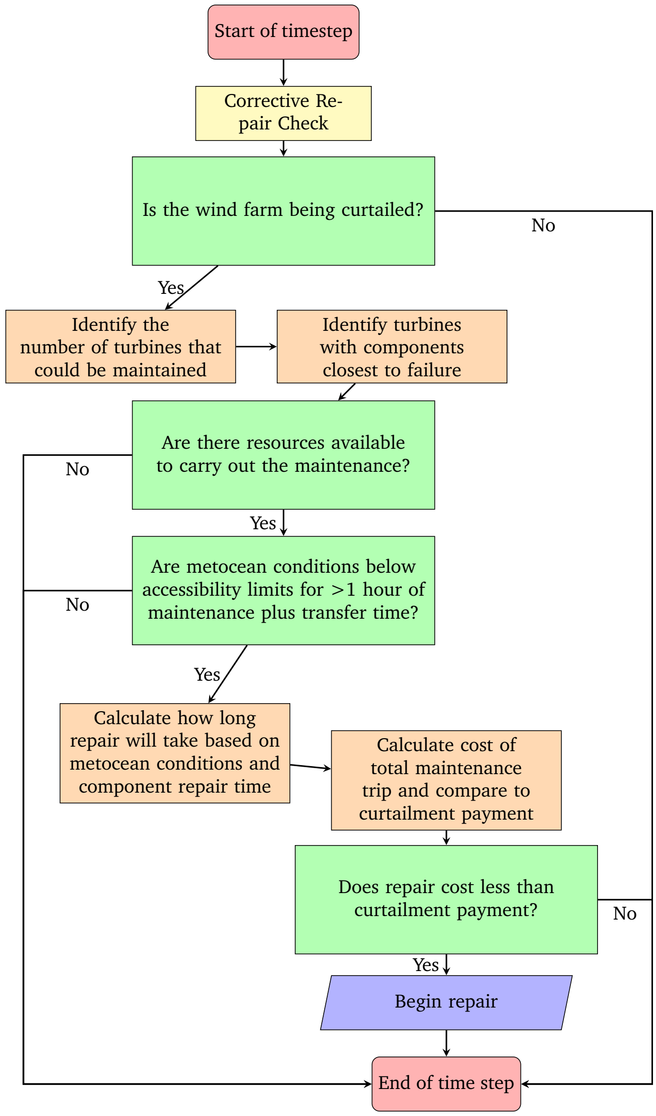

Figure 5.4: Decision flow chart for curtailment induced opportunistic maintenance at each timestep in the model simulation

repair. The categorisation of minor repair, major repair and replacement is based on the costs of each maintenance action, following the work in [52]. The preventive maintenance carried out results in a reduction of the component's age by a ratio of q $(0 \leq q \leq 1)$ as shown in Equation 5.6. The value of q is dependent on the quality of the maintenance, the more effective the maintenance the larger the reduction of the components age. If the maintenance is a perfect action, q is set to 1, thereby resetting the component's age to 0 or 'good as new'. The values of the thresholds and the ratio of the quality of maintenance carried out is up to the user. The assumption is that the preventive repair times are always shorter than the replacement times and that the preventive threshold for major repair is always a higher threshold than the preventive threshold for minor repair. Both corrective and preventive maintenance only occur if there is a sufficient weather window that allows the vessel to access to the turbine and complete transit to and from the port. If there is a mobilisation period associated with the vessel, maintenance can only be completed once mobilisation has ended. After replacement is complete, the model generates a new failure age for the component and sets the turbine status to working.

$$TA_{new,pj} = \begin{cases} TA_{old,pj}(1-q_1), & x_1 \leq TA_{old,pj} < F_{pj} \\ TA_{old,pj}(1-q_2), & x_2 < TA_{old,pj} < x_1 \end{cases} \tag{5.6}$$

During each time step, a curtailment maintenance check also takes place after the corrective check, as seen in Figure 5.4. If there is no curtailment the model moves onto the next time step. If there is curtailment, the number of turbines that can be maintained during an identified curtailment period is based on the % of the wind farm that is being turned off. If 20% of the wind farm is requested to be curtailed, the model identifies the 20% of turbines that have components closest to failure age and selects those turbines to be switched off for the curtailed period. These identified 'worst' components have a maintenance order created and are now subject to a cost benefit analysis, vessel availability and technician availability check. Starting with the component closest to failure, the model will check if there are enough technicians in the pool to carry out the repair and if there is a vessel available. It will complete this check for the next worst component and so on until there are no technicians or no boats left to complete any other maintenance action within this time step.

For each of the selected components, the model will check the weather window for the preventive repair and if the window is sufficient for a repair it will calculate the total time the repair will take based on each component repair time and the met-ocean conditions. A cost benefit analysis of the maintenance trip is required to determine if the cost of sending the vessel out to repair the component is larger than the benefit of reducing the turbine downtime. The cost of the trip is shown in Equation 5.7:

$$C_{maintenance_{pj}} = \sum_{t=t_a}^{t_b} C(t)_{transport_{pj}} + C_{repair_{pj}} + C_{elec} \sum_{t=t_a}^{t_b} G(t)_{pj} \tag{5.7}$$

where $C_{maintenance_{pj}}$ is the cost of the maintenance trip for the component, $C(t)_{transport_{pj}}$ is the transport cost, $C_{repair_{pj}}$ is the repair cost, C_{elec} is the fixed electricity price, t_a is the start of the maintenance trip, t_b is the end of the maintenance trip, $G(t)_{pj}$ is the lost power production in that period. The calculated maintenance cost is the sum of the transport costs for the trip, the cost of repair for the trip and the lost production cost for the duration of the maintenance action, which uses the potential energy generation multiplied by the electricity price. Equation 5.7 is compared against the total reimbursement payment given by the grid operator to the wind farm, as shown in Equation 5.8. It is assumed that the price of electricity is fixed and that the compensation given to the wind farm is equal to the amount of revenue that would have been generated in regular operation. During the maintenance trip, if the grid does not require the turbines to be curtailed then the turbines will not be operational as they are undergoing repair and are assumed to be shut down until repair is complete. The reimbursement payment only takes into account the time during the repair when curtailment is requested and similarly, the lost generation in Equation 5.7 does not include curtailment. The remaining time is classified as downtime.

$$R_{curtail} = C_{elec} \sum_{t=t_a}^{t_b} G(t)_{curtail} \tag{5.8}$$

If the maintenance trip costs more than the compensation that is received by the wind farm for curtailment during the period of the maintenance trip then the trip will not occur. If the compensation is more than the cost of the trip, the trip is deemed beneficial and the maintenance action begins. If multiple components are being repaired, the cost benefit equation will also consider the total cost of any previous maintenance trips within that timestep that have passed the cost benefit analysis. For example, the wind farm has been curtailed and there are enough resources to carry out repairs on component X, component Y and component Z, where X is the closest to its failure age, followed by Y and then Z. The wind farm payment, $R_{curtail}$, to switch off is £5000, the cost of the maintenance trip, C_{xj}, for component X is £3000, component Y, C_{yj}, is £2000 and component Z, C_{zj}, is £200. The model will proceed with maintenance for component X and component Y but will not carry out maintenance on component Z, even though it is the cheapest repair to carry out. The reason for this is that the model prioritises the components closer to failure age first and also determines that it costs more to repair component Z than is being paid to the wind farm in constraint payments. The cost benefit analysis is a simple approach, used as an example, and can be modified and extended in further work but this framework acts as a starting point for research to start introducing more cost focused decisions in opportunistic maintenance.

The degree of repair that the component undergoes during periods of curtailment follows the same methodology as the preventive repair that takes place during corrective action. The thresholds for repair are the same and the reduction in component age remains the same throughout the model.

5.5.3 Outputs

The wind farm's key performance indicators are it's energy production, time based availability and energy based availability. KPI's are output for each simulation and, in post process, displayed as yearly averages and total life time averages. Equation 5.9 shows the total energy produced in a wind farm in its lifetime, where $G(t)_{down,pj}$ is the potential energy not generated due to downtime.

$$E_{prod} = I \sum_{t=0}^{T} (G(t) - G(t)_{down}) \tag{5.9}$$

The energy based availability of the wind farm is calculated using Equation 5.10:

$$A_E = \frac{E_{prod}}{E_{total}} \times 100 \tag{5.10}$$

where the total energy produced in the wind farm, E_{prod} is divided by the total potential energy if there was no downtime during the lifetime, E_{total}. The calculation does not consider curtailment as an outage. The time based availability of the wind farm, as seen in Equation 5.11, is time the turbines were available over the total time of the wind farm lifetime. Curtailment is also not included in this calculation, downtime only considers forced outages. Although time based availability is easier to determine as it does not require a calculation of the energy generated at each hour it does have some shortcomings. If a turbine is experiencing downtime, it is considered unavailable, however, the wind speed at that instance in time could be above or below cut in speed, meaning that if the turbine was operational it would not be generating electricity. In that respect, energy based availability can often be a favourable metric if wind speeds and expected generation is known.

$$A_t = \frac{T - \sum_{t=0}^{T} K(t)_{down}}{T} \times 100 \tag{5.11}$$

The OPEX outputs from the model contain a breakdown of the four main cost contributors: $C_{lostrevenue}$, $C_{transport}$, C_{staff} and C_{repair}. The lost revenue cost is the amount of money that could have been made if the turbines had been operational at all times but due to downtime that potential revenue was lost.

$$C_{lostrevenue} = C_{elec} \sum_{t=0}^{T} G(t)_{down} \tag{5.12}$$

The transport costs for the wind farm are the charter rates and mobilisation costs of the different vessels for the life time of the wind farm. Fuel costs are also summed for each vessel and added to the total transport cost.

$$C_{transport} = C_{CTV} + C_{SOV} + C_{Jackup} + C_{mob} + C_{fuel} \tag{5.13}$$

The repair cost is made up of two main costs, the cost of a new component due to a replacement and the cost of repairing a component preventively either during corrective periods or during a curtailment period.

$$C_{repair} = C_{replace} + C_{prevent} \tag{5.14}$$

The staff costs are calculated by multiplying the number of technicians employed by the wind farm by the salary of the technicians by the number of years in the wind farm lifetime. The staff costs are rough estimates and the assumption is that every technician will have the same salary which is often not the case as different maintenance tasks require a varying level of skill and expertise.

$$C_{staff} = C_{tech} \times L \times N_{tech} \tag{5.15}$$

The total OPEX costs encompass all the above components. The model normalises the costs and outputs an average OPEX cost in a £/MWh format to allow for an easy comparison with other literature. The direct OPEX cost differs from the total, as it does not consider lost revenue costs, this is also normalised in a £/MWh format.

$$OPEX_{total} = C_{lostrevenue} + C_{transport} + C_{repair} + C_{staff} \tag{5.16}$$

$$OPEX_{direct} = C_{transport} + C_{repair} + C_{staff} \tag{5.17}$$

Finally, to ensure the model outputs are not random and variable, Equation 5.18 determines the relative standard error of any chosen key performance indicator in the model. Relative standard error is used in statistics to determine the precision of an estimate by dividing the standard error by the mean of the value. In the model, this will act as a measure of convergence in the results with the theory that more simulations runs will reduce the relative standard error. It is up to the user to determine the level of desired convergence they require for the results which may differ depending on the KPI and the user requirement.

$$X_{KPI} = \frac{\sigma_{KPI}}{\sqrt{N} \times \overline{KPI}} \tag{5.18}$$

5.6 Discussion

This chapter has outlined the development of an opportunistic maintenance model that utilises periods of curtailment for the wind farm as an opportunity to complete maintenance on wind farm turbine components. The model simulates the whole lifetime of the wind farm and produces output metrics such as OPEX, power production and availability. To assess the effectiveness of this maintenance strategy, preventative thresholds relating to the components lifetime are used, similar to previous research. A cost benefit analysis is introduced that determines if the cost of carrying out a maintenance trip is more than the cost incentive given to the wind farm during curtailment, in which case the decision is made not to carry out maintenance and vice versa. The model also utilises traditional opportunistic maintenance strategies, wherein components can be preventatively maintained if a component within the same turbine requires replacement, provided they meet the maintenance thresholds.

Monte Carlo simulations were used to generate lifetime cost estimates, enabling the model to account for uncertainty in key variables such as failure timing, repair costs, and energy output. By running numerous iterations with randomly sampled inputs, the approach provides a distribution of possible outcomes rather than a single estimate, supporting more robust and risk-aware decision-making. The model incorporates preventive maintenance thresholds based on component lifetimes, adopting Weibull distributions to simulate failure behavior. The Weibull distribution was chosen due to its flexibility in modelling varying failure rates over time ideal for components exhibiting both infant mortality and wear-out failures. This probabilistic approach enables the system to estimate the likelihood of component failure and schedule maintenance before failures occur, thereby reducing corrective interventions.

Cost-benefit logic underpins the decision-making process. Maintenance is only scheduled during curtailment periods if the compensation received for curtailed power exceeds the cost of the maintenance trip. The model also allows for intra-turbine opportunistic maintenance, if one component fails or is due for replacement, other components within the same turbine may be serviced simultaneously if they meet preventive thresholds.

5.6.1 Assumptions and Limitations

A number of assumptions have been made to simplify model complexity and achieve faster simulation times:

- Curtailment Compensation: The model assumes a fixed compensation rate during curtailment. In reality, this varies from country to country with each jurisdiction utilising it's own mechanisms and incentives. For instance, in Spain, real-time curtailment is compensated at 15% of the wholesale electricity price, calculated using forecasted wind generation but in the UK, Contracts for Difference (CfDs) and constraint payments are commonly used incentives. This limits the model's applicability to certain regulatory environments but could be altered in the cost benefit analysis if wind farms outside of the UK were being simulated.

- Market Prices: Electricity prices are held constant throughout the simulation. In reality, market prices are dynamic and play a crucial role in determining the profitability of curtailment-based maintenance. Due to the difficulty of sourcing high-resolution electricity price time series, this element is not currently modeled, but could offer another avenue of external opportunistic triggers by looking at periods of time when there is negative pricing.

- Curtailment Bidding Mechanism: While the UK energy market provides a bidding mechanism process for curtailment, where generators are compensated for reducing output, this mechanism has been omitted. Including it would require a more detailed market simulation, which is beyond the scope of this model but warrants future exploration.

- Single-Component Repair Assumption: The model currently assumes one maintenance vessel performs a single repair on one turbine component per curtailment period. In practice, routing strategies could allow vessels to service multiple turbines in a single trip, offering potential cost reductions. Incorporating such route optimisation to the model would give the model higher fidelity.

- Spare Parts Inventory: No limits are imposed on spare part inventory as seen with other literature. While this reduces simulation complexity, it doesn't mirror the reality in industry fully, especially as offshore wind scales up and supply chain bottlenecks become more common. Future models should introduce constraints on material resources.

- Instantaneous Maintenance Assumption: It is assumed that maintenance begins as soon as the vessel arrives and takes exactly one hour, with seamless transitions between day and night technicians. In reality, setup times, shift changes, and working hour restrictions (e.g., daylight-only operations) influence maintenance duration.

