Developing a holistic operation and maintenance simulation tool for emerging offshore wind projects

Nadežda Avanessova

idcore

EPSRC & NERC InDustrial CDT
for Offshore Renewable Energy

www.idcore.ac.uk

Doctor of Engineering

UNIVERSITY OF STRATHCLYDE
THE UNIVERSITY OF EDINBURGH
UNIVERSITY OF EXETER
OFFSHORE RENEWABLE ENERGY CATAPULT

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Abstract

Offshore fixed and floating wind deployment is growing globally every year. According to the ORE Catapult projections there will be over 4000 turbines installed in 2030 in the UK alone. The number of offshore cables and substations will increase proportionally. Operation and maintenance of these offshore assets contributes to a significant portion of project costs. This is particularly due to the growing demand for resources: vessels, ports and personnel. Operation and maintenance simulation tools can support the industry by modelling various scenarios and predicting the cost and downtime difference. This thesis introduces a simulation tool for operation and maintenance, an extension of the pre-existing COMPASS tool, incorporating innovative features.

Existing tools rely solely on the user input which can be problematic considering the lack of public data, the complexity of operation and maintenance and the fact that not all users are familiar with it. This thesis reviews information and data collected from several sources, enhances it with expert knowledge and presents an assembled operation-and-maintenance-inputs guide that can be reliably used in operation and maintenance simulations.

Data analysis of over 2000 major operations presented in this thesis showed that maintenance duration is highly variable but it is modelled as fixed in existing tools. A novel function was developed to capture this variability in COMPASS and the impact of it is demonstrated via a case study. This thesis also presents the variation of major operation rates throughout the lifetime of a wind farm.

Existing operation and maintenance simulation tools either cannot model cable topology impact, floating wind turbine maintenance and multi-rotor turbine maintenance or model these technologies with significant limitations. This thesis presents a function that is able to capture the impact of cable failures in complex array cable networks that existing tools cannot model. Its application is then demonstrated in this thesis via a case study showing how the choice of cable topology can impact the revenue losses.

This research project developed the computational logic for modelling floating turbines, multi-rotor turbines and personnel movement and limitations. These developments are then demonstrated in novel case studies. One compares a service operation vessel with an offshore maintenance base accommodating three crew transfer vessels and finds that the scenario with service operation vessels results in higher energy availability and lower operational expenditure. Another case compares multi-rotor turbines with single-rotor turbines and finds that despite the more frequent tow-to-port operations, the case with twin turbines results in lower operational expenditure primarily due to a smaller number of array cables and hence fewer cable repairs.

This thesis presents a cross-model benchmarking study that includes tow-to-port scenarios that have not been considered in previous model verification studies. This thesis benchmarks COMPASS outputs against the outputs of two other simulation tools, WOMBAT v0.8.1 (developed by the NREL) and the operation and maintenance analysis tool developed by WavEC. The findings from this benchmarking study highlight that the differences in methodology can have a significant impact on the simulation outcomes. In particular the main differences occurred from modelling maintenance activity interruption and towing to port.

The key outcome of this work is the operation and maintenance simulation tool that can guide the industry to finding the best operation and maintenance strategies for emerging wind farm projects.

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I would like to express my heartfelt gratitude to my dearest friends who have been a constant source of support, encouragement, and laughter throughout this academic journey. I am truly fortunate to have kind and inspiring friends by my side, and I extend my deepest appreciation for their friendship and understanding during moments of triumph and the more challenging times.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

Nadezda Avanessova

List of Publications

Avanessova, N. and Gray, A. and Lazakis, I. and Thomson, R. C. and Rinaldi, G. (2022). Analysing the effectiveness of different offshore maintenance base options for floating wind farms. Wind Energy Science (Vol. 7). In (pp. 887-901). doi: 10.5194/wes-7-887-2022

Avanessova, N., Land, J., Lee, A., Lazakis, I., and Thomson, C. (2023) Comparison of Operation and Maintenance of Floating 14 MW Turbines and Twin 10 MW Turbines. ASME Open J. Engineering ASME. 2 021031. doi: https://doi.org/10.1115/1.4062413

Nomenclature

H_s	Significant wave height
AHTS	Anchor Handling Tug Supply
AHV	Anchor Handling Vessel
BFR	Base Failure Rate
BOP	Balance of Plant
CAPEX	Capital Expenditure
CDF	Cumulative Density Function
CfD	Contracts for Difference
CI	Confidence Interval
CLV	Cable Laying Vessel
CoE	Centre of Excellence
COMPASS	Combined Operations, Maintenance, People, Assets and Systems Simulation
CTV	Crew Transfer Vessel
DF	Discount Factor
EA	Energy Availability
ELECTRODE	Electrical cable failure trending and reliability analysis for operational developments
FOW	Floating Offshore Wind
FR	Failure Rate
FT	Fault Tree
FTA	Fault Tree Analysis
H&S	Health and Safety
HFR	High Failure Rate
HLV	Heavy Lift Vessel
HV	High Voltage
JUV	Jack-up Vessel
KPI	Key Performance Indicator
LCA	Life Cycle Assessment
LCOE	Levelised Cost of Energy
MOE	Margin of Error
MPD	Marine Planning Document
MTTF	Mean Time To Failure
NI	No Information
NtM	Notice to Mariners

O&M	Operation and Maintenance
OEM	Original Equipment Manufacturer
OFTO	Offshore Transmission Owner
OMB	Offshore Maintenance Base
OPEX	Operational Expenditure
ORE	Offshore Renewable Energy
OSS	Offshore Substation
PBA	Production Based Availability
PDF	Probability Density Function
RAM	Random Access Memory
RAS	Robotics and Autonomous Systems
ROV	Remotely Operated Vehicle
RSV	ROV Support Vessel
SCADA	Supervisory Control and Data Acquisition
SOV	Service Operation Vessel
SPARTA	System Performance, Availability and Reliability Trend Analysis
TA	Time Availability
TP	Transition Piece
TTP	Tow-to-Port
UKHO	UK Hydrographic Office
WoW	Wait on Weather

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Chapter 1

Introduction

According to ORE Catapult Market Analysis & Insights there are now over 2500 turbines installed offshore in the UK waters (ORE Catapult, 2023c). More than a thousand are expected to be installed in addition to these before 2030. Water depth of the available seabed areas has lead to some projects using or planning to use floating substructure technology. Once commissioned the work on the wind farm does not stop; the condition of each offshore asset is constantly monitored both online and via regular physical visits. Despite the best efforts to keep offshore assets in their best condition for as long as possible, they still occasionally fail and require additional, often expensive visits.

Operation and Maintenance (O&M) analysis is the sector of wind farm analysis that calculates the Key Performance Indicators (KPIs) of the operating stage of the wind farm and selects the best strategies for maximising the electricity output while minimising maintenance costs. O&M simulation tools are the means by which this analysis can be performed. They simulate O&M of wind farms computationally. There are a few tools available already but they have their limitations.

This research addresses the question: what modeling techniques and methodologies can be employed to accurately simulate the O&M of emerging wind farms and guide the industry towards better O&M strategies? This research work identifies the gaps in existing tools and builds in novel O&M simulation features into an existing tool COMPASS, which is the ORE Catapult's in-house O&M simulation tool (ORE Catapult, 2023a). COMPASS stands for Combined Operation and Maintenance, People, Assets and Systems Simulation.

1.1 Objectives of research

All existing O&M simulation tools rely heavily on the user to provide the input. Collecting these inputs can be challenging due to limited public information, different format and level of detail in the available information and the sensitivity of asset failure data. The first objective of this work is to review what is currently available, identify new data sources and assemble an O&M activity input guide that can be used in O&M simulation tools.

Modelling cable topology, Service Operation Vessels (SOVs), turbine Tow-to-Port (TTP) and multi-rotor turbines is either impossible using existing tools or is done with some limitations. Models often simplify the complexity of O&M by neglecting the interaction between activities and assuming fixed activity durations. The second objective of this work is to build in O&M simulation features into the existing tool COMPASS based on the latest evidence so that it can realistically model emerging technologies.

The third objective of this work is to demonstrate that the developed tool works as intended and is capable of producing useful insights by benchmarking its outputs against two other O&M simulation tools.

Due to the limitations of other tools, some features could not be demonstrated via benchmarking alone. The last objective of this work is to demonstrate the use of these novel features via several case studies:

- Comparison of an SOV with an Offshore Maintenance Base (OMB)
- Comparison of twin turbine and single turbine O&M
- Comparison of four array cable topologies and varying cable Failure Rate (FR)
- Estimating the impact of variable maintenance duration on the output

1.2 Research structure overview

Figure 1.1 illustrates the organizational framework of this research. While the figure depicts the research being divided into four segments, it does not necessarily reflect the chronological order of the research process. Work from each segment occurred concurrently, driven by variations in data emergence timing and the availability of individuals crucial to specific aspects of the research presented in this thesis.

The initial section of this thesis is dedicated to investigating the current state of offshore wind and its O&M. The subsequent section involves the search for new O&M data and its analysis. The third part focuses on the structure and development of the O&M simulation tool, while the final part explores the tool's applications through various case studies.

The following paragraphs describe how this research work is broken down into chapters.

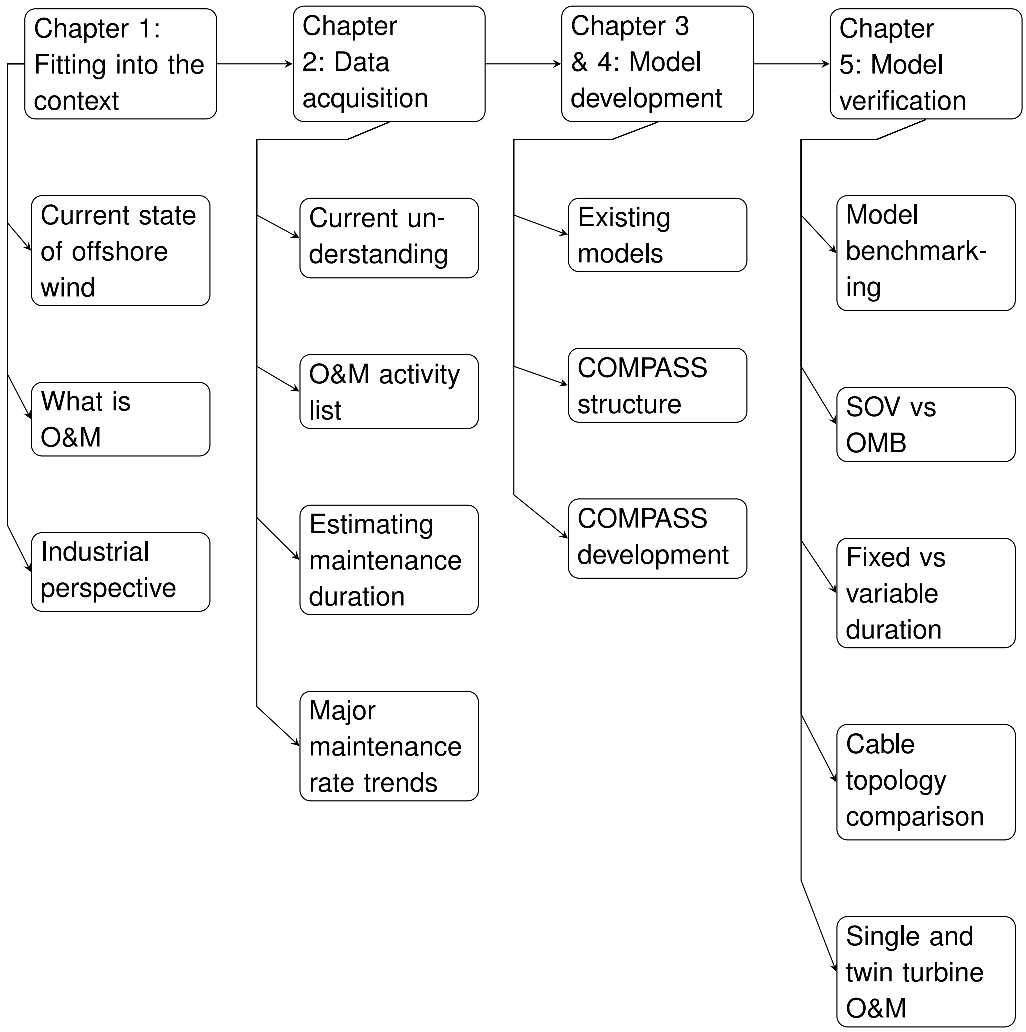


Figure 1.1: High level research structure excluding Chapter 6 which concludes the thesis.

Chapter 1 fits this research work into the context of offshore wind. It provides an understanding of the current state of offshore wind and how this industry is expected to grow in the future. Chapter 1 defines O&M and provides the main terminology that is necessary to understand the research work presented in this thesis. It gives an overview of the main O&M strategies. Chapter 1 also provides the perspective of ORE Catapult and explains their interest in supporting this research.

O&M simulation is not possible without the sufficient data. Chapter 2 provides the overview of data that is currently used by O&M analysts and highlights its drawbacks. Chapter 2 then finds alternative sources of O&M information, and assembles a set of O&M activities with their characteristics, that can be used as an input guide for integration into O&M simulation tools. This chapter looks at the newly available data in more detail and derives a cumulative density function for each component that can then be used to integrate the variation in repair and replacement time into the O&M simulation tools.

Chapter 3 focuses on the computational part of the O&M simulation tools. It gives an overview of existing models and highlights their limitations. Chapter 3 then gives a general introduction to COMPASS and explains its structure.

Chapter 4 goes through each major feature in COMPASS that was developed through the course of this research.

Chapter 5 applies COMPASS on case studies demonstrating its usefulness. The main purpose of the work presented in Chapter 4 is to build confidence in COMPASS outputs. COMPASS outputs are benchmarked against two other O&M simulation tools in Chapter 4. There are other novel case studies presented in the same chapter that provide interesting findings around O&M strategies and offshore wind technologies proving COMPASS to be a useful tool when assessing these.

Chapter 6 concludes this thesis and summarises the research work presented here. It then provides recommendations for the future research in this field.

1.3 Contribution to knowledge

The research presented in this thesis addresses gaps in existing O&M simulation tools, through developing input guidance and novel simulation techniques:

- This work for the first time uses publicly available Marine Planning Documents (MPDs) to assemble a list of O&M activities for the purpose of O&M simulation. This research uses two openly available portfolio reviews published by SPARTA and data from the Sea Impact service. SPARTA stands for System Performance, Availability and Reliability Trend Analysis. Both sources are currently underutilised in the context of O&M simulation. This research uses them to enhance the activity characteristics and consults with several offshore wind experts to fill in the missing data. This work then improves the existing O&M simulation tool COMPASS based on the new findings.
- This work analyses the largest available data set to date and estimates the durations of major operations on fixed wind turbines and their FRs. It shows that existing studies are either underestimating or overestimating major operation durations due to smaller and older data samples used. This research work also demonstrates that the assumption of a FR bathtub curve used in some O&M simulation tools is unjustified.
- This work develops the first method for capturing variability of operation durations in O&M simulation tools which results in increased variability in cost and EA outputs.
- This work presents the first ever method for modelling cable topology in O&M simulation tools that can be applied on complex cable connections beyond the string and ring cable layouts. Capturing cable connection accurately leads to more accurate estimates of turbine downtime and hence revenue loss. This study demonstrates how this method integrated in COMPASS allows to assess revenue loss in different cable topologies.

- This work extends the functionality of an existing O&M simulation tool COMPASS to technologies and O&M strategies that have been gaining their popularity: twin wind turbines, floating wind turbines and SOVs. It then analyses two novel case studies that demonstrate the tools capability to model these and guide the choice of technology and O&M strategy.
- This thesis presents a study where COMPASS is benchmarked against two other O&M simulation tools for the first time and demonstrates how the differences in simulation logic can significantly impact the simulation results.

1.4 Growing offshore wind industry

The fact that the UK is surrounded by the North Atlantic Ocean with abundance of shallow waters and good wind conditions make it a great place for offshore wind development. Wind speeds offshore are higher on average than onshore. Air flow offshore is also less turbulent because of the narrower boundary layer due to lower surface roughness of the sea compared to the land. It is easier to get public approval for building turbines offshore where they do not affect the landscape as much as they do onshore, this particularly relates to higher-rated turbines. All of this does not eliminate the need of onshore wind but highlights the accessibility and abundance of the offshore wind resource. In the UK, other renewable energy alternatives are still required to meet the net-zero target by 2050 set by the government (HM Government, 2021).

The first ever offshore wind farm was built in Denmark in 1991, only 2 km offshore and in waters reaching 4 m in depth (Orsted, 2019). According to ORE Catapult insights there are now over 2500 turbines installed offshore in the UK waters. According to the ORE Catapult Market Analysis & Insights there will be over 4000 turbines installed in 2030 but this will not be enough to meet the UK government target to reach 50 GW of offshore wind by 2030 due to the challenges that offshore wind is currently facing (ORE Catapult, 2023c). There are a few challenges associated with large scale offshore wind deployment globally. These include network grid readiness, supply chain readiness, complex consenting process, rising costs due to inflation, installation vessel availability and lack of experienced workforce.

There is not only the race for the scale of deployment in terms of number of turbines but also in terms of turbine rating. The power rating of a single turbine in the very first offshore wind farm was only 450 kW. At the time of writing the highest commissioned turbine rating is 13 MW at the Dogger Bank Wind Farm (SSE, 2023). In the same year the highest-rated turbine has been installed offshore in China, the MingYang 16 MW turbine (reNEWS biz, 2023a). The same year the MingYang announced the release of a 18 MW turbine followed by GE who have also initiated the development of a 18 MW turbine model (Buljan, 2023; reNEWS biz, 2023b). Later that year MingYang anounced the plans to develop a 22 MW turbine (Cosmo, 2023).

Turbine manufacturers with the largest turbine fleets offshore are currently Siemens Gamesa and Vestas, at the time of writing both manufacturers have designs not exceeding 15 MW. There is however a pressure on these OEMs to build higher-rated models to ensure their competitiveness. It is a question how sustainable this rapid growth in turbine rating is, Siemens Gamesa and Vestas have recently expressed concerns over this growing pressure (Millard, 2023).

Each time a new turbine version is developed the entire supply chain needs to be redesigned starting from blade manufacturing facilities and ending with blade testing facilities and construction vessels. Growing turbine sizes inevitably lead to the demand for larger vessels, expanded port facilities or even brand new ports. Floating Offshore Wind (FOW) turbines (covered in the next section) would require larger ports for assembly and for maintenance. Vessels and ports take time and sufficient financing to build. Larger vessels would also require upgrading existing harbours. Standardising existing models may now be a more sustainable way for the industry to grow.

An alternative to increasing turbine size is the installation of multiple turbines on a single foundation. Section 1.4.2 will discuss the options that are currently available.

In order to ensure continuous energy production offshore wind assets are constantly monitored, serviced and repaired if needed. The larger the scale of offshore wind the more challenging this becomes because of the arising need for more service vessels, longer distances to local ports and harsher weather conditions at these locations. These issues highlight the importance of having tools that are capable of taking these factors into account and estimate their impact as well as guide offshore wind developers to better strategies. This thesis develops such a tool. This tool was developed to capture the O&M of offshore wind including the emerging technologies described in the next two sections.

1.4.1 Floating offshore wind

Currently almost all offshore turbines in the UK are installed on a rigid foundation fixed to the sea floor. There are several fixed foundation designs, the most popular being monopiles and jackets shown in Figure 1.2. Fixed offshore turbines are limited by the water depth. FOW can be put in deeper waters which means more areas available for offshore wind deployment. FOW technology also allows for an opportunity to deploy offshore wind in countries with very limited shallow water areas such as Japan or the West coast of the USA. There is a variety of floating foundation designs, some examples are spar, tension-leg platform and semi-submersible platform as shown in Figure 1.2

Currently there are two demonstration projects in the UK: Hywind and Kincardine that use spar and semi-submersible floating platform technology respectively. ScotWind Seabed Leasing Round 1 results consisted of six fixed offshore wind farms and ten FOW farm projects, one mixed project (fixed and floating), the list was later extended with three additional floating wind farm projects in the area to the east of Shetland Islands in Scotland (Crown Estate Scotland, 2022a, 2022b).

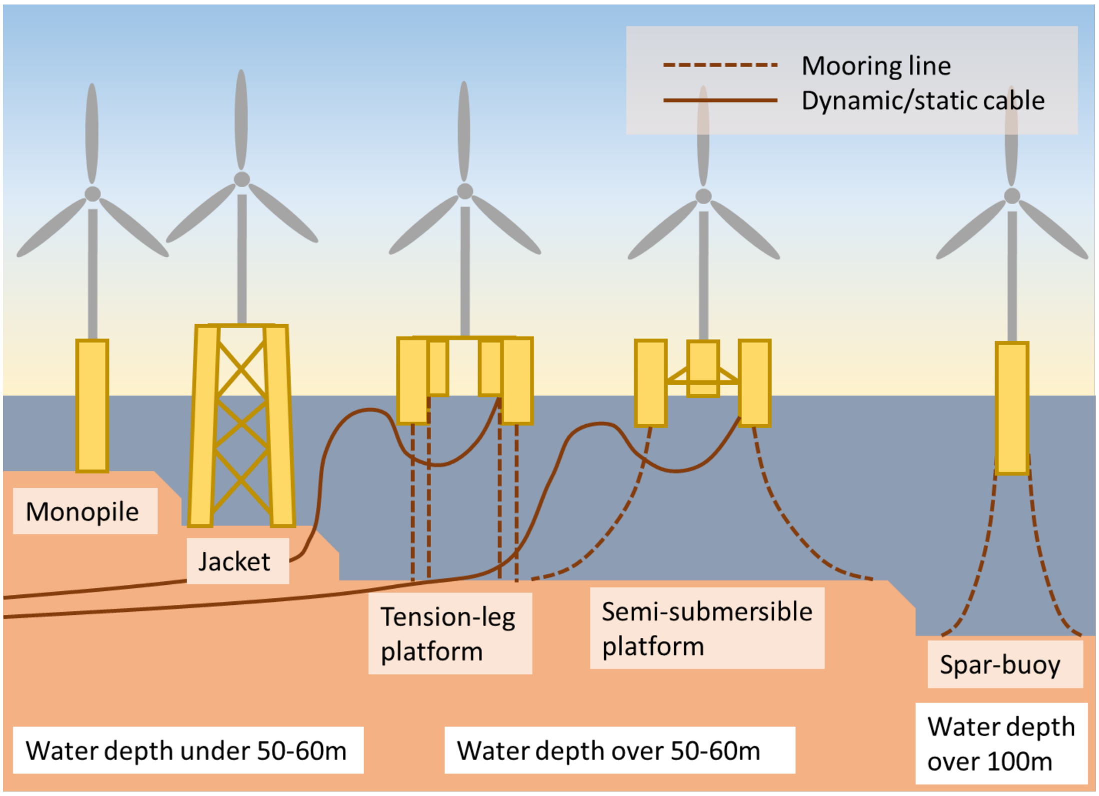


Figure 1.2: Common types of offshore wind turbine foundations. Monopile and jacket (left) are fixed-bottom foundations, tension-leg, semi-submersible and spar-buoy (right) are floating substructures.

1.4.2 Multi-rotor wind turbines

Section 1.4 described the issues arising from the continued increase in turbine sizes. Larger components are not only more expensive but also require larger vessels and cranes to handle them. Vessel cost increases with vessel size and capacity to lift (Correia da Fonseca et al., 2021). When it comes to blade replacement, blade costs have been shown to can scale exponentially with the blade length (Sieros et al., 2012). This makes blade replacement even more costly. The question then arises whether it is practical to keep increasing the turbine rating or is it better to achieve the same turbine rating by installing twin turbines on a single platform? Alternatively to simply increasing the turbine rating, more multi-rotor or multi-turbine structures could be installed offshore.

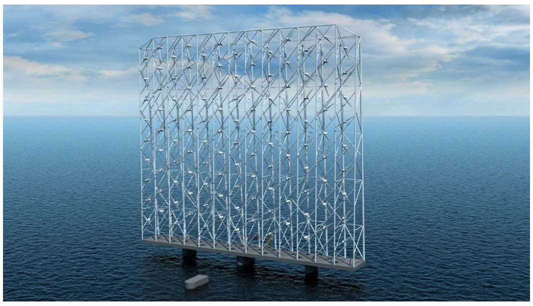
Multi-rotor tidal turbine structures have been in development for many years but the concept of multi-rotor wind turbines (which can also be referred to as twin-rotor turbines or twin turbines) has become more widely discussed only in the last decade. Multi-rotor wind turbines can have different designs. Three themes have been distinguished in these designs and are described below with the support of Figure 1.3:

a) **Two turbines installed on a single foundation** (Figure 1.3a).
So far this is the most advanced design in the list in the context of the offshore wind. One of the major twin-turbine developers, Hexicon AB, is currently planning to install an offshore floating wind demonstrator in the Celtic Sea and has been awarded a Contract for Difference (CfD) in the Allocation Round 4 in 2022 (*Contracts for Difference Allocation Round 4 results*, 2022). EnerOcean and Hexicon AB are currently the biggest developers of offshore floating twin turbines. Another twin rotor floating wind prototype, Nezzy, developed by the EnBW and Aerodyn has completed its tests in the Baltic Sea. It was expected to see the development of the full scale device in the beginning of the late 2022 or early 2023, however at the time of writing the construction and installation of a full scale device has not been completed (de Vries, 2022).

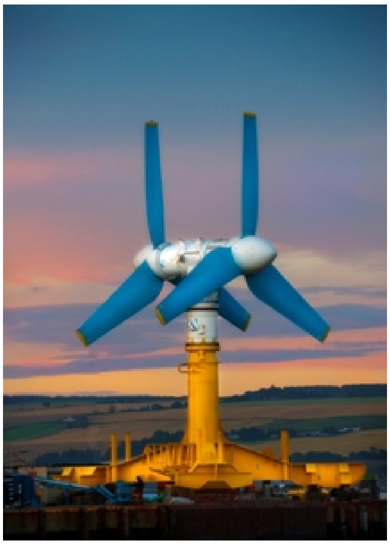
b) **Multiple rotors connected to a "mesh" or "honeycomb" structure** (Figure 1.3b).
The rotors in these structures usually have smaller size and lower power rating than those on twin turbines. In such designs, the failure of one turbine does not affect the operation of other turbines (McMorland, Pirrie, et al., 2022). This concept has not yet been demonstrated offshore.

c) **Co-axial twin rotors:** This concept is a combination of an upwind and a downwind rotor on a single turbine (Figure 1.3c). This is a rare concept for wind turbines, but more common in tidal turbines due to the regular reversing of tide direction which rarely occurs with wind. There were some small-scale projects for such turbines onshore but the concept has never been proposed for offshore wind turbines.

(a) Hexicon twin turbine concept. Source: Hexicon AB



(b) Windcatcher turbine concept (Snieckus, 2021)



(c) Atlantis Resources Corporation AK-1000 tidal turbine (EMEC, 2010)

Figure 1.3: Multi-rotor turbine concepts.

The emergence of the listed technologies in the offshore wind industry means that O&M simulation tools need to be adapted to model the operation of such turbines. Although only the first two options are currently applicable to offshore wind turbines making sure that O&M simulation tools can capture other concepts is useful. Taking into account other concepts when developing O&M simulation tools can make them more flexible and applicable to other technologies.

More information on existing O&M simulation tools and their application on multi-rotor turbines can be found in Section 3.1.

1.5 Operation and Maintenance definition

The definition of operation as seen in the *Oxford English dictionary (Online)* (2000) is *"The action of operating a machine, engine, railway, business, etc."* where the word operate may have two definitions: *"to cause or direct the functioning of; to control the working of (a machine, boat, etc.)."* and *"to manage, to direct the operation of (a business, enterprise, etc.); to carry out or through, apply (a principle, a tradition, etc.)"*

In the same dictionary maintenance is defined as *"The action of keeping something in working order, in repair, etc.; the keeping up of a building, institution, body of troops, etc., by providing means for equipment, etc.; the state or fact of being so kept up; means or provision for upkeep."*

Following these definitions O&M of Offshore Renewable Energy (ORE) assets in this thesis is defined as:

"Monitoring the performance of offshore renewable energy assets, planning offshore activities and taking measures to restore the assets to their original performance levels from the moment of full commissioning to the end of their lifetime. Enabling the safe and cost-effective operation of offshore renewable assets."

ORE assets in this thesis include offshore systems directly related to production and transmission of renewable energy: wind turbines, cables and substations. Alternative assets such as solar panels, wave energy converters, tidal energy converters and hydrogen production units are not considered in this thesis however a lot of development work on the O&M simulation tool discussed in Section 4 is also applicable to these assets.

Section 1.6 discusses the management bodies responsible for O&M. Different management bodies may have different ideas about when and how to perform O&M. Section 1.6 explains the roles of different institutions and organisations in the management of O&M of offshore wind farms.

Theses entities typically aim to strike a balance between asset performance, the associated maintenance costs and carbon emissions. Different management bodies may prioritise costs, performance and carbon emissions in a different order. Section 1.7 covers asset performance in detail.

In the renewable energy sector, there is an increasing emphasis on quantifying the embodied carbon in different components and the carbon released during specific operations, such as offshore vessel movements. It is important to note that this research does not delve into carbon emissions from O&M activities. However, the work presented in this thesis contributes significantly to improving future estimates of emissions.

1.6 Management

In the majority of cases in the UK, there can be distinguished three O&M management bodies:

- Wind farm owner
- Original Equipment Manufacturer (OEM)
- Offshore Transmission Owner (OFTO)

Offshore wind farms from the onshore substation to cables and turbines are procured and constructed by the farm owners, however it is after the full commissioning of the farm that responsibilities shift. In the UK it is a requirement that offshore wind farms sell their substations and export cable to an OFTO appointed by Ofgem via an auction, then the OFTO leads the O&M of onshore and Offshore Substations (OSS) and export cables for the rest of the lifetime of a farm. Inter-array cables remain the responsibility of the farm owner. The wind farm owner's priority is usually to export as much energy as possible, at the most beneficial price. The OFTO on the other hand does not gain from the farm energy production, therefore in the case of substation or export cable faults, its priority is likely to be to perform repairs with minimal costs.

Usually there is a warranty period provided by the OEM (for example, Siemens Gamesa or Vestas) for the first five years of farm operation, during which the OEM provides full service of the wind turbines (but exceptions occur with different contracts). Typical warranty contracts are performance-based i.e. OEM must guarantee a certain farm availability to the farm owner. After that period the owner may decide to extend the warranty agreement (at an additional cost) or to perform the maintenance themselves. The foundation however, and all components below the wind turbine, such as Transition Piece (TP), substructure, mooring lines or anchors, are not manufactured by the OEM and are therefore the responsibility of the farm owner. In the case of FOW there may exist a similar agreement between the wind farm owner and the floating substructure developer as there is between the wind farm owner and the OEM. That means the substructure developer must guarantee the substructure is maintained to a certain standard.

The interplay between wind farm owner, OFTO, OEM and substructure developers may be complex and not consistent between different wind farms. There may be some scenarios where maintenance vessels are shared between these bodies and other scenarios where they are not. In some cases the same technicians may be performing tasks on wind turbines and substructures but in other cases different technician teams are deployed. This thesis does not model this interplay and does not take into account contractual agreements between these bodies however future research should focus more on this topic because it may drive the selection of an optimal maintenance strategy.

The following section shows how the Levelised Cost of Energy (LCOE) is calculated using the Capital Expenditure (CAPEX) and Operational Expenditure (OPEX). Although different portions of OPEX may be covered by different management bodies this breakdown is not the focus of this thesis.

1.7 O&M strategy performance assessment

In the context of offshore wind, where project spending occurs at different scales at different times it becomes necessary to take into account a Discount Factor (DF). DF formula is given in Equation 1.1, where t is time and r is the discount rate. DF takes into account the time value of money. It is applied on the time-dependent components of the LCOE which is the metric used to assess the profitability of offshore wind projects.

$$DF = \frac{1}{(1+r)^t} \tag{1.1}$$

Most of the offshore wind farm projects in the UK are supported by the government via a CfD mechanism. Wind farm projects bid into the CfD based on their LCOE. Reduction in the LCOE increases the chances of offshore wind projects to participate in the CfD. Reduction in the LCOE is also highly desirable in FOW projects that are currently more expensive than fixed (Floating Offshore Wind Centre of Excellence, 2021). LCOE can be seen as a sum of $\mathrm{LCOE_{CAPEX}}$ arising from the initial investment and $\mathrm{LCOE_{OPEX}}$ arising from the O&M as shown in Equation 1.2.

$$LCOE = LCOE_{CAPEX} + LCOE_{OPEX} \tag{1.2}$$

Equation 1.3 breaks it down further and applies a DF on time-dependent components.

$$LCOE = \frac{CAPEX}{\sum_{y=1}^{n} \frac{E_y}{(1+r)^y}} + \frac{\sum_{y=1}^{n} \frac{OPEX_y}{(1+r)^y}}{\sum_{y=1}^{n} \frac{E_y}{(1+r)^y}} \tag{1.3}$$

In Equation 1.3 CAPEX is the capital expenditure or the initial investment in the year y. CAPEX usually includes all the procurement and installation costs, i.e. any costs that occur before the farm is commissioned. $\mathrm{OPEX_y}$ is the operational expenditure in year y, $\mathrm{OPEX_y}$ includes any costs that occur after the farm starts its operation. E_y is the energy production in year y. All costs and energy are discounted with a discount rate r, the purpose of the discount rate is to model a loss of value of money and energy over time.