- Information Supply: The methodology is underpinned by the assumption that the wind farm will be informed of the periods of time they are required to curtail with enough time in advance to prepare for maintenance action. In reality, curtailment can occur unexpectedly or the wind farm operators may struggle to organise maintenance with short notice. However, if the maintenance strategy proved to be effective in terms of cost reductions then more emphasis could be put towards training the maintenance teams for fast response maintenance trips. It also assumes that the information given to the operators from the condition monitoring systems within the turbines is accurate.

- Threshold selection: Age based thresholds are used for the model as they are simple to implement in comparison to reliability based thresholds which requires large volumes of difficult to obtain condition monitoring data. The limitation from this method is the age thresholds remain constant regardless of the component type whereas in reality, priority may be given to more expensive or less reliable components to have preventive maintenance carried out much earlier in their component lifetime.

5.7 Chapter Summary

This chapter has presented a methodology for a novel opportunistic maintenance model that schedules turbine component repairs during curtailment periods in offshore wind farms alongside more traditional opportunistic strategies where preventive maintenance can be triggered by corrective replacements. The model simulates the operational lifetime of the wind farm, using Weibull-distributed failure behavior, climate time series, curtailment time series, vessel logistics and cost inputs to determine the overall lifetime OPEX, availability and power production. Age based thresholds for components are selected to determine when components require preventive maintenance to avoid costly corrective replacements, this preventive maintenance can be carried out in two distinct "opportunities". Using a cost benefit analysis, maintenance trips can be carried out during periods of curtailment when the wind farms avails of "free downtime" due to the constraint payments given by the national grid to the wind farm operator. Future development of the model should focus on several key enhancement including dynamic electricity pricing, to model market behaviour more accurately, route optimisation, to allow the grouping of maintenance tasks, and application of the model to countries that have different curtailment policies to make the model more valuable on in a global context. A more comprehensive cost benefit analysis to ascertain the full benefit from preventatively maintaining a component in terms of its life extension and the extra production gained from that extension would be an interesting future development for the model also. Overall, this methodology serves as a foundation for simulating curtailment-based maintenance strategies and highlights several opportunities for future refinement toward more realistic offshore wind O&M modelling.

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Chapter 6

Validating the opportunistic maintenance model

This chapter presents a practical application of the opportunistic maintenance model developed in Chapter 5, by implementing it in real-world case studies of offshore wind farms. The aim is to evaluate the effectiveness and practical viability of the proposed maintenance strategy, particularly in utilising periods of curtailment as opportunities to perform maintenance tasks. By doing so, the chapter seeks to benchmark the model under realistic operational conditions and explore its potential to reduce maintenance costs and improve overall wind farm availability.

Two offshore wind farms have been selected for this analysis: the Beatrice Wind Farm, located off the northeast coast of Scotland, and the Walney Offshore Wind Farm, situated in the Irish Sea off the coast of Cumbria, England. These sites have been specifically chosen due to their contrasting curtailment profiles. The significant variation in curtailment behavior between the two wind farms provides a valuable basis for assessing how different levels and patterns of curtailment affect the performance and cost-effectiveness of the maintenance strategy. This contrast allows for a better evaluation of whether leveraging curtailment events can lead to improvements in operational efficiency.

The chapter is structured as follows. First, the methodology for the case studies in terms of the input parameters is outlined. Then, the opportunistic maintenance model is implemented for each of the two wind farms using historical curtailment data. The model's performance is assessed by comparing three distinct maintenance strategies:

- V: A strategy that explicitly incorporates curtailment events as opportunities for conducting maintenance.

- V1: A basic corrective maintenance strategy, where maintenance is only performed after failure.

- V2: An opportunistic maintenance strategy that does not consider curtailment.

The end of each case study has several sensitivity analyses to examine how variations in key model inputs, such as failure distributions, distance from shore, turbine size, and availability of maintenance crew can impact the overall cost of maintenance and wind farm availability. This analysis provides a deeper understanding of the robustness and adaptability of the proposed strategy under different assumptions and scenarios. Following the individual case studies, a comparative analysis is carried out to assess if the amount of curtailment experienced at each wind farm has a direct impact on the operational costs of the wind farm or if other factors carry more weight on the overall performance.

Through these investigations, the chapter aims to offer a comprehensive evaluation of the proposed model's real-world applicability and highlight the potential for integrating curtailment based opportunistic maintenance into offshore wind farm operations.

6.1 Methodology

To understand the effectiveness of the curtailment strategy it must be compared against strategies that do not use curtailment as an opportunity. Therefore, the curtailment model (V) was altered to make two separate versions; the first version (V1) has only a corrective maintenance strategy, where a component is only fixed once it has broken. The second version (V2) carries out maintenance so that during a corrective repair, other components within the turbine can have preventive repair take place if the component age falls between predetermined preventive thresholds. V encompasses both V1 and V2 along with the opportunity to complete maintenance during periods of curtailment. Aside from maintenance strategy, in each case study, every other aspect of the models are kept consistent in terms of inputs, outputs and general structure to ensure the fairest comparison.

Each turbine is assumed to have only six components; gearbox, control system, blades, generator, pitch system and yaw system. More components can be included in future studies but lack of failure distribution data has limited this study to only six components per turbine.

The failure distributions of these components can be seen in Table 6.1 and are taken from the work by [4]. Repair and replacement times along with their associated costs are also included in Table 6.1. Inputs regarding transport are found in Table 6.2. All inputs for times, costs and transport are sourced from the previous studies carried out in [5, 6, 7]. Other costs that are fixed throughout the study are electricity price, set at £50 /MWh and the technician salary, set at £40,000.

Table 6.1: Repair inputs for Beatrice and Walney case studies

Component	$C_{prevent}$ **(£)**	t_{repair} **(h)**	$C_{replace}$ **(£)**	$t_{replace}$ **(h)**	β	λ_s
Gearbox	2697	4	1218000	231	2400	3
Control System	6525	7	435000	10	1750	2
Blades	1357	9	12516	21	3000	2
Generator	2697	6	1740000	81	2400	3
Pitch System	2610	9	174000	25	1500	2
Yaw System	3313	5	295800	49	1800	3

Table 6.2: Transport inputs for Beatrice and Walney case studies

Vessel	**Input**	**Value**	**Unit**
CTV	ω_{CTV}	15	m/s
	H_{CTV}	1.5	m
	C_{CTV}	1980	£
	ρ	0.4	m^3/h
SOV	ω_{SOV}	12	m/s
	H_{SOV}	3	m
	C_{SOV}	30000	£
	ρ	0.7	m^3/h
Jack Up	t_{mob}	60	days
	C_{mob}	252000	£
	C_{JackUp}	360000	£
	ρ	1.2	m^3/h

Curtailment data used in this study was sourced from publicly available datasets provided by Elexon, the central body responsible for managing the wholesale electricity market in Great Britain [1]. These datasets contain half-hourly (settlement period) readings for all registered energy generators in the UK and form the basis of the curtailment analysis conducted here. Specifically, the data includes Bid Acceptance Volumes (BAVs), which reflect the volume of energy curtailment accepted by the system operator from each Balancing Mechanism Unit (BMU) during a given settlement period. Each BMU represents a discrete controllable generating entity within the Balancing Mechanism, and for wind farms, a single installation may be composed of multiple BMUs. These BMUs often correspond to distinct turbine arrays or development phases within the same wind farm, which were connected to the grid at different times.

In addition to BAVs, the dataset also includes Maximum Export Limit (MEL) values for each BMU. MELs indicate the declared maximum generation capacity that a BMU is capable of exporting to the grid during each settlement period. Including MEL data in the analysis is crucial, as it accounts for operational constraints such as scheduled maintenance, partial outages, or grid limitations, thereby providing a more accurate representation of the wind farm's available capacity at any given time. This helps avoid underestimating the wind farm's potential output when calculating curtailment.

To compute the total curtailment for each wind farm, the curtailed volumes (BAVs) from all associated BMUs were aggregated per settlement period. Similarly, the MEL values for those BMUs were summed to derive the total active capacity of the wind farm during the same periods. The percentage curtailment for each settlement period was then calculated by dividing the total curtailed volume by the total MEL and multiplying the result by 100. This percentage represents the proportion of the wind farm's available capacity that was curtailed during each settlement period, accounting for all constituent BMUs. The calculation is formalised in Equation 6.1.

$$\%_{curtail} = \left|\frac{\sum BAV}{\sum MEL}\right| \times 100 \tag{6.1}$$

6.2 Beatrice Offshore Wind farm

The case study used for this research is Beatrice wind farm, located on the North East coast of Scotland, chosen due to the availability of curtailment data for an input to the model. The climate data selected comes from the FINO dataset based on the North Sea [2]. The wind farm lifetime is set at 20 years. Beatrice contains 84 turbines, with a 7 MW rating, at a distance 13 km from shore, as outlined in Table 6.3. Power curve data comes from the NREL database and a 7 MW reference turbine is used [3]. The average occurrence of curtailment from the input data is roughly 10% of the total settlement periods. Preventive maintenance thresholds are set for V and V2 are held constant throughout the simulations to allow for fair comparison. T_1 is the set threshold that indicates major repair can occur if an opportunity arises when a component has reached 90 % of it's predicted failure age and q_1 is set at 0.25. Similarly, T_2 triggers a minor repair if an opportunity arises when a component has reached 85 % of it's predicted failure age and q_2 is set at 0.15. These values are selected arbitraily but kept constant throughout simulations to allow for comparison.

Table 6.3: Wind farm description for Beatrice Case Study

Input	Value
Number of Turbines	84
Turbine Rating (MW)	7
Distance from shore (km)	13
Average wind speed (m/s)	9.41
Average wave height (m)	1.07
Average curtailment occurrence (%)	10.82

The overall operational costs for each version of the model are calculated and displayed in Figure 6.1. The $OPEX_{direct}$ and $OPEX_{total}$ are the average lifetime operational costs from 100 simulations of each model. V1, the corrective strategy has the highest overall costs, followed by V2 and then V, which has the lowest operational costs. The opportunistic maintenance strategy in both V2 and V resulted in lower overall operational costs due to the reduction in replacements occurring by completing more frequent repairs on components compared to the corrective strategy. The difference in operational costs between V2 and V, results from the added level of maintenance occurring during periods of curtailment in the V model alongside the repairs occurring during corrective replacement. $OPEX_{total}$ is expected to be higher than $OPEX_{direct}$ as it is factoring in the lost revenue costs on top of repair, staff and transport costs. To further understand the difference between the models, in terms of costs, Figure 6.2 gives a breakdown of the $OPEX_{total}$ into the average transport, repair, staff and lost revenue costs for the lifetime of the wind farm across the 100 simulations. Noticeably, the highest contributions to the cost are repairs and transport. The reduction in overall component replacements occurring due to preventive maintenance in V and V2 lowers the overall lost revenue costs.

Figure 6.3 compares the energy based and time based availability across the models for Beatrice wind farm. The energy based availability is around 5% lower than the time-based availability across all three versions of the model. Lower energy based availability is due to the metric accounting for the total amount of energy lost during periods of downtime whereas time based availability accounts for the total amount of time the turbine is out of operation. For example, if downtime takes place during periods of high wind speed, the energy availability is going to be lower than the time based availability and if downtime took place during low

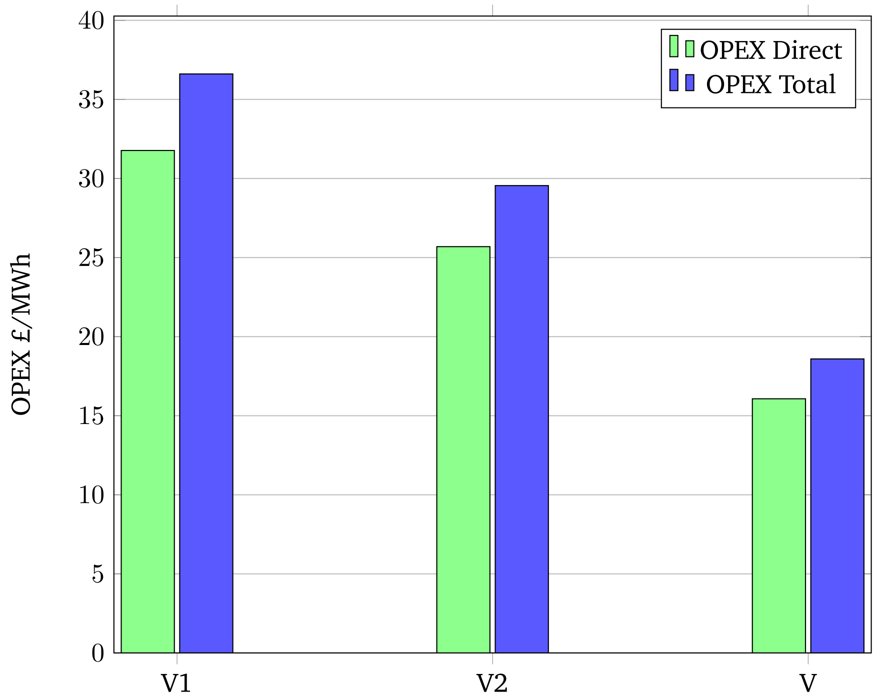

Figure 6.1: Cost comparison of the original model V with V1 and V2 looking at the average OPEX direct and total costs across 100 simulations for Beatrice wind farm.

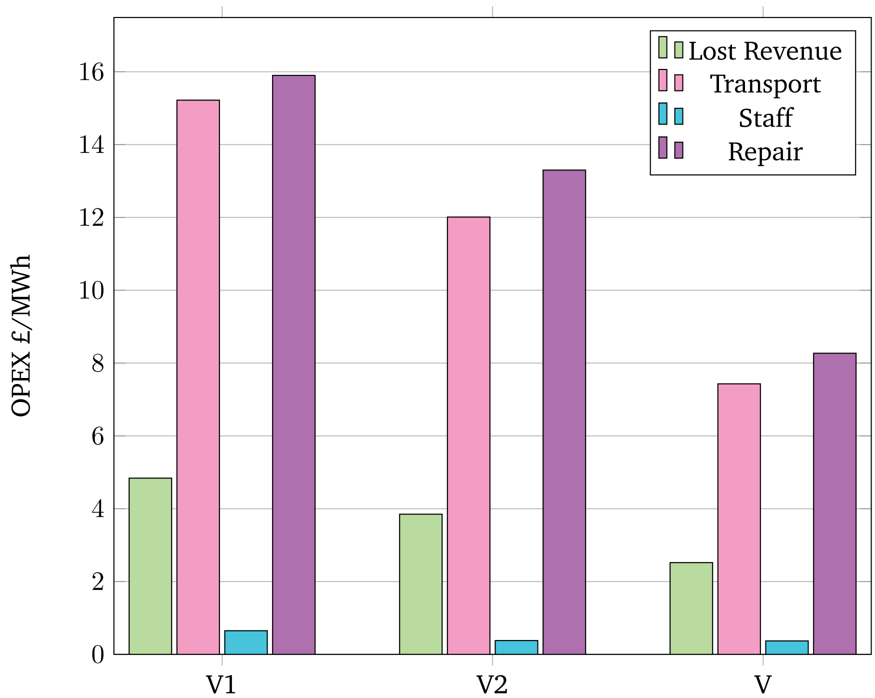

Figure 6.2: Breakdown of the average total and direct OPEX costs for each model, V, V1 and V2, highlighting transport, repair, staff and lost revenue costs for Beatrice wind farm.

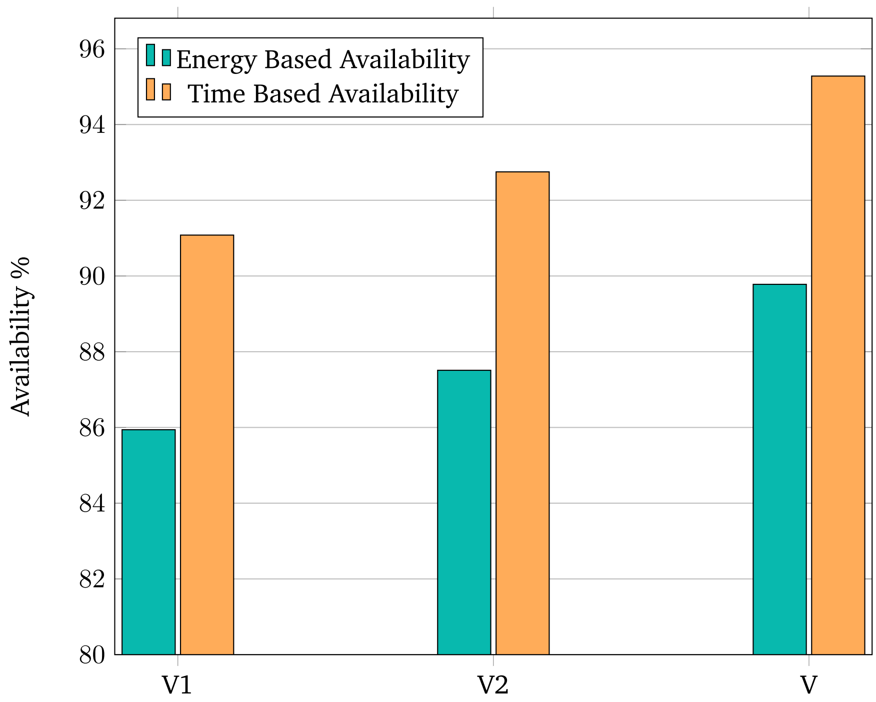

Figure 6.3: Time based and energy based availability values for the three models; V1, V2 and V.

wind speeds then the time based availability would be lower, as explained in [8]. In the case of Beatrice wind farm, downtime occurred more frequently during high wind speeds and due to the accessibility limits imposed during high wind speeds, maintenance is delayed. The delay in component repairs or replacements means the downtime during high wind speeds would last for a longer period of time, thereby reducing the overall energy availability. Comparing the different models, the lowest time and energy based availability is in V1, followed by V2 and then the highest availabilities are found in V. Lower availability for the corrective version of the model, V1, stems from an increased amount of broken components due to the absence of preventative maintenance. More components breaking results in long replacement times which will cause the downtime of the turbines to increase. As expected, the introduction of preventively maintaining the components to increase their useful lifetime, means a reduction in the downtime of the turbines and an increase in the availability of the turbines. V has the highest availabilities as it offers extra maintenance opportunities during curtailment periods on top of the strategy in V2, allowing a further reduction in the downtime however, the difference between these two strategies is around 1% and is not as significant as the difference between V2 and V1. Figure 6.4 shows the convergence of the average time based availability value over

100 simulations, reaching a relative standard error of 0.0005.

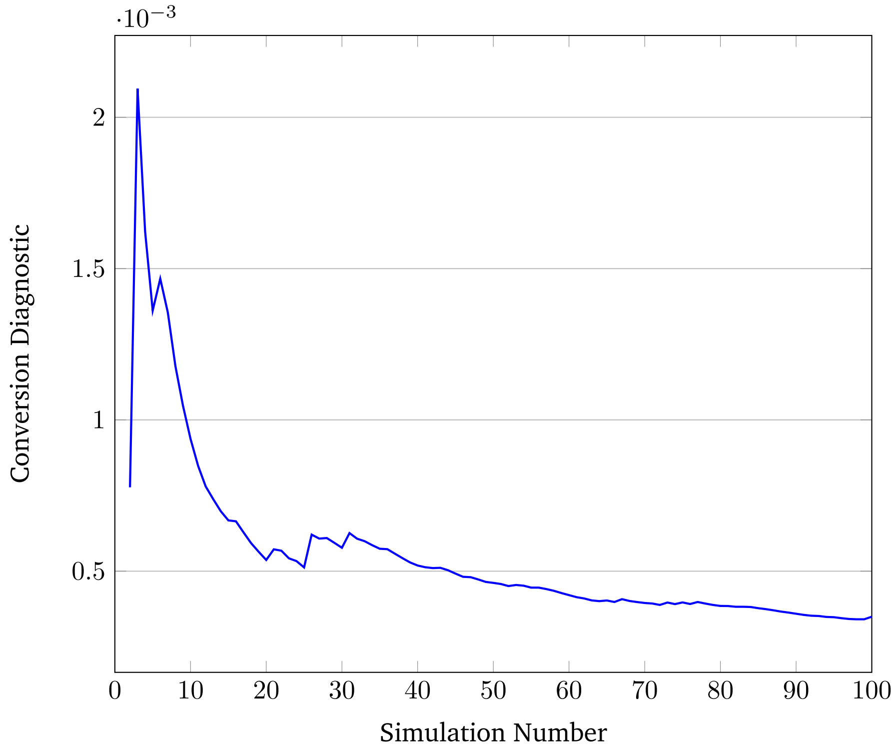

Figure 6.4: The convergence of time based availability results after 100 simulations of the model.

In summation, the comparison of maintenance strategies, using the Beatrice case study, has revealed an OPEX cost reduction and increased availability of the wind farm when employing the opportunistic maintenance strategy in model V. The opportunity to complete maintenance during periods of curtailment and during corrective replacement under the constraints of the specific wind farm chosen is proven to be beneficial to the wind farm owners. To explore how advantageous this strategy is, the following sections alter different inputs, namely turbine size, distance from shore and failure distributions, to see their impact on the output from the model.

6.2.1 Turbine Size

The first input chosen for sensitivity analyses is the turbine power rating for the individual turbines in the wind farm. Beatrice wind farm has 7 MW turbines but future generation wind farms are likely to contain turbines much larger than this, due to the advancement in turbine technology. Apart from the change of power curve inputs, all other inputs are kept the same as the previous simulations. The curtailment model, V, was run with various turbines of different

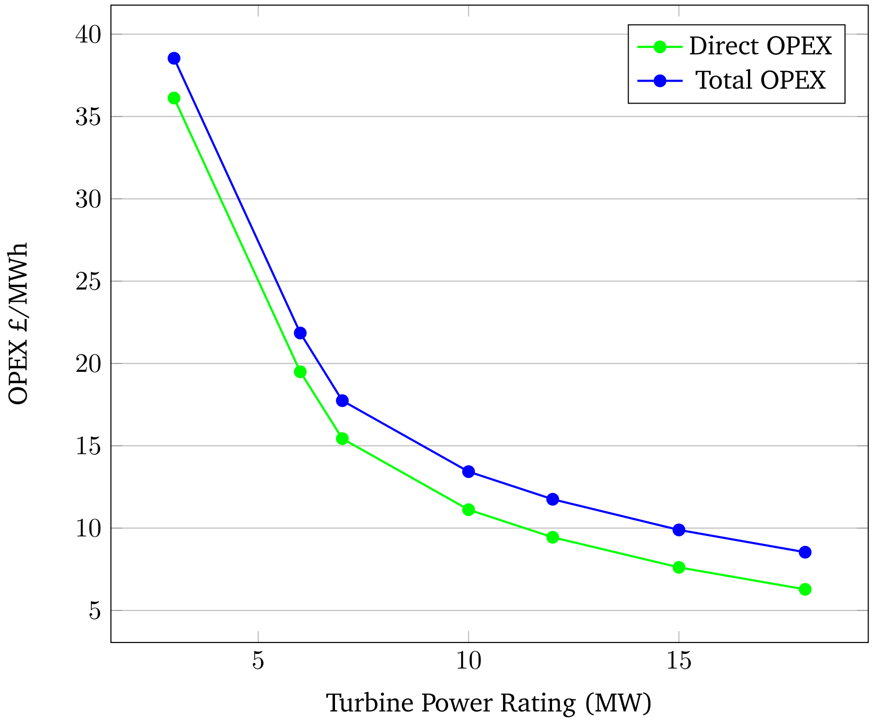

Figure 6.5: Operational costs using the curtailment model for the Beatrice case study with different turbine power ratings.

power ratings. The results from these simulations are shown in Figure 6.5. As expected, the turbines with the lowest rated power produced the highest operational costs per MWh, as the energy production is much lower over the whole wind farm lifetime. Interestingly, the benefit of the larger turbines begins to plateau towards 15 MW and 18 MW turbines. Energy production continually increases as the size of the turbine increases meaning the cost in £/ MWh is continually decreasing. The plateau in cost reduction is a result of operational costs of the wind farm in terms of repairs, transport, staff and lost revenue, that are always present in the overall costs, preventing the outputs from ever reaching zero and slowing the reduction in the the operational expenditure in £/MWh.

6.2.2 Failure Distributions

Due to the lack of publicly available failure distribution data for component lifetimes, the failure distribution is one of the biggest areas for uncertainty in the inputs of the model. The sensitivity analysis carried out in this section uses the original scale parameter values for the six components in Table 6.1 and varies them from -50% to +50% of their original value. All components are varied the same amount for each simulation to allow for fair comparison. Smaller scale parameter values should result in more frequent repairs of the components resulting in higher O&M costs and the larger scale parameter values indicate less frequent repairs resulting in lower costs. The shape parameter was kept the same to allow for consistency and a clear conclusion to be drawn.

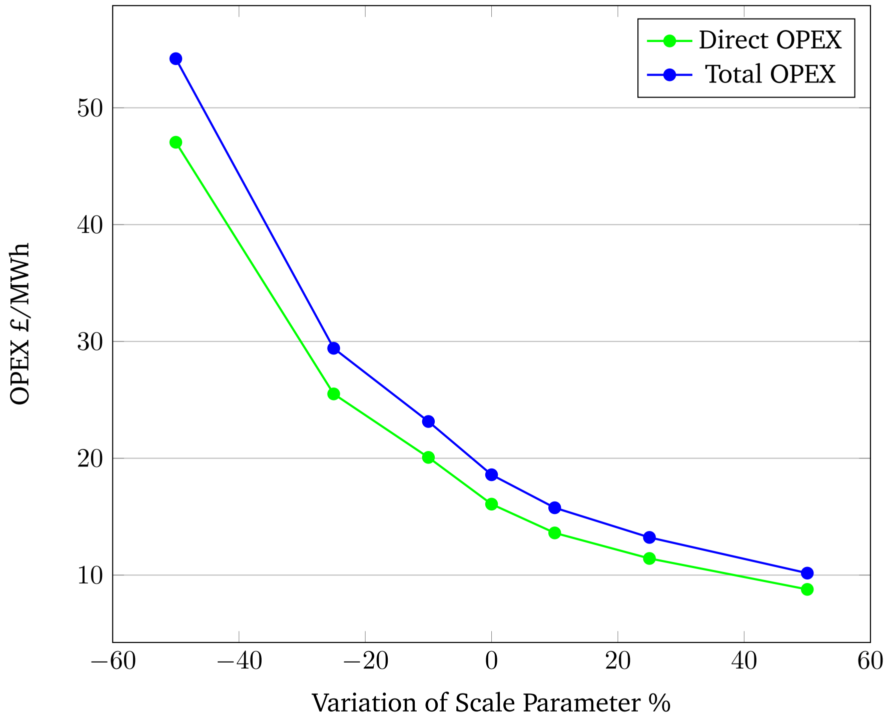

Figure 6.6: Operational expenditures for Beatrice wind farm with varying scale parameter values.

The operational costs, shown in Figure 6.6, follow a similar trend for both direct and total costs. For scale parameters at 50% of the original value, the operational costs are the highest, with total operational costs at £42 /MWh. Whereas, increasing the scale parameters by 50% of the original value, results in the lowest operational costs at roughly £10 /MWh. The significant decrease in costs stems from the less frequent failures in the components resulting in less downtime, less repairs and less requirement for transport vessels. The reduction in costs begins to plateau as the energy production begins to reach it's maximum capabilities due to the reduction in downtime experienced by the turbines. Hypothetically, if failure distributions of the components were set such that failures only occur after the end of the wind farm lifetime, the energy production would be at a maximum and the costs would keep reducing until the only

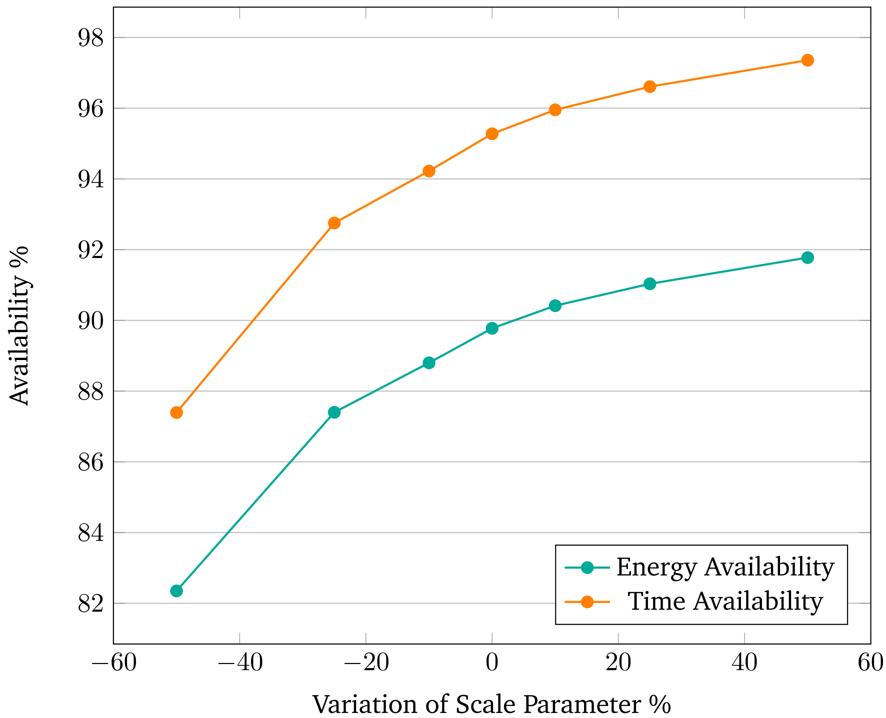

Figure 6.7: Availability for Beatrice wind farm for varying scale parameter values.

remaining costs would be the staff costs, causing another dip for the shape of the graph. Similarly, in Figure 6.7, the availability of the wind farm increases as the scale parameter increases because the failures in the wind farm are less frequent thereby reducing the downtime.

Overall, it is clear that the failure distributions have a large effect on the outputs of the wind farm. Further analysis could also investigate the individual components being changed while others remain constant or changing the value of the shape parameter also.

6.2.3 Number of Technicians

The number of available technicians was set to 30, with a fleet comprising of five CTVs. To assess the impact of resource constraints, a sensitivity analysis was conducted on the number of technicians. The model does not permit repairs at the wind farm if an insufficient number of technicians are available. However, replacements can still be performed under the assumption that external personnel are hired for large scale replacements.