As can be observed in Equation 1.3, LCOE reduction can be achieved my minimising OPEX and maximising the energy output. It is estimated that $\text{LCOE}_{\text{OPEX}}$ makes between 20% and 30% of the LCOE (Feng et al., 2010; Maples et al., 2013). Finding the ways to decrease the $\text{LCOE}_{\text{OPEX}}$ can lead to a faster reduction in the LCOE. Reducing OPEX and minimising turbine downtime (thus maximising energy output) is challenging particularly for future wind farms that would be installed far offshore outside the reach of Crew Transfer Vessels (CTVs), in harsher weather conditions and requiring larger vessels and cranes because of the increase in turbine component size.

Section 1.11 will discuss the O&M strategies that are currently used. The best way to model these strategies is to use O&M simulation tools. These tools can estimate OPEX, energy output and other KPIs and guide the selection of optimal O&M strategies and innovations.

As was shown in Equation 1.3, LCOE is also inversely proportional to the energy production, the higher the production, the lower the LCOE. Energy production depends on several factors:

- Turbine power curve
- Wind speed
- Wake effects
- Any power losses
- Turbine downtime due to turbine failures
- Turbine downtime due to maintenance

Although comparing the energy output directly is an option, there exist other KPIs that have been historically used for assessing wind farm performance. These are:

- Time availability (TA)
- Energy availability (EA)

These two KPIs can be used to assess and compare turbine downtime under different scenarios. TA is the time that the turbine was operational T_o divided by the total lifetime T_t.

$$TA = \frac{T_o}{T_t} \tag{1.4}$$

EA is the actual energy production E_a divided by the expected energy production E_e (if the turbine was operating continuously at its capacity defined by the power curve).

$$EA = \frac{E_a}{E_e} \tag{1.5}$$

Other names for EA that can be seen in the literature are Production Based Availability (PBA) and yield-based availability.

Another KPI often used in the industry is the Capacity Factor (CF). CF is the actual energy production E_a with respect to the energy production E_r at the rated power. Ideal energy is the energy produced if the turbine was continuously operating at its rated (for example, 10 MW if it is a 10 MW turbine).

$$CF = \frac{E_a}{E_r} \tag{1.6}$$

The following example will explain the difference between these three KPIs. Table 1.1 presents an example where a 15 MW turbine operates for a period of 24 hours and experiences an 8-hour maintenance campaign during that period. In one case (Option 1) it happens during a period of low wind while in the other case (Option 2) it happens during a period with sufficient wind.

Table 1.1: 24 hours of wind turbine operation with two options for an 8-hour maintenance campaign and the corresponding E_e and E_a. E_e is based on the power curve estimated by NREL (2020). In one case the maintenance campaign happens at the time of low wind when the turbine cannot produce any energy. In another case the same campaign happens when there is sufficient wind and the turbine could produce energy if it was operational.

<table>
<tr><th>Time stamp</th><th>Wind speed (m/s)</th><th>E_e (kWh)</th><th>Option 1: turbine state</th><th>Option 2: turbine state</th><th>Option 1: E_a (kWh)</th><th>Option 2: E_a (kWh)</th></tr>
<tr><td>07:00</td><td>5.93</td><td>1695</td><td rowspan="9">Operating</td><td rowspan="8">Repairing</td><td>1695</td><td>0</td></tr>
<tr><td>08:00</td><td>7.33</td><td>4339</td><td>4339</td><td>0</td></tr>
<tr><td>09:00</td><td>7.65</td><td>5339</td><td>5339</td><td>0</td></tr>
<tr><td>10:00</td><td>7.9</td><td>5339</td><td>5339</td><td>0</td></tr>
<tr><td>11:00</td><td>7.43</td><td>4339</td><td>4339</td><td>0</td></tr>
<tr><td>12:00</td><td>6.67</td><td>3615</td><td>3615</td><td>0</td></tr>
<tr><td>13:00</td><td>5.91</td><td>1695</td><td>1695</td><td>0</td></tr>
<tr><td>14:00</td><td>5.31</td><td>1695</td><td>1695</td><td>0</td></tr>
<tr><td>15:00</td><td>4.77</td><td>1185</td><td rowspan="16">Operating</td><td>1185</td><td>1185</td></tr>
<tr><td>16:00</td><td>4.12</td><td>595</td><td rowspan="8">Repairing</td><td>0</td><td>595</td></tr>
<tr><td>17:00</td><td>3.54</td><td>302</td><td>0</td><td>302</td></tr>
<tr><td>18:00</td><td>2.69</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>19:00</td><td>1.96</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>20:00</td><td>1.61</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>21:00</td><td>1.2</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>22:00</td><td>0.86</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>23:00</td><td>0.99</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>00:00</td><td>1.74</td><td>0</td><td rowspan="7">Operating</td><td>0</td><td>0</td></tr>
<tr><td>01:00</td><td>2.58</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>02:00</td><td>3.1</td><td>70</td><td>70</td><td>70</td></tr>
<tr><td>03:00</td><td>3.76</td><td>302</td><td>302</td><td>302</td></tr>
<tr><td>04:00</td><td>4.7</td><td>965</td><td>965</td><td>965</td></tr>
<tr><td>05:00</td><td>5.9</td><td>1695</td><td>1695</td><td>1695</td></tr>
<tr><td>06:00</td><td>6.61</td><td>3615</td><td>3615</td><td>3615</td></tr>
<tr><td>Total</td><td></td><td>36786</td><td>Operating: 16</td><td>Operating: 16</td><td>35889</td><td>8729</td></tr>
</table>

Table 1.2 presents the TA, EA and CF based on the 24 hours of turbine operation presented in Table 1.1. Option 1 results in the much higher CF and EA than Option 2 because in the case of option 1 turbine repair happens during low wind. CF and EA are equally sensitive to the shift in turbine repair timing. TA however does not change because in both Option 1 and Option 2 there are 16 hours when the turbine is in the operative state (out of 24 total).

Table 1.2: TA, EA and CF resulting from a 24-hour operation of a turbine presented in Table 1.1

	Option 1	Option 2	% change
TA	66.6%	66.6%	0%
EA	97.6%	23.7%	76%
CF	1.0%	0.2%	76%

This example demonstrates that EA and CF can capture the effect of moving the period of downtime. EA and TA are also common metrics reported by offshore wind farms in publicly available reviews published by SPARTA, EA however is referred to as PBA there (SPARTA, 2022, 2023). The lower the EA the higher are the revenue losses which makes it an important metric to assess wind turbine or wind farm performance. Revenue losses can be calculated using Equation 1.7.

$$\textit{Revenue losses} = (100\% - EA) \times E_e \times \textit{Electricity price} \tag{1.7}$$

Revenue loss and EA metrics will be mentioned throughout this thesis and used extensively to assess different O&M strategies in Chapter 5.

Wake effects have not been considered in this study. Although they affect turbine energy output, they are not expected to impact the choice of O&M strategies. Power losses through cables have also not been taken into account but the choice of cable topology is. The method developed for modelling the cable topology may allow for capturing power losses in the future.

Grid curtailment is a result of the balancing electricity demand and supply (called the balancing mechanism) and is controlled by the electricity system operator in the UK. Grid curtailment may also have a significant impact on EA but this impact is out of the scope of this thesis.

1.8 O&M planning horizon

Michael Welte et al. (2018) defines three O&M simulation tool groups based on the planning horizon under consideration. These are listed below:

- **Operational**: short-term planning knowing the current condition of your assets e.g. a digital twin of a wind turbine can be considered as an operational simulation tool. These tools can help the operators to find the optimal O&M strategy for the next couple of days, e.g. to answer the question whether to perform the maintenance on a single turbine tomorrow, or on two turbines the day after where the weather window is longer.
- **Tactical**: long term planning knowing the current state of your system e.g. finding the best time to charter a vessel knowing its availability and the best time to perform the maintenance operation at the location where the system is installed
- **Strategic**: long term planning before the system starts operating (i.e. using high level knowledge of the system and previous experience)

This thesis is focused on strategic planning and presents a strategic O&M simulation tool discussed in Section 3.3. Normally, strategic tools are applied on renewable energy farms that do not yet exist or are not even planned, so the scenarios modelled may be completely hypothetical. In some exceptional cases, strategic tools may be applied on renewable energy farms that are already commissioned. In these cases there is still some flexibility in selecting an O&M strategy.

Some innovations that could be implemented to improve the O&M of renewable energy farms such as using robotic systems instead of rope access technicians to inspect and repair wind turbine blades. In theses cases all three types of tools may be useful. The choice of the right tool should depend on the nature of the problem.

In summary, strategic tools can guide the long term decision making of wind farms operators. The following is the list of stakeholders or people who could benefit from using strategic simulation tools:

- Renewable energy farm developers or operators who are interested in finding the best O&M strategies for specific wind farms or selecting an optimal cable layout.
- O&M analysts who want to analyse different O&M strategies and find the strategies that perform the best overall. This analysis can then help the renewable energy industry converge on certain strategies.
- Technology innovation developers who are interested in finding how their technology could impact KPIs associated with O&M.

The main challenge of strategic simulation tools is that they usually model hypothetical scenarios, often for wind farms that are still in the consenting or development stage, where asset design and layout have not been finalised.

Operational and tactical tools usually have access to the current condition of a turbine, there is a clear idea what maintenance campaigns are expected on a turbine and what is the remaining life of these turbines based on their current condition. Operational and tactical planning is done in real time, there is information about how much vessels cost, what personnel is available and there is a weather forecast available for the nearest future.

Strategic tools on the other hand rely heavily on assumptions. The better the assumptions are, the more accurate are the estimations from these tools. These assumptions are often based on historical data and experience of existing renewable energy farms. Section 2.2 explores what inputs are required for O&M simulation tools and challenges the assumptions that are commonly used in these tools. Section 2.3 then proposes a new list of O&M activities based on new information.

1.9 Definitions

This section provides the definitions for the crucial terms that are used throughout this thesis.

There are three maintenance types distinguished in this thesis:

- **Planned maintenance or preventive maintenance** - the type of maintenance that is planned in advance, normally annual inspections and surveys fit into this category.
- **Unplanned maintenance or corrective maintenance** - this type of maintenance that usually occurs as a result of a component failure. Unplanned inspection, repair or replacement fit into this category.
- **Condition-based maintenance** - this type of maintenance occurs as a result of condition monitoring of offshore components. Condition monitoring systems can be installed on components offshore along with computer algorithms that can be used to track the component health and predict its failure time.

As seen in other research work, unplanned maintenance activities and activities arising from the condition monitoring can be additionally categorised into minor repairs, major repairs, minor replacements and major replacements. There is no strict rule defining the difference between these types. One way of classification of activities into these categories according to the material costs and downtime can be found in Carroll et al. (2016). An alternative approach employed by Anderson et al. (2021) involves the use of person-hours values to classify activities into three categories: minor repairs, major repairs, and major replacements.

Current work breaks down O&M activities into minor activities and major operations according to their logistical requirements:

- **Minor maintenance activities** in this thesis are defined as the repair and replacement events on a turbine that do not require heavy lift operations and can be resolved by a visit of a CTV or an SOV.

- **Major operations** are defined as the repair and replacement events on a turbine that require lifting heavy components at the turbine hub level i.e. they require specialised HLVs or towing the turbine to the port.

In addition, there are three other terms that can be seen throughout this thesis. Definitions are provided here for clarity:

- **Forced outages** are defined in SPARTA (2022) as instances where turbine generation is disabled as a result of unforeseen damage, fault or failure. Major operations and cable outages are excluded from forced outages. Forced outage is not equivalent to minor activities, however a subset of forced outages may lead to minor activities.
- **Downtime** is defined as the total time during which an asset spends in a non-operational state due to its failure. Downtime usually includes any waiting time prior to the start of the minor activities or major operations. This waiting time may be caused by various reasons. **Weather downtime** may also be used to describe the downtime that occurs due to waiting for favourable weather conditions.
- **Duration** of any maintenance activity or operation is defined as the time from the start of the maintenance event to the end of it. Duration does not include any preparation prior to the event or travel time.

1.10 Cable-related failures and maintenance

Cable failures can cause a significant loss of power production, in particular export cable failures that can disconnect the entire farm from the grid. Many wind farms may have two or more export cables or add redundancy to the cable layout to prevent some of these losses. According to Offshore Wind Programme Board (2017) wind turbine production can stop for a period of several weeks to 3-5 months until the cable issues are resolved. The cost of export cable failures was estimated in 2017 to be nearly £170,000 for every km of high voltage export cable (Offshore Wind Programme Board, 2017). This cost includes the cost of the lost production as well as the cost of the repair itself (new cable, vessel cost etc.). Another news article from 2021 has reported that damage in cable protection systems occurred more often on projects built in the past 5 years (2016-2021) as these projects lie in areas with tougher weather conditions (reNEWS biz, 2021b).

Ørsted reported in 2021 that an array cable fault could affect up to 10 of its offshore wind farms in the UK and Continental Europe. That could have a total financial impact around €403 million (New Power, 2021). Power and Energy Solutions (2023) reports that an array cable repair cost is €9.6 million per cable while an export cable repair cost is €14.3 million per cable with reference to 4C Offshore. It is worth noting that the specific details supporting these estimates were not provided in the report. According to the same source, the cost of downtime (€27.5 million) is the same for array cables and export cables despite the export cables linking the entire farms to the onshore electrical grid. A more detailed breakdown of costs could be useful for understanding where the majority of costs come from and why it was the same for array and export cables.

According to one insurance firm export cable failures accounted for 29% of insurance claims by value and inter-array cables account for 17 % (Allianz, 2023). This statistics is based on 126 claims from wind farms in Germany and Central and Eastern Europe from 2014 to 2020.

Floating turbines require dynamic cables (see Figure 1.2). These cables are more susceptible to hydrodynamic loads, but they are designed to sustain them. It is currently unknown whether dynamic cables perform better or worse than static cables because of the very few FOW turbines installed to date.

With the increase in turbine rating and farm capacities, cable ratings also have to increase and cable costs increase exponentially with their rating (Ikhennicheu et al., 2020). This suggests that cable repair campaigns will be even more expensive in the future than they are now.

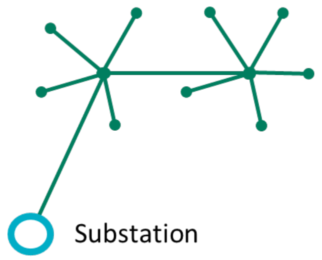
Turbine component failures usually affect the performance only of that turbine and not the others. Some exceptions may occur in the case of transformer failures that can cause a surge of power to the rest of the turbines on a string or a ring.

There is also an uncertainty around the impact of towing the turbine to the port for maintenance. It is not yet clear whether floating turbine disconnection from an array cable (for towing) could cause a temporary disconnection of that part of an array cable. Principal Power have developed an I-tube connection technology to overcome this issue and speed up the connection and disconnection process however it has not been used in commercial wind farms yet (Principal Power, 2022).

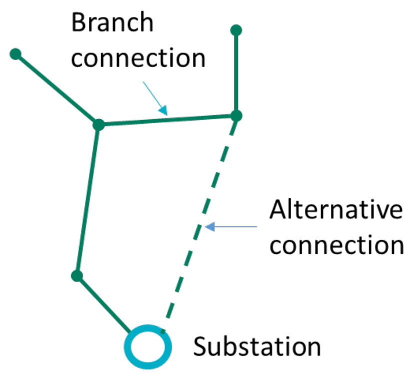
As Section 5.6 will demonstrate, different cable topology designs result in different revenue losses. This thesis distinguishes between five types of cable topologies, three of which were obtained from Fjellstedt et al. (2022):

- **Radial connection (string connection)**: Cables in this topology are connected on a single string, in the case of a single cable failure, there is no redundancy i.e. all turbines after that cable would be disconnected from the substation.
- **Ring connection**: Cables in this topology are connected in a loop (ring). Such design adds redundancy to the system. Electrical energy can be sent to the the grid through both sides of the ring if cable capacity allows that. If cables are not thick enough to carry the electrical energy of all turbines on the ring then only a portion of electrical energy will be sent to the grid through both sides of the ring, causing some production loss but not the entire production of that ring.

- **Star Clusters**: In this topology energy converters are all connected to the same turbine forming a "star" shape as shown in Figure 1.4b. This way the failure of a single cable does not lead to a disconnection of other turbines from the grid. One exception is the cable that connects the cluster to the substation or another cluster, if that fails, the entire cluster would be disconnected.
- **Branch connection**: This connection is similar to a radial connection but in this case one string could be connected to another forming cable "branches". Such connection can be useful to save cable length and avoid installing an additional string connection for turbines located far from a substation. An example is shown in Figure 1.4b.
- **Collector Network Configuration**: In this configuration several wind turbines are connected to a shared array cable, and multiple array cables are then bundled together to form a collector cable. Each collector cable then connects to either an offshore or onshore substation.



(a) Star connection



(b) Branch connection and alternative string connection to the substation

Figure 1.4: Array cable connection alternatives.

Some cable networks can be complex combinations of different connection types, such as that used in a Triton Knoll offshore windfarm shown in Figure 1.5. Triton Knoll is an example of a ring and a string cable topologies combined.

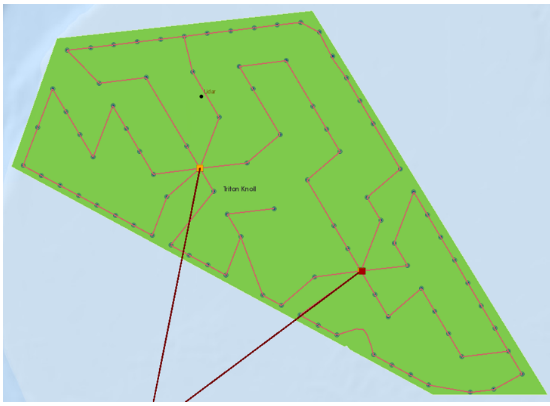


Figure 1.5: Triton Knoll wind farm cable layout (4C Offshore, 2023a)

It is expected that the choice of a cable topology can significantly impact revenue losses because cable failures can affect the amount of lost production for affected turbines.

There are multiple reasons why cable maintenance and cable topology should be included in the O&M analysis:

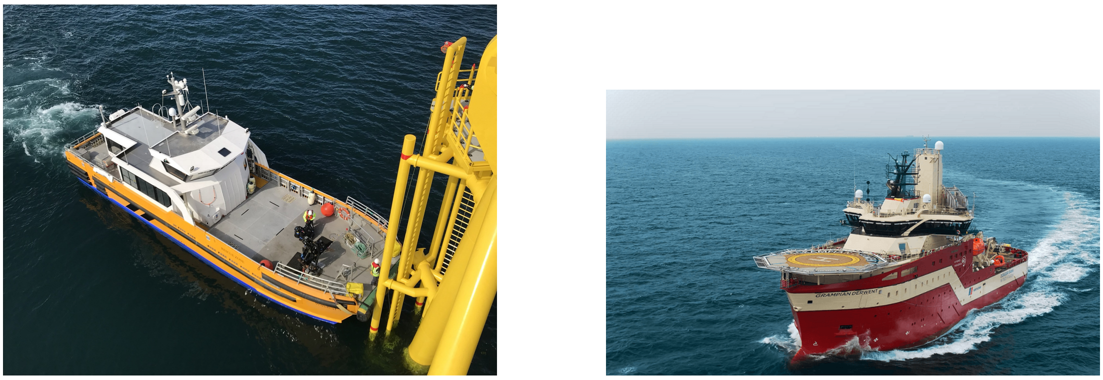
- To understand the value of redundancy for different cable topologies and for a range of cable failure rates
- To include the cost of spare cables and Cable Laying Vessels (CLVs) into OPEX.
- To understand the impact of cable downtime on turbine downtime, particularly in cases with less redundant cable topologies.
- To avoid the overestimation of TA and EA which may happen when cable topology is excluded from the O&M assessment. This is particularly important when O&M estimations are benchmarked against publicly available data such as SPARTA (2022), where cable failures cannot be excluded.
- To guide the selection of the optimal cable topology.

Currently cable redundancy modelling is limited in existing O&M simulation tools (see Section 3.2). Section 4.8 presents a new method for modelling cable topology. Section 5.6 then demonstrates its use in a case study comparing four different cable layouts with varying level of redundancy.

1.11 Current O&M strategies

1.11.1 Strategies for minor maintenance activities

Most of the currently installed wind farms utilise CTVs for maintenance not requiring heavy lift operations and Jack-up Vessels (JUVs) for repairs and replacements involving lifting heavy components using a crane. CTVs are used to bring personnel to the turbines and then return them back to the port within a single work shift. CTVs do not have accommodation on board which means that all personnel must return to the port before their shift has ended. Figure 1.6a shows an example of a typical CTV.



(a) CTV example, Source: Workboat Association (Buljan, 2020)

(b) SOV example, Source: North Star Shipping (North Star, 2022)

Figure 1.6: CTV and SOV examples.

CTVs would not be suitable for wind farms located further than 70 km from an O&M port because at this distance the crew would not be able to travel to the site, perform the maintenance and return back to port without risking to exceed the work shift duration (Fitch-Roy et al., 2013). 4C Offshore data shows that some wind farm operators may sometimes opt for SOVs even if a wind farm is located 30-50 km offshore meaning that there are factors other than a distance that can affect the selection of the appropriate strategy (Allen et al., 2022).

CTVs are also more limited in terms of the wave conditions that they can handle. Typical H_s limits for CTVs range between 1.5 m and 2.0 m, but operation in wave heights up to 2.5 m may be enabled by motion compensated gangways (Dewan & Asgarpour, 2016; Hu & Yung, 2020). CTVs can transfer personnel at higher wave heights when the wave period is also higher (Ikhennicheu et al., 2020).

SOVs and fixed offshore bases can shorten the time required to reach an offshore wind turbine that needs maintenance. SOVs can be used with all-in-one facilities: accommodation, walk-to-work gangway, maintenance and spare parts platform, and a launch and recovery system for a daughter craft. An example of an SOV is shown in Figure 1.6b. SOVs have higher H_s limits than CTVs, typically ranging between 2.5 m and 3.5 m (Hu & Yung, 2020). This allows them to operate in harsher weather conditions.

A fixed OMB can be similar in its facilities to a SOV; it accommodates CTVs and personnel. The OMB can either share the foundation with the OSS or have a separate foundation and connect to the substation via a bridge. It is likely that the emergency recovery system and the helicopter base would be shared between the substation and the OMB. Section 5.4 will compare OMB and SOV strategies.

4C Offshore data shows that some wind farm operators may sometimes opt for SOVs even if a wind farm is located 30-50 km offshore meaning that there are factors other than a distance that can affect the selection of the appropriate strategy (Allen et al., 2022).

The concept of an OMB has been presented in the news in 2015 by Fred. Olsen Windcarrier (Fred. Olsen, 2015). They claimed to have performed O&M simulations in collaboration with an unrevealed major developer in the UK, but the assumptions or the software used in these studies are unknown. They have claimed however to achieve the best results (98% availability) with the scenario employing three CTVs combined with an offshore accommodation platform (Fred. Olsen, 2016). Horns Rev 2 wind farm commissioned in Denmark in 2009 and located 32 km from the shore has also used this concept with a limit of 24 technicians on the platform; however the number of CTVs used is unknown. Two wind farms in Germany, Global Tech 1 and DanTysk (both commissioned in 2015), also have offshore accommodation for 34 and 50 technicians respectively, but the number of CTVs used is unknown (Echavarria et al., 2015). According to the 2018 development plans, Hornsea Project Three has plans to install up to three offshore accommodation modules close to the farm; however the characteristics of the future accommodation modules are not yet known (DONG Energy, 2017).

At the same time the SOV technology is in high demand for the future multi-gigawatt projects. For example, North Star has recently received an order for three SOVs to be used in the Dogger Bank Farm in the east UK, which was later updated to four SOVs (Durakovic, 2021; reNEWS biz, 2021a). One of them, with the capacity to accommodate 78 crew members, will perform scheduled maintenance, and the other three will accommodate 60 persons each and will be used for corrective maintenance activities.

The StrathOW-OM tool (Strathclyde University strategic O&M tool) has been used to analyse the strategies with mother ships, floatels and fixed accommodation (Dalgic et al., 2015a). The results indicated that fixed accommodation platforms and mother ships can be beneficial for the O&M of wind farms in far offshore locations. A mother ship concept which can deploy CTVs has also been proposed for wind farms located at a significant distance to the O&M port (Mccartan et al., 2015). The concept has never been used on the existing wind farms.

There have been very few studies analysing the usage of SOVs for offshore wind farms (Endrerud et al., 2015), most of these studies simulated SOVs using operational O&M tools. The study performed by Besnard et al. (2013) has also compared OPEX and availability figures between onshore and OMB scenarios; however this study only looked at the use of CTVs. It found that having an OMB is beneficial only in the case if technicians are available 24h a day 7 days a week. The study considered a generic wind farm with 100 turbines, 5 MW each. In reality, CTVs are unlikely to perform any maintenance at night, ulike SOVs.

Section 4.6.1 of this thesis presents how SOVs can be modelled with daughter crafts. OMBs can be modelled as offshore "ports". Functionality that captures SOVs and OMBs is then demonstrated in a case study in Section 5.4 comparing a SOV strategy with an OMB strategy.

1.11.2 Heavy component exchange strategies

SOVs and CTVs are not capable of handling heavy component exchange on a turbine. These activities require cranes capable of lifting heavy components such as blades or a gearbox at a turbine hub height. These are referred further in this thesis as major operations.

For major operations JUVs are normally utilised but semi-submersible Heavy Lift Vessels (HLVs) could also be used. Figure 1.7a shows an example of a JUV. These vessels have cranes installed on board that are capable of handling heavy turbine components. O&M jobs will also compete with turbine installation jobs that often require the same vessels. Installation jobs however are more attractive to vessel owners because they offer longer-term profit unlike one-off O&M jobs. Wood Mackenzie research is claimed to show that there is an anticipated 19-vessel gap between the supply and demand of installation vessels due to the rapidly growing offshore wind industry (Chetwynd, 2023).

(a) JUV example, Source: SSE Renewables (2023)

(b) Turbine towing example, Source: WindEurope (OffshoreWIND biz, 2023b)

(c) Semi-submersible HLV example, Source: Heerema (Killoh, 2022)

Figure 1.7: Fixed and floating turbine heavy-lift maintenance options.

Growing turbine rating means that components get so heavy that existing vessels cannot handle them. One way to solve that is to equip the vessels with larger cranes which some vessels have done. Sea Impact service collects data about heavy-lift O&M of offshore turbines. This data will be discussed in detail in Section 2.4. Interestingly, the data set covers 34 different heavy-lift vessels. Out of these 34 only 3 have been or are planning to be upgraded with larger cranes (doubling their lifting capacity), these models are Blue Tern, Sea Installer and Wind Orca.

An alternative to this is to build new vessels. It has been reported that RWE's 1.4GW Sofia project would charter a vessel before its construction has even finished (reNEWS biz, 2022a). The lack of vessels suitable for larger turbines means that securing vessels for O&M projects may become problematic. This can be reflected in the lead time of O&M vessels in the O&M simulation tools (see Section 3.2).

In the case of floating wind there are several options for major component exchange. McMorland, Collu, et al. (2022) presented a review on O&M simulation of FOW farms. Initially it identified several heavy lift maintenance types. These included in-situ maintenance (floating-to-floating) using a floating semi-submersible vessel (shown in Figure 1.7c), tow to shallow and TTP (see Figure 1.7b). TTP is currently the only method that has been used on a demonstration floating wind farm Kincardine (Scotland) in 2022 (first turbine) and 2023 (second turbine). Both turbines were towed from Scotland to Netherlands (Rotterdam port) which was justified by supply chain being located there and a suitable water draft. The reason for maintenance was unknown. The first operation took 47 days, the second took 29 days (Sea Impact, 2023). Kincardine wind farm developers and operators achieved a substantial reduction in time in the second maintenance campaign primarily due to the reduction in turbine preparation for towing and towing time itself.

Alternative to TTP is tow-to-shallow, where a turbine is towed to a shallow location where a JUV could be used. In-situ maintenance also has several options. These options are: floating-to-floating operations using a semi-submersible HLV, using a crane installed on the turbine or its platform (Figure 1.8), using a self climbing system (Figure 1.8) or an air lift drone. Major component exchange using a nacelle-based crane has been demonstrated on a 3MW wind turbine at the Swedish lake Vänern (Fenger, 2022). Most concepts still need to be proven in practice.

Ongoing work at the ORE Catapult is investigating different concepts further with the help of COMPASS. The following section shows the ORE Catapult perspective on O&M.

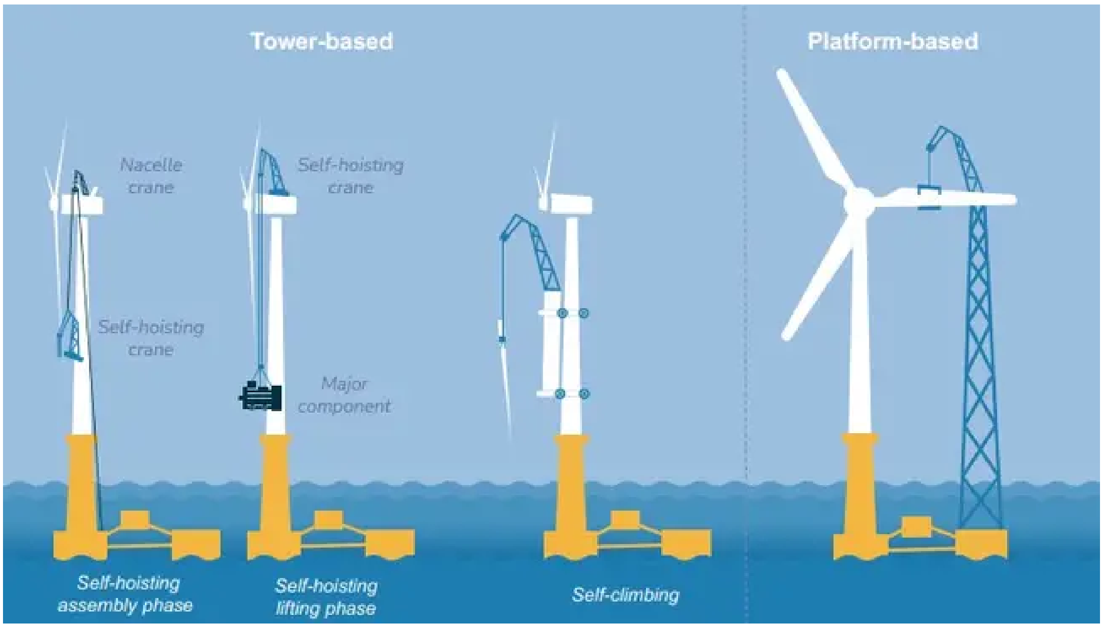


Figure 1.8: Turbine-based heavy-lift maintenance options. Source: World Forum Offshore Wind (2023)

1.12 ORE Catapult perspective

ORE Catapult is the UK's leading Technology Innovation and Research Centre for ORE. ORE Catapult has partially sponsored the work presented in this thesis.

Engineers at the ORE Catapult developed the first version of COMPASS and initiated this research project to extend COMPASS functionality further. Section 3.3 describes the original COMPASS structure in detail and the following sections describe the novel additions to the tool. ORE Catapult objectives and projects have driven the development of the O&M activity input presented in Section 2.3 and COMPASS functionality itself presented in Section 4. Some major projects that have been ongoing in ORE Catapult that use or intend to use COMPASS are highlighted below:

- **FOW Centre of Excellence (CoE)** is the centre that was developed to support the growth of the FOW industry. There are several O&M projects that are currently ongoing in this centre. A few of these projects utilise the new functionality of the COMPASS O&M simulation tool to perform O&M analysis and assess different O&M strategies. In particular, TTP functionality presented in Section 4.9 and the cable topology modelling presented in Section 4.8. The latter is useful for assessing the impact of turbine disconnection for towing on the rest of the farm.
- **Cost model development:** ORE Catapult have developed an in-house cost model over the years that is capable of estimating project LCOE. The part of the cost model that estimates OPEX is currently deterministic i.e. it does not capture the full complexity of O&M and makes high-level estimates. COMPASS outputs could be used to either calibrate these estimates or replace them.
- **Project ELECTRODE** is currently under way to understand offshore cable reliability (ORE Catapult, 2023b). ELECTRODE is the electrical cable failure trending and reliability analysis for operational developments, similar to SPARTA. The outcomes of this project if made public could help offshore wind analysts understand the impact of cable reliability on OPEX by modelling cable failures using COMPASS. Nevertheless, Section 2.3.2 covers the maximum cable FRs that are currently anticipated.
- **Robotics and Autonomous Systems (RAS) and clean maritime.** This item encapsulates all projects that are related to RAS and clean maritime. Clean maritime deals with reducing emissions from vessels used offshore. These are the ongoing innovations in the offshore wind field. Assessing the impact of these innovations on OPEX can help these technologies move forward.

Figure 1.9 illustrates using a chart how COMPASS tool development meets the demands of the ORE Catapult projects and the emerging industry challenges.