The simulation was executed for 10 cases, varying the number of technicians from 10 to 100, with the results presented in Figures 6.8 and 6.9. The operational costs, depicted in Figure 6.8, are highest when the technician pool is limited to 10 personnel, as the lack of workers

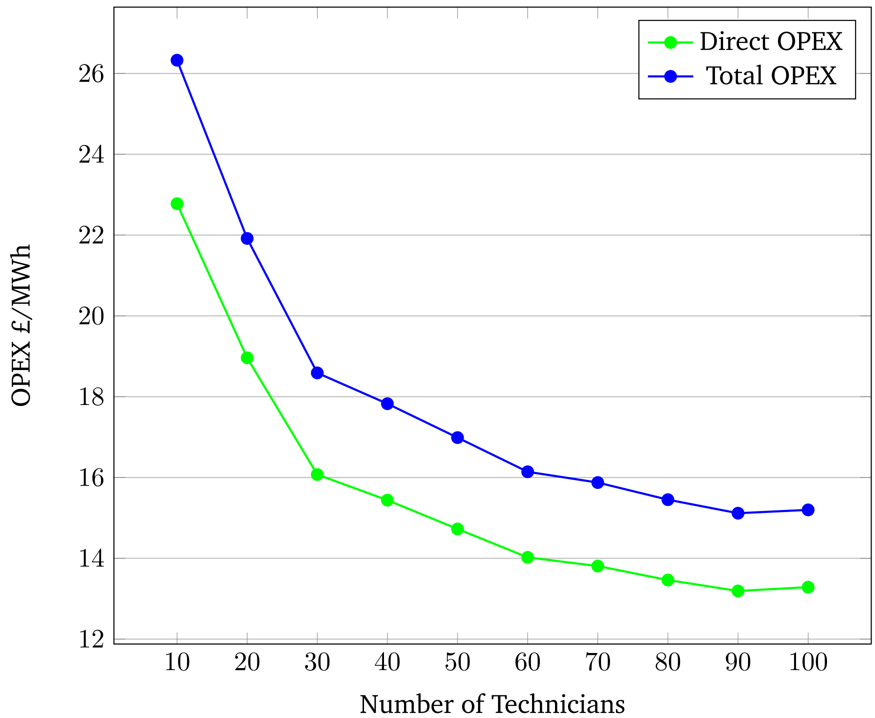

Figure 6.8: Operational expenditures for Beatrice wind farm with varying number of technicians.

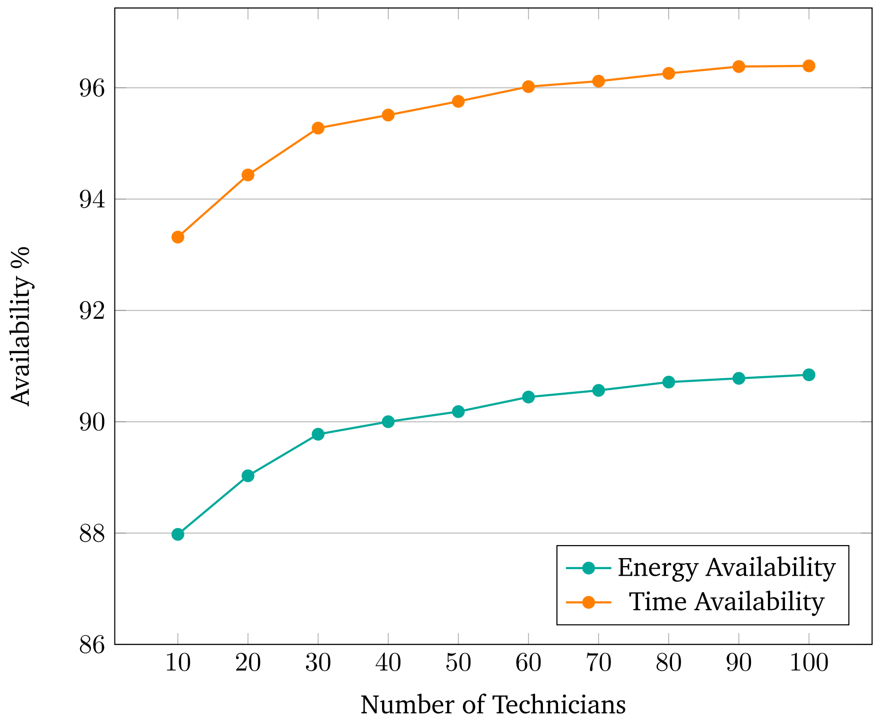

Figure 6.9: Availability for Beatrice wind farm with varying number of technicians.

restricts preventive maintenance, leading to an increased reliance on costly replacements. As the number of technicians increases, operational costs decrease; however, the marginal benefit diminishes, as indicated by the plateau in OPEX.

Similarly, the availability of the wind farm, shown in Figure 6.9, improves with a larger technician workforce, as more repairs can be undertaken. A greater number of technicians allows for an increased number of preventive maintenance tasks to be performed, thereby reducing overall turbine downtime. A plateau effect is evident for both energy and time based availability, suggesting that beyond a certain threshold, further increases in maintenance capacity provide diminishing returns. At this point, the improvements in availability are counterbalanced by the additional staffing costs.

6.2.4 Distance from Shore

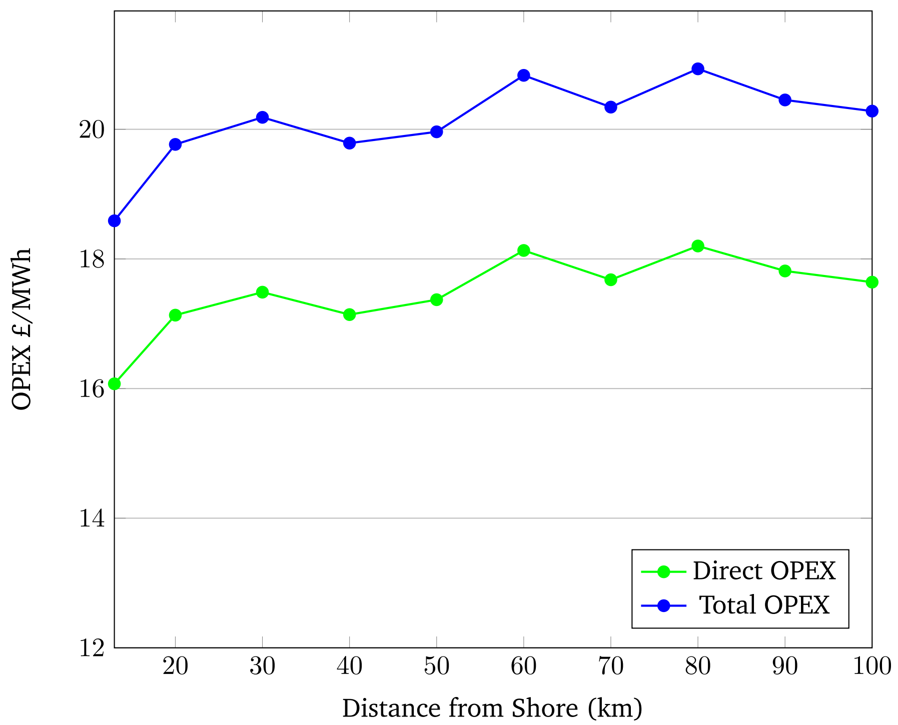

Figure 6.10: Operational costs using the curtailment model for the Beatrice case study with varying distances from shore.

In keeping with other simulations, the Beatrice case study uses the exact same inputs, while the distance from the wind farm to the shore changes. Figure 6.10 outlines the cost outputs from the simulations that were ran from 10 to 100 km. For both the $OPEX_{direct}$ and

$OPEX_{total}$, the general trend shows increasing costs as the distance from shore increases. The increased costs as distance increases predominately stem from the increased transport costs and increased lost revenue costs. The transport costs increase with distance from shore as the journey to site is longer and therefore fuel consumption for vessels is higher. Another reason for transport costs to increase is that the longer transit time may result in less time during a weather window to complete a repair. If a repair is not completed within a day it results in an extra day of work along with an additional charter cost for the vessel. The lost revenue costs increase for a similar reason. If the turbine is broken and the site is further from shore, a longer weather window is required to account for longer transit times. The longer weather windows increases the chance of repairs not being completed as quickly, resulting in an increased amount of downtime and consequent increased lost revenue costs. In comparison to the turbine size and failure distributions, the distance to shore appears less significant to the overall costs of the windfarm when looking at 10 km to 100 km and may require a much larger distance before a stark increase in the OPEX is produced.

6.3 Walney Offshore Wind farm

In contrast to Beatrice wind farm, Walney, an offshore wind farm with a lower occurrence of curtailment, is also simulated. The wind farm description for Walney is given in Table 6.4. Walney contains 189 turbines in total and is situated 14km from the port of Barrow on Furness, where the operations and maintenance base is located. The wind farm under consideration comprises turbines of three different rated capacities: 3.6 MW, 7 MW, and 8.25 MW. However, the modelling framework employed supports only a single power curve input. To address this limitation, a weighted average approach was adopted to derive a representative power rating of 5 MW. Accordingly, the NREL 5 MW reference turbine was selected to define the power curve used in the model. This approximation was considered acceptable, as any overestimation or underestimation in lost revenue due to a particular turbine failure is expected to balance out over time. Furthermore, the model, consistent with many other opportunistic maintenance frameworks, assumes homogeneity among turbine components. That is, failure distributions are not differentiated by turbine type. This assumption further justifies the use of a representative 5 MW turbine in the analysis. Again, wind farm lifetime is set to 20 years and the FINO data set is used for input to the climate data. Preventive maintenance thresholds are set for V and V2 are held constant throughout the simulations to allow for fair comparison. T_1 is the set threshold that indicates major repair can occur if an opportunity arises when a component has reached 90 % of it's predicted failure age and q_1 is set at 0.25. Similarly, T_2 triggers a minor repair if an opportunity arises when a component has reached 85 % of it's predicted failure age and q_2 is set at 0.15. These values are selected arbitraily but kept constant throughout simulations to allow for comparison.

Table 6.4: Wind farm description for Walney Case Study

Input	Value
Number of Turbines	189
Turbine Rating (MW)	5
Distance from shore (km)	14
Average wind speed (m/s)	9.41
Average wave height (m)	1.07
Average curtailment occurrence (%)	1.56

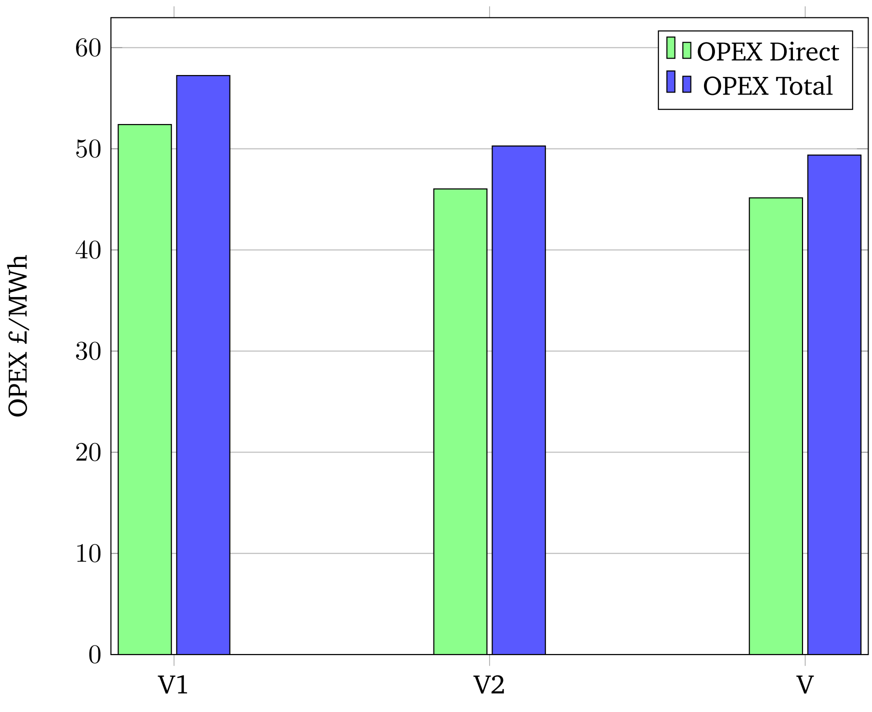

Figure 6.11: Cost comparison of the original model V with V1 and V2 looking at the average OPEX direct and total costs across 100 simulations for Walney wind farm.

Figures 6.11 and 6.12 present a comparison of the overall operational expenditures (OPEX) and a detailed breakdown of these costs, respectively. Among the three strategies assessed, V1, which represents a corrective maintenance approach, results in the highest operational costs in

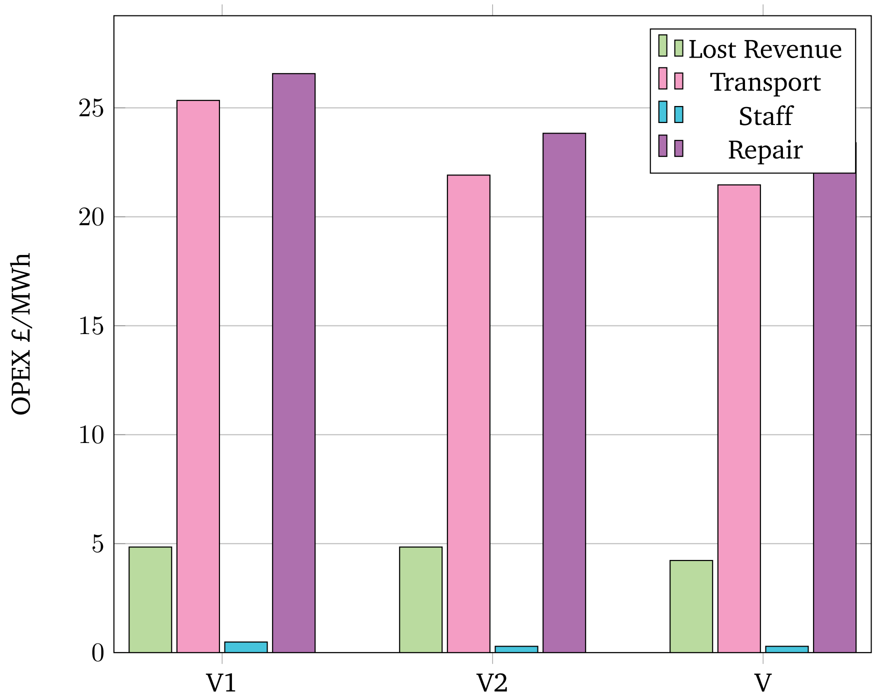

Figure 6.12: Breakdown of the average total and direct OPEX costs for each model, V, V1 and V2, highlighting transport, repair, staff and lost revenue costs for Walney wind farm.

terms of both direct and total OPEX. This is followed by V2, a basic preventive maintenance strategy, and finally V, the curtailment-based strategy, which yields the lowest overall costs.

Notably, the total OPEX for the Walney wind farm is significantly higher compared to the Beatrice case study. These higher costs are primarily attributed to elevated repair and transport costs at Walney, likely driven by the greater number of turbines and the corresponding increase in maintenance-related travel over the farm's operational lifetime. Although Walney achieves higher total energy production than Beatrice, its larger scale also introduces higher logistical and operational complexity. To explore the effect of wind farm size in more detail, a sensitivity analysis is conducted in Section 6.3.1.

Despite the overall higher OPEX, the relative cost difference between the V1 and V2 strategies at Walney, approximately £7/MWh, is consistent with the findings from the Beatrice analysis. The most notable shift occurs with the V strategy, which incorporates curtailment periods as windows of opportunity to perform preventive maintenance. While this strategy results in the lowest OPEX values (both direct and total), the cost advantage over the simple preventive strategy (V2) is marginal. This limited benefit is due to Walney's relatively low curtailment rate of just 1.5%, which provides fewer viable opportunities to effectively schedule and execute maintenance during non-operational periods. As a result, the strategy's full potential, as demonstrated in the Beatrice case, is not fully realised in this scenario. Figure 6.13 illustrates

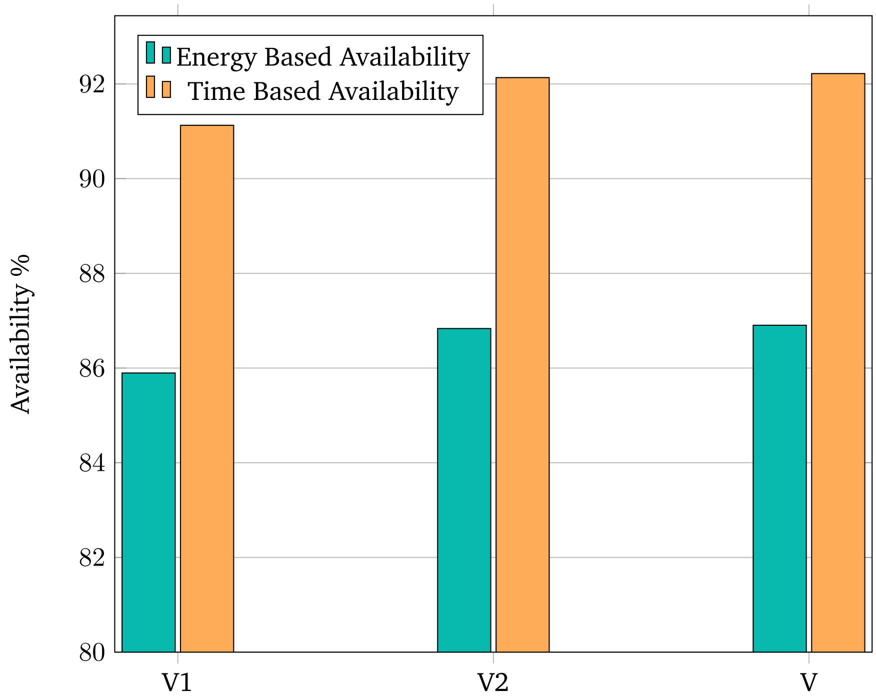

Figure 6.13: Time based and energy based availability values for the three models; V1, V2 and V for Walney wind farm.

the time-based and energy-based availability of the Walney wind farm over its lifetime. As expected, availability is lowest under the corrective strategy (V1), moderately improved under the simple preventive strategy (V2), and highest when using the curtailment-based strategy (V). However, the difference in availability between V2 and V is minimal. This again reinforces the conclusion that the curtailment-based strategy offers limited improvement at Walney, due to the infrequency of curtailment events and, consequently, reduced opportunities to exploit these periods for maintenance activities. The findings suggest that while curtailment-based maintenance can be highly effective under the right conditions, its success is heavily dependent on the operational characteristics and curtailment profile of the wind farm in question.

6.3.1 Number of Turbines

To understand the high operational costs for the Walney wind farm, a sensitivity analysis on the number of turbines is carried out and can be seen in Figure 6.14. The operational costs increase as number of turbines increase in the wind farm, which compounds the reasoning that the high operational cost for the wind farm is not to do with the strategy itself but with the number of components that require maintenance. To counteract the number of turbines, the model would benefit from grouped maintenance tasks and the ability to perform mutliple maintenance tasks on different turbines in one trip, which is currently a limitation within the model. If maintenance could be grouped, the overall transport costs would be reduced which in turn would reduce the operational costs. Furthermore, the uncertainty around the failiure distributions used as inputs also highlights that these costs are subject to change as the components are directly effected by those values and an increase in failures will undoubtedly effect larger wind farms more than smaller wind farms. Equally, for larger wind farms there may be more emphasis on having more vessels within the fleet or more technicians within the maintenance crew to account for the increased number of potential failures throughout a larger area. Therefore, it is also important to consider how the availability of maintenance personnel will effect this wind farms operational costs.

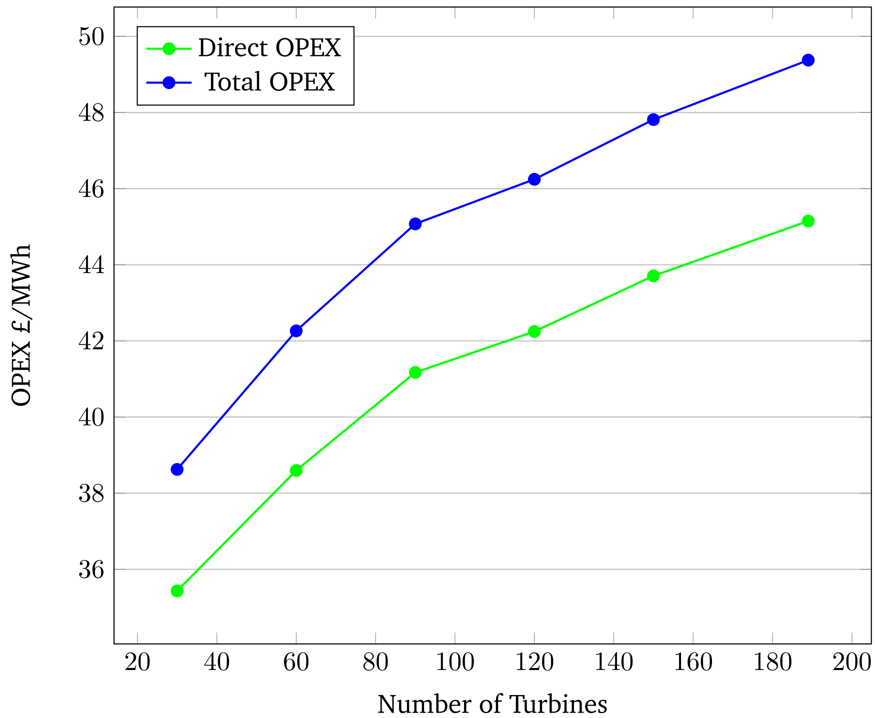

Figure 6.14: Operational costs for Walney wind farm with adjusted number of turbines within the wind farm.

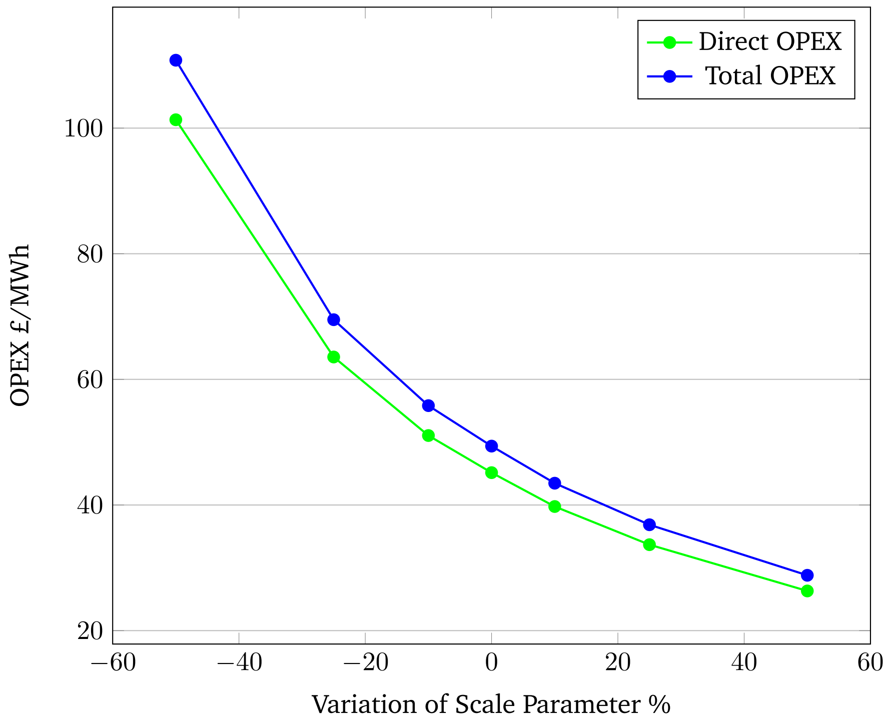

Figure 6.15: Operational expenditures for Walney wind farm with varying scale parameter values.

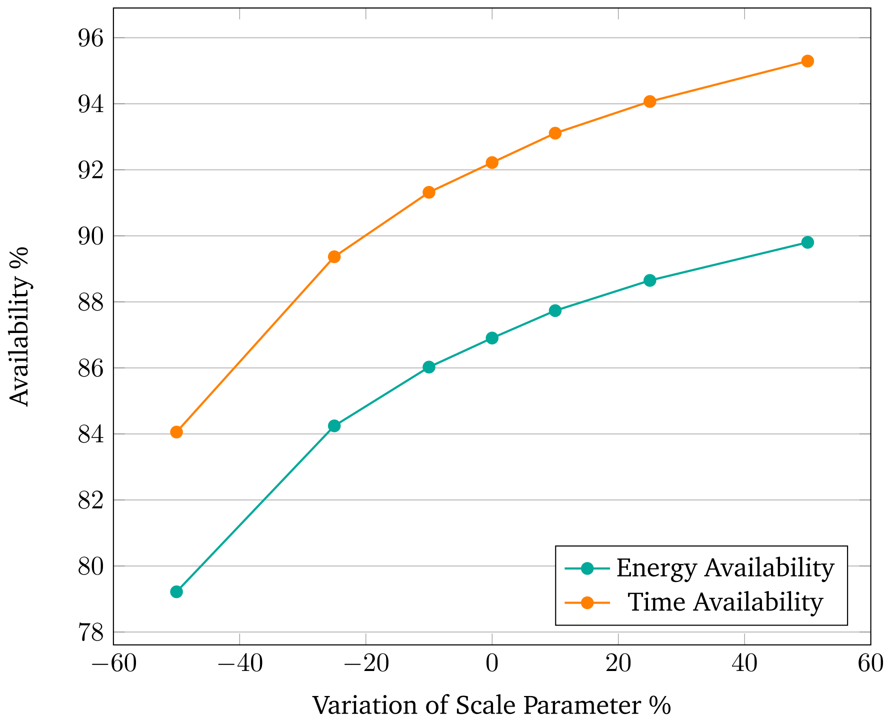

Figure 6.16: Availability for Walney wind farm for varying scale parameter values.

6.3.2 Failure Distributions

The failure distributions for Walney are altered in the same manner as in the Beatrice wind farm study. The scale parameter is adjusted from -50% up to +50% of it's original value for each of the components that are outlined in Table 6.1. Figure 6.15 shows the simulated operational costs, including direct and total OPEX, for the range of failure distribution scenarios. As expected, the smaller the value of the scale parameter, the more frequent the repairs on the components required and subsequently the higher operational costs for the wind farm. As the scale parameter increases there is a steep drop in operational costs which eventually will plateau as failures become more infrequent but there is the leftover fixed operational costs that are present regardless of the change in scale parameter. Figure 6.16 outlines the energy and time based availability for the wind farm with varying scale parameters. A similar trend is seen where the availability will be lowest with low scale parameter values as mean time to failure is lower causing an increased amount of downtime contributing to lower availability values. As scale parameter increases availability improves and then begins to level off.

In comparison to the Beatrice case study where the failure dsitributions are varied it is clear that there is much more dramatic change in operational costs and availability for Walney. The range of operational costs for Walney goes from above £100/MWh to approximately £30/MWh, whereas in the Beatrice case, the range of output operational costs is much smaller, with a maximum of £50/MWh to a minimum of around £10/MWh. This indicates that the impact of failure distribution values has a much more pronounced effect on Walney than on Beatrice. The reasons behind this sensitivity to failure values could be attributed to the larger amount of turbines at Walney wind farm. There are an increased number of failures occuring in the wind farm in the baseline case, therefore, the costs are heightened when scale parameters are lowered and similarly, can result in a greater reduction in costs when the scale parameters are higher in value.

6.3.3 Distance from Shore

The Walney wind farm is located approximately 14 km from the nearest port, a distance comparable to the Beatrice wind farm. Figure 6.17 presents the impact on operational costs when the assumed distance from shore is varied up to 100 km. The analysis reveals only a modest increase in both total and direct operational expenditure (OPEX) as distance increases. Despite the significant increase in travel distance, the cost variation remains relatively constrained. The main driver behind the observed cost increase is vessel travel time. As the wind farm is placed farther offshore, vessels require more time to reach turbines, which not only increases fuel and operational costs but may also reduce the effective working time available within a given weather window. This has a knock-on effect, potentially delaying maintenance operations and contributing to increased downtime-related costs. However, even with these factors considered, the cost sensitivity to distance remains considerably lower than that observed for other variables in the model (e.g., technician availability or turbine failure rates). This result suggests that, within the distance range analysed, the offshore location of Walney (and similar nearshore wind farms) does not exert a dominant influence on lifetime OPEX. This is particularly relevant when comparing to deeper, more remote sites where accessibility issues may scale more dramatically. The finding also supports the assertion that once logistical support and operational protocols are in place, the marginal cost impact of increasing distance (within moderate bounds) may be relatively manageable under current vessel and maintenance technology assumptions.

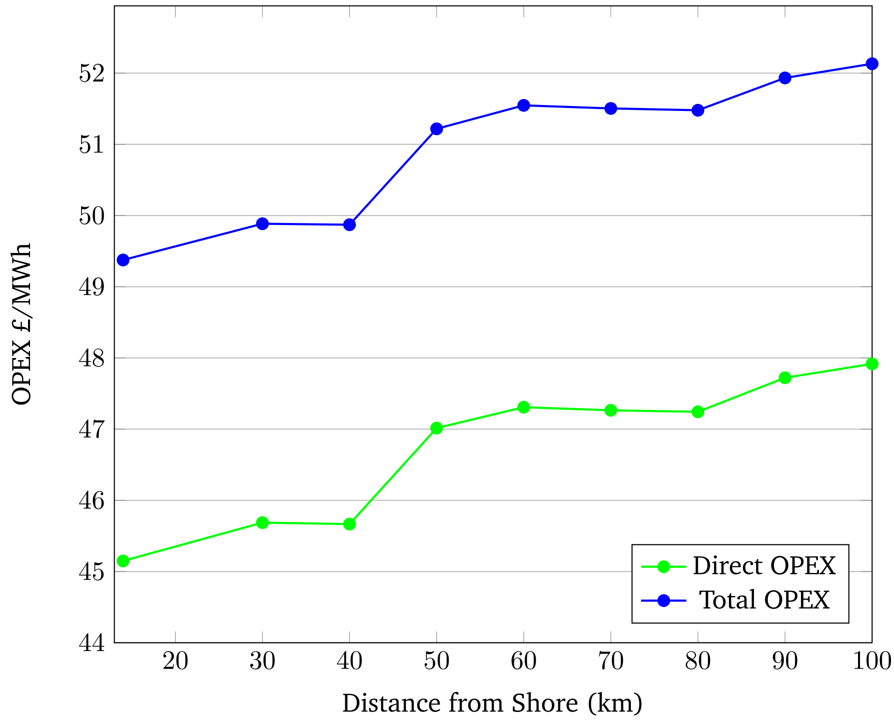

Figure 6.17: Operational costs for the Walney case study with varying distances from shore.