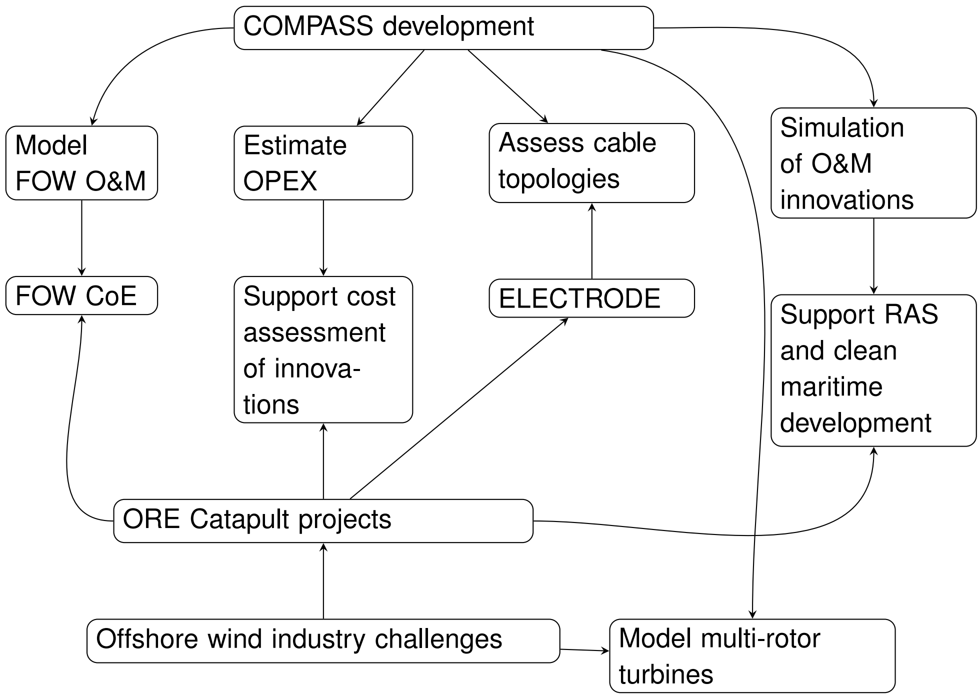


Figure 1.9: How the O&M simulation tool COMPASS development feeds into the work ongoing at the ORE Catapult.

Chapter 2

Operation and Maintenance Activities

2.1 The gap between real and analytical O&M

The major requirement that drives COMPASS and other O&M simulation tool development is generating meaningful outputs that can inform real world decisions. Reliable outputs are not possible without the understanding of what O&M of offshore wind farms consists of. Capturing current O&M practices using COMPASS as realistically as possible will allow to make more reliable estimates of wind farm KPIs and better assess the impact of any changes in these practises.

O&M can be viewed from two different perspectives: *real* and *analytical*. ORE farm operators, OEMs and any other organisations that are actively involved in managing the O&M activities on existing ORE farms have a real perspective on O&M. These organisations have access to real ORE assets, their condition monitoring system and are actively planning O&M activities based on the real ORE farm data. Because of the sensitivity of ORE farm performance and the competition between OEMs and operators, real O&M is often hidden from the public view. O&M simulation tool developers and the users of such tools (both are referred as "O&M analysts" further in this thesis) have the analytical perspective on O&M. O&M analysts who do not belong to either the wind farm operator or OEM group rely on assumptions and historical data and try to predict what the future O&M would look like. O&M analysts who do not have access to real wind farm data include academics specialising in O&M, OPEX analysts, analysts looking at the impact of technological innovations and other groups as Figure 2.1 demonstrates.

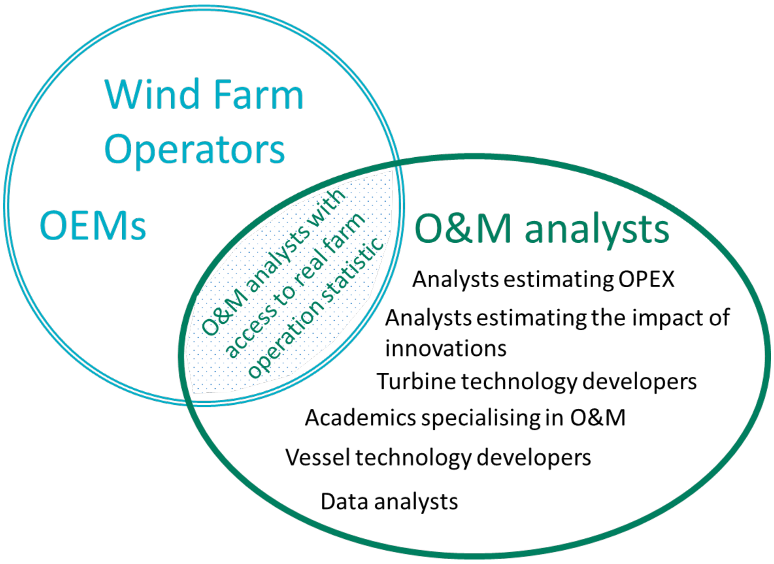


Figure 2.1: The overlap between OEMs, wind farm operators and O&M analysts

Most O&M simulation tools rely on a defined list of O&M activities, but expect the users of the tools to provide such information. An accurate list of O&M activities allows the user to explore different maintenance scenarios, simulate the impact of maintenance strategies, optimise resource allocation, and fine-tune operational plans - all while minimizing risks, costs, and environmental impact. If the user of the tool does not have access to data from a real ORE farm and does not have experience of operating an ORE farm then coming up with a list of O&M activities can be problematic.

O&M analysts working with simulation tools require detailed characteristics of maintenance activities including:

- Major operation rates
- Minor maintenance activity rates
- Preventive (planned) maintenance rates
- Duration of all maintenance events
- Weather data at the site
- Equipment and consumables costs associated with each activity
- Personnel requirements
- Vessel requirements
- Vessel data including speed, lead time, weather limits, cost (mobilisation and day rate), capacity
- Personnel data such as shifts, rates

This is not an exhaustive list as depending on the selected tool there could be other inputs defined additionally. For the best estimation of OPEX, users also need to define the fixed costs that they expect. Fixed costs however are not within the scope of this thesis.

Most of the O&M inputs in COMPASS, particularly those that define the activities required on a wind farm were copied from the pre-existing Excel-based model prior this research work. Unfortunately, due to the lack of traceability of this data it is difficult to determine the accuracy of these inputs. These inputs were also developed for the Excel-based model and are not fit-for-purpose within COMPASS which models wind farm lifetime by time increments. Section 2.2 explores the alternative data that is currently available in the literature.

Section 2.3 then aims to bridge the gap between the real O&M and analytical perspective via learning more about real O&M and convert that knowledge into a format that is helpful for O&M simulation tools. This learning was made possible via the review of previously unused sources of data and information. These include: MPDs, 4C Offshore (2023b), Notices to Mariners (NtMs), interviews with ORE Catapult and external experts, public reviews and services tracking unplanned activities on offshore wind turbines such as SPARTA (2023) and Sea Impact (2023). The resulting tables with O&M activities and their characteristics can be used as a guide for O&M analysts to form the inputs of O&M simulations.

2.2 Current understanding

2.2.1 Existing O&M activity input guidance

The majority of the O&M simulation tools rely on the user of the tool to provide the O&M assumptions. For example, one of the DTOCean+ reports expects that a list of preventive maintenance tasks is taken from a maintenance manual, most likely referring to the maintenance manual that each turbine model has to have (Yang et al., 2020). However these catalogues are only accessible to OEMs and wind farm operators who own these turbines. Moreover, catalogues will only cover turbine maintenance operations, anything related to topside, substructure, cables and substations would have to be sourced elsewhere.

For corrective maintenance DTOcean tools rely on a fault tree (FT) in combination with a maintenance catalogue. A fault tree can estimate the impact of one component failure (fault) in the rest of the system (tree). It requires the FR of each component in a system which can either be approximated by experts or obtained from FRs of existing farms. The granularity of FRs reported in public studies is not enough to be used in a FT analysis because failure statistic is usually reported at a system and subsystem level (Carroll et al., 2016; SPARTA, 2022).

Verification study performed with several O&M simulation tools uses an activity list that breaks down maintenance into six activities: manual reset, minor repair, medium repair, major repair, major replacement and annual service (Dinwoodie et al., 2014). This is a much higher-level compared to the activity list established in Section 2.3. Failure data in that study was provided by a developer based on their expert knowledge without disclosing the name of the developer name or the turbine rating. It is unclear from the study whether the durations were also based on expert knowledge or if they were estimated by the study authors. Carroll et al. (2016) then compared the durations to Dinwoodie et al. (2014) and found that the estimated durations of minor and major repairs are shorter than those previously reported and major replacement durations are longer than that previously reported.

This thesis provides more up-to-date estimates of the durations of major operations based on a bigger pool of data and reports that they are shorter than those reported in Carroll et al. (2016) despite higher rated turbines being included in the data pool.

Dinwoodie et al. (2014) too does not break down activities into component type and annual service consists of one visit to a turbine per year. This chapter improves upon the previous by considering repairs at the more granular level of components and by broadening the scope of annual servicing to encompass routine inspection and servicing activities beyond the turbine OEM's prescribed annual service.

Carroll et al. (2016) is currently the most commonly used source of FR and maintenance duration data and repair costs. Carroll et al. (2016) reports statistic observed from around 350 turbines with exact turbine rating not specified but stated it is between 2 and 4 MW. Carroll et al. (2016) then compares the results with those observed in Dinwoodie et al. (2014) that has been discussed previously. The statistic observed in Carroll et al. (2016) are more recent and reported with higher transparency than in the previous works. Section 2.2.2 reviews this and other FR data sources available in the public domain and highlights the reasons why they may not be applicable to a modern wind turbine fleet. Section 2.3 of this thesis proposes new values to use for minor and major repair characteristics based on a larger pool of data and higher-rated turbines than what has been reported previously. Maintenance activity characteristics are then further enhanced by consultation with experts in offshore wind. Section 2.3 also considers planned maintenance activities on wind turbines and substations that have not been the focus of existing works because existing works such as that of Carroll et al. (2016) focused on corrective maintenance.

Another example of an activity list for O&M of offshore wind projects is that provided by COREWIND (Schwarzkopf et al., 2021). COREWIND made a list of corrective maintenance activities based on several sources: Carroll et al. (2017, 2016); Gintauntas and Sorensen (2017); Walgren (2019).

Recognising that some data is outdated it adjusted the data. The report identifies additional activities based on internal expertise or interviews with several companies involved in offshore wind which can be found in Schwarzkopf et al. (2020). The report however does not disclose which values were estimated using internal expertise and which ones with interviews and how these values were estimated (whether they were an average of the values reported by the interviewed companies or estimated in a different way).

Expert knowledge can be very valuable in the absence of data but the downside is the bias that it comes with. If expert judgement is used it is better to provide a range of values or a distribution. Recognising this and the lack of reliable data Jenkins et al. (2022) has estimated 5th, 50th and 90th percentile for the major repair rates based on the survey of experts in offshore wind rather than estimating the average thus reducing bias. The results of this work are particularly useful for understanding the experts' view on future FRs of floating wind turbines compared to the fixed ones. The rates however are estimated only per turbine and not per component.

Expert judgement can also vary depending on the level of involvement into offshore wind O&M, some people may have participated in O&M directly while others obtain theoretical knowledge only. There is currently no established and consistent metric in the literature that is used to evaluate the level of expertise in the offshore wind industry. For this reason this thesis relies on data from MPDs and real operational data sources as much as possible but uses expert knowledge in an attempt to fill in the data gaps.

COREWIND takes the frequencies of corrective repairs from Carroll et al. (2017, 2016) and presumably Gintauntas and Sorensen (2017). COREWIND takes into account major operations on seven components: direct drive generator, power converter, main shaft, power electrical system, yaw system, pitch system and blades. Gearbox was not included in the list despite some OEMs still using gearboxes.

COREWIND reports activity durations, portions of which are also based on Carroll et al. (2016) but scaled up by Walgren (2019). Walgren (2019) increased durations reported in Carroll et al. (2016) by a factor of three. This estimation was presumably justified by assuming the durations of maintenance operations would scale linearly with turbine rating however the research presented further in this section finds that recent data do not support that assumption. The durations reported for 10MW turbines are exactly three times longer than those reported in Carroll et al. (2016) for 2-4MW turbines. With this approach the blade repair or replacement resulted in taking 36 days, Section 2.4 finds that this is an overestimation. Section 2.4 of this thesis analyses data on turbines up to 8 & 9 MW in rating and estimates major operation durations. Despite the higher rating the analysis finds that durations are shorter than those reported in Carroll et al. (2016) and durations of 20 days or longer were observed in less than 0.6% of operations. Other replacement durations reported in Schwarzkopf et al. (2021) are significantly longer than those estimated in this thesis. Therefore, scaling up major repair durations taken from Carroll et al. (2016) proportionally to turbine rating is viewed as unnecessary based on the findings of the current work and can lead to the underestimation of TA and EA and overestimation of costs due to increased weather-associated downtime and prolonged usage of HLVs.

Corrective maintenance on auxiliary systems is not included in Schwarzkopf et al. (2021) as well as other works. This study identified auxiliary system inspections and repairs required which are reported in Section 2.3.

Planned maintenance on a wind turbine in another COREWIND deliverable is simplified into one activity named "Inspection of Wind Turbine components" that happens once a year (Schwarzkopf et al., 2021). Section 2.3 of this study identifies four planned inspections that are required on each turbine that have to be performed separately from each other meaning that they would require separate visits and, potentially separate technician teams. In fact, it was found that some planned activities need several visits to the turbine a year (per activity). Identifying planned maintenance inspections correctly is important as it may impact the estimation of the total number of vessel visits. It may also decrease CTV and SOV availability for performing other tasks on the wind farm, thus delaying them (or vice versa, an unplanned activity may impact the planned activity schedule). The same applies to personnel.

Similarly, planned maintenance on an OSS reported in Schwarzkopf et al. (2021) is reported as "Inspection of the OSS" that happens once a year but this thesis finds a few planned visits required on a substation that also happen multiple times a year rather than once. Similarly to the previous point, tasks on the OSS can impact the availability of CTVs and SOVs and personnel to perform other tasks on a farm. The impact may become stronger in the new generation wind farms that will be using 15+ MW turbines. Due to the limited capacity of an OSS, multiple OSS will be required. For example, a 270-turbine wind farm may require six OSSs (OffshoreWIND biz, 2023a).

Rinaldi et al. (2021) is an example of how O&M simulation tools can be used to enhance LCOE estimation. Rinaldi et al. (2021) uses UNEXE O&M simulation that utilises a time-domain approach based on the Markov Chain Monte Carlo technique. Similarly to COMPASS and other O&M simulation tools the tool relies on detailed inputs. Rinaldi et al. (2021) assembled a set of inputs for floating wind O&M simulation and OPEX estimation, however this thesis suggests to use updated inputs listed in Section 2.3. The set consisted of unplanned maintenance on turbines and their substructures and replacement campaigns on array and export cables.

The UNEXE O&M tool was applied on Kincardine and Hywind wind farms which do not have OSSs, therefore substation O&M activities were not included in the analysis. Planned inspection was not included in the analysis either, however it is common to have a permanent contract between a service vessel and wind farm operator to support planned inspections and minor maintenance activities. With this contract in place, vessel day rate is paid every day even when the vessel is not used thus contributing a significant portion of O&M costs. Planned maintenance can also interfere with other activities if vessel on a contract is used for both planned and unplanned activities. Existing literature often excludes planned maintenance from analysis or simplifies it into a single visit a year. Section 2.3 will demonstrate that there are several planned activities required on each turbine, its substructure and each offshore substation.

Section 2.2.2 and 2.2.3 will discuss in detail what FR and maintenance duration data are currently available in the literature. Major operation and minor maintenance activity rates are driven by FRs. Picking the right rates at which maintenance happens can affect the accuracy of results of O&M simulation. Rinaldi et al. (2021) used FRs and the corresponding activity durations reported in Carroll et al. (2016) and adjusted the data taking average FR per component and average repair duration while this thesis suggests to revise these assumptions. According to Carroll et al. (2016) pitch, generator and gearbox components are more likely to fail than blades. Figures reported in SPARTA (2022) contradict this assumption showing that major operations involving blades are much more frequent than any other major operations. Section 2.3 of this thesis will support the observation reported by SPARTA and provide more evidence showing that blade repairs and replacements are the most common major operations. Moreover, Section 2.3 demonstrates how the major operation rates change with time. Section 2.4 of this thesis will also provide estimates of major operation durations based on a bigger pool of data and a wider range of turbines compared to Carroll et al. (2016). The findings of this thesis can support future OPEX estimations with O&M simulation tools.

Rinaldi et al. (2021) also presents assumptions for floating turbine components such as mooring lines, anchors and floating platforms using publicly available sources. Due to the absence of real data from floating wind farms and the immaturity of these farms Rinaldi et al. (2021) uses values derived from Fault Tree Analysis (FTA).

This research work finds that annual inspections on floating wind turbines will be risk-based which means only a portion of substructures will be inspected each year, i.e. around 20% of wind turbines in a farm would be inspected per year. Any faults on the substructure are most likely to be identified during these inspections. Therefore it is fair to assume that the frequency of unplanned activities on substructures should be either the same or less that the frequency of inspections (0.2 per turbine per year with a risk-based approach).

Similarly mooring failure in Rinaldi et al. (2021) is assumed to be higher than 0.14 failures per turbine per year. That is equivalent to approximately 14 mooring failures in one year of operation of a 100-wind-turbine farm. Presumably the anticipated FR of mooring lines is much lower to make the wind farm economically viable and insurable. It is expected that the FR would be in the scale of 2×10^{-5}, closer to that of chain moorings used in other applications offshore (mostly oil and gas extraction). It is expected that in other applications moorings are longer and therefore in FOW applications they would fail less frequently. This study uses a much lower FR value. Rinaldi et al. (2021) assumes over 0.16 failures per year for an anchor connecting that mooring to the sea surface. For the same reasons, this value is believed to be too high and this study suggests a different value to be used.

On the other hand, the inter-array cable FR used in Rinaldi et al. (2021) is almost negligible, less than 1 cable failure in 10000 turbine years. The offshore wind industry has adopted a more conservative approach as is evidenced by Kincardine wind farm in Scotland installing two different export cable routes to allow transmission of electricity to the grid even if one array cable fails.

Project ELECTRODE that is currently undergoing at the ORE Catapult may provide more insight into array cable failures in the future. It is currently at its early stage and it is not known to what extent the data will be available publicly. The project is similar to SPARTA, it collects cable failure data from wind farm operators and may in the future report the failure statistic in a similar way that SPARTA does (ORE Catapult, 2023b). Cable insurers may have some information about cable repairs but not all cable repairs are covered by insurance. Some cable failures cannot be claimed if the wind farm operator cannot prove that these failures were not preventable. Based on the review of MPDs current study also reports the maximum cable FRs that wind farm operators currently anticipate.

Due to the disadvantages of existing O&M simulation tool input assumptions this research created a new list of O&M activities from the ground up. It is evident that O&M activities may change depending on the technology and the operator of a farm but as the overview of MPDs has demonstrated (discussed in more detail in Section 2.3) there is a significant number of common O&M activities that happen on wind farms irrespective of the project. The aim of this research is to create a list of O&M activities with their characteristics that can act as a guide for O&M simulation tool inputs and support those O&M analysts who do not have access to a real farm data (see Figure 2.1). The results are reported in Section 2.3. The following bullet points summarise how an O&M activity list was compiled.

- MPDs were obtained from the Marine Scotland Information and the National Infrastructure Planning websites (GOV.UK: The Planning Inspectorate, 2023; Scottish Government, 2023). It is believed that because the activities in these documents are related to real wind farms they are a more reliable source of information than existing activity lists. There are nine documents reviewed, the benefit of having a few documents available is that if one piece of information is missing in one it can often be found in another document.

- Specialists with expertise in offshore wind operation were then consulted to combine certain activities identified in MPDs, if they can be performed in a single trip by the same group of technicians. Expert judgement of these specialists was also applied to fill in the missing characteristics of these activities such as their personnel requirements, vessel requirements and time requirements.
- Frequencies of unplanned maintenance activities are often not reported in MPDs, therefore the majority of these were obtained from data publicly reported by SPARTA (SPARTA, 2022, 2023) and modified. Section 2.2.2 discusses what FR data is currently available in the public domain and why SPARTA (2022) is chosen to be used for the activity list.
- Durations of maintenance activities are also not reported in MPDs. Section 2.2.3 explains the drawbacks of existing literature estimating durations of major operations and why it is crucial to estimate these accurately. Section 2.4 then estimates the durations of major operations based on the data sources that have not been used in the literature before and fits them into the activity list.
- In the case of cable repairs and FOW turbine substructure repairs there is little information available in MPDs, therefore other literature sources were used to compile this data in the activity list. Maximum anticipated repair rates were collected from MPDs and can be also used as guidance for O&M input.

2.2.2 Failure rates

There are a few challenges associated with acquiring accurate reliability data (i.e. FRs) for offshore wind farms:

- Reliability data is often seen by wind farm operators and OEMs as sensitive information that could potentially damage their reputation and undermine the trust in the developed technology. For this reason turbine failure and maintenance history is often not made public.
- Where provided, data is in the form of the number of alarms and the downtime associated with each alarm. Alarms are not always representative of the actual failures of the turbines. It is also common that multiple alarms go off at the same time (in sequence, e.g. Control System, then Generator, then the Generator Bearing). In real life, technicians and engineers can assess these alarms remotely or visit the turbine and make the judgement about what component failed, however when these alarms are collated on an electronic cloud, it is not always possible to analyse the root cause of the failure. In some cases these alarms are analysed by experts to form the reliability statistic (Artigao et al., 2021). In other cases, such as SPARTA, it is assumed that the component that has caused a forced outage is the one that triggered the first alarm in the alarm sequence.

- Not all alarms will lead to a turbine visit with a maintenance activity. SPARTA (2022) reports the statistics for forced outages but outages are not equivalent to turbine failures. In SPARTA a forced outage is defined as an event where a turbine is shut down following an alarm. Forced outages in SPARTA are distinct from scheduled campaigns and major operations. Section 2.3 will cover that further.
- Most offshore wind farms are quite young and estimating FRs on young turbines may not be representative of the average FR over the lifetime of a farm.
- Reliability data can depend on the type of technology used and the definition of failure that can vary from farm operator to farm operator.

Currently there is no database containing FRs for floating wind turbines and their substructures. There have been however a few studies investigating the reliability of fixed wind turbines onshore and offshore. As reported in the previous section most commonly used reliability source for offshore turbines is Carroll et al. (2016) which provides the frequency of minor repairs, major repairs and major replacements for a range of offshore wind turbine components (but does not include the substructure and cables).

The overview of earlier works, less commonly used sources of reliability data can be found in Cevasco et al. (2021). Cevasco et al. (2021) reviewed initiatives that collected both onshore and offshore wind reliability data but the vast majority of these initiatives have looked at onshore wind statistics rather than offshore. The maximum turbine rating of the initiatives looking at offshore wind was 4 MW and it belonged to the Carroll et al. (2016) initiative that has already been discussed.

Anderson et al. (2021) is a more up-to-date source that estimates operational performance metrics for a particular offshore wind farm but it does not break down the FR by component type. Anderson et al. (2021) demonstrated that FR depend on the position of the turbine within the farm. Based on the analysis of one offshore farm that study found that turbines that operate in the wake of others experience more frequent major failures. It also found that tidal currents significantly affect technician access restrictions leading to an increase in mean time to repair.

The downside of using all of the data sources listed in Cevasco et al. (2021) is the fact that it may no longer be applicable to modern technology and modern O&M approach. It is a challenge of any reliability statistic, there is currently a significant gap in turbine capacity between the turbines that are currently operating offshore and those that are planned to be installed in the next decade. It is questionable whether Carroll et al. (2016) data is still valid, considering the turbines in the data set are rated up to 4 MW. Turbine rating in the Anderson et al. (2021) is unknown.

SPARTA benchmarking service covers a wider range of turbines and includes turbines from multiple OEMs, more than two dozen wind farms, and turbines up to 8 MW in capacity. SPARTA is an anonymised operator benchmarking project for operational offshore wind farm production, operations and reliability KPI's. It is the biggest database for offshore wind turbines currently existing. Raw data collected via SPARTA is not available publicly however some statistic is reported annually as SPARTA Porfolio Review. SPARTA (2022) is the first SPARTA report that provides extensive statistic of offshore O&M trends based on data from 1505 offshore wind turbines. It is a preferred source in the current work for estimating the rates of corrective maintenance activities. There is a list of trends that have been observed there alongside the possible reasoning behind these trends:

- **Forced outages increase with turbine rating.**
  Although SPARTA results show a linear increase, the exact correlation between turbine rating and failures is unknown because higher rated turbines tend to be put further off-shore in harsher weather conditions and are also younger, hence they could experience more forced outages.
- **Forced outages increase with wave height at the site**
  The exact correlation is unknown, because there could be mixed effects of higher failures due to turbine rating and early-life failures. There have been however other studies looking at the effects of weather on wind turbine failures. Wind speeds, humidity and temperature may influence the frequency of turbine failures according to Reder et al. (2018). Carroll et al. (2016) also argued that there is a strong correlation between wind speeds and FRs.
- **Forced outages are the highest in the first year of the wind turbine operation and also peak in years 6-8 after the warranty period of wind turbines ends.**
  Similar to above, the exact correlation is unknown, because there could be mixed effects of higher failures due to turbine rating and harsher weather conditions in sites where newer turbines are put.
- **The rate of major repairs is lower in the first couple of years of turbine operation than it is in the second half of its lifetime. The rate peaks in years 5-6.**
  As explained in SPARTA (2022) this may be due to the end of a warranty agreement and the fact that major repairs on blades happen in bulk once a defect has been accepted by the OEM at the end of the warranty.

As the last two points have stated, the rates of forced outages and major operations are not constant. Many O&M studies assume that FRs follow a "bathtub curve" even though there is currently no evidence that this is the case (Bakken et al., 2017; Gray, 2017; Martin et al., 2016; Rinaldi, 2018). The term "bathtub curve" is used to describe the change of FR throughout the lifetime of components. "Bathtub curve" is based on the assumption that there is a higher likelihood of early failures due to the immaturity of the technology and installation mistakes and late failures due to wear-out. Only one study has demonstrated a weak "bathtub curve" evidence for gearbox and converter components (Carroll et al., 2015). That study is based only on one wind farm, one OEM and turbines up to 4MW in capacity.

SPARTA (2022) provides some evidence that there are much more forced outages in the beginning of the lifetime of a farm, but forced outages are not equivalent to FRs and the increase may be caused by adjustment of turbine sensor thresholds. There is no evidence of wear-out failures because SPARTA statistic ends on year 11. Only one wind farm in the UK, the Blyth Offshore Wind Farm, has reached the end of its lifetime and been decommissioned. The lack of data for the end of life of offshore wind turbines makes it hard to prove whether the bathtub curve concept is accurate. Interestingly, in one of the service vessel reports 4C Offshore has shown the variation of CTV days over the lifetime of a farm (Allen & Markatselis, 2020). 4C Offshore reported a higher number or CTV days in the beginning of the lifetime of a farm compared to year 2-3, however that number was even higher in years 4-5 and the highest in year 11 and over (Allen & Markatselis, 2020).

Section 2.5 of this thesis explores other data sources to look for the evidence of a bathtub curve prior to integrating FR variation into COMPASS. Section 2.4 will analyse the data from Sea Impact, enhance it with observations from 4C Offshore database, NtMs and news articles and investigate the major operation rate trend in greater detail in Section 2.5. For other corrective maintenance events more data and research is required.

All data that currently exist in the public data pool is applicable to fixed offshore wind turbines. There are some sources of FRs from the oil & gas and ship industries (DTOcean, 2015; Fontaine et al., 2014; Hallowell et al., 2018; Javad Moharrami & Shiri, 2018). For preventive maintenance of floating wind turbine components there are a few recommendations in the literature for cables (Jensen et al., 2015) and mooring lines (Ma et al., 2019).

Another method used in literature for estimating FRs for floating wind turbine components is the Failure Mode and Effect Analysis (FMEA). This method has been used in Li and Guedes Soares (2022). The work let four or five offshore wind experts identify 104 failure causes and allocate the severity, occurrence and detection ranking to each of them. Exact number of specialist is not clear as the earlier work refers to five specialist, while the later one to four (Li et al., 2021, 2022). Only one of these specialists worked in the floating wind sector at the time of survey. The same expert was also the only expert in the list of specialist who had experience in turbine maintenance. It is also the expert that was removed from the list of specialists in the later work (Li et al., 2022). It is difficult to evaluate how representative these occurrence, severity and detection rankings are of real turbines considering the specialists' lack of practical expertise in O&M.

All experts in that study identified blade faults as low occurrence, this evaluation will be challenged in current work (Li et al., 2021). SPARTA (2022) has demonstrated that the most common major operation is that related to blades. The results of this work presented in Section 2.4 are in line with SPARTA and also demonstrate that it is the most common major operation. Neither earlier nor later works present any durations and other characteristics associated with these 104 failures such as the number of personnel, vessels required or lead time for components (Li et al., 2021; Li & Guedes Soares, 2022; Li et al., 2022). These characteristics are essential for O&M simulation tools. Current work not only looks at the frequencies of maintenance activities but also identifies other characteristics using MPDs and expert judgement of specialists who worked with fixed offshore turbines directly.

One may argue that the results in these works are validated as they have been compared with Carroll et al. (2016) and aligns quite well if total FR is compared (8.34 compared to 8.3 failures per turbine per year) however it is not enough to compare the two (Li & Guedes Soares, 2022). Firstly, Carroll et al. (2016) reported values for offshore fixed wind and thus does not include FRs on floating turbine subsea components that are included in Li and Guedes Soares (2022). Secondly, FRs should be compared per subsystem or component rather than per turbine otherwise the comparison may be misleading. Lastly, this work has listed the limitations of Carroll et al. (2016) and identifies more up-to-date information when generating the attributes for the list of O&M activities in Section 2.3.

Another study that uses expert survey to estimate FRs is that of Jenkins et al. (2022). The study surveyed six experts that have knowledge in different fields including O&M and FOW. Unlike the previous studies this one did not aim to make a one-figure estimate but provided a range within which the FRs are expected to lie and gives the resulting values for P5, P50 and P90. It showed that experts expect wind turbines with gearboxes to fail more often than direct-drive ones and FOW turbines to fail more often than fixed turbines. The study estimated FRs on system-level, FRs are not reported per turbine components. This research aims to look at FRs with more granularity for a more detailed O&M analysis.

To estimate the FRs of cables, literature usually refers to the reports published by CIGRE working groups B.10 and B1.21 (CIGRE Working Group B1.21., 2009; Jensen et al., 2015). A more recent study claims that the reports underestimate the cable FRs and provides updated rates based on the information collected from 4C Offshore service and news articles (Warnock et al., 2017). Section 2.3 reviews MPDs in order to provide more information on cable repair and reburrial.

Reliability datasets are often incomparable because of different definitions of failure and the breakdown of a wind turbine into subsystems. Various standards exist for classifying turbines components, one example is RDS-PP® classification for power plants. Information on RDS-PP® classification can be found in Richnow et al. (2014). RDS-PP® breaks an asset down into a system, subsystem, basic function and product. Reliawind project that collected the reliability data of European wind turbines suggests to use a different taxonomy that would permit reliability data from different studies to be more easily compared (Michael et al., 2011). The Reliawind taxonomy is a hybrid approach, with a positional grouping for mechanical components and a functional grouping for electrical elements however it does not provide any additional information that would allow to adopt this taxonomy. FR figures reported by Reliawind are given in % rather that numerical values making it hard to compare them with other sources. SPARTA database also uses RDS-PP® system for grouping components into systems, subsystems and components (SPARTA, 2022).

This chapter aims to break down the entire wind farm system into subsystems and components following the taxonomy of the available dataset. Selecting a taxonomy before having an understanding of the level of detail available in the data may lead to making a lot of assumptions in order to fill in the data gaps. It is therefore recommended that taxonomy in the inputs should be equivalent to the taxonomy of the data available. For example, if turbine failure frequency is known but its component failure frequencies are not known then it is best to not break down the turbine into components. On the other hand if there is high level of detail in the reliability data then it is sensible to breakdown the system into components and get a breakdown of results from simulations.

2.2.3 Durations of major operations

Accurately modelling major operation durations using O&M simulation tools is particularly important, because these activities contribute to the majority of O&M costs for multiple reasons:

- JUVs are normally used to perform such operations and this type of vessel is one of the most expensive vessels used in offshore wind. For example, in the 2023 investor presentation Eneti and Cadeler reported vessel cost to be €240k-320k per day (Cadeler and Eneti, 2023). Another source cites Cedeler supplying a JUV for $412k per day (Chetwynd, 2023). These costs are indicative of long-term installation contracts and not one-off maintenance contracts that can be even more expensive. These findings indicate that just three days of using a JUV can cost a wind farm (or the OEM) over 1 million EUR. Section 2.4 will demonstrate that there have been examples of even longer operations.
- In case of the floating wind turbines that may require TTP, onshore cranes and tug vessels can also be expensive, especially in the summer when the weather conditions are better. According to the Seabrokers Group monthly report of February 2023, the Anchor Handling Tug Supply (AHTS) vessels can cost three or even four times more in June and July compared to any other month in 2022 (Seabrokers Group, 2023b). Interestingly, this trend was not observed in June and July 2023 which was explained by fewer projects that year requiring AHTS (Seabrokers Group, 2023a, 2023c).