6.3.4 Number of Technicians

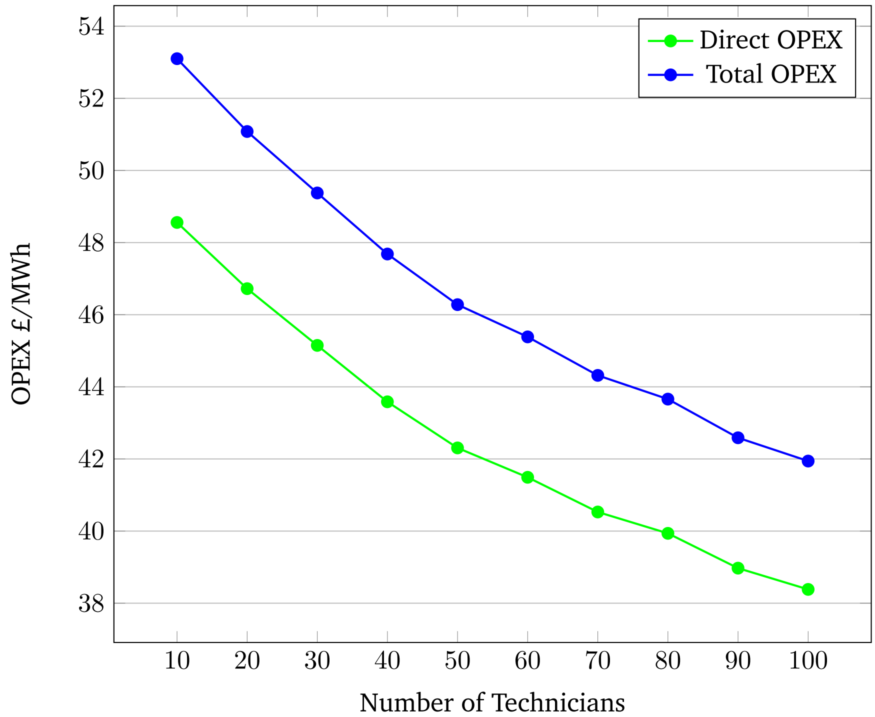

Figure 6.18: Operational expenditures for Walney wind farm with varying number of technicians.

The number of technicians at Walney is an important factor to consider in the simulations. The increased turbine count at Walney naturally implies a higher number of components susceptible to failure or routine maintenance, thereby necessitating a larger and more responsive O&M workforce.

To evaluate the sensitivity of operational performance to workforce size, a range of technician numbers was simulated from a minimum of 10 to a maximum of 100 personnel. The operational cost implications of varying technician numbers are illustrated in Figure 6.18, while the resulting availability levels are depicted in Figure 6.19.

The results indicate that the operational cost difference between the lower and upper bounds of technician availability is approximately £11/MWh. This aligns closely with the observed cost variation at the Beatrice wind farm, which also reported an £11/MWh differential. This similarity underscores a broader insight: regardless of the overall scale of the wind farm, the number of available maintenance personnel exerts a meaningful influence on operational expenditure. The ability to respond swiftly to maintenance requirements, minimising downtime and mitigat-

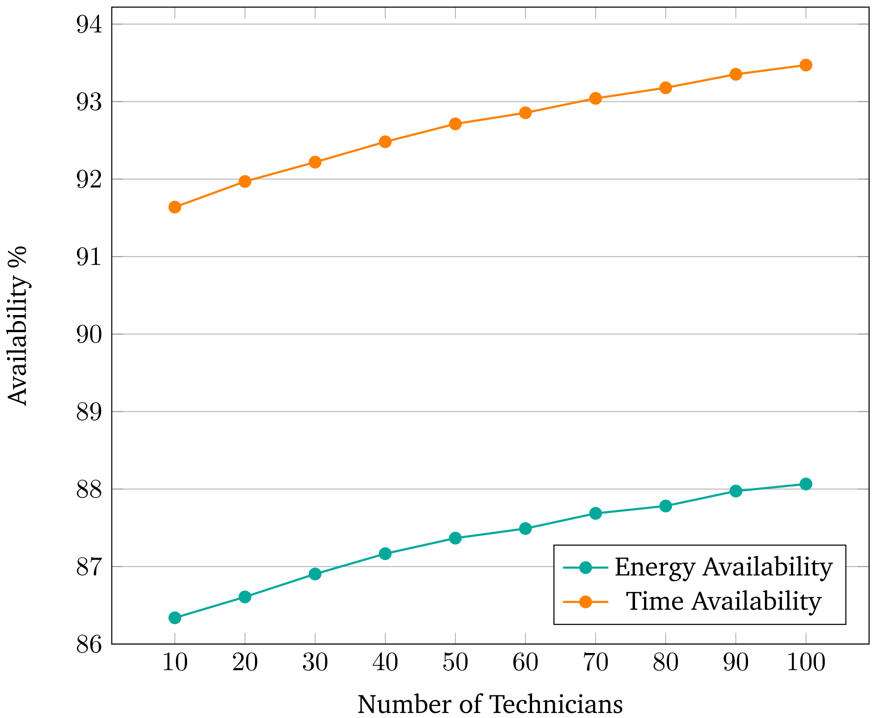

Figure 6.19: Availability for Walney wind farm with varying number of technicians.

ing prolonged losses in energy production, is evidently critical for both large and moderately sized offshore wind farms. For Walney, the availability across the simulated range of technician numbers exhibits a relatively modest variation of approximately 1.8%. In contrast, Beatrice demonstrates a greater sensitivity, with a variation exceeding 3%. This suggests that while additional technicians contribute to cost savings across both sites, their marginal impact on availability is more pronounced in smaller-scale operations. This divergence in the sensitivity analysis for the availability may be attributed to the technician-to-turbine ratio. At Walney, the higher absolute number of turbines dilutes the benefit of each additional technician, making it more challenging to achieve substantial improvements in availability without significantly scaling the workforce. In contrast, at Beatrice, with fewer turbines, each technician can cover a larger proportion of assets, leading to more observable improvements in uptime. Consequently, downtime at Walney may remain elevated even with increased technician deployment due to the sheer scale of assets requiring maintenance. In conclusion, these findings highlight the dual role of technician workforce optimisation: while it is a lever for cost control across all scales of offshore wind operations, its effect on availability is more contingent upon wind farm size. Strategic workforce planning, therefore, must consider not only absolute technician numbers but also the technician-to-turbine ratio and logistical constraints inherent to each site.

6.4 Curtailment Comparison

To solidify the results from the two case studies and validate the model further, the final section is a comparative study to see what effect the curtailment amount experienced in Beatrice (averaging around 10%) would have on the operational costs for Walney and similarly, how the operational costs at Beatrice would be effected if it experienced the curtailment amount at Walney (average at around 1.5%). By completing this analysis, it will be clear if the curtailment amount is having a significant impact on the operational costs for each wind farm or if the other wind farm characteristics are influencing the costs.

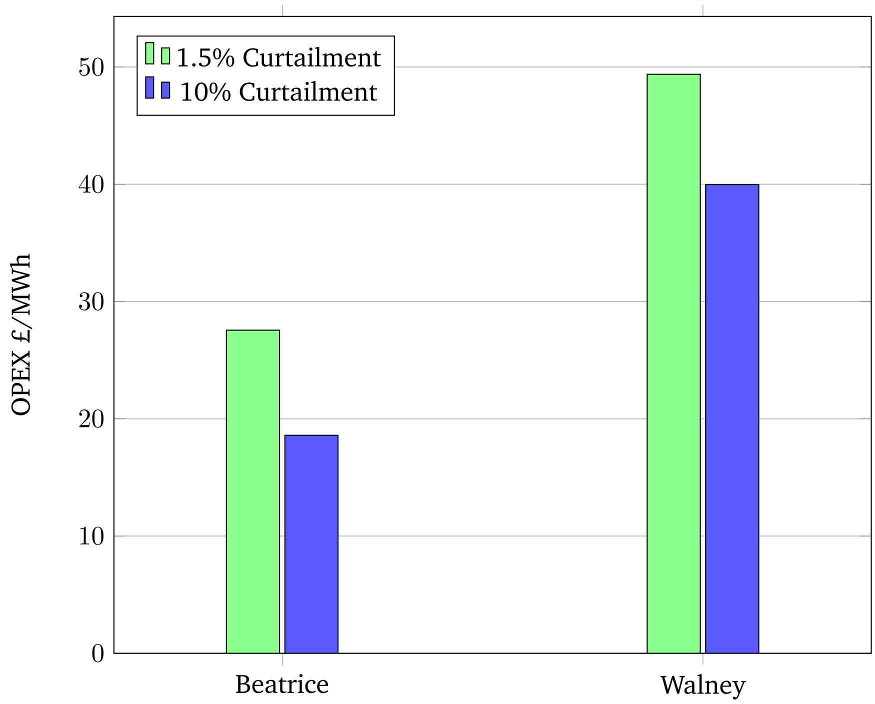

Figure 6.20: Comparing total operational costs for Beatrice and Walney wind farm with different average curtailment rates. The two scenarios have an average curtailment over the wind farm lifetime of 10% and 1.5%.

Figures 6.20 and 6.21 present the total operational expenditure (OPEX) and time-based availability results obtained from the simulation models for the Beatrice and Walney offshore wind farms. These figures compare two curtailment scenarios: one with an average curtailment of 1.5% and another with a higher average curtailment of 10%.

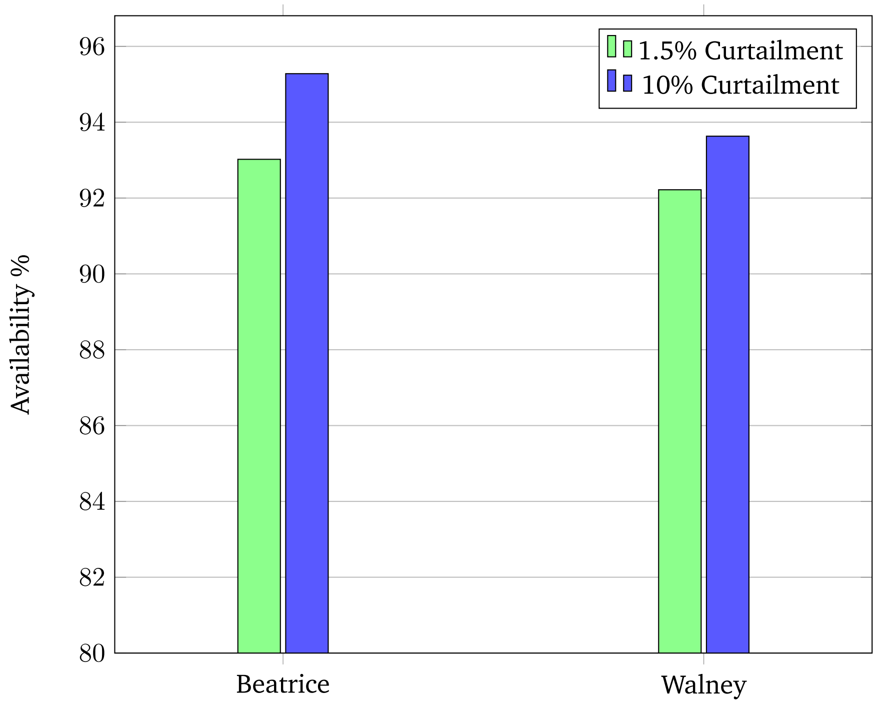

Figure 6.21: Comparing time based availability for Beatrice and Walney wind farm with different average curtailment rates. The two scenarios have an average curtailment over the wind farm lifetime of 10% and 1.5%.

In terms of operational costs, it is evident that for both Beatrice and Walney, the scenario with 1.5% average curtailment results in higher OPEX than the 10% curtailment scenario. Specifically, the total operational cost for each wind farm is reduced by approximately £9/MWh under the 10% curtailment case. This finding highlights the critical role that the volume of curtailment plays in enabling a more cost-effective maintenance strategy. In essence, the capacity to shift maintenance activities into curtailment windows, periods when energy production is intentionally limited, can significantly lower overall operational expenditure.

Despite the cost reduction observed in both cases, Walney continues to exhibit the highest absolute OPEX across both scenarios. This suggests that other underlying factors, such as the total number of turbines and their individual power ratings, still have a substantial influence on overall maintenance costs. Nonetheless, the results clearly demonstrate that higher levels of curtailment, when effectively utilised within a maintenance strategy, can reduce O&M costs.

Figure 6.21 also shows a corresponding improvement in time-based availability for both wind farms under the 10% curtailment scenario. Walney experiences an increase in availability of 1.41%, while Beatrice sees a larger improvement of 2.25%. This further supports the argument that curtailment can be leveraged to enhance the effectiveness of maintenance strategies, not only in cost reduction but also in operational performance.

The discrepancy between the improvements in availability at the two sites may be attributed to differences in the scale and configuration of each wind farm. Overall, these findings underscore the fact that the success of this maintenance strategy is highly contingent upon the level of curtailment an offshore wind farm experiences, as well as the specific characteristics of the site.

6.5 Summary of analysis

The model was compared to two less complex maintenance strategies, a corrective strategy and a simple opportunistic strategy. Using Beatrice offshore wind farm as the first case study, simulations showed 50% decrease in operational costs when utilising the curtailment strategy in comparison to the corrective strategy. The simple opportunistic strategy has a 34% reduction in costs compared to the corrective strategy. Time based availability and energy based availability were also compared across the three models with curtailment strategy providing optimal time based availability and energy based availability at 95% and 90% respectively, 1% higher than the basic opportunistic strategy for both time and energy based availability.

The second case study chosen was Walney wind farm, as it had a lower average rate of curtailment at around 1.5% compared to Beatrice which was approximately 10.5%. In this case study, the model simulated the corrective strategy, the simple opportunistic strategy and the curtailment strategy and found that the corrective strategy still produced the highest operational costs, 16% higher than the curtailment strategy. However, the reduction in costs between the simple opportunsitic and curtailment strategy was only 1.8% for Walney. Due to the lower curtailment rates, the benefit of the curtailment strategy was minimised for Walney wind farm. The availability was also compared for this case study and followed a similar trend to the operational costs, with the corrective strategy producing the lowest availability at 91.1% time based availability and 85.8% energy based availability, and the other two strategies improving availability by 1% for both time and energy metrics.