- These are usually the longest maintenance operations that can happen on a wind turbine that usually take days to complete.

Carroll et al. (2016) is the only publicly available source to date that provides repair times for minor and major repairs and major replacements per component which is a significant input for O&M simulation tools. It is currently the most widely used source for the durations of major operations of wind turbine components. Anderson et al. (2021) also reports the durations of major operations however they are all combined together and are not broken down into component types. Work presented in Anderson et al. (2021) is based on two years of SCADA data and maintenance activity logs from a single wind farm. The capacity of the farm and the rating of turbines is not disclosed there however it is stated that these are multi-MW turbines. Anderson et al. (2021) is the first study known to date that acknowledges the variability of offshore operation duration and fits a distribution curve into the data.

Work presented here will provide updated values for the durations of major operations which are more accurate, include higher-rated power turbines and are based on a much greater number of wind turbines than what was used in Carroll et al. (2016) and Anderson et al. (2021). Existing studies use a fixed value to characterise the duration of an operation which is usually either an author's assumption or a value based on Carroll et al. (2016), but that study reports only the mean duration of major operations. This work will not only report the mean value but will also show that these durations are not limited to a single value and can vary significantly. Unlike Anderson et al. (2021) the data presented here will be broken down into component types.

There are currently no O&M simulation tools known at the time of writing that would use the distribution of major operation durations rather than a fixed value. All O&M simulation tools presented in Section 3.2 are designed to use a fixed value. None of the tools separate the planned activity duration from the actual duration either. This means that if an activity is set in the inputs to last two days, the duration of the suitable weather window searched for this activity by simulation tools will also be two days. It is expected that there should be a safety margin when an activity is planned i.e. the weather window should be longer than the anticipated activity duration.

Section 2.4 will demonstrate that there is a high chance of major operations to take shorter or longer time than the mean duration. In order to represent this behaviour this work will attempt to fit a log-normal, gamma and a Weibull distribution into the collected data and model the resulting Cumulative Density Function (CDF) using the statistical analysis software R Studio. The same section will then provide duration estimates and fit them into the O&M activity list presented in Section 2.3. Section 4.3 then describes how this CDF can be implemented in an O&M simulation tool COMPASS in order to model the durations of activities stochastically, this way realistically capturing the described variations. Section 5.5 then demonstrates the impact that variation in duration has on O&M simulation results.

2.3 Understanding O&M activities of offshore wind farms

2.3.1 Overview of marine planning documents and offshore wind experts

Information provided in publicly available offshore wind farm MPDs were used to develop the foundation of the O&M activity input guide for offshore wind farms. MPDs reviewed in this section can be accessed on the National Infrastructure Planning and the Marine Scotland Information websites (GOV.UK: The Planning Inspectorate, 2023; Scottish Government, 2023). MPDs were written as part of the consenting process, and were not developed for guiding the O&M simulation inputs but they still contain a lot of useful data and information that may be absent elsewhere. Unlike SPARTA, Sea Impact or 4C Offshore, in MPDs reported rates of corrective O&M activities cannot be traced back to individual data points. In some cases these rates are reported as the worst case scenarios, rather than average FRs.

Two of the MPDs are related to FOW turbines (Kincardine and Hywind Scotland), the rest of them are fixed-bottom offshore wind farms. With the information currently available it is believed that the majority of maintenance activities, particularly planned activities will be similar to those in fixed-bottom wind. All of them are based in the UK. The main difference between the O&M of fixed-bottom and floating wind turbines is assumed to be in the maintenance of the substructure and subsea components. In total, nine MPDs have been reviewed. These wind farms along with some of the specifications are listed in Table 2.1.

Table 2.1: Overview of the publicly available MPDs used in this research work.

Farm name	Foundation type	Turbine rating	Number of turbines	MPD name
Hywind	Spar	6 MW	5	Hywind Scotland Pilot Park Project Plan for Operation and Maintenance (C178-HYS-Z-GA-00004) (Statoil, 2017)
Kincardine	Semi-submersible	2 MW, 9.5 MW	5	Kincardine Offshore Wind Farm Project O&M Programme (KOWL-REP-0001-001) (KOWL, 2019)
Aberdeen	Jacket (Suction Bucket)	8.8 MW	11	O&M Offshore Environmental Management Plan (ABE-ENV-DB-0012) (RPS Group, 2020)
Beatrice	Jacket (Piled)	7 MW	84	Beatrice Offshore Wind Farm Consent Plan - Operation and Maintenance Programme (Wind Farm Assets) (Beatrice Offshore Windfarm Ltd., 2018)
Moray East	Jacket (Piled)	9.5 MW	100	Moray East Offshore Wind Farm - Wind Farm Operation and Maintenance Programme (Moray East Offshore Windfarm, 2021)
Norfolk Boreas	Monopile	14 MW	120	Norfolk Boreas Offshore Wind Farm. Outline Offshore Operations and Maintenance Plan (Royal HaskoningDHV, 2019)
East Anglia ONE	Jacket (Piled)	7 MW	102	East Anglia ONE North Offshore Windfarm - Outline Offshore Operations and Maintenance Plan (Scottishpower Renewables, 2021)
East Anglia THREE	Monopile	14 MW	100	East Anglia THREE - Outline Offshore Operations Maintenance Plan (Vattenfall & Scottishpower Renewables, 2015)
Neart na Gaoithe	Jacket (Piled)	8 MW	54	Neart na Gaoithe Offshore Wind Farm - Operation and Maintenance Programme (EDF Renewables, 2022)

Details of all activities identified within these documents were collected in an Excel table for further processing. MPDs lack format consistency, but the best attempt was made to collect the information from them and record it in a table format. Most of the documents provide information about the planned operations that are expected to happen on each farm throughout the lifetime of that farm. Some documents provide more detailed information about the planned wind farm operations, particularly Aberdeen Bay Farm, Moray East farm and Neart na Gaoithe farm provide more information on the frequency of some O&M activities and their vessel requirements. Other documents e.g. those associated with Hywind and Kincardine projects provide only the high level O&M information.

The information sought in the documents consisted of:

1. O&M activities and descriptions
2. Rates of these activities
3. Durations of these activities
4. If an activity is planned – the rate at which it happens
5. If an activity is unplanned – the maximum rate at which wind farm operators expect them to occur (MPDs usually report the worst case scenario)
6. Number of personnel required for each activity
7. Equipment requirements for each activity
8. Vessel requirements for each activity
9. Whether an activity needs to be performed in isolation or can be combined with other activities

Most of the activities identified from the MPDs are planned activities i.e. routine surveys and inspections, most of which are done annually, with some exceptions requiring twice a year visits and other exceptions requiring less than once a year visit.

The activity list formed from these documents was then reviewed internally by two ORE Catapult experts. Some details of these activities were further enhanced by discussions with four additional experts from three different organisations. Activities were then updated and further enhanced with findings obtained from discussions with these experts.

Below is the list of experts involved in shaping the final list of O&M activities:

- A specialist working on a supply chain in a major company that offers project services and vessel solutions to the offshore wind industry and has experience in spare part supply logistics.
- Experienced production manager of offshore wind farms of sites at all stages of O&M lifecycle from construction handover, under warranty, and self-maintained. Responsible for overseeing planned and unplanned maintenance activities of turbines, balance of plant and OFTO assets, including vessel and spare parts logistics.
- Experienced site manager, operations manager, and project manager who has successfully delivered numerous O&M campaigns globally. These projects focused on corrosion protection/repair, retrofits, Balance of Plant (BOP), and framework agreement work scopes. Previous work involved planning and execution of annual O&M maintenance.
- A marine ecologist who was involved in setting up the MPD for one of the offshore wind farms listed in Table 2.1.

- Two specialists from the major certification society specialising in marine and offshore applications.
- A specialist involved in substation inspections on offshore wind farms around the UK

According to these discussions some activities were combined together into a single maintenance operation (i.e. a single visit to the asset or a farm). Main focus of the discussions with experts was to identify the characteristics and requirements of each activity according to the list presented above. These characteristics are mainly the team size and the activity duration. Characteristics that have been consulted with specialists are marked accordingly in relevant tables in the following sections.

O&M activities identified in this work have been grouped into cable, substation and substructure activities, routine turbine service, minor maintenance activities on internal wind turbine components, minor maintenance activities on other components and major operations. Following sections will discuss the O&M activities identified for each group.

2.3.2 Cable O&M activities

According to the MPDs the following activities have been associated with offshore cables:

1. **Cable inspection and scour protection survey:** Surveys using multibeam echo sounder, magnetometer, side scan sonar and depth of burial surveys.
2. **Additional cable inspection:** Additional cable inspection in case if any issues are identified.
3. **Additional scour protection:** Deployment of rock protection around areas of excessive scour
4. **Cable reburial:** Reburial of a cable in the case of sediment movement or unexpected cable exposure.
5. **Cable repair:** Replacement of an entire cable or a section of a cable. In the case of fixed wind turbines the activity may also include a J-Tube replacement.

According to RPS Group (2020) unplanned cable operations can be divided into two groups: cable reburial and cable repair. The steps required for the two activities may also differ depending on whether it is an array cable, export cable or inter-tidal section of the export cable. Cable exposure due to sediment movement is a common cause for cable reburial activities.

O&M simulation tools model cable failures the same way that turbine failures are modelled. Array cable is considered an asset with a corresponding FR and once the failure occurs it is common to assume that a CLV will be used to repair it. Cable repair is often seen in O&M simulation tools as a single-action activity i.e. CLV travels to the site, repairs the cable and returns to the port. Single-action activity is easy to implement in O&M simulation tools, tools presented in Section 3.2 cannot model a sequence of activities following a cable failure. This is a common limitation of O&M simulation tools. According to MPDs cable reburial and repair is performed in several steps rather than a single action. These steps have been recorded from MPDs and presented in Appendix B.

Information obtained from MPDs regarding cables is based on fixed-bottom offshore wind farms. In floating wind farms dynamic cables would be used. It is not yet clear whether dynamic cable would be used only for the hanging section of the cable or in the full length of the cable. If the dynamic cable is used for the full length of the cable, then during the repair it is likely that the entire cable is replaced. In the case of the set-up where a dynamic cable is connected to a static cable, just the dynamic cable section may be replaced in case of a dynamic cable failure and a static section replaced in case of a static cable failure.

MPDs do not report exact rates at which cable repairs happen but provide statements for the worst case scenario from which FRs were estimated. These estimates are presented in Table 2.2. It can be noticed that the maximum FR associated with inter-array cable repair is twice higher than the average cable FR reported in Warnock et al. (2019). FRs are presented in terms of failures per km per year and failures per cable per year. The choice of units should depend on the O&M analyst's preference. More research is required in order to understand the nature of cable failures. If cable failures occur only at the cable ends, then using failures per cable may be more appropriate. If cable failures occur throughout the length of the cable (for example, due to cable exposure) then using failures per km may be more appropriate. The preference in this thesis is to use failures per km, which is consistent with existing research work on cable O&M.

Reburrial and repair rates in Table 2.3 are based on the estimates from Table 2.2. Table 2.3 summarises the maintenance activities collected from MPDs and their characteristics that can be used in O&M simulation tools. Team size and duration of these activities were not found, expert knowledge was also lacking in that area. One exception is cable replacement which is reported to require 40 people on board of a CLV.

Project ELECTRODE may provide more insight into realistic figures for cable failure and repair frequency in the future however the data listed in Table 2.3 can be used as a guidance for the anticipated range of cable failure frequencies.

Table 2.2: MPD statements converted to FRs for offshore cables.

Activity type	MPD statement	Total number of cables	Total cable length	Max FR (per cable per year)	Max FR (per km per year)
Inter-array cable repair	up to 2 cables per wind farm per year (includes reburrial) (Vattenfall & Scottishpower Renewables, 2015)	95	275 km	0.021	0.006
Inter-array cable reburrial	up to 3 per lifetime (maximum 100m each) (RPS Group, 2020)	10	13 km	0.015	0.012
Export cable reburrial	up to 5 over the lifetime (maximum 800m each) (RPS Group, 2020)	2	26 km	0.1	0.008
Inter-array and export cable reburrial	up to 10% of the entire cable per 5 years (Scottishpower Renewables, 2021)	N/A	N/A	N/A	0.02
Inter-tidal export cable reburrial	up to 1 over the lifetime (RPS Group, 2020)	2	26 km	0.05	0.038
Export cable repair	up to 1 over 10 years (Royal HaskoningDHV, 2019)	2	360 km	0.05	0.0003

Table 2.3: All cable operations and their characteristics.

Cable type	Activity	Rate (per cable per year)	Rate (per km per year)	Vessel
All cable	Survey	up to 0.5-1*	N/A	CTV/SOV
All cable	Additional scour protection			fallpipe vessel
Inter-array	Reburrial	up to 0.015	up to 0.012	CLV
Export	Reburrial	up to 0.1	up to 0.008	CLV
Intertidal Export	Reburrial	up to 0.05	up to 0.038	CLV
Inter-array	Repair	up to 0.021	up to 0.006	CLV, diver vessel + ROV
Export	Repair	up to 0.05	up to 0.0003	CLV

**In some MPDs it is reported to be only required when there is a risk of exposure.*

2.3.3 Offshore substation O&M activities

Unlike turbine and cable activities, OSS activities are often neglected in the existing literature. Unlike turbine O&M activities there is no database or a review of major operations that would give the statistics for OSS failures.

OSS failures are less known, primarily because there are fewer OSSs installed offshore than there are offshore wind turbines. Not all MPDs provide a detailed information on OSS O&M. Unlike other MPDs, EDF Renewables (2022) provides the most detail on OSS maintenance activities on a Neart na Gaoithe wind farm which are summarised below.

1. **Inspection of the main equipment:** Inspection of the lifting equipment, auxillary and electrical equipment, navigation aids, lifesaving equipment, handrails, gratings and lighting.
2. **Inspection of the firefighting equipment:** Testing, calibration and maintenance required to maintain fire detection and suppression system.
3. **Inspections of the oil spill kits and the weather system:** Inspection of all spill kit components including bunds, bundle arms, spill kits, etc. Inspection, cleaning and calibration of sensors and monitoring equipment.
4. **Davit crane repair or replacement:** Davit crane replacement is expected to happen on a OSS once in a lifetime of a farm. According to the interviewed experts however davit crane is more likely to be repaired rather than replaced.
5. **Equipment repair and refuel:** Navigation aids, High Voltage (HV) equipment repair, lifting and lifesaving equipment repair, generator refuelling.
6. **Major component replacement:** A switch gear or a transformer may need to be replaced once in a lifetime of a project, however this rate is stated to be precautionary in the MPD.
7. **Foundation inspection:** Inspection of the foundation above and below the water level.
8. **Foundation repair:** Application of primer and paint or other coatings to protect the foundations from corrosion.
9. **Removal of marine growth:** If necessary, removal of marine growth from the foundation and ladders
10. **Cable repair:** Any cable related repairs.

Table 2.4 provides a list of OSS activities with the relevant data associated with them that could be used in O&M simulation tools. For some O&M activities No Information (NI) on some characteristics was found.

Table 2.4: OSS O&M activities based on Neart na Gaothe MPD (EDF Renewables, 2022)

Service type	Part of the routine service	Rate (per year) or schedule	Craft	Team of	Duration
Annual Inspection	Yes	Yearly	CTV/SOV	6	under 1 week
Inspection of the firefighting equipment	Yes	At 6 months, 1 year, 5 years and 10 years	CTV/SOV	3-4*	1 shift*
Inspections of the oil spill kits and the weather system.	Yes	Every 4 months	CTV/SOV	3-4*	1-2 shifts*
Davit crane repair	No	0.04	JUV	NI	NI
Removal of marine growth	No	1	CTV/SOV	NI	NI
Equipment repair and refuel	No	NI	CTV/SOV	NI	NI
Major component replacement	No	0.04	JUV	NI	NI
Foundation inspection	Yes	NI	CTV/SOV	NI	NI
Foundation repair	No	NI	CTV/SOV	NI	NI
Cable repair	No	NI	NI	NI	NI

**Based on consultation with offshore wind specialists.*

2.3.4 Substructure maintenance

List of maintenance acitivities required on a substructure is also based on MPDs and is presented below.

1. **(Floating/Fixed) Inspection below the water level of all subsea components**: These components are floating or fixed-bottom substructure, moorings and dynamic cables (in case of floating wind turbines). It has been confirmed via consultation with the experts that these components will be inspected together in a single survey by Remotely Operated Vehicles (ROVs).This activity does not require switching off the turbine.
2. **(Floating/Fixed) Marine growth removal**: This activity will depend on the location of the turbine and the marine life conditions there. According to the MPDs this activity should happen approximately once in 5 years.
3. **(Floating/Fixed) Unplanned maintenance on floating or fixed-bottom substructure**.

4. **(Floating) Complete mooring replacement**: This activity was not identified in the MPDs but was a result from discussion with experts. It was found that although this event is extremely unlikely, there needs to be an emergency procedure in place for the case when one or multiple moorings fail and the turbine drifts off its original position.
5. **(Floating/Fixed) Inspection above the water level**: Visual inspection of coatings, glass reinforced plastic gratings, boat landings, railings, steps, staircases for the signs of corrosion and degradation.
6. **(Floating) Internal Inspection**: Inspection of ballast and any other internal components
7. **(Floating/Fixed) Visual inspection of anodes and anode testing**: Measurement of anode potential with a probe deployed from the external platform and/or ROV. Visual inspection of anodes and consumption verification of anodes (includes volume assessment). It can be performed while a turbine is still operating.
8. **(Floating/Fixed) Replacement of corrosion protection anodes**: Replacement in case of corrosion or other issues.

Table 2.5 contains the listed activities together with associated variables necessary for O&M simulation. The team size was not reported neither by the MPDs nor by interviewed experts. Duration of activities is also unknown in most cases.

In small scale demonstration floating farms these inspections are reported to happen every year in the beginning of the lifetime of a farm and then reduced to every 2 years (KOWL, 2019). In commercial scale farms risk-based approach is to be implemented meaning that only the certain percent of wind turbines in a farm will be inspected, 20% is the currently recommended proportion of assets to be inspected. This is also the approach reported to be used on jacket structures (EDF Renewables, 2022). The rate of inspections may change throughout the lifetime if there is no observable risk. RPS Group (2020) reports inspections to happen in the 2nd and 5th year and then every 5 years afterwards. Moray East Offshore Windfarm (2021) plans inspections every year but that frequency may change after 3 years.

There is a lack of actual reliability data from floating wind turbines due, in part, to limited deployment to date. Therefore, most FRs are inferred from the oil and gas industry, reliability data from ships, and other research areas. Future-generation floating turbines are likely to have hybrid moorings with a chain-synthetic mooring configuration for several reasons including reduced loads, better fatigue life and durability, reduced corrosion, and easier installation and maintenance due to the lighter weight of these moorings (Weller et al., 2015).

Synthetic mooring components' FRs can be found in the DTOcean+ project, it reports "Polyester rope", two "Connectors" and "Other" components' FRs (DTOcean, 2015). Combined they result in 0.0017 failures per mooring per year assuming two connectors and negligible FR of the chain part of the mooring. Chain part of the synthetic mooring will lie on the seabed where the tension is significantly lower than in the hanging section of the mooring (Borg et al., 2020). Synthetic ropes are resistant to corrosion and have a much greater fatigue life, therefore it is expected that their FR would be below that of chain moorings. In the literature chain mooring FR is reported to be 0.0025–0.00378 failures per mooring per year (DTOcean, 2015; Fontaine et al., 2014). On the other hand DNV estimated mooring system FRs for floating wind of between 0.001 - 0.02 per mooring line per year (Floating Offshore Wind Committee, 2021). It is not stated how this value would change with the length or the thickness of the mooring line. Statistic obtained from floating wind installations may provide more insight into the failure trends for mooring lines. Considering the range of mooring line FR reported and the lack of data on mooring line trends it is recommended to use a range of values for O&M simulations rather that a specific value.

DNV range is given in Table 2.5. The anchor FR provided in Table 2.5 was taken from a reliability study of drag embedment anchors (Javad Moharrami & Shiri, 2018), which are most commonly used for semi-submersible platforms.

Structural damage frequency was assumed to be the same as it is in the oil industry data for mobile platforms (Moan, 2009).

Table 2.5: Substructure activities and their characteristics.

Activity	**Rate (per turbine per year)**	**Duration**	**Craft**
Internal inspection	1	NI	CTV/SOV
Marine growth removal	0.2	NI	CTV/SOV
Subsea inspection (floating-demonstration or fixed, early-lifetime)	0.5-1	3 days	ROV support vessel or CTV
Subsea inspection (floating-commercial or fixed)	20% of assets a year	up to 3 days	ROV support vessel or CTV
Substructure repair (floating)	0.018	NI	Repair-specific
Substructure repair (fixed)	NI	NI	Repair-specific
Synthetic mooring replacement (together with anchor)	0.001-0.02 (anchor FR: 0.00012)	NI	AHTS
Above sea inspection	1-2	1 shift	CTV/SOV
Anode inspection and testing	1 initially, reduced to 0.2 later in life	NI	CTV/SOV

2.3.5 Preventive maintenance activities on a wind turbine

Inspection activities listed below are also based on information collected from MPDs and enhanced with expert knowledge.

- **Annual inspection of main components (excluding HV equipment)**: Components, navigation aids, tower, nacelle, signage, marker boards and stickers are inspected. Consumable items such as filters, brake linings, carbon brushes, grease cartridges are replaced as required. In addition to the regular annual visits an extra visit is required 500 hours or three months after the wind farm is commissioned.
- **Annual inspection of HV equipment**: This inspection requires to be carried out separately from the inspection of main components because specialised equipment and technicians are required. The team of technicians in this activity will differ from that used in the inspection of main components. The turbine will be switched off, local safety measures will be put in place. Anything starting from the low-voltage side of the transformer will be inspected. Examples of such components are a transformer and a switch gear.
- **Lifting and safety equipment service and certification**: Davit crane, safety retracting line service, certification, lifts and lifting eyes, pad eyes, anchorage points maintenance and examination. According to the interviewed experts and several MPDs, this activity is done annually (Beatrice Offshore Windfarm Ltd., 2018; EDF Renewables, 2022; Moray East Offshore Windfarm, 2021; RPS Group, 2020). According to one of the experts, there is almost always an issue identified (nine out of ten times). Usually there is a visit for inspection and then another visit for repair.
- **Inspection of leading edge protection**: It is listed separately because it usually requires a separate vessel (according to the interviews with experts). It could be any vessel that is available on the market. It can either occur every three years on each turbine or on 33% of turbines every year (EDF Renewables, 2022; RPS Group, 2020).
- **Seabird monitoring equipment inspection**: This activity can be combined with other inspection activities but is listed separately because the monitoring equipment is likely to be installed on just a couple of wind turbines.

Table 2.6 summarises the regular inspection activities required on each turbine. Activity characteristics were found through the review of MPDs and discussion with experts.

Table 2.6: Regular inspection activities required on a wind turbine and their characteristics.

Wind turbine component	Rate (per turbine per year)	Team of	Duration
Components excluding HV	1	4-6*	up to 16h*
HV equipment	1	2*	8-12h*
Lifting and safety equipment	1	3*	4h*
Leading edge protection	0.33	3*	15-60min
Seabird monitoring equipment	2		

**Based on consultation with offshore wind specialists.*

2.3.6 Minor maintenance activities on a wind turbine

Minor maintenance activities can be undertaken using CTVs and SOVs. The breakdown of minor maintenance activities is the same as the breakdown of forced outages seen in SPARTA (2023): rotor system, generator system, drive train system, transmission system, yaw system, central hydraulics system, other (may include paint repairs, access ladders/boat landing repair, davit crane replacement, repair of navigation aids). Table 2.7 provides a list of minor maintenance activities that are expected on a turbine.

The vast majority of the forced outages caused by SCADA alarms can be resolved remotely, the exact number is not known but Siemens Gamesa estimates 85% of turbine issues identified with SCADA can be resolved remotely (SiemensGamesa, 2022). This same value was also found during analysis of alarms from an offshore wind farm (Koltsidopoulos Papatzimos et al., 2019). The rates of forced outages reported in SPARTA (2022) were reduced by 85% to get an estimate of a minor maintenance activity rates. Lack of data transparency limits any further improvements in this assumption. More research may become necessary when more data becomes available to understand the ratio of turbine visits for minor maintenance to the total number of forced outages. 85% reduction is applied universally on all subsystems but more research is needed to justify this assumption. Resulting values are presented in Table 2.7.

Table 2.7: Minor maintenance activities on Turbine and TP as seen in SPARTA (2023) and updated with new information.

Subsystem	Rate (per turbine per year)	Duration	Craft	Team of
Rotor system	1.87	up to 2 shifts*	CTV/SOV	3-4*
Generator system	1.13	up to 2 shifts*	CTV/SOV	3-4*
Drive train system	0.79	up to 2 shifts*	CTV/SOV	3-4*
Transmission system	3.64	up to 2 shifts*	CTV/SOV	3-4*
Yaw system	2.34	up to 2 shifts*	CTV/SOV	3-4*
Central Hydraulics System	1.15	up to 2 shifts*	CTV/SOV	3-4*
Other	0.65	up to 2 shifts*	CTV/SOV	3-4*

**Based on the consultation with offshore wind specialists.*

2.3.7 "Other" minor maintenance activities

Some of the minor maintenance activities identified as "Other" in SPARTA (2023) may include paint repairs, access ladders/boat landing repair, davit crane replacement, repair of navigation aids. These activities were explored in greater detail using the MPDs and the expert knowledge. Activities are described below and summarised in Table 2.8.

- **Paintings or other coatings (nacelle, tower):** Very rare activity according to the interviewed experts. It is expected to happen more often on older turbines. This activity may require a rope access technician.
- **Lift equipment:** Repair of the wire for the lifts inside the wind turbine tower. This activity is initiated when a lift has recorded 50 hours of usage, all key components get exchanged: lift wire, gear box, lift motor and lift brake.
- **Paint repairs:** Boat landing area and foundation areas may occasionally require a paint campaign. Whether or not such campaign is required is decided during the annual inspection of the wind turbine. This makes it an unplanned activity that follows a planned activity. It can be performed while the turbine is operating but requires several visits because the paint needs to be applied in several layers.
- **Access ladder and boat landing repair:** Very rare campaign, it is thought that it may be required in the case of a collision with a vessel.
- **Davit crane repair:** According to EDF Renewables (2022) davit crane replacement is anticipated to happen on each turbine once in its lifetime. Interviewed experts however believe that davit crane is more likely to be repaired rather than replaced.
- **Navigation aids repair:** Claimed to be a rare activity by the interviewed specialists but is considered an urgent one if required because of strict offshore regulations around navigational aids.

Table 2.8: Minor activities on Turbine and TP that may have been identified as "Other" in SPARTA (2023)

System	Subsystem/ Description	Rate (per turbine per year)	Duration	Craft	Team of
Turbine	Painting or other coatings (tower, nacelle)	up to 0.05*	up to 2 shifts	CTV/SOV	3-4* (may require rope access)
Turbine	Lift equipment	up to 0.05*	up to 2 shifts	CTV/SOV	3-4*
TP	Paint repairs to boat landing and foundation areas	0.3-1*	2-3 visits (30-180min each)*	CTV/SOV	2* (may require rope access)
TP	Replacement or repair of access ladders, boat landing, TP platform	NI	up to 2 shifts	CTV/SOV	NI
TP	Davit crane replacement or repair	up to 0.04*	up to 2 shifts	JUV	NI
TP	Repair of navigation aids	NI	up to 2 shifts	CTV/SOV	NI

**Based on consultation with offshore wind specialists.*

2.3.8 Major operations on a wind turbine

Major operations require a visit by a HLV or in the case of FOW, a TTP or a tow-to-shallow operation. In the 2021 review SPARTA reported that 95% of blade repairs are likely to be part of a planned campaign (SPARTA, 2022). This implies that these activities are anticipated in advance. Thus it is possible that the majority of these major operations do not cause turbine downtime prior to the start of the operation.

Components that may require major operations include blade, pitch bearing, gearbox, main shaft, generator, main bearing, hub and yaw bearing. Transformer and switch gear may sometimes also require a JUV visit, depending on the nature of an operation and the location of these components inside the turbine. Section 2.4 will provide evidence that transformer replacement with a JUV is often an opportunistic maintenance (i.e. it happens together with other activities).

According to the ORE Catapult experts six people will be undertaking the work on the turbine during the major maintenance campaign. The team would comprise of electricians, mechanical technicians and riggers (people who are qualified to control lift operations on the turbine). There could be more people on the HLV itself (or in port in case of in-port maintenance). Section 2.4 will demonstrate that it takes different time to perform different major maintenance activities and therefore it is better to model these activities separately rather than group them into one.

Spare part lead time is often neglected in O&M analysis, possibly due to high uncertainty around the assumptions. Spare part lead time in COMPASS is defined as the time it takes from the moment the old part fails to the moment the new part arrives at the O&M port.

One study collated data from other sources and resulted in spare parts under 10,530 EUR requiring 1-2 weeks lead time and parts costing 100,000 –113,000 EUR requiring 10 weeks of lead time (Jäger-Roschko et al., 2019). Although the report was written in 2019 the sources used in the study to collate the lead time statistic are dated 2014 and earlier. Another study conducted several interviews with service technicians and managers at four Vattenfall wind turbine service stations (Lindqvist & Lundin, 2010). According to that study, a replacement blade and a transformer would take 8 and 16 weeks of lead time respectively. Each of the other components would take one week. The study was concerned about 2 MW and 2.3 MW turbines and the interviews were conducted in 2010, therefore the information may be outdated. Nevertheless, spare part lead time values in Table 2.9 are based on that data. According to one of the interviewed experts, a transformer lead time would be around 6 weeks.

Differences in wind farm operator strategies can also result in high variability of spare part lead time estimations. Some farm operators will prefer to keep some spare parts at an O&M base, others will decide against it due to the lack of storage space. Other operators may decide to get replenishment from a distribution centre (e.g. Hull, UK). Lead time is highly dependent on the market size and supply chain, some components may be only manufactured abroad. One way to overcome long lead times is to refurbish components rather than replace them, that also removes the need to recycle old blades. Blade replacement and refurbishment campaign at the Burbo Bank wind farm in 2023 is one example of that (reNEWS biz, 2023c). In this case blades were replaced at one turbine, then old blades were taken ashore for refurbishment. Refurbished blades were then used to replace the blades at the next turbine. The process was repeated until the blades on 32 turbines were replaced. These works were planned for 12 weeks, with an average of three days spent on each turbine meaning that blade refurbishment would take a couple of days.

Major replacement campaign on a KIN02 floating wind turbine from the Kincardine wind farm in 2023 took place in Rotterdam (i.e. the turbine was towed to that port). It could be observed from a publicly available web camera located at the Rotterdam port that the turbine had to wait over ten days at the port before the major operation started (Port of Rotterdam, 2023). This waiting time could have been caused by the lead time or spare parts required, crane mobilisation time or the availability of port facilities.

Lead time values given in Table 2.9 may be out of date in most of the cases. They may also depend on wind farm repair strategy. MPDs do not report these values. Spare part lead time could benefit from more research in the future, particularly as turbines get larger and the pressure on supply chain increases.

Vessel information was taken from MPDs and team size was provided by the ORE Catapult experts. Team size is indicative of the number of people working on the turbine itself however there may be more people present on a HLV. Section 2.4 will provide information about the duration of major operations and their frequency.

Table 2.9: Major operations on main wind turbine components and their logistical requirements.

Component	Component lead time (max)	Vessel	Team of
Blade	8 weeks	JUV/HLV/Tug	6*
Pitch Bearing	1 week	JUV/HLV/Tug	6*
Transformer	6 weeks*	CTV/SOV/JUV/HLV/Tug	6*
Switchgear	1 week	CTV/SOV/JUV/HLV/Tug	6*
Gearbox	1 week	JUV/HLV/Tug	6*
Main Shaft	1 week	JUV/HLV/Tug	6*
Generator	1 week	JUV/HLV/Tug	6*
Main Bearing	1 week	JUV/HLV/Tug	6*
Yaw Bearing	1 week	JUV/HLV/Tug	6*
Hub	1 week	JUV/HLV/Tug	6*
Other	1 week	JUV/HLV/Tug	6*

**Based on consultation with offshore wind specialists.*

2.3.9 Health and safety

Health & Safety (H&S) is often neglected in O&M simulation tools. There are however certain H&S limits that affect the operations and cause delays in the case of unexpected incidents. These H&S limits depend on the regulations in a given country and wind farm operators strategies. The H&S information listed below has been obtained via the interview with the service manager of the Lynn and Inner Dowsing (LID) farm based in the UK (Murrell et al., 2022).