Due to the sensitivity of the model to various inputs, multiple sensitivity analyses were performed. The inputs focused on were turbine size, failure distribution values, distance from shore, number of technicians and number of turbines. For the number of technicians available at each wind farm, it was found that costs could change as much as £11/MWh when varying technicians from 10 personnel to 100 for both Beatrice and Walney. The change of scale parameter for the failure distribution inputs was the most significant sensitivity analyses carried out as it showed the biggest change in operational costs for both wind farms, highlighting how sensitive the results are to failure inputs and how important accurate failure data is to the success of O&M modelling. The model showed a decrease in costs as turbine size increased, due to the increase in overall energy production. The number of turbines in the Walney wind farm were varied and showed that operational costs come down significantly with a lower number of turbines as there are less components to repair. Finally, the distance from shore analysis revealed that an increased distance from shore increases the operational costs due to increased transport costs and longer periods of downtime.

Finally, to ensure that the curtailment was the main driver for the difference in operational costs for the two wind farm case studies, the average curtailment experienced by the wind farms was changed. It was found that with low levels of curtailment of 1.5%, that the Beatrice costs increased by £9 /MWh compared to the scenario with 10% average curtailment rated and similarly for Walney, when curtailment was at 10% the maintenance costs decreased by £9/MWh compared to the 1.5% curtailment scenario. Availability also increased for both wind farms when curtailment was higher due to the increased opportunities to complete maintenance during curtailment periods thereby reducing overall downtime.

This chapter successfully benchmarked the model created in Chapter 5 by comparing the model against two other maintenance strategies for two separate case studies. Then the multiple sensitivity analysis gave further insight into the parameters which have most influence on the availability and cost metrics that are output from the model. Most importantly, the chapter affirms that the maintenance strategy can reduce operational costs for a wind farm, with emphasis on wind farms that experience a higher level of curtailment. For wind farms with lower levels of curtailment, the benefit of the strategy is only slightly better than a simple opportunistic so although it will provide cost savings it is important that operators consider the other costs associated with implementing this maintenance strategy such as additional training required, the level of condition monitoring systems and the logistical planning required.

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Chapter 7

Discussion

This chapter provides a critical reflection on the core themes, methodologies, and findings of the thesis. While the analysis has offered several potential strategies to improve operational efficiency and reduce costs in offshore wind, particularly in maintenance planning and curtailment management, there are important limitations and feasibility concerns that must be acknowledged. These relate to data reliability, jurisdictional differences, operational constraints, and broader market dynamics. The discussion also highlights areas where further industry engagement is required to enhance the real-world applicability of the findings.

7.1 Climate Data Selection

The accuracy and applicability of O&M simulations for offshore wind projects are significantly influenced by the quality and granularity of the climate and metocean data used. Weather and ocean conditions directly affect key operational variables such as vessel access, downtime, failure rates, and logistics planning. However, obtaining reliable environmental data over a sufficiently long timeframe, with appropriate spatial and temporal resolution, remains a major challenge in offshore wind modelling.

In Chapter 2 and Chapter 4, ERA5 reanalysis data, available via the Copernicus Climate Data Store, was used as a primary environmental input for the case study on Darwin, Australia and for the case studies analysing Scotwind sites. While ERA5 has become increasingly popular due to its global coverage, free accessibility, and growing reliability, it suffers from limited spatial resolution, especially in complex or coastal environments. Hindcast datasets, like ERA

5, rely on historical data and numerical models to simulate what conditions were like in the past. This coarse resolution means that it may not accurately capture localised wave and wind conditions that are critical for site-specific O&M planning, particularly for nearshore projects or those in topographically complex regions like parts of the Scottish coastline (e.g. ScotWind developments). Additionally, reanalysis data tend to smooth out short-duration extreme events, which can lead to underestimation of access restrictions or failure-driving conditions. Within the thesis, these disadvantages may result in the operational costs for the Darwin, Australia study to be under or overestimated, meaning the effectiveness of nightshift may also be over or under appreciated. For the sea ice data, the daily inputs for the sea ice concentration and thickness utilised Global Ocean Ensemble Physics Reanalysis, having similar drawbacks to the ERA 5 reanalysis. The assumption within the sea ice analysis was that the coverage of ice throughout the day would not vary whereas in reality there may be changes that effect the accessibility of the sea ice vessels on a day to day basis.

In contrast, measured observational data, such as that obtained from offshore platforms (e.g. the FINO datasets in the German Bight or the Martha's Vineyard coastal observatory in the U.S.), can offer higher fidelity and site-specific accuracy. These data sets are invaluable when available, but often suffer from limited temporal coverage and data gaps. For example, in the case of the Martha's Vineyard site, while high-quality metocean observations were available, only 18 months of cleaned data were usable due to missing or incomplete hourly records across the broader dataset.

A further complication arises from the scale and layout of modern offshore wind farms, which may span tens of kilometres. As a result, accurate modelling may require multiple environmental data points per site to capture spatial variability across the array, particularly in large-scale floating wind deployments where wind, wave, and current conditions may differ across turbine locations. For both models, the climate input data is limited to only one specific point within the wind farm location, using the assumption that the weather parameters would be consistent across the whole wind farm. The assumption could result in characteristics of the metocean profile for the whole wind farm to be overlooked, resulting in uncertainty in KPI estimations.

Moreover, for the purposes of the thesis, the metrics for vessel accessibility were limited to wind speed, significant wave height and the novel sea ice metric, which overlooks key variables such as wave direction, period, current velocity, and wind-induced drift. This simplification can significantly underestimate or overestimate accessibility windows, especially for floating platforms, where dynamic motion responses are more complex. Incorporating more realistic marine environment modelling, including multi-directional wave and current effects, can improve model accuracy and would allow the mdoels to be adapted for floating wind farm analyses.

In summary, while reanalysis products like ERA5 offer valuable accessibility and consistency, they must be used with caution in high-resolution operational studies. Measured datasets can enhance model accuracy, but are constrained by availability, and coverage. Improving O&M simulation fidelity depends on striking a balance between data resolution, availability, and computational efficiency, while also developing models that can better integrate the complex environmental dynamics faced by both fixed and floating offshore wind farms.

7.2 Modelling Limitations

One of the recommendations in this thesis is to conduct an assessment for site specific locations regarding the effectiveness of night shifts. While previous work suggests that the use of night shifts could help optimise availability and reduce overall OPEX, the feasibility of such a strategy is highly dependent on regulatory, safety, and practical considerations. The thesis does not explicitly model legal or regulatory variations across jurisdictions. Differences between UK, EU, and US markets, particularly in terms of health and safety legislation, energy market structure, and offshore labour regulation, can have significant impacts on the feasibility of operational strategies. For example, a strategy that appears viable under UK regulations may not be permissible under stricter US offshore labour laws, or vice versa. As the offshore wind industry continues to expand into new regions, these jurisdictional differences will become increasingly relevant and should be considered in future studies. The thesis does not directly account for these differences, which limits the generalisability of the results. Additionally, the analysis does not model the increased costs associated with night-time safety requirements, lighting, or crew fatigue management, all of which could significantly alter the economic case for night shift deployment. The appendix to the thesis outlines some of the industry discussions that were carried out for the analysis and some further considerations for night shift.

Another chapter of this thesis examined the OPEX implications of different drivetrain configurations, comparing MS and DD turbines under varying failure rates through O&M simulation.

The analysis highlighted the potential for DD turbines to deliver lower long-term maintenance costs due to their reduced component count and elimination of the gearbox. However, the model assumed that major component replacement (MCR) on DD turbines could be performed in a modular or component-based manner, similar to MS turbines. This assumption does not fully reflect the current state of the market, where most commercially available DD turbines require a full nacelle replacement for MCR, due to the absence of a detachable generator or modularised subcomponents. In reality, there are only a limited number of crane vessels globally with the lift capacity to carry out such operations offshore, and their availability and cost can be a significant constraint, especially in remote or weather-limited sites.

However, this modelling approach can be understood as a forward-looking scenario that anticipates future developments in DD turbine design. There is ongoing research and industry interest in improving the maintainability of direct drive systems by introducing detachable or modular components that would enable partial nacelle disassembly or uptower repair. Several OEMs and research institutions are actively exploring solutions to reduce reliance on heavy-lift vessels for major repairs. If such designs become commercially viable and widely adopted, the operational disadvantages currently associated with DD MCR could be substantially mitigated, potentially validating the cost-saving projections suggested by the model.

That said, the omission of current logistical challenges does limit the present-day applicability of the conclusions. In particular, the model does not account for the cost and lead time implications of full nacelle swaps, nor does it include the operational advantages offered by uptower MCR capabilities, a key innovation in MS turbine maintenance over the last two decades. Uptower MCR enables in-situ repair of major components without the need for expensive vessel mobilisation, significantly reducing downtime and cost. Therefore, while the model provides useful insight into the potential future advantages of DD systems, it may understate the current real-world benefits of MS turbines, especially in sites with difficult access or constrained crane logistics. Future work should differentiate between present-day and future-state turbine architectures and include repair logistics as a critical variable in O&M cost modelling.

Another major focus of the thesis is the use of opportunistic maintenance scheduling, where maintenance is aligned with favourable market conditions, namely curtailment periods, but could be applied to environmental conditions such as low wind speeds. This approach relies heavily on the availability and accuracy of forecasting data. In principle, operators could avoid high-revenue periods or unfavourable weather windows by scheduling work during times when production or market prices are lower. However, implementing this strategy in practice would require advanced short-term forecasting tools, flexible workforce deployment, and effective coordination between operational and market teams. Many current offshore wind operations are not structured to support this level of adaptability. The model assumes a relatively high degree of centralised operational control. In practice, O&M activities are often distributed across multiple contractors and service providers, each with their own constraints, priorities, and contractual obligations. This fragmentation can limit the operator's flexibility in scheduling maintenance precisely in response to curtailment events or changing environmental windows. Moreover, the success of strategies such as night shift deployment or curtailment-informed maintenance is heavily influenced by the local policy environment and infrastructure. For example, port availability, labour regulations, vessel access, and grid curtailment compensation rules can vary significantly between countries and even between regions. These site-specific policy factors can either support or inhibit the implementation of the strategies proposed in this thesis. As such, while the modelling demonstrates the theoretical value of adaptive, data-driven O&M planning, real-world deployment will require closer integration with local regulatory frameworks, stakeholder coordination, and logistical realities.

Data quality and modelling assumptions also represent key limitations in the thesis. Much of the failure rate data used was drawn from publicly available sources or industry reports, which often rely on aggregated figures that do not reflect the variability between turbine models, operating environments, or maintenance regimes. In particular, the treatment of reliability inputs in failure rate analysis is somewhat simplified due to a lack of detailed, publicly available data on larger rated turbines. This introduces potential inaccuracies into the reliability analysis, particularly given the growing adoption of larger rated turbine technology in new offshore wind projects. A more granular dataset, ideally provided by OEMs or operators, would significantly improve the robustness of future modelling efforts. For the opportunisitic maintenance model, failure rates were modelled using a two-parameter Weibull distribution, which is commonly used in wind turbine reliability analysis due to its flexibility in representing various types of failure behaviour. However, it is important to clarify that in this implementation, the Weibull parameters used effectively result in a constant failure rate over time and therefore do not explicitly capture component aging or degradation.

This approach reflects a practical limitation in the availability and quality of failure data. As noted in the literature, there is often insufficient long-term, high-resolution operational data to confidently estimate time-varying failure rates, particularly those that represent aging effects. Most public datasets and even many OEM-released summaries only support aggregated failure rates or assume a stationary process. In line with this, the modelling in this work assumes a time-invariant failure distribution, meaning that the probability of failure in any time interval remains constant regardless of component age or usage history. The failure rate applied in the simulations does not vary as a function of turbine age, nor does it account for early-life defects or wear-out phases. The thesis does not attempt to model phenomena such as infant mortality or end-of-life degradation. The use of the Weibull distribution in this thesis should be interpreted as a convenient statistical model for representing average or steady-state failure behaviour across a fleet, not as a dynamic aging model. Future work with access to more granular and long-term operational data could expand on this by incorporating time-dependent failure modelling and maintenance strategies tailored to component aging.

In summary, while the models and recommendations in this thesis offer valuable insights into how offshore wind operations can be optimised through better alignment with weather and market conditions, the real-world feasibility of these strategies is constrained by technical, regulatory, and data-related factors. These limitations suggest that the findings should be viewed as directional rather than definitive, and further work is needed to refine the models, incorporate jurisdiction-specific factors, and assess the full range of economic incentives at play in curtailment and maintenance decision-making.

7.3 Recommendations to Industry

Based on the findings and models developed in this thesis, several recommendations are proposed for key stakeholders in the offshore wind industry. These insights aim to enhance decision-making around operations, maintenance, and overall project strategy, especially in challenging environments or under cost constraints.

7.3.1 Wind Farm Developers and Operators

Effective planning and operation of offshore wind farms require a holistic approach that integrates technical, environmental, and economic considerations. Based on the findings of this thesis, the following recommendations are proposed for wind farm developers and operators:

Log O&M Activities by Shift: Original Equipment Manufacturers (OEMs), in collaboration with operators, should implement separate logging of repair and replacement durations during day and night shifts. This would enable empirical analysis of workforce productivity across different timeframes and improve the accuracy of O&M modelling. With shift-specific data, operators can evaluate whether night shifts result in lower productivity or extended repair durations. This insight can refine simulation models and influence decisions around workforce scheduling and shift deployment.

Improved OPEX Forecasting: Understanding performance variations between shifts supports more accurate OPEX forecasting, particularly when night shifts are introduced to reduce downtime. Data-driven assessments can better quantify cost savings and operational trade-offs.

Planning for Sea Ice Conditions: In regions prone to seasonal sea ice, developers must consider limited accessibility during winter months. Currently, no dedicated icebreaking vessels exist for offshore wind applications, which could lead to significant downtime. Early planning should assess whether projects in such regions are viable given these constraints.

Turbine Selection and Reliability Trade-offs: Where accessibility is restricted during certain times of the year, higher-reliability turbines may be necessary. Although such models may incur higher CAPEX, they could reduce OPEX through fewer failures and shorter downtime. Turbine size, model, and expected failure rates should be evaluated with site-specific constraints in mind.

Failure Rate Sensitivity: Inaccessibility magnifies the cost of failures, both in terms of lost production and delayed repairs. Developers should use failure rate studies, such as those explored in this thesis, to guide turbine procurement and maintenance planning, especially in remote or environmentally challenging locations.

Long-Term Profitability Assessment: Prior to investment, developers should perform scenario analyses that incorporate environmental constraints, failure rate data, and maintenance access limitations. This will support a more realistic assessment of long-term project profitability.

Use of Market Forecasts: Developers should explore the use of day-ahead electricity market forecasts and wind curtailment predictions to inform maintenance planning. This may require improved analytics capabilities or collaboration with external data providers. In regions or periods where curtailment is high, during low wind or low market price shceduling maintenance could reduce opportunity cost and improve asset utilisation.

Adaptable Maintenance Strategy: A flexible, responsive maintenance strategy should be established during the planning phase. This includes:

- Investing in technician training to enable adaptable and opportunistic scheduling.
- Ensuring access to real-time and forecasted weather and market data.
- Integrating maintenance scheduling with broader project financial planning and grid operation considerations.

7.3.2 Insurance Providers and Risk Assessors

The insurance sector plays a critical role in de-risking offshore wind investments. However, insurance models must evolve to better reflect the unique operational risks associated with offshore wind projects.

Clarify Risk Priorities for Offshore Wind: Insurers should clearly define what constitutes the greatest risks in offshore wind. This may include turbine failure, weather-induced inaccessibility, or market-related impacts such as curtailment. Clearer prioritisation will enable better alignment with project development and operational strategies.

Align with Maintenance and Access Risk: Insurance products and premiums should reflect project-specific risks, such as:

- Larger rated turbine model reliability and expected failure rates.
- Geographic and seasonal risks, including sea ice, harsh environmental conditions and distance from shore.
- The extent to which developers implement predictive maintenance and flexible scheduling strategies.

Data-Driven Insurance Policies: Collaboration between insurers, OEMs, and developers is essential to improve insurer accuracy. Access to operational data, including downtime logs, repair times, and failure frequencies, would support more refined and fair insurance pricing.

7.3.3 General Stakeholders

Improving offshore wind performance and cost-effectiveness requires greater coordination and transparency across the industry. Several general recommendations are outlined below:

Data Sharing and Standardisation: There is a strong case for industry-wide standardisation of O&M data, including failure logs, downtime events, and curtailment data. Standard formats would enable benchmarking, facilitate cross-project learning, and improve modelling accuracy.

Cross-Disciplinary Coordination: Maintenance and operational planning should not be siloed. Financial analysts, operations managers, OEMs, and insurers should collaborate from the design phase onwards to ensure that maintenance and risk strategies are both technically sound and economically viable.

Chapter 8

Conclusions and Future Work

This thesis set out to investigate how operations and maintenance (O&M) strategies for offshore wind energy can be enhanced and adapted to address the challenges posed by the next generation of offshore wind farms. As outlined in the introduction, the offshore wind sector is evolving rapidly, in terms of turbine scale, site location, environmental conditions, and technological complexity. Maintaining low operational costs while ensuring reliability is essential if offshore wind is to remain a competitive and viable solution within a net zero energy future. O&M modelling has therefore become a crucial tool for anticipating future conditions and guiding investment and strategy.

The research was structured in two parts, each contributing to this aim from a different perspective. Part I focused on extending an existing O&M model with new capabilities, inputs and environmental considerations, while Part II developed a novel modelling framework that introduced an opportunistic maintenance strategy.

Chapter 1 examined two distinct but thematically connected accessibility challenges facing the future of offshore wind operations and maintenance: daylight availability and sea ice constraints. These factors are increasingly relevant as offshore wind expands into more geographically diverse and climatically challenging regions. The first analysis focused on the cost implications of limited daylight hours across three offshore wind sites. By comparing three maintenance strategies, daylight limited, daylight not limited, and night shift, the study found that the economic viability of night shift operations varies significantly by location. For instance, the North Sea site showed a substantial £32.74 /MWh reduction in costs under the night shift strategy, while the Darwin site saw an increase in costs. These results highlight that maintenance strategies must be adapted to site-specific daylight conditions, reinforcing the view that no single operational approach is universally applicable. Alongside economic considerations, the chapter also highlighted the largely underexplored issue of technician health and safety during night shifts. Fatigue, visibility challenges, and the overall impact on workforce welfare must be carefully weighed when assessing the feasibility of such strategies. This analysis emphasised the importance of integrating human factors and safety concerns into the economic optimisation of O&M strategies, particularly as the industry seeks to expand capacity and efficiency. The second analysis addressed the operational impact of sea ice on maintenance vessel accessibility. By integrating sea ice metrics into an existing O&M model, the study evaluated the performance of vessels with varying ice-breaking capabilities across three cold-climate sites: Finland, China, and Canada. The findings demonstrated that vessels with higher ice-breaking capacity improved turbine availability, particularly at the Canadian site, which showed a 10 percent increase in availability and associated cost reductions. However, the study also found that benefits plateau beyond a certain ice-breaking class, varying by location depending on sea ice thickness and concentration. This analysis provided an important foundation for understanding how to maintain wind farms in ice-prone waters, a topic previously underexplored in the literature. The results underscore the need for location-specific vessel strategies and suggest that further research into turbine reliability in cold climates is warranted to support future offshore deployments in such regions. Together, the chapter demonstrated that accessibility challenges can have a considerable impact on the cost and feasibility of offshore wind maintenance. It reinforced the necessity of location-sensitive modelling approaches and the inclusion of broader operational and human factors in the planning of O&M strategies.

Chapter 2 explored the implications of scaling offshore wind turbines from current commercial sizes to next-generation 10 MW machines, focusing on the resulting changes in operations and maintenance (O&M) costs. As the industry moves towards larger, more powerful turbines, understanding how size influences cost-effectiveness is essential for informed technology selection and project planning. This chapter contributed to that understanding by examining whether upscaled turbines can deliver economic advantages under equivalent reliability assumptions and how drivetrain configuration and site-specific factors modulate these outcomes. The analysis revealed that 10 MW turbines, when modelled with the same failure rates as 3 MW turbines, yielded lower total and direct OPEX across both case study sites, the North Sea and the US, regardless of configuration. This supports the notion that turbine scaling can lead to operational cost savings, primarily due to higher energy production. However, the results also demonstrated that the magnitude of this advantage is sensitive to failure rate increases. While 10 MW direct drive turbines had lower O&M costs compared to 3 MW turbines until they had 18% and 24% failure rate increase at the North Sea and US sites respectively, the 10 MW medium speed turbines had the same operational costs as 3 MW turbines at just 8% and 16% increase in the failure rates. This reinforces the critical role of maintaining high reliability as turbine capacity increases. The analysis reaffirmed earlier findings that direct drive turbines are generally more cost-effective than medium speed alternatives, largely due to reduced use of heavy lift vessels. Yet, the study also revealed that this advantage is not absolute. In particular, the US site favoured the medium speed configuration more than the North Sea site due to lower lost revenue costs, indicating that drivetrain suitability is influenced by local accessibility, availability, and energy market conditions. These findings highlight an important trade-off: while direct drive turbines offer lower failure risks and simplified mechanical systems, they are more sensitive to downtime losses in high-capacity applications. This makes the economic case for direct drive configurations highly dependent on ensuring high availability and suggests that reliability degradation disproportionately affects larger turbines. The chapter also acknowledged modelling limitations, including the assumption of uniform failure rate scaling across all components and the use of static cost assumptions across sites. Despite these simplifications, the comparative trends offer valuable insights. Further research could disaggregate O&M costs by failure category, particularly the role of converters, and explore site-specific drivetrain optimisation as a route to enhanced cost performance.

Chapter 3 focused on assessing whether conclusions from earlier reliability studies on smaller turbines could be applied to the new generation of larger turbines, specifically 15 MW machines. The study collated updated failure rate data for key components, namely the generator, gearbox, and main bearing, and ran simulations across three case study sites. The results showed that direct drive turbines consistently achieved lower operational costs and higher availability than medium speed turbines at all sites. However, the cost advantage of direct drive configurations was less pronounced than in previous studies of smaller turbines. Sensitivity analyses revealed that replacement rate assumptions had a significant impact on outcomes. High replacement scenarios led to increased costs of around 10 percent, while low replacement rates produced cost savings of a similar magnitude. These variations were more pronounced for medium speed turbines, particularly at sites with limited accessibility, further favouring direct drive designs due to their lower failure frequencies and reduced need for major interventions. Importantly, the analysis found that while direct drive turbines are generally more economical at sites with limited accessibility, medium speed configurations could become more cost-effective if failure rates fall below specific thresholds. This finding underscores the importance of obtaining high-quality, component-specific reliability data for large turbines. The chapter concludes that selecting an optimal drivetrain configuration for future offshore wind farms must take into account site-specific accessibility and evolving failure rate data. It highlights the need for continued research into the reliability of larger turbines and calls for expanded datasets beyond the core components studied here. These insights provide valuable guidance for developers aiming to minimise operational costs while ensuring reliable long-term turbine performance.

Together, these chapters demonstrated that enhancing existing models with updated inputs and expanded capabilities can yield deeper insight into future operational scenarios. They also validated the value of targeted scenario analysis in guiding technology choices and site planning.

Moving into Part II, Chapter 4 introduced a new modelling framework aimed at enhancing offshore wind O&M strategies through the integration of curtailment events into preventive maintenance scheduling. As the offshore wind industry evolves, so too must its operational strategies, particularly in response to increasing system complexity, fluctuating power market dynamics, and greater emphasis on cost optimisation. This chapter presented a novel approach to opportunistic maintenance that builds on traditional preventive strategies by capitalising on "free downtime" during grid-imposed curtailment periods. The model simulates the full operational life of a wind farm, combining Weibull-distributed failure behaviour with real-world weather and curtailment time series, vessel constraints, and cost parameters. A key feature of the methodology is the implementation of age-based thresholds to determine when components are eligible for preventive maintenance. These preventive actions are triggered in two ways: during major corrective replacements (traditional opportunistic maintenance) and, uniquely, during curtailment windows when turbines are already offline. This dual-trigger system allows the model to evaluate whether taking advantage of curtailment can reduce OPEX and improve overall turbine availability. By framing maintenance scheduling as a cost-benefit analysis, the methodology offers a dynamic, economically-informed alternative to static maintenance intervals. This strategy is especially relevant in energy systems where curtailment is prevalent and offers wind farms compensation through constraint payments. Although the model's current version is focused on UK-based assumptions, it lays the groundwork for broader applicability. Future development of the model should include the integration of dynamic electricity pricing to better reflect real-time market conditions, route optimisation for clustering maintenance tasks efficiently, and testing in international markets with differing curtailment mechanisms. Additionally, a more in-depth valuation of preventive maintenance, including life extension benefits and increased generation from avoided downtime, would improve the robustness of the model's cost-benefit outputs and provide interesting insights into other benefits from the maintenance strategy. Overall, the chapter advances the concept of maintenance flexibility in offshore wind and demonstrates the potential for smarter, more responsive scheduling to reduce costs and improve performance. The curtailment-aware approach presented here not only enhances existing modelling practices but also anticipates the increasingly interconnected relationship between power market behaviour and O&M strategy.

Chapter 5 demonstrated the effectiveness and applicability of the curtailment maintenance strategy developed in Chapter 5 through comparative analysis against two benchmark approaches: a corrective maintenance strategy and a simple opportunistic strategy. By applying the model to two distinct offshore wind farms, Beatrice and Walney, the strategy was shown to offer considerable reductions in operational expenditure, particularly for sites with higher levels of energy curtailment. In the case of the Beatrice wind farm, which has a higher average curtailment of approximately 10.5%, the model achieved a 50% reduction in operational costs compared to a corrective approach, and a 34% reduction relative to a simple opportunistic strategy. Availability metrics also improved under the curtailment strategy, reaching 95% for time-based availability and 90% for energy-based availability, outperforming the other strategies by 1% in both categories. Conversely, for the Walney wind farm, where curtailment is limited to around 1.5%, the performance gains were less pronounced. The curtailment strategy still produced the lowest operational costs, but only marginally so, achieving a 1.8% cost reduction compared to the opportunistic strategy. This indicates that while the curtailment strategy offers tangible benefits, its effectiveness is strongly dependent on the level of curtailment available for scheduling maintenance. Sensitivity analyses further reinforced the robustness of the model and identified the most influential parameters affecting OPEX and availability outcomes. Key sensitivities included failure distribution parameters, technician availability, turbine size and count, and distance from shore. Notably, variation in the scale parameter of the failure distribution produced the largest shifts in cost outputs, emphasising the critical importance of reliable failure rate data in offshore maintenance modelling. Additionally, the curtailment sensitivity analysis confirmed that operational costs decreased by £9/MWh when curtailment levels were increased from 1.5% to 10% for both wind farms. Availability likewise improved under higher curtailment conditions, as more opportunities arose to conduct maintenance with minimal impact on energy production. These findings collectively validate the model's potential to reduce operational costs and improve asset availability, particularly in offshore wind farms with significant curtailment. However, for sites with limited curtailment, the marginal cost advantage of the strategy must be weighed against the additional implementation challenges, such as enhanced condition monitoring requirements, operator training, and complex logistical planning. Therefore, a cost-benefit assessment tailored to each wind farm's specific operating conditions is essential when considering the adoption of this maintenance strategy.

This thesis has demonstrated that effective modelling plays a vital role in preparing for and managing the O&M challenges of future offshore wind farms. Whether through extending existing models or creating new ones, the ability to simulate, test, and evaluate maintenance strategies under changing conditions is essential for supporting the industry's long-term cost efficiency and reliability. The findings across both parts of the thesis contribute to the broader understanding of how to reduce the levelised cost of energy through smarter maintenance approaches. They also reinforce the need for continuous model development to ensure that O&M practices keep pace with technological and environmental shifts. As offshore wind expands into new regions and adopts increasingly advanced turbine designs, the ability to pre-emptively identify cost risks, access limitations, and logistical trade-offs will become even more critical. Modelling, especially when combined with high quality failure data, real-time monitoring, and flexible operational strategies, will be central to this effort.

There are several opportunities to build upon the research presented in this thesis. One key area for future investigation lies in the acquisition of accurate operational cost and reliability data for higher-rated turbines. This will require access to a larger and more representative dataset of turbine failures, derived from real-time performance monitoring. Improved access to such data would significantly enhance the precision and realism of offshore O&M models. In particular, the opportunistic maintenance framework developed in Chapters 4 and 5 would benefit greatly from more reliable failure distribution inputs. Incorporating statistically robust failure data would not only improve the model's accuracy but also provide deeper insights into the practical effectiveness and limitations of the curtailment-based strategy. Several assumptions and limitations of the model also present avenues for further development. Integrating additional functionalities, some of which were explored within this thesis, from existing tools such as the Strath OW O&M model could improve the model's adaptability and relevance to real-world applications. Notable examples include accounting for daylight restrictions, enabling night shift maintenance operations, and incorporating environmental constraints such as sea ice. The integration of these aspects would yield a more flexible and industry-ready model, capable of supporting a wider range of operational contexts.

The central takeaway from this research is the importance of improving offshore wind O&M through real-world data acquisition and enhanced collaboration between academia and industry. Without prioritising these two aspects, the offshore wind sector will continue to face challenges in proactively identifying and mitigating the most pressing O&M risks. Strengthening the connection between research and operational practice will enable earlier identification of emerging issues, helping to reduce associated costs and ensuring a more resilient and cost-effective offshore wind industry.

Appendix

Table 1: Industry Feedback gathered over the course of the thesis project. Feedback is anonymised for confidentiality reasons.

Who	Description of Feedback	Role	Date Obtained	Method of Feedback
OW OceanWinds	Utilisation of curtailment as a method of carrying out maintenance would currently be difficult to implement due to the organisation and logistics involved in mobilising teams..	Operations Project Engineer	09/2024	Site Visit
OW OceanWinds	Night-time strategy was not favoured for Moray East wind farm; a daytime CTV strategy was chosen for the foreseeable future.	Operations Project Engineer	09/2024	Site Visit
Siemens Gamesa	Night shift implementation often resulted in lower productivity during night shift for offshore wind workers.	Ex-Operations Manager	01/2024	Industry Talk
Suomen Hyötytuuli Oy	Tahkoluoto wind farm strategy discussed. Nearshore location requires only one CTV. Steel-hulled vessel Mekkari can navigate 20 cm thick ice (Polar Class IC). Ice rarely prevents access, 1 or 2 days a year. Ice condition monitoring uses: Finnish ice charts, turbine webcam, and local fishermen reports.	Occupational Safety Manager	06/2024	Zoom Interview