- The maximum of people that can be present on the nacelle at a time is 4, can be extended to 6 with additional equipment installed on turbines. This limit is required for personnel to safely descend down in case of a fire alarm activation. Figure 2.2 demonstrates an example of the consequences of a fire incident on a wind turbine.
- There must always be a rescue team within a 20 minute reach distance to the personnel. That team can either be located on a separate vessel or on the same vessel that carries out the maintenance (e.g. a CTV).
- In the case that one of the crew members is sea sick, the CTV would need to return back to the port unless there is a separate rescue vessel that can pick them up.
- The majority of operational offshore wind turbines do not have toilet facilities installed in them which can also impact the number of transfers onto and off the turbines.
- H&S has a priority over contractual regulations e.g. where a contract says that an activity can be performed if H_s is under 2 m it may still be postponed if it is believed it is unsafe for technicians to go offshore.

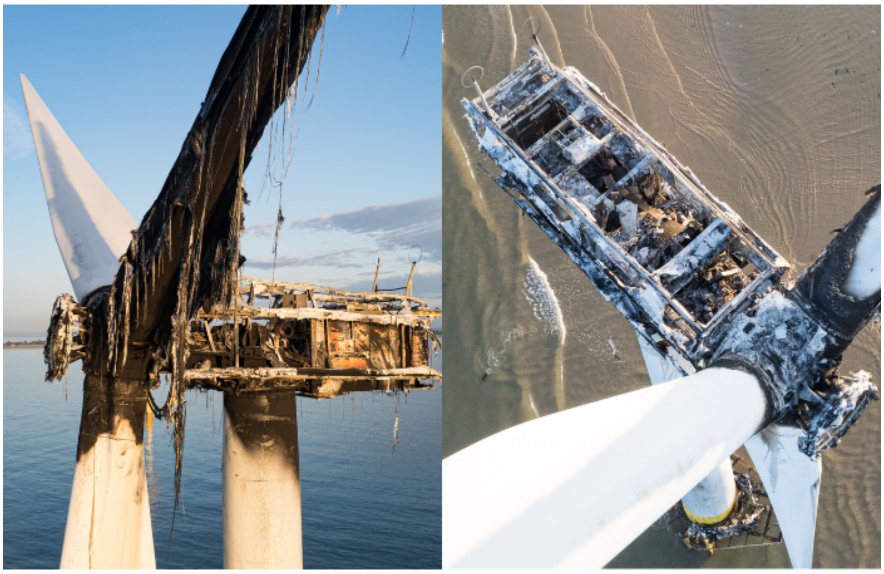


Figure 2.2: Wind turbine after the fire on one of the Scroby Sands (UK) wind farms. Source: Oliv3r Drone Photography (4C Offshore, 2023c)

2.3.10 Additional lessons learnt from the review of MPDs

Sections 2.3.2 - 2.3.9 provide the review of MPDs enhanced by interviews with specialists with experience in offshore wind O&M. There were a few lessons learned from this review that were not captured in the O&M activity input guidance and are particularly relevant in the context of O&M simulation:

1. A few corrective maintenance activities result from planned inspections. Later in this thesis Section 3.2 reviews existing O&M simulation tools. These tools (including COMPASS) model FRs stochastically resulting in repair activities scattered over each operation year. This assumption may be valid for some activities caused by forced outages but not for other that result from regular inspections.
2. Neither MPDs nor specialists categorise activities into minor or medium. Some activities however are categorised as major in MPDs, these are the activities that require a HLV or TTP.
3. There exist corrective maintenance activities that do not require the turbine to be stopped prior the start of that maintenance activity.
4. Some minor maintenance activities such as subsea ROV inspections and paint campaigns can happen without switching off the turbine.
5. Some O&M activities have to be done in isolation from the other but there are some that can happen in parallel with other activities. Later in this thesis Section 2.4 also demonstrates some cases where multiple components are repaired or replaced in a single visit.

Next section enhances the collected information with data on durations of major operations.

2.4 Estimating the duration of major operations

MPDs do not report durations, i.e. how much time it takes to complete each major operation from the arrival of the necessary HLV to the turbine to the end of the operation. This section aims to find the durations of major operations missing in Table 2.9.

2.4.1 Data Sources

This work is based on four sources of data, the first two of which can be accessed with a paid subscription and the other two are available publicly:

- Sea Impact
- 4C Offshore
- NtMs
- News articles

Sea Impact is a service that tracks the movement of JUVs using marine traffic data and aligns JUV positions with turbine locations (Sea Impact, 2023). Sea Impact service then records the time when a JUV arrived to the turbine and when it left and calculates the total duration of each operation. JUV operations in that service are tracked since 2012. There are 2318 operations reported in the Sea Impact database between the start of 2012 and the end of 2022 that are analysed in this study. These operations cover over 80 wind farms, over 4800 wind turbines, making it the largest known database recording major operations. Moreover, seven OEMs are captured in this database. For each operation Sea Impact provide the wind farm name, the name of the OEM, the turbine model name, turbine ID, the JUV used and the start and the end date of the operation which include hour, minutes and seconds at which the operation started and ended. Marine traffic sources may not always provide the exact position of a vessel at the exact hour however there is no data that could be used to estimate the level of uncertainty in the Sea Impact data.

In 662 cases (out of 2318) Sea Impact reports the type of intervention that happened during that operation i.e. whether it was a blade replacement, a gearbox exchange or any other operation type. Additional information was collected from the 4C Offshore service, NtMs and news articles (obtained from a web search) in order to increase the number of known intervention types. 4C Offshore database provides a log of activities on each offshore wind farm with an approximate date at which they happened. Missing intervention types in the Sea Impact data sheet were then filled in with that information. The work process is described below:

1. Read the description of the activity in the 4C Offshore log of activities and identify the major components involved and the name of the JUV used (if listed).
2. Skip the description if no component is identified.
3. If there is a component specified, keep the record of the approximate date and the wind farm at which it happened.
4. Find that wind farm in the Sea Impact data sheet. Find the date that is the closest to the date reported by the 4C Offshore and make sure the name of the JUV is the same in both sources.
5. Fill in the missing intervention type.

This way, additional 252 intervention types were identified.

Another useful source for the types of major operations is NtMs. NtMs are released by wind farms to the UK Hydrographic Office (UKHO) which in turn distributes these notices. The main purpose of NtMs is to inform mariners about the upcoming works on wind farms to make them aware of any activities and potentially hazardous operations (especially those with JUVs). These NtMs can be found in the archives of the UKHO or on port websites. UKHO was also contacted with an attempt to get access to other NtMs that were not listed on the ports websites. UKHO provides a paid research service, however no clear quote was given for extracting wind farm NtMs from the archives. NtMs from wind farms are mixed with all other NtMs in the archives and hence this research may take a substantial amount of time. It also was not clear how much value it would bring because the majority of all known NtMs do not provide the intervention types.

NtMs used in this study were primarily obtained using a web search. This way 53 additional intervention types were identified using a web search, 50 of which were sourced from the NtMs obtained from several port and wind farm websites (Eastern Inshore Fisheries and Conservation Authorities, 2023; Galloper Wind Farm Ltd, 2023; Island Yacht Club, 2023; PD Ports, 2023; Ribble Cruising Club, 2019) and 3 of which were found in the news articles (OffshoreWIND biz, 2013; reNEWS biz, 2022b; Van Oord, 2019). In the majority of NtMs cited in this work readers can find the name of a JUV that is due to perform a major operation, the IDs of the wind turbines on which these operations were performed and in some cases the types of the components on which these operations were undertaken. In the future it would be beneficial to have a database with all NtMs that are relevant for offshore wind, so that this work can be done more efficiently.

Table 2.10 provides the number of major operations on each component type collected from the described sources. The table provides the number of operations where one type of component was involved, the number of operations where two or more components were involved and the resulting total. For example, for blade components there are 566 interventions known where only blade components were repaired or replaced. There are 29 additional interventions where blades were repaired or replaced together with other components such as a gearbox or a generator.

Table 2.10: Overview of the data combined from Sea Impact, 4C Offshore, NtMs and news articles.

	One component type	**Several component types**	**Total operations**
Blade	566	29	595
Gearbox	93	57	150
Generator	18	4	22
Pitch Bearing	31	1	32
Main Bearing	49	23	72
Transformer	2	21	23
Main Shaft	2	3	5
Blade (other)	-	-	94
Bearings (unknown type)	-	-	6
Regrouting	-	-	8
Turbine replacement or decommissioning	-	-	8
Foundation removal	-	-	2
Incident	-	-	4

When analysing the data sources, it was noted that blade operations are named differently in some cases. The options are:

- Blade Exchange
- Blade Repair
- Blade Replacement

These activities were grouped together. Same approach was taken for other components because there was not sufficient data to distinguish between repairs and replacements. Some blade interventions were excluded from further analysis on blades, these are marked as "other" in Table 2.10. These are namely "Blade Exchange ($\times 2$)", "Blade Exchange ($\times 3$)", "Blade Repair (part 1)" and "Blade Repair (part 2)". The aim was to look at how much time just one component takes (so that it can be used in O&M simulation tools) and these data points do not provide such information.

As can be observed in Table 2.10 blade repair and replacement was the most commonly reported major operation in the collected data. This is consistent with the data reported by SPARTA, where around 63% of major operations are associated with a turbine rotors (SPARTA, 2022). The second and the third most frequent major operations were found to be associated with gearboxes and main bearings respectively.

It can be seen that for some components the data is scarce, particularly for generators, transformers and main shafts. Wind farm operators tend to not reveal much information on these components.

Table 2.10 shows that almost all of the transformer repairs and replacements happened together with other components. This is likely due to opportunistic maintenance strategies. Faulty transformers are repaired or replaced using a JUV when there is an opportunity to do so while other components undergo major maintenance.

There were also some activities in the data set that were not specific for a particular turbine component. A few activities were associated with regrouting, turbine replacement, turbine decommissioning and monopile removal. Additionally, four of the operations were found to be incidents, the nature of these incidents is unknown.

2.4.2 Estimated durations compared with actual durations

In order to highlight the importance of capturing the duration of major operations, the expected duration can be compared with the actual duration measured by the Sea Impact service. Table 2.11 provides a list of estimated durations taken from NtMs and the identifier "Shorter" or "Longer" indicating whether the actual duration seen in the Sea Impact was longer or shorter than the planned. NtM format can vary from an operator to operator, in some cases the duration is given as a range ("2-3 days"), in other cases it is given as a maximum expected duration ("up to 10 days"). In other cases, particularly in the cases of blade repairs and replacements, the operations would be done on a bundle of turbines. For example, NtMs could report that 20 turbines would be serviced under three months. Table 2.11 only reports cases where three or less turbines would be serviced. It is assumed that for longer durations where a big group of turbines is involved, the estimated duration would have a large safety margin and involve the JUV movement around the site, JUV contract could be different too.

In 12 out of 32 cases the actual duration was longer than the estimated duration. Even in some cases where an operation would take place in summer months, the duration of an activity would be underestimated. The average estimated duration in this list is 6.6 days. The average actual duration in this list is 7.1 days. The sample presented here is quite small covering only 32 NtMs and may not be indicative of the whole population but it highlights both the expected and the actual variability in durations that is not captured in any of the O&M simulation tools known to date.

2.4.3 Fitting a probability distribution using R Studio

For blades, gearboxes, pitch bearings and main bearings, having the sufficient data, additional analysis was performed. Analysis was performed in the following steps:

1. Python script was written to iterate through the data and distribute all operations into groups. The first group was named "All", this group includes all major operations. All other groups would have a label "single", "multiple" or "stacked" and another label indicating a component type. Those labeled "single" include operations only on one component type. Those labeled "multiple" include operations on two or more component types. Those labeled "stacked" include operations on one or more component types. Table 2.10 highlighted the results of these groupings.
2. R Studio script was used to fit a probability distribution given the sorted data. This research work analysed three common distribution types: Weibull, gamma and log-normal. R Studio was used to see how well these distributions fit the data by assessing the Q-Q plot and performing a Goodness of Fit Kolomogorov-Smirnov (K-S) test where appropriate.
3. A probability distribution is then selected for each dataset (where possible), the Probability Density Function (PDF) coefficients recorded and then used to plot a CDF. If no suitable distribution type is found then either a step CDF is used or a fixed duration is assumed based on the mean value of the results.
4. The results of a CDF were exported as a table for each component (for which the results were sufficient) and moved to COMPASS. Section 4.3 demonstrates how a CDF can be used to model the variation in the duration of major operations. Section 5.5 compares the simulation results between fixed and variable duration scenarios.

Table 2.11: Estimated durations reported in NtMs compared to actual durations based on Sea Impact data

Component Exchange	**Planned dur-n (days)**	**Month**	**Actual (dur-n)**
Blade (Gunfleet Sands Demo Ltd, 2013)	3	Jul	Shorter
Blade (Gunfleet Sands Offshore Wind Farm Ltd, 2015c)	2	May	Shorter
Blade Bearing (Gunfleet Sands Offshore Wind Farm Ltd, 2015b)	3	Jul	Longer
Gearbox (EDF Renewables, 2021b)	8	Aug	Shorter
Gearbox (Orsted, 2021b)	7	Dec	Longer
Gearbox (Watson, 2019)	2	Feb	Longer
Gearbox (Watson, 2019)	3	Mar	Shorter
Gearbox (Orsted, 2020)	10	Oct	Shorter
Gearbox (at 2 turbines) (Orsted, 2021c)	5	Jun	Shorter
Gearbox (at 2 turbines) (Orsted, 2021d)	5	Jun	Shorter
Gearbox and Main Bearing (Watson, 2019)	5	Feb	Longer
Gearbox and Main Shaft (EDF Renewables, 2021a)	7	Aug	Shorter
Generator (Watson, 2019)	2	Feb	Longer
Generator (Galloper Offshore Wind Farm, 2019)	10	Jul	Longer
Generator (Orsted, 2022b)	10	Mar	Shorter
Generator (Orsted, 2022a)	4	Oct	Longer
Generator (Orsted, 2022e)	7	Sep	Shorter
Generator (at 2 turbines) (Gunfleet Sands Offshore Wind Farm Ltd, 2015a)	5	Jan	Longer
Generator (at 2 turbines) (Orsted, 2022d)	7	Jul	Shorter
Main Bearing (Orsted, 2021e)	7	Aug	Longer
Main Bearing (Orsted, 2022c)	6	Jun	Longer
Main Bearing (Orsted, 2021a)	6	Oct	Longer
Unknown (Gunfleet Sands Offshore Wind Farm Ltd, 2012)	9	Aug	Shorter
Unknown (Lynn and Inner Dowsing Offshore Wind Farm, 2021c)	10	Jul	Shorter
Unknown (Lynn and Inner Dowsing Offshore Wind Farm, 2021d)	14	May	Shorter
Unknown (Lynn and Inner Dowsing Offshore Wind Farm, 2020)	14	Nov	Longer
Unknown (2 turbines) (Lynn and Inner Dowsing Offshore Wind Farm, 2021b)	7	Jun	Shorter
Unknown (2 turbines) (Lynn and Inner Dowsing Offshore Wind Farm, 2022a)	5	Mar	Shorter
Unknown (2 turbines) (Lynn and Inner Dowsing Offshore Wind Farm, 2021a)	5	Oct	Shorter
Unknown (3 turbines) (Lynn and Inner Dowsing Offshore Wind Farm, 2022b)	6	Aug	Shorter
Unknown (3 turbines) (Gunfleet Sands Offshore Wind Farm Ltd, 2019)	4	Mar	Shorter
Unknown (at 2 turbines) (Gunfleet Sands Offshore Wind Farm Ltd, 2016)	15	Aug	Shorter
Average planned duration	**6.6**		

R Studio was used to perform a statistical analysis on the data on operation durations obtained from the discussed sources. Figure 2.3 shows the histogram for durations of all major operations observed in the Sea Impact database. The histogram is skewed towards the right side. Similar trend was observed in the subsets of data specific to blades and gearboxes in Figures 2.4a, 2.4b. This trend is also suspected in the cases of the data subsets for pitch bearings and main bearings (see Figures 2.4c, 2.4d).

According to the histogram shown in Figure 2.3 operations are most likely to take 1-3 days however they can be much longer, reaching over 20 days in some cases. This research investigates how three common probability distribution types could represent this behaviour: gamma, Weibull and log-normal distributions.

It was assumed that a sample size of 20 or less is not large enough to perform any statistical analysis (commonly, data set sizes of at least 30 observations are used). Therefore, for generator, transformer and main shaft this analysis was not applied.

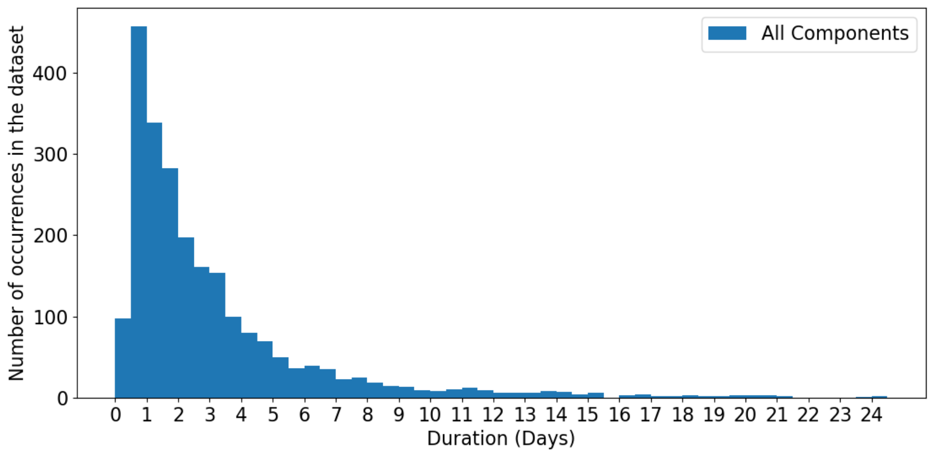
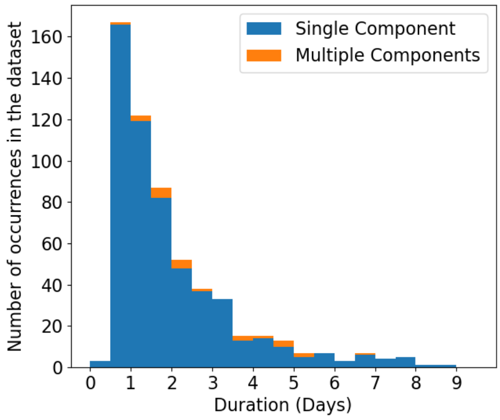
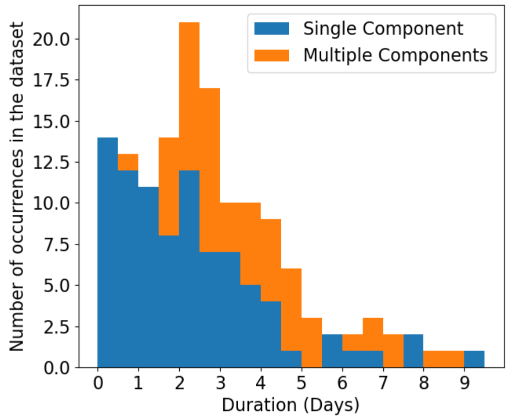


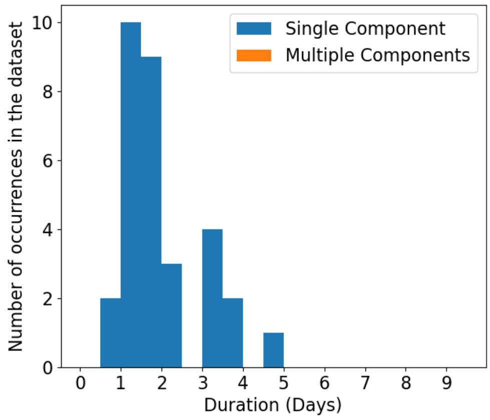
Figure 2.3: Histogram with durations of major operations of all components.



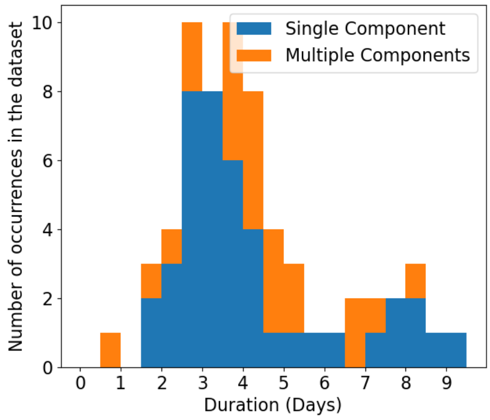
(a) Blade



(b) Gearbox



(c) Pitch Bearing



(d) Main Bearing

Figure 2.4: Stacked histograms with durations of JUV operations associated with four major components.

The test was performed using a `fitdistrplus` package in R Studio. The script used in R Studio is given in the Appendix C. The fitness of each distribution was then assessed graphically using the plots produced with the `fitdistrplus` package. A suitable distribution was found based on the fitness of the empirical values to the theoretical values on the Q-Q plot and the P-P plot. When analysed graphically, the closer the empirical values are to the theoretical values on the Q-Q plot and the P-P plot, the better the fitness of a distribution. On the Q-Q plot the lower left corner represents the match between the left tail of the modelled distribution and the actual values and the upper right corner the match between the right tail of the modelled distribution and the actual values. The next sections present the Q-Q and P-P plots for different components.

All major operations

Distribution plots along with the Q-Q and P-P plots are shown in Figures 2.5, 2.6, 2.7 for the gamma, Weibull and log-normal distribution fit respectively. It can be seen that in the cases of gamma and Weibull distribution, the empirical quantities deviate from the theoretical line. In these cases they are shifted upwards from the theoretical quantity of around 7 and above, it means these distributions underpredict the likelihood of longer operations. In the case of the log-normal distribution the fitness looks better in both the Q-Q and P-P plots but some deviation from theoretical lines can still be observed. In this case the distribution underpredicts the durations in the middle of the distribution and overpredicts the longer durations of activities.

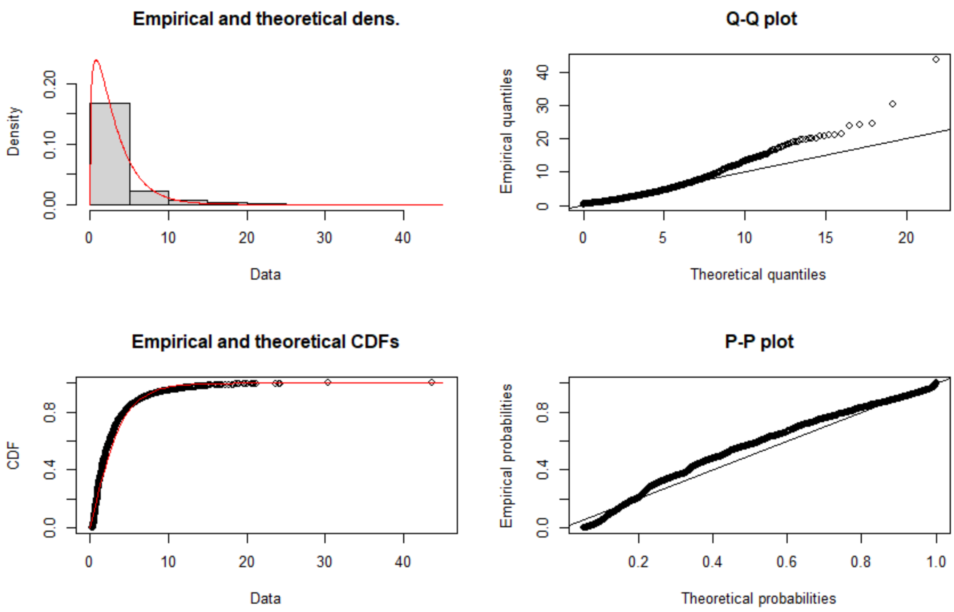


Figure 2.5: Gamma distribution fitted to data on all major operations

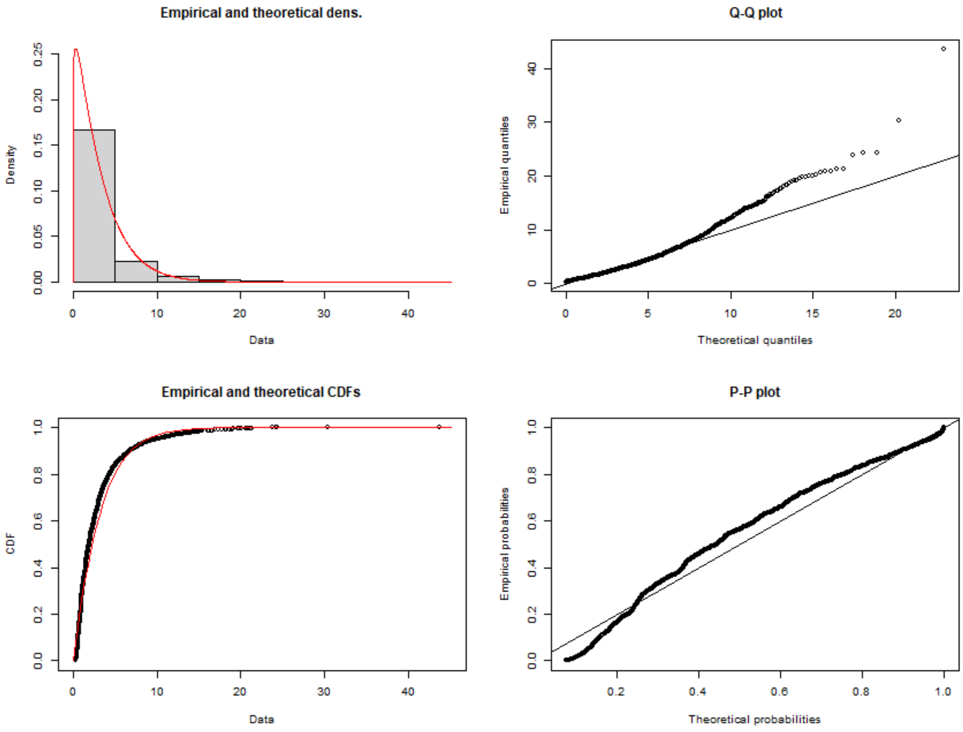


Figure 2.6: Weibull distribution fitted to data on all major operations

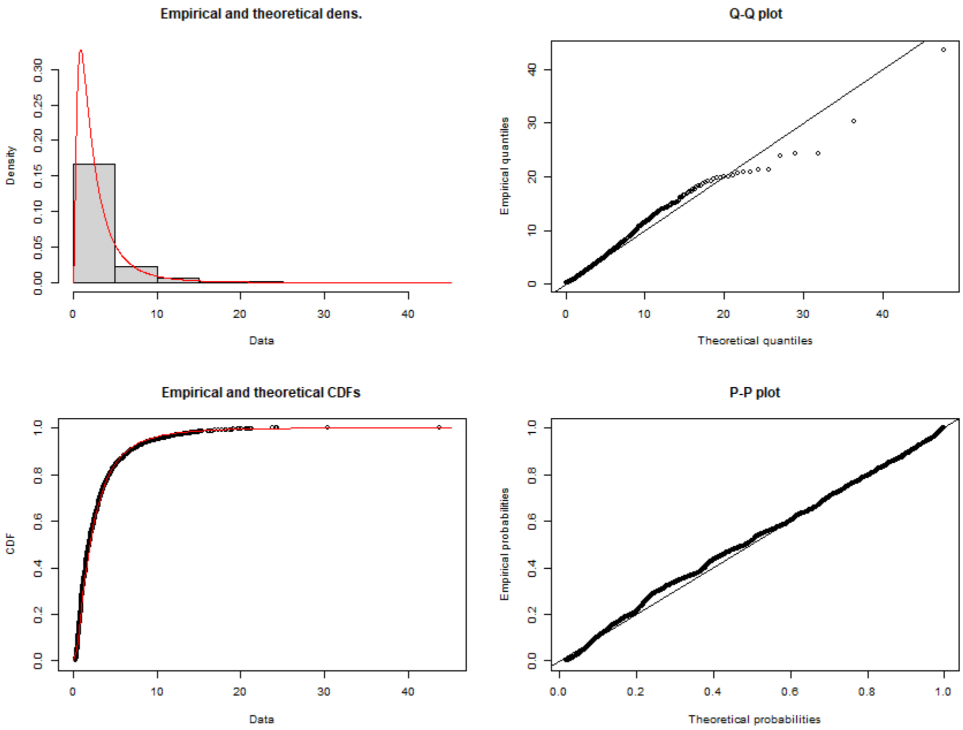


Figure 2.7: Log-normal distribution fitted to data on all major operations

Blade operations

In the case of the data set associated with turbine blades the empirical values deviated more from the theoretical values on both the Q-Q and the P-P plots. In this case all modelled distributions under-predict the likelihood of longer operations quite significantly. This could be to do with some blade operations involving more than one blade. Another reason could be caused by a higher likelihood of incidents that may cause the extension of operations. Presumably, incidents are more likely to happen during major operations on blades rather than any other components due to their size and complex shape. Alternatively, other distribution types or combinations of multiple distribution types may be considered, but this is out scope of this research.

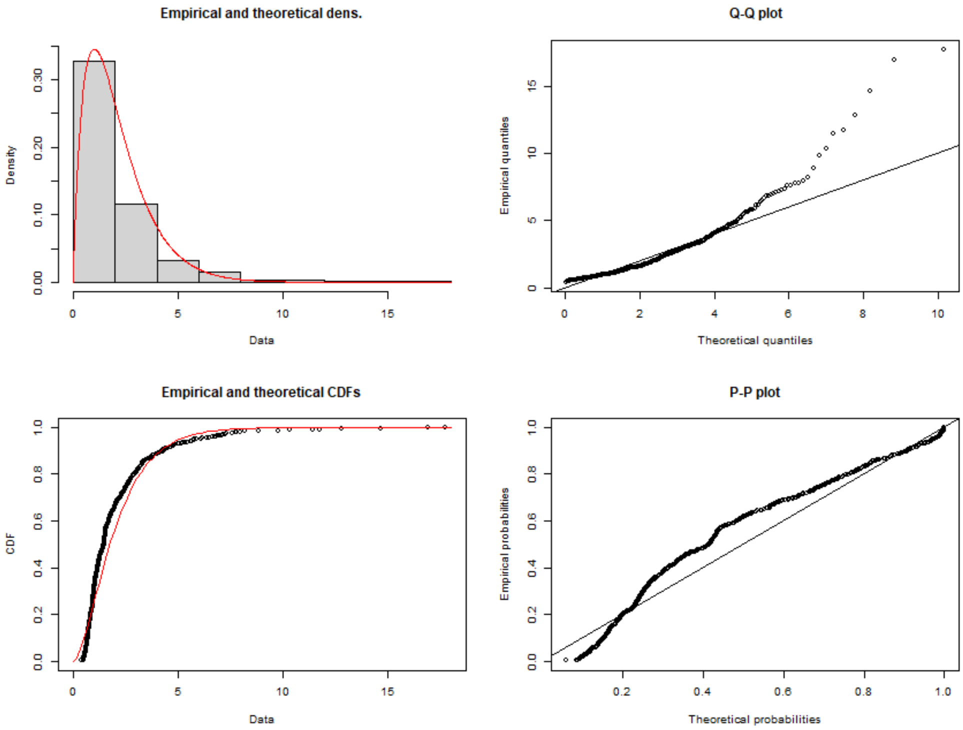


Figure 2.8: Gamma distribution fitted to data on blade operations

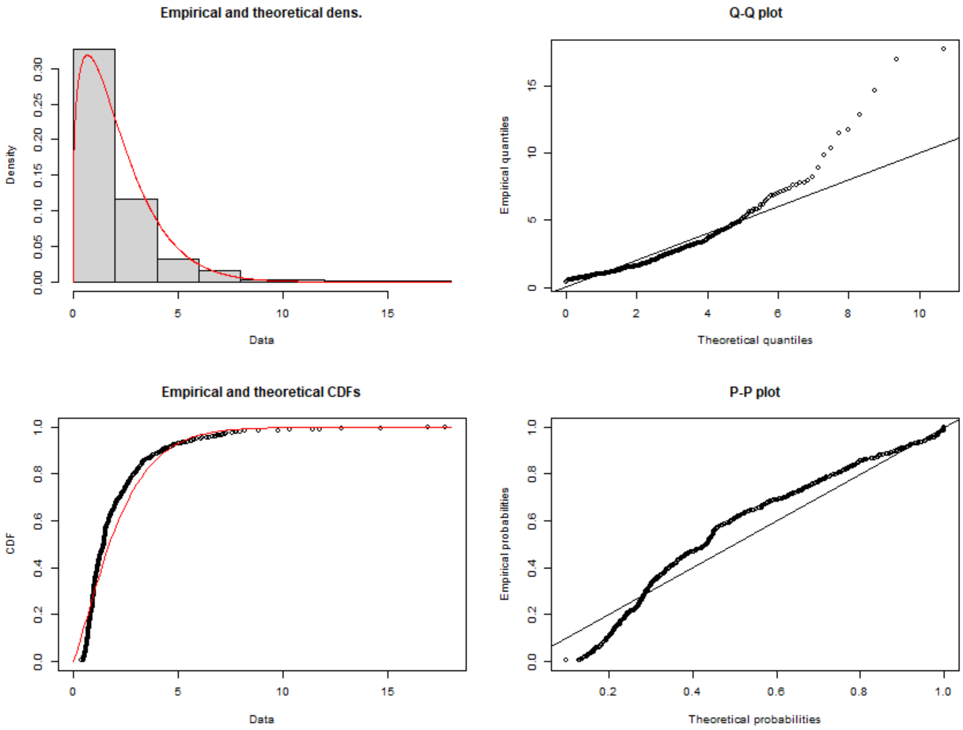


Figure 2.9: Weibull distribution fitted to data on blade operations

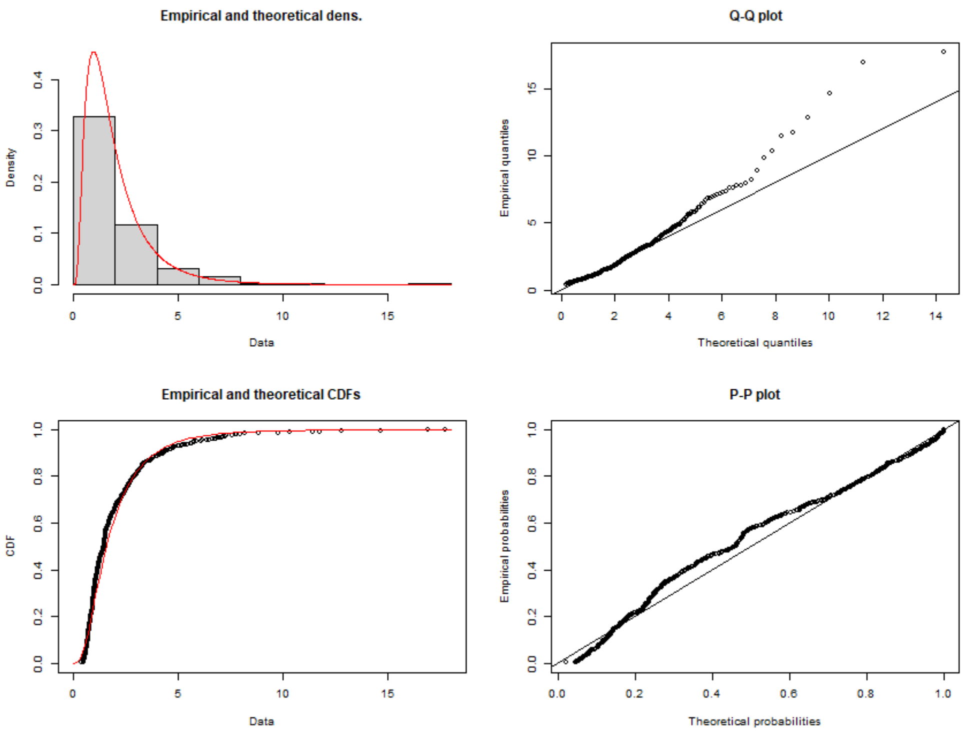


Figure 2.10: Log-normal distribution fitted to data on blade operations

Gearbox operations

Q-Q and P-P plots for the log-normal distribution and Weibull distribution for gearbox operations where only a gearbox would be replaced or repaired are shown in Figures 2.11, 2.12. In this case log-normal distribution fits the data the best however in all distribution cases the model tends to underpredict the likelihood of longer operations, this is the trend that was observed in the blades statistics as well. Interestingly the fitness of the distribution becomes better in the case of the "stacked" data shown in Figures 2.13, 2.14. It may have been caused by the larger size of the data set in this case.

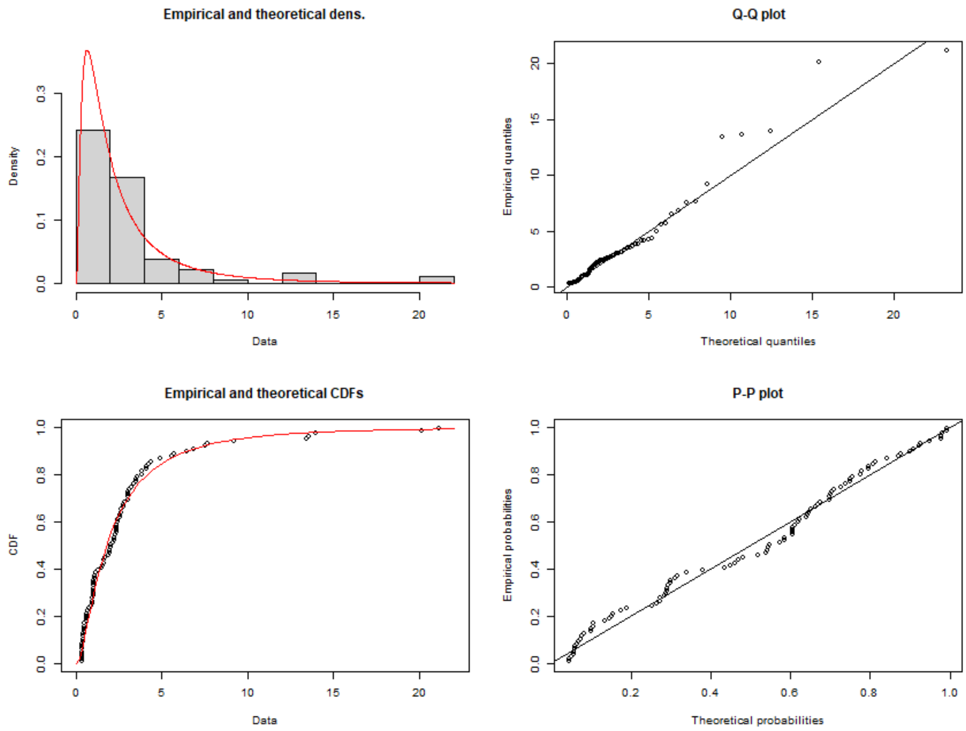


Figure 2.11: Statistical analysis plots for the lor-normal distribution fitted into the data with only gearbox operations.

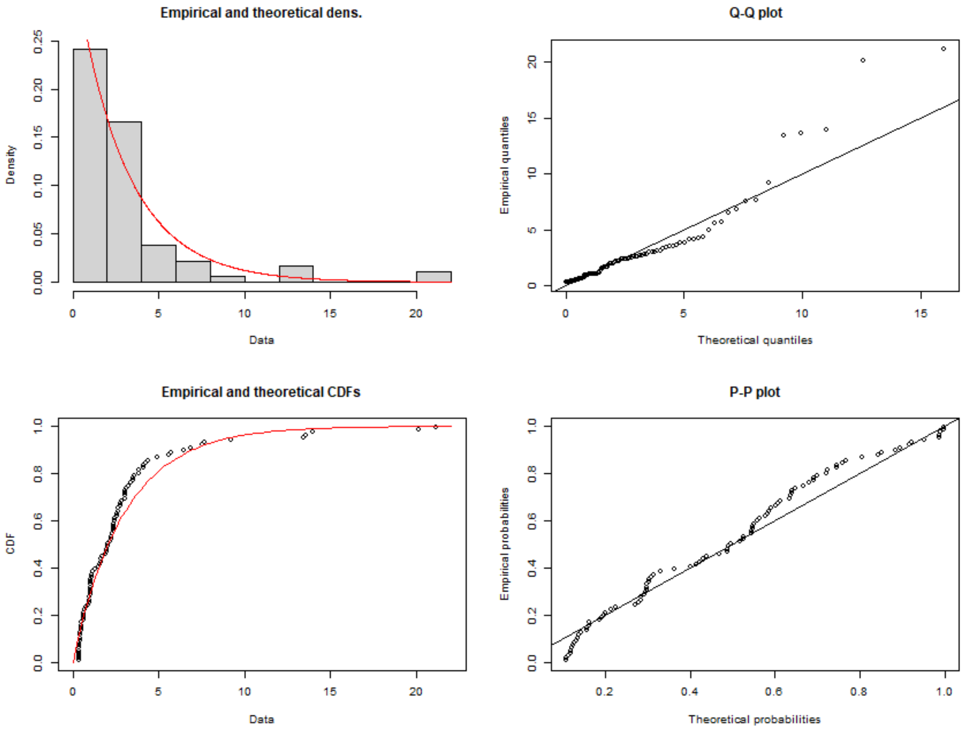


Figure 2.12: Statistical analysis plots for the Weibull distribution fitted into the data with only gearbox operations.

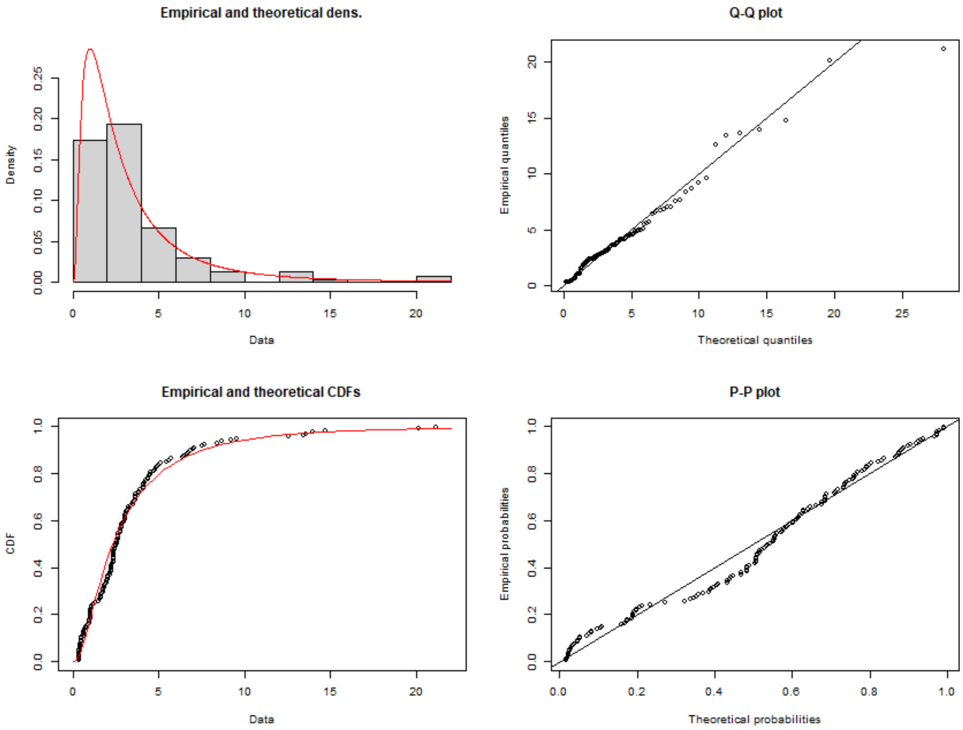


Figure 2.13: Statistical analysis plots for the log-normal distribution fitted into the data with all operations that involved a gearbox.

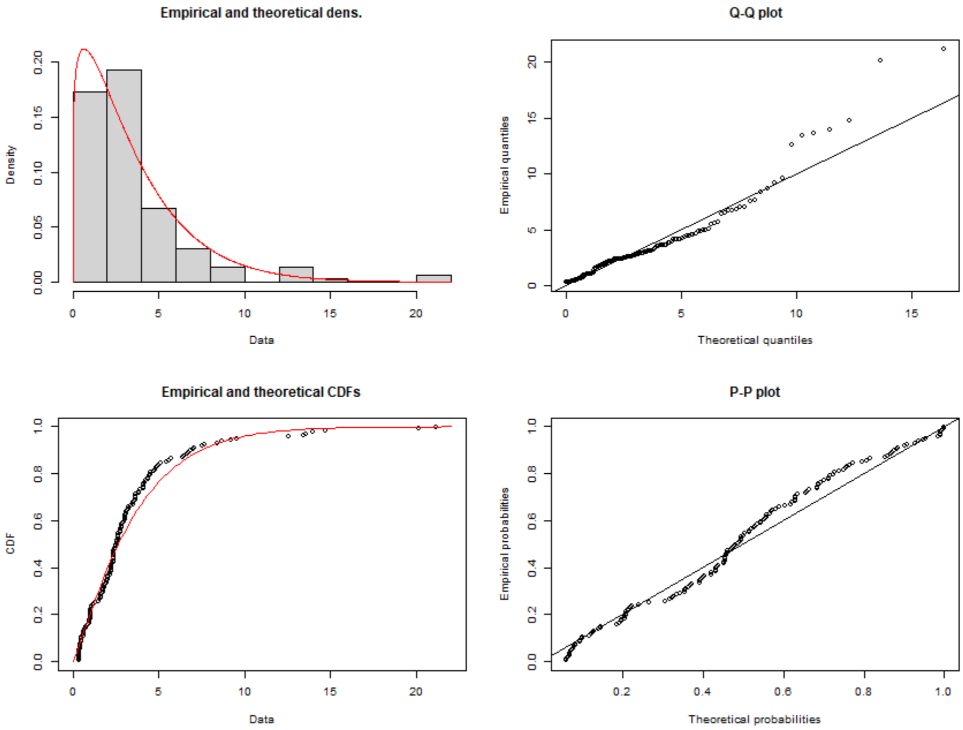


Figure 2.14: Statistical analysis plots for the weibull distribution fitted into the data with all operations that involved a gearbox.

Other Components

In the cases of pitch bearing and the main bearing operations it is difficult to draw any conclusions because the data is scarce. From the observations of the graphs log-normal distribution type seems to fit the data better than other types but the difference observed is very subtle. The results can be found in Figures 2.15, 2.16, 2.17, 2.18. Interestingly, the log-normal distribution fits data even better for the "stacked" dataset associated with main bearings, similarly to the gearbox case, this can be attributed to the larger dataset size. The results for the log-normal distribution in the "stacked" case can be observed in Figure 2.19.

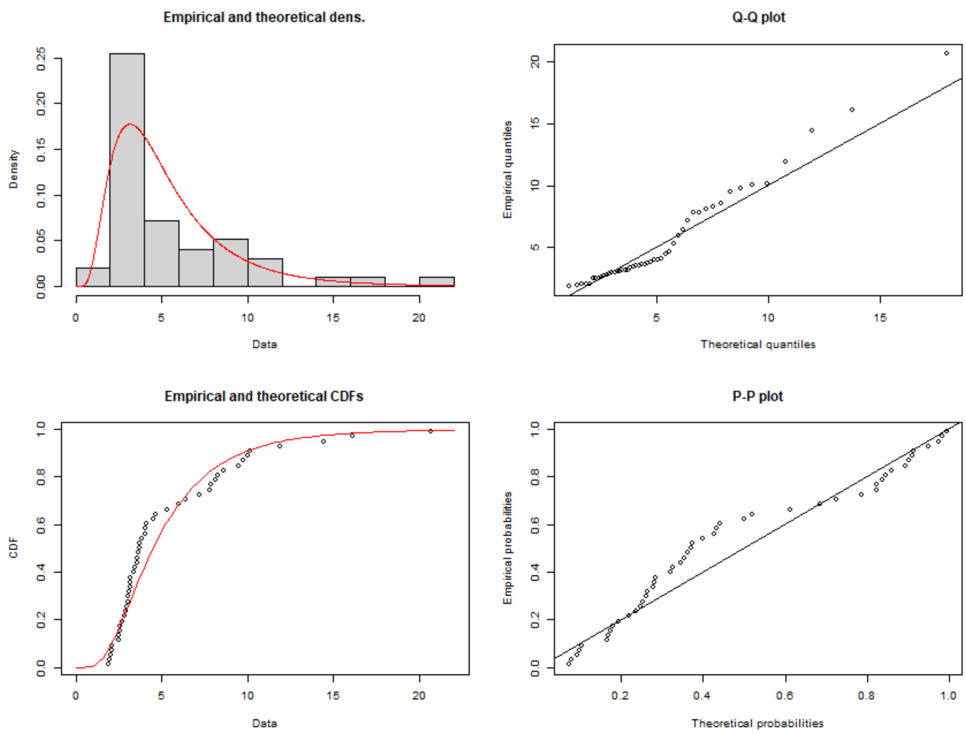


Figure 2.15: Statistical analysis plots for the log-normal distribution fitted into the data with operations on main bearings only.

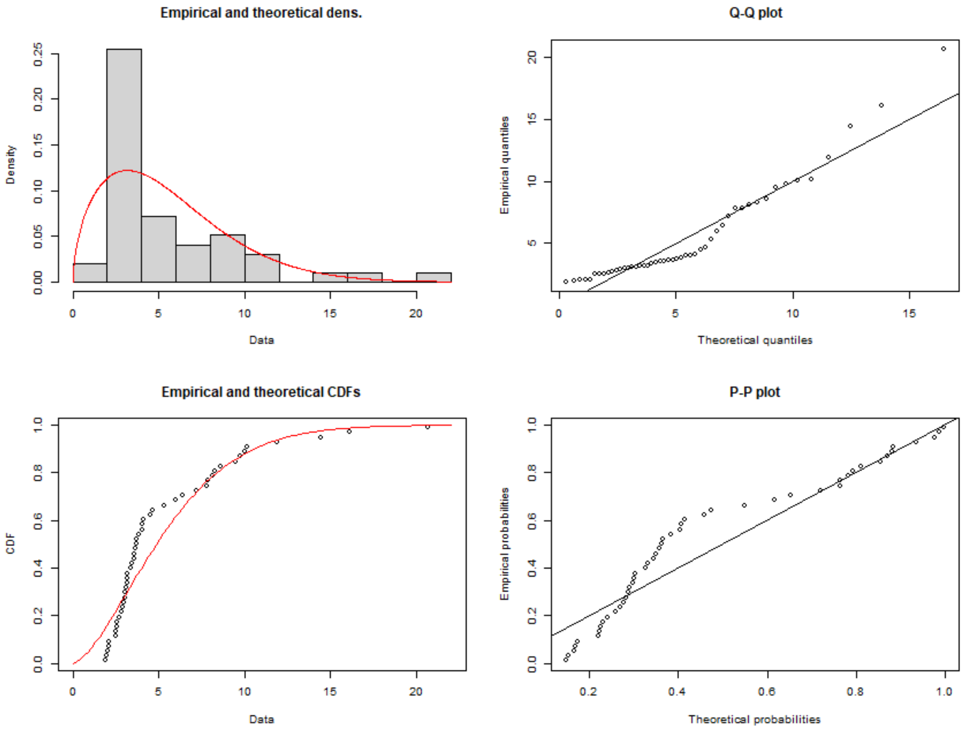


Figure 2.16: Statistical analysis plots for the Weibull distribution fitted into the data with operations on main bearings only.

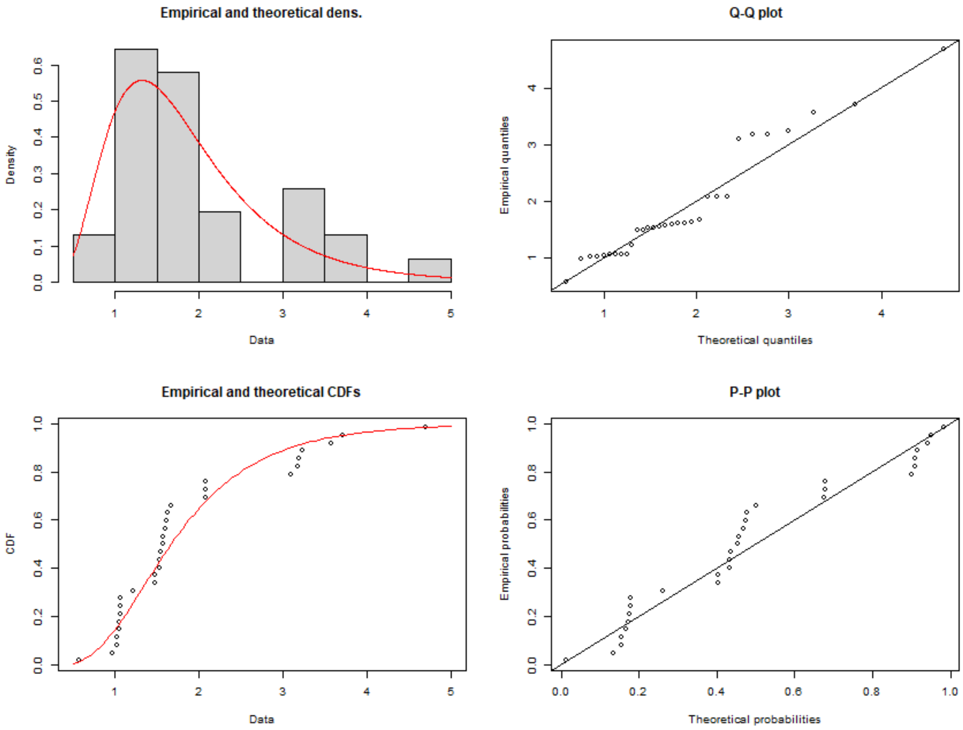


Figure 2.17: Statistical analysis plots for the log-normal distribution fitted into the data with operations on pitch bearings only.

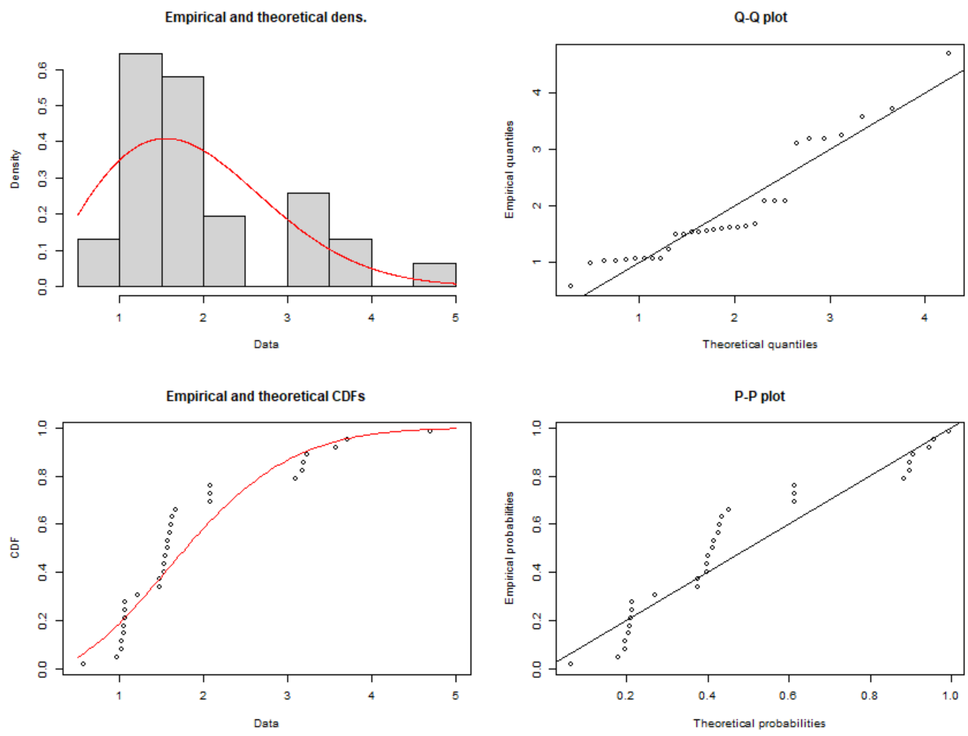


Figure 2.18: Statistical analysis plots for the Weibull distribution fitted into the data with operations on pitch bearings only.

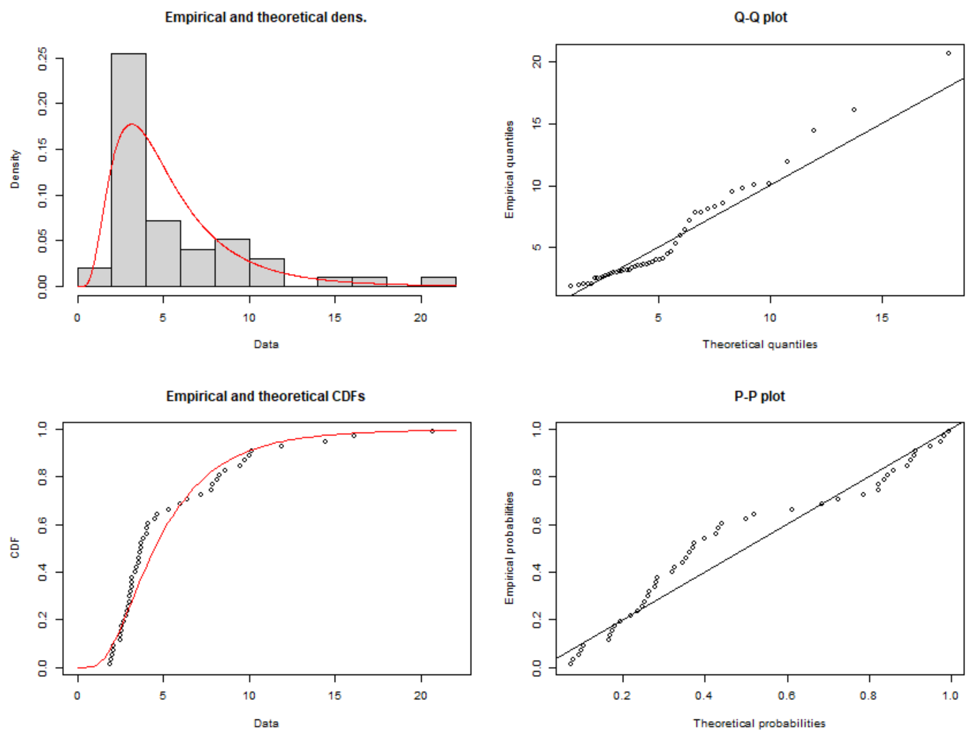


Figure 2.19: Statistical analysis plots for the log-normal distribution fitted into the data with all operations that involved main bearings.

Kolomogorov-Smirnov Test

Additionally, one-sample K-S test was performed on all cases where a distribution was fit. K-S test is a goodness of fit test, it is used to compare a sample with a reference probability distribution. Another alternative is a Chi-squared test. Chi-squared test requires binning the data, that on its own can affect the resolution of the data and hence the result of the test. K-S test can work with smaller sample sizes compared to the Chi-squared test. K-S test was also considered favourable because it uses CDF unlike the Chi-squared test that uses PDF and it is CDFs that are used for modelling activity durations (see Section 4.3).

There are other alternative test such as Anderson-Darling and Shapiro-Wilk test that are more powerful than the K-S test, especially at small sample sizes (Mohd Razali & Bee Wah, 2011). These tests however currently cannot be applied in R Studio without data manipulation and work only on normal distributions in the software. K-S test package is readily available in R Studio. Future work may consider including data transformation that could allow using these test. K-S test however is well documented in R Studio and can be easily applied on log-normal, Weibull and gamma distributions. K-S test works best on medium sample sizes (50-500 samples) and is recommended to be applied on sample sizes of 30 and above. R Studio script used in this analysis is given in Appendix C. K-S test workflow is explained below.

1. K-S test requires two inputs: the sample and the distribution under investigation. First, the null hypothesis is identified. According to the null hypothesis (H0) the values are sampled from the distribution under question. K-S test calculates the p-value by which this hypothesis is either accepted or rejected. If the p-value is higher than the significance level, then H0 is accepted, if it is lower, it is rejected. Significance level used in this thesis is 5%. The value of 5% is usually considered the threshold for statistical significance, meaning that the null hypothesis can be rejected however whether a smaller value should be used is still debatable (Di Leo & Sardanelli, 2020).
2. In the cases with "All" operations and "Blade" operations the sample size is selected to be 200. Samples were selected randomly using the `sample()` function in R Studio. In all other cases the sample was all the data from the data set. The sample in K-S tests does not have to be a subset of a data set, but the size of the sample can impact the outcome. With small sample sizes that are too small the K-S test has little power to reject the null hypothesis. With large sample sizes the test has too much power to reject the null hypothesis i.e. they can detect even minor deviations from the ideal distribution.
3. Table 2.12 provides the results of K-S test on all data sets and three distribution types. H0 can be accepted in all cases except all three types of distributions fitted into blade operation data and the Weibull distribution fitted into the dataset with all operations. It can also be rejected for Weibull and gamma distributions fitted into the "Main Bearing (single)" data.

Selecting the distribution type

Following the analysis presented in this section, the most appropriate distribution type can be selected. In the case of the data set representing the major operations on turbine blades, no distribution type was selected because none of them performed well on the Q-Q plot and failed the K-S test. In all other cases, log-normal distribution was selected with the following reasoning:

1. The tails of the log-normal distribution are thinner than those of other probability distributions. This is a useful feature of this distribution because all activities will have a minimum duration i.e. the probability that an activity will take a very short time is very low. The probability that an activity will take a very long time is also low. It is expected that the more the industry matures the likelihood of longer operations would reduce. The characteristics of the log-normal distribution are more fit for purpose.
2. Log-normal distribution performs better than Weibull or gamma distribution according to the Q-Q plots. In the cases of pitch bearing and main bearing there is not enough data to draw a conclusion around the fitness of a certain distribution type but a log-normal distribution is still selected to represent the variation in operation durations.
3. Fitted log-normal distributions pass the K-S test with the significance level of 5% in all cases apart from the dataset with major operations on turbine blades.

Table 2.12: R Studio analysis results

Distribution type	**Log-normal**			**Weibull**			**Gamma**		
Parameter name	mean	sd	p-value	shape	scale	p-value	shape	rate	p-value
All operations	0.708	0.897	0.389	1.084	3.214	0.007	1.322	0.426	0.003
Blade (single)	0.471	0.700	0.041	1.275	2.317	0.002	1.924	0.907	0.000
Blade (stacked)	0.511	0.734	0.042	1.188	2.462	0.000	1.712	0.746	0.000
Gearbox (single)	0.584	1.004	0.606	0.984	2.984	0.212	1.102	0.366	0.262
Gearbox (stacked)	0.840	0.920	0.089	1.155	3.631	0.279	1.415	0.412	0.378
Pitch bearing (single)	0.511	0.482	0.249	2.060	2.137	0.070	4.313	2.293	0.110
Main bearing (stacked)	1.535	0.625	0.449	1.569	6.380	0.121	2.645	0.466	0.141
Main Bearing (single)	1.503	0.598	0.102	1.550	6.168	0.037	2.670	0.487	0.027

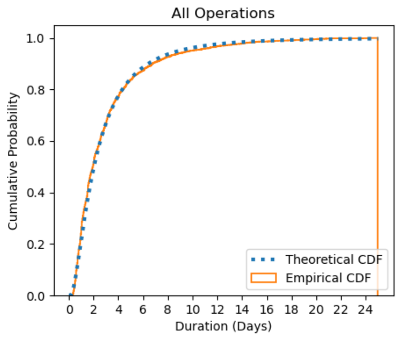
This study was limited to three distribution types that were available via the `distrplus` package in R Studio. There could be other types of probability distributions or mixed probability distributions that fit the data better.

It is important to highlight here that the accuracy of these distributions for this problem is not as significant as it may be in other fields (for example fitting a correct Weibull distribution into wind speed data can impact revenue estimation). This is due to vessel operation contracts. It is not expected to see the difference in vessel costs if an activity takes 15 hours or 20 hours because vessels are charged per day. The accuracy of the selected distribution may however impact the estimation of the downtime of a turbine, but the revenue losses due to downtime are expected to be significantly lower than the costs associated with the vessel hire. Nevertheless, the best attempts were made to fit a correct distribution type with the aim to accurately capture duration variability.

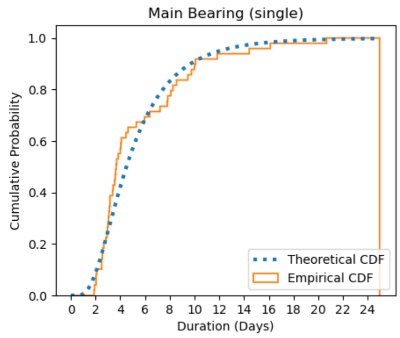
2.4.4 Cumulative Density Function

Results for the mean and the standard deviation of the log-normal distribution presented in Table 2.12 can be used to plot CDFs for three components: main bearing, gearbox and pitch bearing. Figure 2.20 shows the empirical CDF compared with theoretical CDF for these three components and the CDF for all major operations.

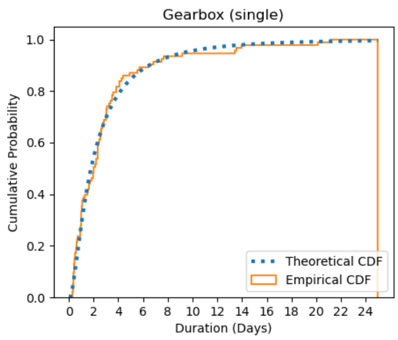
Major operations on multiple components may be performed at the same time but it is not clear whether they are performed in parallel or in series. There is a lack of clarity on how major operations are combined and the lack of data covering JUV visits where it is known that multiple components were involved. Results for stacked data are included in the Table 2.12 but are currently not used for modelling CDFs as it was done for operations with single components. Combining activities together can be quite challenging computationally. Section 4.4 presents current logic and assumptions for scenarios where multiple component repairs and replacements are combined into a single event.



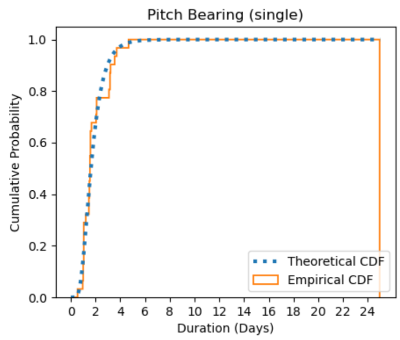
(a) All operations



(b) Main bearing



(c) Gearbox



(d) Pitch bearing

Figure 2.20: Stacked histogram with durations of major operations that utilised JUVs

Blade data failed the K-S test and therefore a theoretical CDF was not derived for it. Blade dataset however is quite large and therefore empirical CDF can be used instead. Section 4.3 will provide more clarity on how operation durations can be modelled using CDFs.

All derived CDFs start at zero, but it is assumed in this thesis that there will be a minimal time duration that a major operation can take. The minimum duration observed in the data is 7 hours. According to the CDF derived for all major operations, 99.5% of operations will be completed within 20 days. Although there are operations that have had longer durations (possibly due to incidents or storms), 20 days is assumed as the maximum time and 7 hours as the minimum time that an operation can require in COMPASS.

2.4.5 Results and discussion

Table 2.13 presents the P50, P90, mode and median values derived from the fitted probability distribution for each component. Mean values based on raw data are also presented there. Because the fitted distribution failed the K-S test for blade operations, P50, P90 and mean values are calculated separately using raw data in Table 2.14.

Table 2.13: Statistic presented in terms of days resulting from analysis of major operation data on each component

	P50 (Days)	P90 (Days)	Mode (Days)	Mean (Days)	Mean based on raw data (Days)
All	2.03	6.41	0.91	3.04	3.10
Gearbox (single)	1.79	6.49	0.65	2.97	3.01
Gearbox (stacked)	2.32	7.54	0.99	3.54	3.43
Pitch Bearing (single)	1.62	2.95	1.31	1.81	1.88
Main Bearing (single)	4.50	9.68	3.14	5.38	5.48
Main Bearing (stacked)	4.64	10.34	3.14	5.64	5.68
Generator (single)					3.68
Transformer (single)					3.55
Main shaft (single)					9.80

Table 2.14: Distribution results for operations on blades based on raw data

	P50	P90	Mean
Blade (stacked)	1.51	4.61	2.30
Blade (single)	1.49	4.28	2.12
Blade (multiple)	3.55	17.37	5.68

P50, P90, mode and mean are common statistic describing a dataset. Although CDFs presented in previous sections can be used to model actual durations of major operations, mode, median, P50 and P90 can be useful metrics for planning major operations and performing simplified analyses. Depending on the purpose of one's analysis different variable can be used.

- P90 represents the value below which the duration of an operation would be 90% of the time. If a wind farm operator needs to plan the operation with minimal risks, P90 is the recommended duration that they should plan the activity for. Depending on the risk tolerance that the operator is accepting, this percentage level could be increased or decreased.
- P50 represents the value below which the duration of an operation would be 50% of the time and above which it would be the other 50% of the time. Figure 2.21 shows P90 and P50 values compared with P90 values being significantly higher than P50.
- Mean represents the average duration of an operation. Mean is the recommended value to be used by O&M analysts. Mean value can be used where distribution is not known or in O&M simulation tools without duration variability.
- Mode represents the most likely duration of a major operation. It may be useful for deciding the contract conditions between a wind farm operator and a JUV operator.

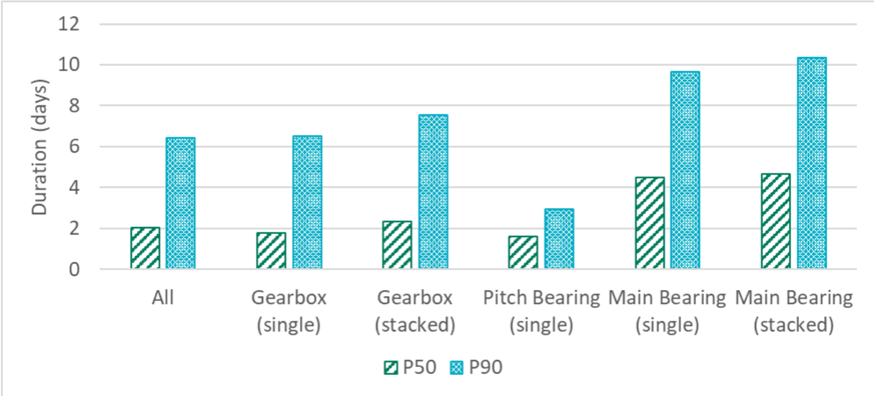


Figure 2.21: P50 and P90 values for the durations of major operations

This research does not cover the operations where multiple components were involved in much detail due to the lack of data and clarity on these operations. Figure 2.22 however shows how the duration of a major operation can significantly change if there are multiple components involved. It can be seen that if a blade repair or replacement campaign is supplemented with repairs on other components then the operation duration can more than double. On the other hand this behaviour is not observed in gearbox operations. In the case of gearbox operations, the duration of an operation is prolonged if other components are involved but not as much as in the case of blades. This could be explained by the time it takes to access the nacelle. In case of an operation on blades, opening the nacelle is not required, however if an additional component needs to be repaired or replaced (for example, a generator) then the duration of an operation increases significantly.

In the case of a gearbox, adding additional component operations does not add as much time (presumably unless that additional component is a blade). In the cases of transformer, bearings and main shaft data on visits involving multiple components is very scarce which possibly leads to overestimation and underestimation of operation durations.

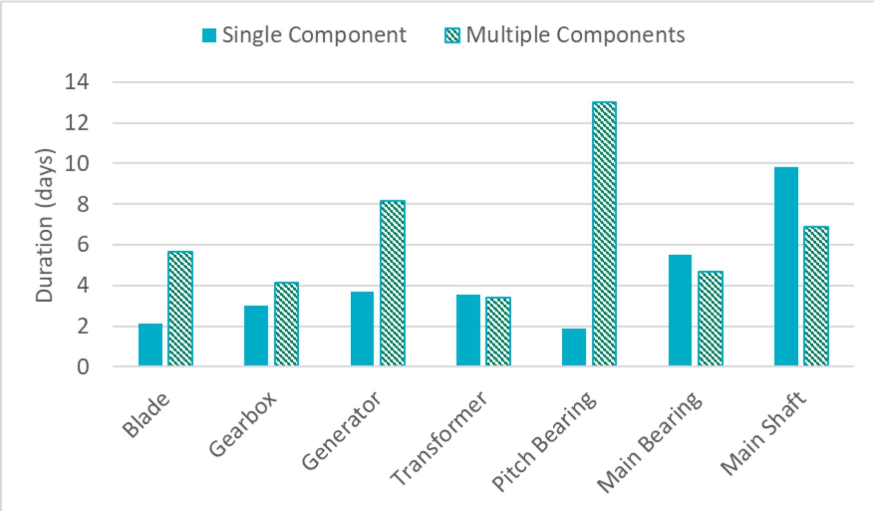


Figure 2.22: Mean duration of a major operation on a component of a single type compared with that of a multiple type.

Major operation may be interrupted due to weather and personnel delays. The effect of these factors is still unexplored but future research work may include looking for correlations between the durations and the weather at the site.

Sea Impact measures the duration based on the arrival and the departure times of each JUV to and from each turbine. This means that the data includes any interruption in the major operation. In the context of O&M simulation, it may or may not be an issue depending on the modelling method used in the simulation. The choice of the modelling method should depend on the nature of the input data. If the major operation duration data includes any interruptions then these interruptions should not be modelled in the O&M simulation. If the major operation duration data includes delays then these delays should not be modelled in the simulation to avoid double counting turbine downtime. Future work may also study what major operations can or cannot be interrupted. Section 5.3 will discuss how O&M activity interruption can affect O&M simulations.

2.4.6 Comparison with existing studies

Table 2.15 compares the results of this work with results presented in Carroll et al. (2016) and Anderson et al. (2021). In Carroll et al. (2016) failures are grouped into minor, medium and major according to the consumables costs. If consumables cost are less than €1000 it is considered a minor repair, between €1000 and €10,000 a major repair and above €10,000 a major replacement. It is not known what proportion of these repairs would require a JUV. Anderson et al. (2021) defines minor and major repairs and major replacements by the man-hours required for these activities. Repairs requiring up to 30 man-hours are considered minor, those requiring between 30 and 120 man-hours are considered major and anything above

120 man-hours counts as a major replacement. Lack of consistency in the definitions of major repairs should be taken into account when comparing the results of current research with existing studies. Assuming that none of the minor repairs in either Carroll et al. (2016) or Anderson et al. (2021) required a JUV, the results of this study are compared in Table 2.15 with the results from both studies for major repairs and major replacements.

Table 2.15: Comparison of the results from the current analysis and the existing studies.

	(Carroll et al., 2016)		**(Anderson et al., 2021)**		**Current analysis**	
	Major Replacement (Days)	Major Repair (Days)	Major Replacement (Days)	Major Repair (Days)	P90 (Raw data)	Mean (Raw data)
All	4.83	0.74	2.28	0.62	6.79	3.10
Blades	12.00	0.88			4.28	2.12
Gearbox	9.63	0.92			6.34	3.01
Generator	3.38	1.00			6.49	3.68
Pitch Bearing	1.04	0.79			3.24	1.88
Transformer	0.04	1.08			3.99	3.55

Results reported in Carroll et al. (2016) are significantly higher than the results of this research presented in the table above. Particularly in the cases of major replacements associated with blades and gearboxes, the results presented in Carroll et al. (2016) exceed the P90 values derived in the current study. Generator and the pitch bearing results however do not differ as much.

Anderson et al. (2021) does not distinguish between different components types. In both major repair and major replacement cases Anderson et al. (2021) results are lower than those presented in the current work. The difference between major replacement durations reported in Anderson et al. (2021) and JUV visits presented here is 0.82 days, much smaller than the difference with Carroll et al. (2016) which is 1.73 days.

Anderson et al. (2021) also fits the Exponential Modified Normal distribution into the data for major repair durations and fits the Alpha distribution into the data for major replacement durations. Figure 2.23 shows the CDFs derived from the distribution coefficients reported there for major repairs and major replacements and compares it with the empirical and the theoretical CDFs derived in the this thesis. It can be seen that the CDF derived in this thesis captures a wider variation in major operation durations.

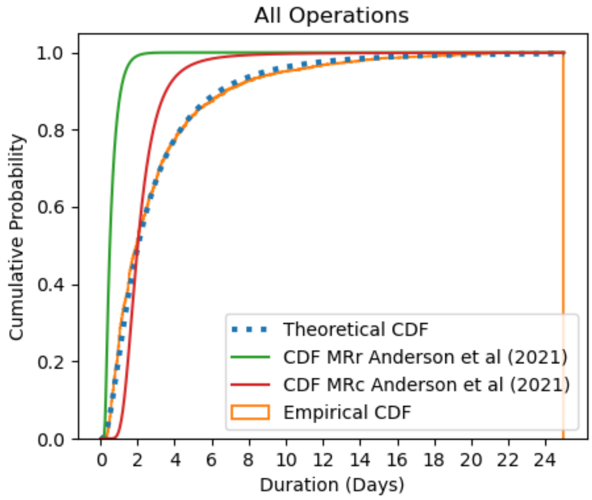


Figure 2.23: CDFs compared with distributions derived in Anderson et al. (2021) for Major Repairs (MRr) and Major Replacements (MRc)

Other reasons for differences between studies may be attributed to the following reasons:

- The differences in turbine ratings considered in the studies.
- Both Carroll et al. (2016) and Anderson et al. (2021) cover only one OEM while the current research covers seven.
- The locations of the wind farms used in Carroll et al. (2016) and Anderson et al. (2021) are not disclosed however they also may have an impact on the difference in operation durations.
- Work by Carroll et al. (2016) has been published in 2016, it may be the case that maintenance techniques have improved since then which may have resulted in shorter maintenance durations observed in the current work.

2.4.7 Fitting the durations into the list of major operations

In SPARTA the definition of a major operation is the same as the definition used in this study, it is an operation that requires lifting heavy turbine components at the turbine hub height. SPARTA groups major operations into seven categories: Blade, Electrical, Gearbox, Generator, Main Bearing, BOP and Other. According to the authors of SPARTA public reviews, blade bearing operations (i.e. pitch bearing) are included in the "Blade" group. Transformer and switchgear operations are included into the "Electrical" group and the "BOP" group consists of operations on substations and turbine foundations. Yaw bearing, any hub repairs and turbine decommissioning are included in "Other" but there may be other types of operations in that group as well. Main shaft was assumed to belong to the Gearbox category as it only occured on gearboxed turbines in the Sea Impact data.

Table 2.16: Rates of major operations based on SPARTA (2022) adjusted using the information obtained in the current study and the corresponding operation durations. Rates are given per turbine per year.

Name in SPARTA	Rate (per year)	Name(s) adjusted	Rate adjusted	Planning duration basis	Planning duration (days)	Actual duration
Blade	0.0598	Blade	0.0567	Blade, P90	4.28	CDF
		Pitch Bearing	0.0031	Pitch Bearing, P90	2.95	CDF
Electrical	0.0065	Transformer	0.0065	Transformer, mean (raw data)	3.55	Mean
		Switchgear	0.0000	NI	NI	NI
Gearbox	0.0150	Gearbox	0.0147	Gearbox, P90	6.49	CDF
		Main Shaft	0.0003	Main shaft, mean (raw data)	9.80	Mean
Generator	0.0052	Generator	0.0052	Generator, mean (raw data)	6.49	Mean
Main Bearing	0.0020	Main Bearing	0.0020	Main Bearing, P90	9.68	CDF
BOP	0.0008	BOP	0.0008	NI	NI	NI
Other	0.0052	Yaw Bearing	0.0017	All, P90	6.41	CDF
		Hub	0.0017	All, P90	6.41	CDF
		Other	0.0017	All, P90	6.41	CDF

Table 2.16 was generated using the information provided above. It was assumed that main bearing is a part of the "Gearbox" group because all operations that involved main shaft in the Sea Impact data occurred on geared turbines. Major operation rate was then adjusted according to the major operation occurrence in the Sea Impact data. For example, for blades the rate was split in the ratio 566 to 31 to represent blade and pitch bearing rates according to Table 2.10.

A suitable planning duration for each activity was then based on P90 values derived in this work using a fitted probability distribution. An actual duration of an activity could be modelled using an appropriate CDF. Not in all cases P90 value and the relevant CDF is available. In these cases either the data for "All" components is used or the mean value is used instead of a CDF. In the cases of the generator and the main shaft it was assumed that using a mean value would be more representative of an actual duration rather than using a CDF derived from "All" component operation durations. It was found that these operations take longer time that an average operation on a general component. Yaw bearing and hub repairs were not found in the Sea Impact data. In Table 2.16, SPARTA major operation rate representing "Other" was split equally between yaw bearing, hub and other operations. Table 2.16 can be used as a guide for O&M simulation inputs along with Table 2.9.

2.4.8 Comparing the findings to the initial list of activities that existed in COMPASS.

The resolution of the initial data in COMPASS inputs was very high without the evidence base for it. It was derived from the pre-existing Excel-based model. This original list lacked traceability and was not designed for incremental time modelling. This list also did not take into account that some activities can happen together. For example a regular planned inspection on a turbine was unnecessarily broken down into inspection on each component.

Table 2.17 compares the original activities that existed in COMPASS with the newly derived activities. Performing a like-for-like comparison is difficult because the activities that were originally set in COMPASS are significantly different from those derived in the last two sections. For this reason rather than comparing the activities on the individual level they were grouped together and groups were compared. Four characteristics were compared: total number of activities in each group, the average rate, the average duration and the average team size in each activity group. Because in the newly developed activity list variables are stored as ranges rather than exact values the rates, durations and team sizes were not averaged out but are given as a range in Table 2.17.

A significant reduction in the number of planned and minor activities can be observed compared to the original data. The rate of planned activities was much lower in most cases than that in the new list. There is also a significant reduction in the number of unplanned activities on array cables and substations. In the majority of activities the team size for of these activities has increased. In some cases, particularly in the case of major unplanned activities the duration has increased significantly.

Two case studies in Sections 5.4 and 5.7 were modelled when the findings from this chapter were not yet available. For this reason the original COMPASS data was adjusted with author's knowledge.

Table 2.17: Comparison of original COMPASS database with adjusted data and data developed using a the research presented in this section. Rates are given per turbine per year unless specified. Durations are presented in hours unless specified.

		Wind turbine planned	Wind turbine minor unplanned	Wind turbine major unplanned	Substructure planned	Substructure unplanned	Array cable planned	Array cable unplanned	Substation planned	Substation unplanned	Export cable planned	Export cable unplanned
Original data COMPASS	Total number	42	65	10	14	16	1	6	3	10	1	4
	Rate (average)	0.4	0.16	0.009	0.260	0.013	1	0.009	1	0.113	1	0.213
	Duration	8.1	13	21.6	4.8	20.5	2.7	20.4	32	28.8	56	48
	Team size	2	3	9	3	4	3	6	3	5	3	6
Adjusted data for Section 5.4	Total number	41	65	10	13	13	3	9				
	Rate	0.4	0.13	0.009	0.260	0.008	0.73	0.011				
	Duration	7.9	12.6	21.6	10.9	11.1	9	27.9				
	Team size	2	3	9	3	6	5	9				
Adjusted data for Section 5.7	Total number	39	50	13	12	15	3	4				
	Rate	0.4	0.08	0.06	0.281	0.009	0.73	0.014				
	Duration	8.1	10.7	21.5	6	11.9	9	18.7				
	Team size	2	3	6	3	6	5	7				
Current research work	Total number	5	13	11	4	3-4	1	3	4	6	1	3
	Rate (range)	0.33-2	0.05-3.64	0.0017-0.0567	0.2-1	0.001-0.2	0.2-1	<0.02 (per km)	1-3	0.04	0.2-1	<0.2 (per km)
	Duration	0.25-16	8-16	93	8-16	NI	NI	NI	1-7 days	NI	NI	NI
	Team size	3-6	3-4	6	NI	NI	NI	40	3-6	NI	NI	40

2.5 Failure rate variability

Section 3.2 will give an overview of existing O&M simulation tools. One of the common features of these tools will be discussed in that section is modelling FR variability. Most O&M tools assume a "bathtub curve" for FR variability throughout the wind turbine lifetime. Bathtub curve represents higher likelihood of early failures that is expected due to installation mistakes and new technologies. It also represents higher likelihood of late failures due to the wear out of turbine components. Many O&M analysts have used it when modelling FRs (Gray, 2017; Martin et al., 2016; Rinaldi, 2018)

Very limited evidence currently exists that supports the bathtub curve theory in the context of offshore wind turbines. The most significant evidence can be found in Carroll et al. (2015) and SPARTA (2022). Carroll et al. (2015) evidence is based on the same data as in Carroll et al. (2016) discussed in Section 2.4. Analysis in Carroll et al. (2015) was split into four categories: "power converter", "gearbox", "generator" and "the rest of the turbine". Carroll et al. (2015) fitted failure intensity curves into the data and performed the goodness of fit tests on them. Their analysis shows that in the cases of the "generator", "power converter" and "the rest of the turbine" there is an evidence of the beginning of the bathtub curve. Although the curve fitness tests were performed, the data presented there shows significant variation in FRs for these components throughout the years. Two latest SPARTA public reviews show that there is a significantly higher number of forced outages in the first year of turbine operation than in the consequent years (SPARTA, 2022, 2023). Forced outages do not necessarily indicate component failures and reduced outages in the consequent years may be an indication of Supervisory Control and Data Acquisition (SCADA) and turbine sensors adjustments. SPARTA 2022 review also reports another peak in forced outages in the eighth year of turbine operation. It is reported to be associated with the end of a warranty period (SPARTA, 2023).

SPARTA also reports how the share of major operations on different components changes throughout the years. The largest share of major operations according to it is attributed to the blades. That share increases throughout the turbine years (SPARTA, 2022). Similarly, generator shows a similar pattern. On the other hand, the share of major operations associated with gearbox and electrical system reduces through the years. This indicates that there are certain component-specific degradation patterns, some of which may potentially support the bathtub curve concept (gearbox and electrical system components) but others do not (blade system and generator). In 2022 SPARTA publicly reported a more detailed variation of major component repairs throughout the years than the previous SPARTA reports. In the report there is a distinct peak in blade major operations in year 4-5 that is not observed for other major components. SPARTA also reported significant differences in the rates of forced outages and major operations for two OEMs. Section 2.5.1 will compare the rates observed with data analysed in this thesis with the published rates from SPARTA (2023).

This thesis aims to provide more clarity on whether or not the rate of major operations changes throughout the age of a wind turbine. Data described in Section 2.4.1 is currently the most useful for estimating the durations of major operations but it can also be used to estimate the frequencies of these operations. Section 2.5.1 will investigate how major operation rates vary throughout the turbine lifetime. Currently Sea Impact do not track smaller vessels and hence only major operations are analysed.

Section 2.5.1 will look at these trends separately for different components however this is limited by the number of known interventions per major operation. Figure 2.24 shows the ratio of major operations each year for which the intervention type is known. It can be seen that the ratio of known operation types is not constant and is the highest in years 5-7.

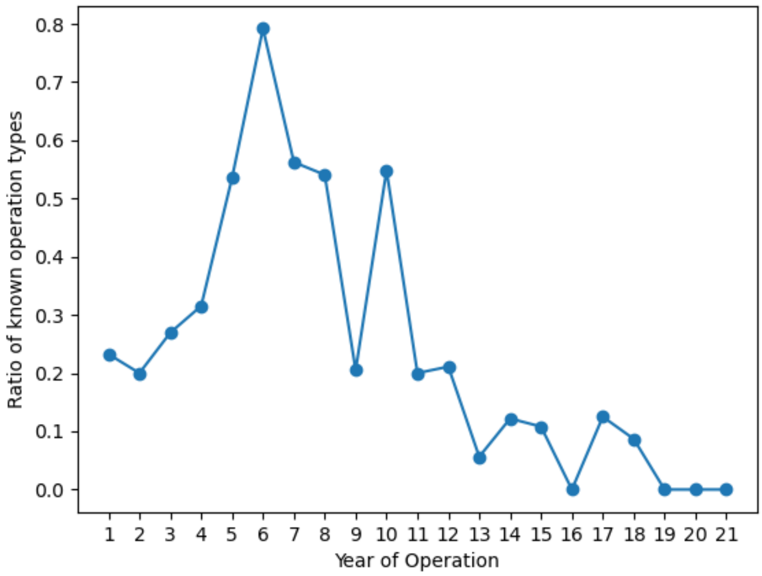


Figure 2.24: Ratio of known intervention type (out of all major operations in each year) in each year of turbine operation.

2.5.1 Major operation rate variation with turbine age

Major operation rate in each year of turbine operation was calculated as following:

$$MOR_n = \frac{F_n}{T} \tag{2.1}$$

Where MOR_n is the major operation rate in year n of operation, F_n is the number of major operations in year n and T is the total number of turbines in all farms that have been tracked by the Sea Impact service and that have reached the year n of operation. The closer the farm gets to the end of its lifetime the less reliable the result of such computation becomes because there are not many wind farms that have reached 10 years of operation. It is possible to apply the formula 2.1 on all major operations, but it is not as straightforward to apply it on operations related to specific components because not all intervention types in the data are known.

Figure 2.25 shows the variation of turbine major operation rate with turbine age. In SPARTA (2023) the statistic is grouped into 2-year intervals and grouped for all major operations on turbines over the age of ten. For comparison with the data presented in this study SPARTA (2023) statistic was ungrouped and the rates were copied over 2 year intervals. For turbines older than 10 years old, the rate given in SPARTA (2023) was assumed to stay constant. Although SPARTA (2023) results do not align precisely with the data collected in the current thesis, an alignment in major operation rate variation through the years can be observed.

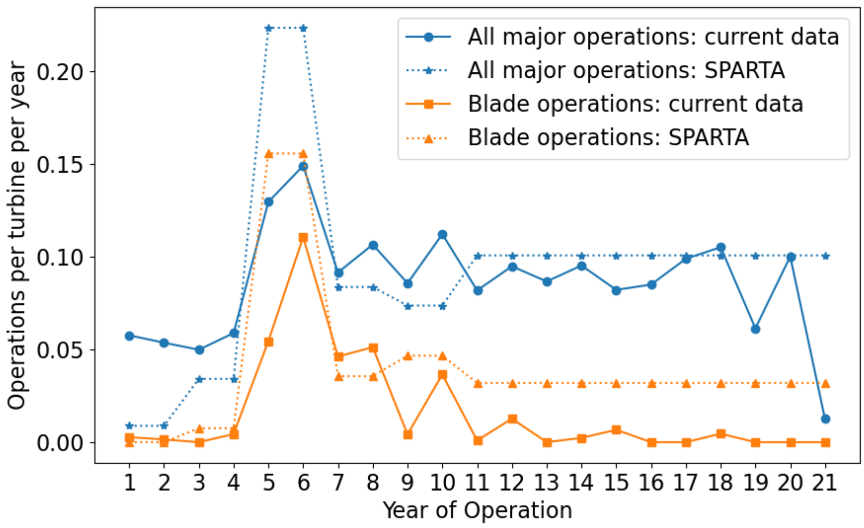


Figure 2.25: Rate of major operations in each year of turbine operation observed in the data collected in the current work and compared with data reported in SPARTA (2023). Graphs are presented for all major operations and major operations on blades.

Interestingly, the rates observed in SPARTA in the first 4 years of turbine operation are significantly lower than the ones calculated in this thesis. This is partially to do with how rates were estimated based on the Sea Impact data. If a wind farm has only been in operation in couple of years and has not experienced any major repairs then it will not appear in the Sea Impact database because that only contains wind farms that have experienced repairs. That can lead to an underestimation of T in Equation 2.1 and hence an overestimation of MOR_n.

There is also a distinct peak in major operation rate in the fifth and the sixth year of turbine operation observed in both data sources. That peak may be associated with the end of a warranty period that usually lasts about five years. That peak in SPARTA is significantly higher than that observed in the data collected in this thesis.

When only blade operations are considered there is also a considerable peak in operations in years 5-6. Interestingly, this trend was observed in SPARTA (2023) which is not limited by the unknown intervention types (see Figure 2.25). Assuming that blade degradation follows a cycle, it was expected to observe another peak in years 10-12. The peak was not observed. One possible explanation is that there is certain improvement in technology that allowed to avoid the same type of degradation.

The difference in results between SPARTA and current data in the first seven years of turbine operation may also be attributed to the fact that the set of wind farms used in SPARTA (2023) is smaller than in the currently used data set.

When blade operations are excluded the data set becomes significantly smaller. The number of known major operations on different components was reported in Table 2.10. Major repair rates per component type other than blade were not reported in SPARTA (2023). For a fair comparison between SPARTA (2023) and current data, blade operations were subtracted from all major operations in both data sets and the resulting graphs are presented in Figure 2.26. Similarly to Figure 2.25, Figure 2.26 shows how major operation rates change throughout the lifetime of a wind turbine.

Similarly to blades, SPARTA rates are lower in the first two years of turbine operation than in the consecutive years. There is a noticeable peak in year 5 in both data sets. This is possibly due to the end of the warranty period, similarly to the trend observed in blade operations. There is also a drop in the rate in years 6-8 of the current data and in years 7-10 in the SPARTA (2023) data. This could be attributed to the repairs that happened in years 5-6 and returning the components to the "as good as new" state.

There is another increase in major operation rates in year 9 in the current study data and in year 11 in SPARTA (2023). This could indicate the periodicity at which components get repaired and wear out again or the end of an extended OEM contract. There is also a slight increase in repairs in year 14 and 18 however the quality of statistic declines with each year. There are not many wind farms that have reached even 10 years of operation.

The proportion of known operation types also declines with each year which means that some operations that are currently included in Figure 2.26 may be associated with blade repairs and replacements.

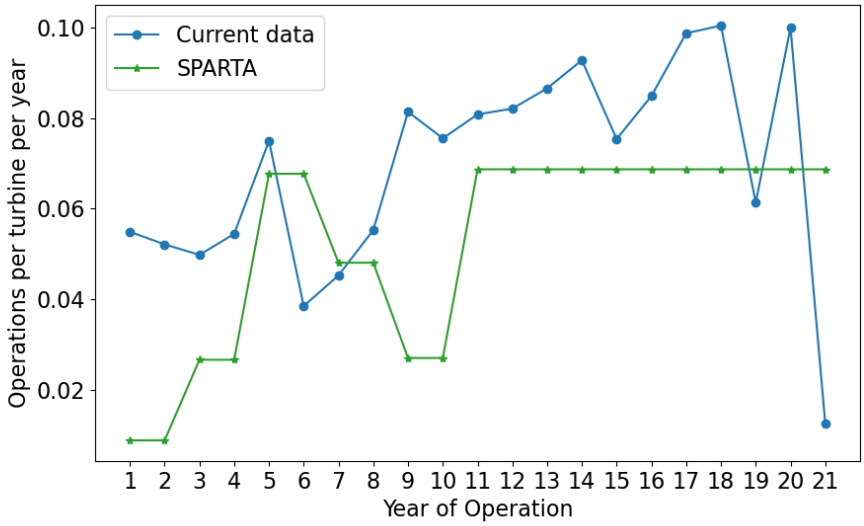


Figure 2.26: Rates of major operations excluding known blade operations in each year of turbine operation observed in the data collected in this thesis and compared with trends published by SPARTA (2023).

Figure 2.25 and 2.26 demonstrated that the trend based on data from SPARTA (2023) and the major operation data collected in this thesis does not represent the bathtub curve and there is a tendency for the rates of major operations to fluctuate, starting low in the first four years of operation.

Although the rate of major operations stays stable after year seven, it can be noticed that the rate is significantly higher after year seven than it was before the year four of operation. This is observed in both blade-related and non-blade-related major operations.

SPARTA (2022) reported an increase in forced outages with turbine rating however neither SPARTA (2022) nor SPARTA (2023) have shown whether major operation rates change with turbine rating. On the other end of the spectrum, according to the Kincardine project plan for O&M, the planning assumptions for a 2 MW and a 9.5MW turbine are the same: 6 days scheduled maintenance and 10 days unscheduled maintenance per year on average (KOWL, 2019). This indicates that there is no expectation that FRs would change depending on turbine rating.

Table 2.18 shows the average major operation rates R_{avg} derived with the Sea Impact data for turbines with different turbine rating. Turbines have been grouped into capacity categories with a range of 2 MW. The average values are weighted according to the number of turbines that existed in each historical year as Equation 2.2 demonstrates.

$$R_{avg} = \frac{\sum_{2012}^{2022} R_i \times n_i}{\sum_{2012}^{2022} n_i} \tag{2.2}$$

In Equation 2.2, R_i is the rate in historical year i and n_i is the number of turbines of that turbine rating existing in year i.

As Table 2.18 demonstrates major operation rates of 4-7.9 MW turbines are smaller than those of 2-3.9 MW turbines but they also smaller than the rates of 8-9.9 MW turbines. Higher rates in the 2-3.9 MW group could be associated with the immaturity of the industry and installation mistakes. These turbines are also the oldest in the data pool and it has been demonstrated that turbines over 7 years old tend to fail more often. Higher major operation rate of 8 - 9.9 MW turbines could be attributed to the fact that the majority of these turbines have recently reached the end of the initial warranty agreement.

Table 2.18: Average major operation rate on turbines obtained using Sea Impact data over all observable years (2012-2022) sorted by turbine ratings.

Turbine rating	R_{avg} (Number of major operations per turbine per year)
2 - 3.9 MW	0.067
4 - 5.9 MW	0.047
6 - 7.9 MW	0.048
8 - 9.9 MW	0.067

2.5.2 Summary

- There is a fluctuation in rates of major operations throughout the lifetime of a wind turbine but it does not resemble the bathtub curve. Gradual decrease of major operation rates in the first years of turbine operation was not observed. Some evidence of an increase of major operation rates in year nine and over was observed when blades were excluded from the data however the data is limited to lower-rated turbines that have reached that age and may not be representative of the entire population.
- There is a peak observed in major operation rates in years 5-6 of a turbine lifetime which is associated with the end of a warranty agreement. The peak is particularly driven by blade operations which are the most common in those years.

- Major operation rates were found to vary depending on the picked turbine rating. Rates presented here are the lowest for 4-7.9 MW turbines and the highest for 2-3.9 MW and 8-9.9 MW turbines. More data is needed to find if the rates increase or decrease with turbine rating.
- Trends based on the data accumulated in this thesis show consistency with those published by SPARTA but provide more insight due to the transparency of the data used.

Chapter 3

O&M Simulation Tools

3.1 What are O&M Simulation tools

O&M simulation tools are computational tools that can support O&M analysis. The purpose of this analysis may vary from OPEX and energy output estimation to comparison of logistical strategies to estimating cost and time savings from O&M innovations.

Although there is a significant variability in the different methods used in O&M simulation tools, they can generally be broken down into deterministic and stochastic. Deterministic tools perform a single computation while stochastic tools model a series of events stochastically. Deterministic tools are not able to capture the full complexity of O&M. For this reason stochastic tools have emerged.

Stochastic tools usually model a series of time steps where each time step represents an increment of a wind farm lifetime. At some time steps these tools model events such as asset failure, maintenance, personnel pick-up etc. Some events and elements of simulation are modelled stochastically i.e. they can occur at random time increments resulting from a certain probability of occurrence. Most commonly offshore asset failures are modelled stochastically but there are also other examples where the weather is modelled stochastically, Section 3.2.1 will discuss this in more detail. Section 2.4 also demonstrated that maintenance activity duration is not always constant and Section 4.3 will show how duration was implemented in COMPASS as a stochastic variable.

There are many stochastic tools other than COMPASS, each with their own unique attributes and capabilities. The aim of this chapter is to provide an overview of existing tools (Sections 3.2 and 3.3), their failure modelling methods (Section 3.2.1) and discuss their readiness for modelling emerging wind farm technologies and recognising cable failures (Sections 3.4 - 3.7).

3.2 Overview of stochastic O&M simulation tools

There are O&M simulation tools designed specifically for fixed offshore wind farms, there are others designed specifically for wave energy farms. Most O&M tools are written quite flexibly, so that they can be used for a range of energy converters but for some particular scenarios these tools may require adjustments. The main purpose of O&M simulation tools is to identify the best O&M strategies that minimise OPEX and minimise revenue losses. The strategies depend on the data available for simulation and the planning horizon under consideration.

Section 1.8 provided a description of different planning types. This thesis covers only on strategic O&M simulation tools, these are the tools that usually model the entire lifetime of a renewable energy farm and are based on historical statistic rather than real life data from an existing ORE farm.

Some simulation tools may have elements of the tactical and operational tools in the strategic simulation. For example, a strategic tool could generate a set of activities and then optimise the sequence in which these activities are carried out. The main difference from operational tools would be the fact that these activities are synthetically generated rather than based on a real operating farm. Additionally to analysing the long-term O&M strategies, O&M simulation tools can be used to:

- Analyse the impact of innovations (for instance to identify the benefits of using a drone instead of a rope access technician to inspect turbine blades).
- Calculate OPEX and energy output more accurately.
- Support LCA by estimating vessel usage.

Table 3.1 provides an overview of the existing strategic O&M simulation tools. The table is based on the simulation tool review studies (Anaya-Lara et al., 2018; Correia da Fonseca et al., 2021; Kolios & Brennan, 2018) and updated with latest findings. Some of these tools also have the elements and/or can work as tactical and operational tools. Some of these tools are commercial which limits the visibility of the logic used in these tools and hence their advantages and limitations may not be transparent.

O&M simulation tools included in Table 3.1 are:

- COMPASS
- O2M and OMCAM, both commercial tools developed by the DNV-GL (DNV-GL, 2021, 2022)
- ECN O&M Access, a commercial tool developed by the Energy research Centre of the Netherlands (ECN), currently part of TNO (Stumpf & Hu, 2018).
- ECN O&M Cost Estimator (OMCE), another commercial tool developed by TNO (Byon et al., 2011; Rademakers et al., 2008)

- DTOceanPlus software suit. Several packages have been developed for modelling installation and operation of wind farms (Correia da Fonseca et al., 2021). DTOceanPlus Reliability, Availability, Maintainability and Survivability (RAMS) package contains most of the functions used in O&M simulation (Yang et al., 2020).
- WOMBAT, an open-source tool developed by NREL (Hammond & Cooperman, 2022).
- ROMEO O&M, a tool developed as part of the ROMEO project backed by Horizon 2020 programme. The tool has some documentation online but the script itself is not open source (Kolios & Brennan, 2018).
- NOWIcob, a tool belonging to SINTEF Energy Research institute. Although the tool is commercial, it was developed as part of a PhD project and has sufficient documentation online (Bakken et al., 2017; SINTEF, 2017).
- Decision Support System (DSS) for Vessel Fleet Analysis developed by MARINTEK (now SINTEF Ocean). It is another commercial tool that started as a research project (Stålhane et al., 2016).
- Shoreline O&M Design (formerly MAINTSYS), a commercial tool managed by Shoreline Wind (Shoreline, 2022).
- StrathOW-OM, a non-commercial tool developed by the University of Strathclyde, not open-source, it is primarily used for research purposes by the university (Dalgic et al., 2015b; Dinwoodie et al., 2014; McMorland, Pirrie, et al., 2022; Sperstad et al., 2017).
- OPERA, a tool specifically designed for wave energy technologies is another project funded by Horizon 2020 programme. The tool is not available freely, but its methodology is described in Lopez-Mendia et al. (2017).
- UoE/JFMS (also known as UNEXE O&M), a tool developed as a doctoral research project. The script is not publicly available however the methodology used in the tool is extensively described in Rinaldi (2018).
- ECUME-I, a commercial tool managed by the EDF Group (Douard et al., 2012).
- Wave Energy Scotland (WES) O&M Simulation Tool, open-source tool, result of a doctoral research project, its development is described in Gray (2017)
- Mermaid, a commercial tool developed via a doctoral research project at the University of Exeter and currently managed by Mojo Maritime (part of James Fisher and Sons) (James Fisher Renewables, 2015; Mojo Maritime, 2022). Main focus of the tool is weather risk modelling.
- ForeCoast Marine, a commercial O&M simulation tool developed by JBA Consulting (JBA Consulting, 2023).
- Integrated Decision Support Tool, a tool that resulted from a master's project in TU Delft (Koopstra, 2015).
- Logistics and Service model that resulted from a master's project in TU Delft supported by Fraunhofer IWES (Dewan, 2014).

- Stochastic Wind Park Model, a tool was developed to demonstrate the influential factors in O&M modelling as part of a research project (Seyr, 2020). The tool is based on one of the existing tools reviewed in Seyr and Muskulus (2019) however it is not stated which model.
- WavEC O&M simulation tool, a part of the software solutions that WavEC is offering (WavEC, 2023).

The majority of these tools are written in MATLAB or Python. A couple of models either consider or are moving their code from MATLAB into Python. Two main reasons behind this are possibly cost and expertise. Python is free while MATLAB requires a paid license. Python also has a wider pool of users making it easier to engage new O&M tool users and developers. It is an important factor that should be taken into account in models that are ongoing development. A few other coding options were used in other models e.g. Visual Basic (VBA) and Simio. The latter is an object-oriented programming language that can model objects graphically making it easier to visualise the O&M process. It is also claimed to have a risk based planning and scheduling feature but as is the case with MATLAB, it is not free and would require additional training.

FICO Xpress is another interesting example, DSS for Vessel Fleet Analysis tool uses FICO Xpress for optimising the vessel fleet (Stålhane et al., 2016). Unlike Python, FICO Xpress is a commercial software that requires a license and training. It is, however, one of the only two tools in the list that have built-in optimisation. Although there is an efficient optimisation algorithm built into the tool, this tool does not take into account many factors such as vessel lead time, consumables lead time or variation of the FR with time. The derivation of the probability of failure is also lacking clarity. The probability is defined there as FR/N where N is the number of timesteps, however the resulting value is not the probability but the FR per timestep. Whether a correct calculation is used in the program itself is unclear.

DSS for Vessel Fleet Analysis tool takes into account vessel limitations but assumes the same number of technicians for any maintenance activity because it sees the turbine as one unit rather than a set of components. In reality, it is expected that some maintenance activities would require a smaller team or a larger team depending on the component of interest and the nature of the maintenance activity. Section 2.3 described the complexity of O&M in great detail.

Another tool that optimises O&M strategies is Rinaldi (2018), it uses genetic algorithms and generates a set of optimal solutions for O&M. Both tools have demonstrated optimisation of a hypothetical case studies, however no examples of their real-life applications have been found. O&M strategy optimisation in other tools is usually manual and is achieved by modelling different scenarios and then selecting the best one according to the preferred KPIs.

Table 3.1: Overview of existing O&M simulation tools. Information about some tools was not available (N/A). Operational, Tactical and Strategic tools are marked as O, T and S respectively.

Organisation	Product Name	Open Source	O/T/S type	Model type	Language	Verification
ORE Catapult	COMPASS	No	S	both	Python	-
DNV-GL	O2M	No	T, S	deterministic	N/A	-
DNV-GL	OMCAM	No	S	deterministic	N/A	-
ECN	ECN OM Access	No	S	deterministic	MS-Excel (VBA)	Reviewed by GL Wind (Rademakers et al., 2008)
ECN (TNO)	OMCE	No	S	stochastic	MS-Excel (VBA)	Yes
DTOceanPlus	DTO + RAMS+ LMO module	Yes	T, S	stochastic	Python, other	No
NREL	WOMBAT	Yes	S	stochastic	Python	Section 5.3
ROMEO	ROMEO O&M Tool	No	S	stochastic	MATLAB	No
SINTEF Energy Research	NOWIcob	No	S	stochastic	MATLAB	Yes (Sperstad et al., 2017)
SINTEF Ocean (MARINTEK)	DSS for Vessel Fleet Analysis	No	T, S	stochastic	MS-Excel + FICO Xpress	Yes (Dinwoodie et al., 2014; Sperstad et al., 2017)
Shoreline with the University of Stavanger	Shoreline O&M Design (MAINTSYS)	No	S	stochastic	N/A (has GUI)	Yes (Sperstad et al., 2017)
Strathclyde University	StrathOW-OM	No	S	stochastic	MATLAB	Yes (Dinwoodie et al., 2014; Sperstad et al., 2017)
University of Edinburgh	OPERA O&M	No	S	mixed	N/A	No
University of Exeter	UoE/JFMS (UNEXE O&M)	No	S	stochastic	MATLAB	Yes (Rinaldi et al., 2018)
EDF Group	ECUME-I	No	S	both	N/A	Yes (Dinwoodie et al., 2014; Sperstad et al., 2017)
Wave Energy Scotland	WES O&M Tool	Yes	S	stochastic	MS-Excel (VBA)	No
James Fisher and Sons	Mermaid	No	N/A	stochastic	N/A	-
JBA Consulting	ForeCoast Marine	No	T, O, S	stochastic	N/A	-
TU Delft	Integrated Decision Support Tool	No	S	stochastic	Simio	Yes (against ECN, and reviewed by Vatenfall)
TU Delft	Logistics and Service model (Dewan)	No	S	stochastic	MATLAB	Yes (via a sensitivity study)
NTNU (Helene Seyr) and AWESOME	Stochastic Wind Park Modelling and Maintenance Scheduling under Uncertainty	No	S	stochastic	MATLAB, Python	No
WavEC	WavEC O&M Tool	No	S	stochastic		Section 5.3

Offshore wind industry is growing rapidly and so does the O&M industry, it is hard to predict what technologies would be there in the future. Depending on the location of a wind farm and the region where it is based, wind farm operators may also have limits on what O&M strategies they have access to. Due to these uncertainties and limitations, optimisation for the best solution via complex algorithms is currently considered unfeasible. It is not expected that wind farm developers would have more than ten O&M strategy options under consideration, hence manual optimising via running several simulations is seen as sufficient.

Another challenge behind simulating the O&M is the lack of consistency. Normally, most simulation tools model the significant wave height H_s, planned and unplanned activities and the vessels with certain H_s limitations, speed and costs. In reality, the system may be much more complex. There could be unplanned failures that lead to planned repairs, vessels could additionally depend on wave period as well as wave direction, personnel could experience sea sickness, postpone the task and return to the port. As Section 2.3 has demonstrated, the same activity can take a different amount of time each time. JUVs and SOVs may be able to stay offshore for weeks, other vessels like CTVs would need to return to port. Some vessels emerge that are unmanned and can stay offshore for several weeks at a time while conventional vessels keep being used but these require returning to port to recharge (Seabrokers Group, 2023c). There could be drones that have to travel to the farm and back and drones that would stay offshore full time (MARSHALL, 2023). There is a lot of variability in options available for O&M making it difficult to develop an optimisation algorithm that can capture them all. Therefore, manual selection of an optimal strategy is the current preference.

3.2.1 Stochastic failure modelling

Despite the best efforts of wind farm operators and OEMs to design fault-free systems, failures still occur. Offshore asset failure can have a different meaning in different context. For the context of O&M simulation this thesis suggests a following definition for an offshore asset failure. Offshore asset failure in COMPASS is defined as an unplanned incident or an alarm on an asset or any of its subsystems that requires physical actions offshore. Those physical actions may include turbine visits for a manual reset, surveys, inspections, repairs and replacements. In O&M simulation tools, each activity is usually given a name of the physical action that follows the failure and the associated FR. Other attributes of that activity can be included as discussed in Section 2.3.

In reality some failures can be predicted by condition monitoring systems turning an urgent unplanned repair or replacement into a planned maintenance campaign. Other failures are unpredictable and can lead to a forced turbine outages.

Failure modelling is the core of all O&M simulation tools presented here. Failures in O&M simulation tools are modelled stochastically. There are different ways to model them computationally. Poisson process is one way to do it (Seyr & Muskulus, 2019). Poisson distribution describes the probability of occurrence of a number of events in a given time interval, given the expected number of events in that interval (which can be estimated from failure statistics). The longer the time interval, the more likely it is that multiple failures will occur. This method is good when the same failure can occur multiple times. There are different levels of input granularity in O&M simulation tools, some developers may choose to consider only major operations on a system level, others may break them down to the component level (e.g. blade repair). In the first option Poisson process is useful because it can allow to model multiple failures happening at the same time. This way allows the inputs to be simple, saving computational time and simulation preparation time. However, if failure inputs are specific to components, then it is unlikely that the same component will fail multiple times.

MARINTEK vessel optimisation model uses a different logic. It uses binomial distribution and estimates the probability of multiple turbines failing knowing the probability of a single turbine failure. This is done to model all possible scenarios for the vessel travel between multiple turbines and the probability of each scenario. It estimates a wide range of parameters that are then put into the objective function for optimisation. The tool is limited to modelling the turbine failure rather than component failure. Different components have different logistical requirements. The lack of granularity can lead to greater uncertainty in simulation outputs. This approach also has limitations for modelling cable topology, TTP operations or multi-rotor turbines.

Probability of the event occurrence also changes with the time interval under consideration. Most O&M simulation tools use a time interval of 1 hour because this is a common resolution of historical reanalysis weather data such as ERA5 (Copernicus, 2018). There are however events that may take even less than 1 hour (e.g. pick up personnel from a turbine, transit between turbines, some short inspections) and hence the accuracy of modelling such events may be impacted by the 1-hour resolution. Nevertheless, in COMPASS time interval remains as 1 hour. The following paragraphs describe methods how failure events are modelled in O&M tools that use time intervals.

The probability of a failure at any timestep can be modelled using an exponential probability distribution. PDF for an exponential distribution is given in Equation 3.1.

$$PDF = \lambda e^{-\lambda t} \tag{3.1}$$

Here λ is the FR of a wind turbine component and t is time. PDF can then be used to derive the probability of a failure $P(T < t)$ occurring before time t. $P(T < t)$ can be calculated as an integral of the PDF and results in Equation 3.2.

$$P(T < t) = 1 - e^{-\lambda t} \tag{3.2}$$

If a component has a failure rate of 0.2 failures per year, that can be converted to failures per timestep. By dividing that by 8760 hours in a year, the failure rate is approximately $2.28e^{-5}$ failures per hour. The probability of the component failure happening before the next timestep is then:

$$P(t) = 1 - e^{-2.28E^{-5} \times 1} \approx 2.28E^{-5} \tag{3.3}$$

If at the current timestep the random number generator generates a number below $2.28E^{-5}$, then the software generates a failure, if the number is above that value, no failure gets generated.

Some developers may choose an approach to model a time to failure (TTF) probability instead of a probability of an event happening at the current timestep. There are packages available in Python and other software that are capable of generating a random number based on a PDF. For example, Python users may opt for a `random.exponential()` function from the `numpy` package. This function draws samples from an exponential distribution. Its PDF as given in the Python `numpy` package documentation as

$$f(x; \frac{1}{\beta}) = \frac{1}{\beta} exp(-\frac{x}{\beta}) \tag{3.4}$$

where β is the scale parameter which is the inverse of the rate parameter $\lambda = 1/\beta$. The equation is identical to Equation 3.1 given above. Hence, knowing the FR λ, one can calculate the scale parameter β which is the same as mean time to failure (MTTF) in the context of O&M simulation as shown in Equation 3.5.

$$\lambda = \frac{1}{MTTF} \tag{3.5}$$

This way the probability of TTF can also be estimated using an exponential probability distribution. This method can save computational time because rather than applying the Monte Carlo method at every timestep it could be applied only at timesteps at which the last failure has happened.

The third method that was seen in a few O&M simulation tools (that are presented in Section 3.2) derives the equation for TTF from Equation 3.2. The equation then becomes:

$$TTF = -\frac{1}{\lambda} \ln P \tag{3.6}$$

In this method P can be drawn from a uniform distribution between 0 and 1.

The following paragraphs provides more clarity on the three methods:

Method 1: Calculate the probability of failure at each timestep

Starting at timestep n:

1. Generate a number between 0 and 1.
2. Calculate the probability of failure at this time step $P(T < t)$.
3. Compare the two values - if the probability is lower than the generated value, then the failure does not happen.
4. Switch to the next timestep and repeat the process.

Method 2: Generate a random TTF based on a PDF

Starting at timestep n:

1. Generate a random number based on a PDF $f(x; \frac{1}{MTTF})$ for example using the `random.exponential()` function from the `numpy` package in Python. This value is the new TTF.
2. Check if the TTF is less than the lifetime of a farm.
3. Skip to the timestep $(n + TTF + T_r)$, where T_r is the time it takes to bring the asset back to the working state and repeat the process.

Method 3: Generate a random TTF based on a probability function

Starting at timestep n:

1. Generate a random number between 0 and 1
2. Feed it into Equation 3.6 and caluclate the corresponding TTF
3. Check if the TTF is less than the lifetime of a farm.
4. Skip to the timestep $(n + TTF + T_r)$, where T_r is the time it takes for a repair activity to bring the asset back to the working state and repeat the process.

Python script was written to compare the efficiency of these methods, it can be found in Appendix A. The script proves that the MTTF converges to the same value using each method. Method 3 has proven to be the most computationally efficient, followed by Method 1 and Method 2. These results were computed only for the exponential failure probability distribution. If Method 3 was used with a Weibull distribution, more complex maths would be required. With a Weibull distribution TTF cannot simply be derived from a single probability equation and would either require a complex derivation of a PDF that takes into account early failures and wear out failures, or derivation of mathematical formulae as presented in Bakken et al. (2017) which may be quite complex to implement in O&M simulation tool scripts.

Not all simulation tools have sufficient documentation in the public domain but those that do have primarily used Method 3 for modelling stochastic failure events. They model constant FR and use exponential distribution. It is reasonable as it is an easy and efficient way to model failures. UoE/JFMS, ECUME-I, WES O&M Tool and NoWIcob model FR as a changing variable with a bathtub curve assumption (Bakken et al., 2017; Gray, 2017; Martin et al., 2016; Rinaldi, 2018). Out of the presented tools, only NOWIcob has provided a derivation for the TTF that takes into account the bathtub curve (Bakken et al., 2017). Section 2.2.2 showed that failure rate is not constant over time but it does not steadily decline in the first years of the turbine lifetime, neither it steadily increases in later years questioning the necessity of modelling such behaviour in O&M simulation tools. Section 2.5 describes the development of a new function in COMPASS to model FR variability based on user input.

NOWIcob also has exponential distribution and triangle distribution options for the users. DTOcean and ROMEO tools use only the exponential distribution. OPERA tool provides additional option to the exponential distribution: Gaussian (i.e. normal) distribution with varying standard deviation parameters.

Method 1 is used in COMPASS to model FR, which allows to model user-defined FR variability variability, described further in Section 4.2.

3.3 COMPASS tool structure

3.3.1 What is COMPASS

The COMPASS O&M simulation tool is the ORE Catapult's in-house Python-based software tool which utilises Microsoft Excel for the input and output interfaces (see Figure 3.1). The COMPASS model development was initiated to obtain reliable estimates of OPEX of ORE farms for informing internal cost modelling projects, compare various O&M strategies and analyse the impact of innovations. This industrial research project was then initiated to continue the development of COMPASS in order to improve its speed and accuracy and expand the range of scenarios where it can be applied to fit the emerging technology and O&M trends.

Initial development of COMPASS was based on the ORE Catapult's Excel-based O&M cost model. Due to the growing understanding of the intricacies of O&M, Excel-based cost model reached the level of complexity that was simply hard to manage. This inspired the ORE Catapult team to start the development of a brand new model that would run in Python. The inputs and outputs of the new model however were kept in Excel to allow non-Python users to understand and continue using the new model. Input-simulation-output diagram is shown in Figure 3.2.

Figure 3.1: COMPASS logo and acronym

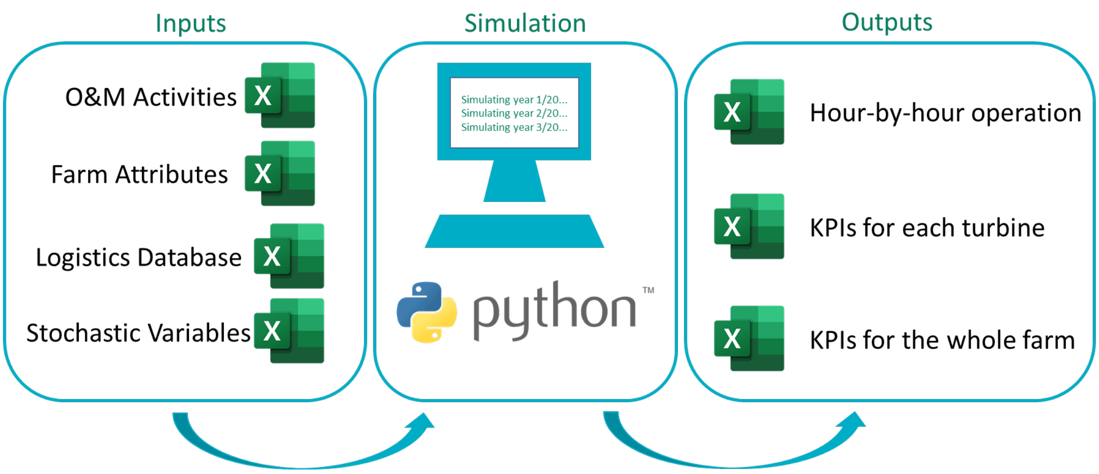


Figure 3.2: Workflow in COMPASS. Inputs and outputs are stored in Excel spreadsheets while all the computation is made via a software written in Python.

COMPASS relies on detailed inputs. These inputs are categorised into four groups:

- **O&M activities** - all activities (events) that are required on an offshore wind farm throughout its lifetime and their characteristics.
- **Farm attributes** - this type of input defines all wind farm characteristics. These include wind turbine ratings and locations, cable locations and connections, ports, vessels and the associated contract types.
- **Logistics database** - this database contains current assumptions for logistics such as vessel and personnel rates, vessel speeds and capacity on board as well as the longest time between refuelling.
- **Stochastic variables** - this database was added to COMPASS during this research project. It contains stochastic variables. Currently these include FR variability and CDFs derived in Section 2.4.

Section 2.3 has shown that some activities have attributes that have not been anticipated in O&M simulation tools before. These new attributes were added to the activity inputs in COMPASS and are listed in Table 3.2. Section 4 describes how these inputs are incorporated into O&M modelling in COMPASS.

Table 3.2: Activity attributes that existed before this research project and the new attributes that were added following the findings from Section 2.3

Existing inputs	**New attributes**
Planned or unplanned	Rate variability reference
Rate	Final year
Risk (consequence)	Consumables lead time
Risk (probability)	Duration CDF reference
Equipment costs	Switch on or off (during maintenance)
Consumables costs	Merging with other activities (allowed or not)
Task duration*	Percent of assets
Downtime	
Urgency	
Personnel	
Crafts	
On or off site	

**Task duration now means the initially planned duration.*

COMPASS reads these inputs and initiates the simulation. The basic functionality of COMPASS is very similar to existing strategic O&M simulation tools that were presented in Section 3.2. Figure 3.3 shows the high level logic diagram in COMPASS. Diagram is simplified for space and explanation purposes. As shown in Figure 3.3 COMPASS breaks down the lifetime of a farm into 1-hour-long time intervals. This is consistent with the time intervals in weather data sets of ERA5 (Copernicus, 2018). It then iterates through these time steps and activates necessary functions until the final timestep representing the end of lifetime is reached.

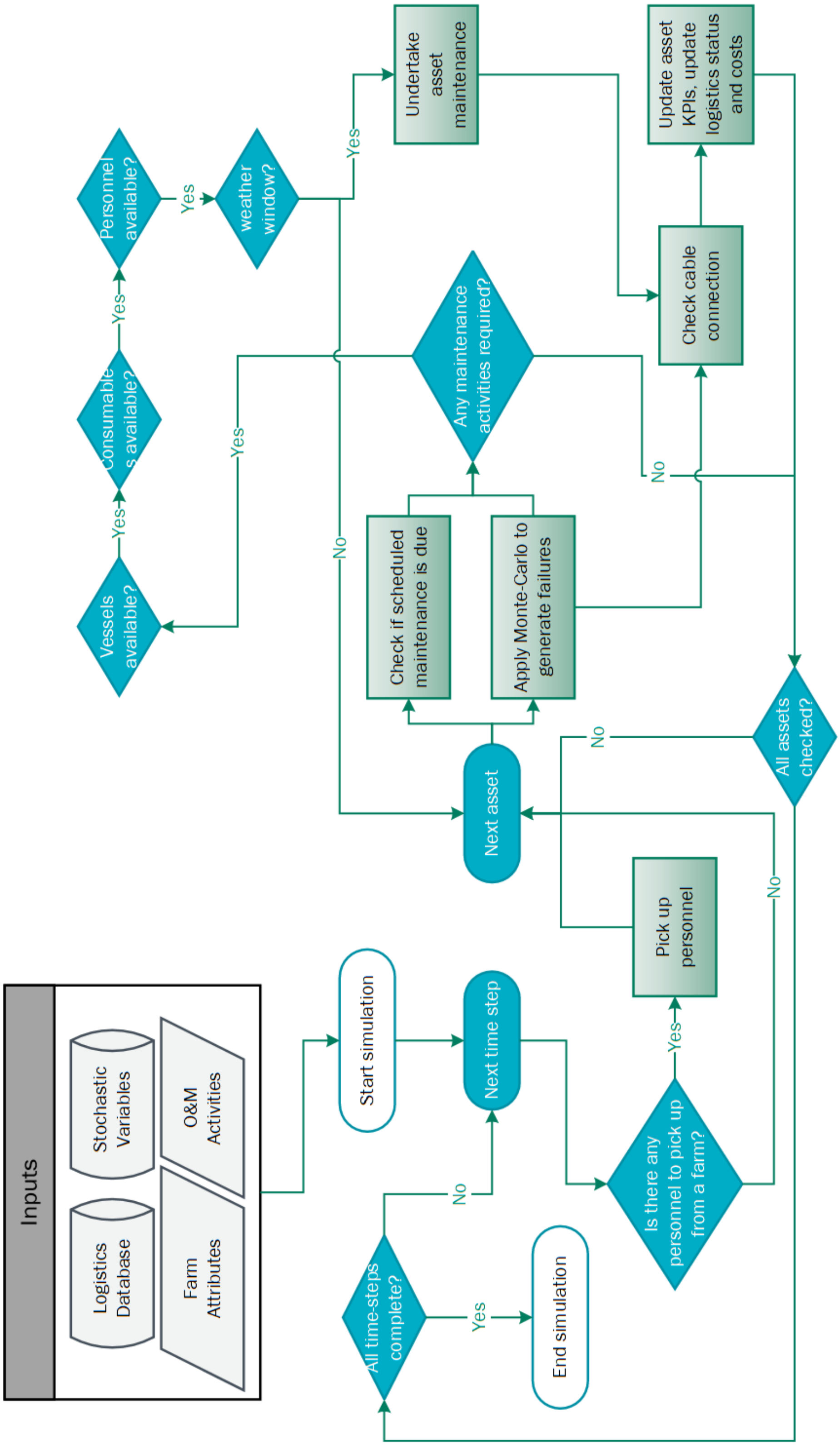


Figure 3.3: High level diagram describing the basic logic in COMPASS

Within each timestep COMPASS iterates through all offshore assets (i.e. cable, substation, wind turbine). Within each asset (system) it also iterates through its subsystems and components (if an asset can be broken down into components). For each system or component COMPASS checks whether any maintenance is required. That can be either a maintenance due to a failure generated via the Monte Carlo method or a scheduled maintenance initiated using the inputs at the start of the simulation. If maintenance activities have been identified then COMPASS checks for any logistical requirements for these activities. If there are available vessels, personnel, consumables and the weather suits the requirements of the vessels then it will proceed with the maintenance activity.

In some cases an asset failure can lead to a disconnection of a cable. For example, certain substation failures and array cable failures can lead to that. In the case of floating wind turbines, their disconnection for TTP may also temporary disconnect the array cable. This is taken into account before asset KPIs are updated. At the end of the simulation COMPASS combines the outputs and presents them in different output formats listed further below.

- **Hour-by-hour operation** - this is an optional output that was designed to sense check the validity of the computation (see Section 5.2). With this type of output COMPASS will provide the hourly status of each asset, each craft and each personnel and the associated costs in an Excel spreadsheet.
- **KPIs for each turbine** - Each wind turbine will have a list of KPIs associated with it, the list is given in Table 3.3. Some KPIs existed before this research work while others were added during this work. Turbine KPIs are also broken down by month and by year to assess variation due to seasonal changes and occurrences of some rare planned campaigns.
- **KPIs for each vessel** - Each vessel also has a list of KPIs that is associated with it. Previously only two variables were measured however with the development of this work more outputs were introduced as shown in Table 3.4.
- **KPIs for the whole farm** - These KPIs are a combined output summary from all wind turbines, cables, substations, vessels and personnel used in the farm over its lifetime as modelled in COMPASS. These include fixed costs, consumables and equipment costs, vessel costs, personnel costs and wind farm outputs combined from all wind turbines. The breakdown of outputs is similar to that given in Table 3.3 without the breakdown by month or by year.

Table 3.3: Wind turbine KPIs measured by COMPASS. New additions are the KPIs that have been added during this research work.

Existing outputs	New additions
TA	EA
Revenue	Planned maintenance time
Energy output	Unplanned maintenance time
	Number of planned visits
	Number of unplanned visits
	KPI breakdown by month
	KPI breakdown by year

Table 3.4: Vessel KPIs measured by COMPASS. New additions are the KPIs that have been added during this research work.

Existing outputs	New additions
Travelled distance	Mobilisation time
Usage time	Wait on weather
Total cost	Unused hire time
	Hire cost
	Mobilisation cost

3.3.2 Class diagram

Python operates with classes. The main purpose of classes is to create objects with unique attributes and methods. An attribute in Python is any characteristic of that object. If a reader is not familiar with Python they can think of an object attributes as certain features by which one would describe that object and possibly even compare it with a different object. For example if an object is a vessel then examples of its attributes are its speed, its personnel capacity and its significant wave height (H_s) limit. Methods that belong to each class are the functions that this class is capable of performing. For example, a vessel class may be able to transit i.e. move from one latitude and longitude coordinate to another, hence there will be a function within the vessel class that is capable of modelling just that.

Figure 3.4 represents the class diagram of COMPASS. Classes regularly interact with each other within a simulation. Class diagram resembles a hierarchy within a company team. Class diagram for COMPASS is shown in Figure 3.4. Within that "team" there is a team lead who overlooks over the entire team and makes sure all team members follow the pre-defined objectives. This is the responsibility of the Wind Farm class in COMPASS, Wind Farm initiates and overlooks the entire farm constantly tracking any activity on the farm and making sure managers are activated when necessary over the entire lifetime of that farm. As mentioned, the team lead may have a couple of managers under their supervision where each one is responsible for a particular area. In COMPASS these managers are the Logistics Manager and the Assets Manager. The Logistics Manager is responsible for running any logistics such as crafts (vessels) and personnel. Asset Manager leads all the assets within the farm.

It is quite rare that modifying one class does not lead to modifying the other because objects interact with each other. For example, when building in the TTP functionality one cannot simply change one class. WindTurbine would need to be modified to allow for the change of status to "towing", "disconnecting" and "connecting" (before that it was only "operating", "awaiting repair" and "undergoing maintenance"). Similarly, Logistics Manager would need to be modified to allow for towing, and Asset Manager would require changes in how it checks cable connection as towing may cause a temporary disruption in the cable. Output Manager may need to be modified to capture the outputs associated with towing such as quayside costs. This is just one example of how just adding a towing operation may lead to multiple changes across the classes. Green ticks in Figure 3.4 mark the classes that have been modified throughout this research project to accommodate the changes that will be discussed in Section 4.

It can be seen in Figure 3.4 that classes associated with fixed costs have been left intact. Fixed costs can contribute to a significant portion of OPEX but they are not the focus of this research work. This thesis presents only on the time-dependent computational logic. Only classes with time-dependent attributes and variable-adjusting methods have been modified with an exception for the class Constants. This is due to some constant variables being added which impact the time-dependent computation. Examples of such variables are vessel capacity in terms of personnel and TTP limits. These stay constant throughout the simulation but may impact the outcomes of the simulation.

3.4 How existing tools are fitted to capture O&M activities.

Most O&M simulation tools listed in Table 3.1 are capable of modelling both planned and unplanned activities. When it comes to condition-based maintenance activities there usually is no specific module to model them in the tools. This limitation arises from the fact that these O&M simulation tools operate with historical data without the access to real wind turbine condition. The effect of condition-based maintenance can however be modelled via a workaround. The aim of condition based maintenance is to better predict failures and convert what would otherwise be an unplanned activity into a planned one. Condition-based maintenance can therefore be modelled by reducing the number of unplanned activities (i.e. reducing the failure rate) and increasing the number of planned activities.

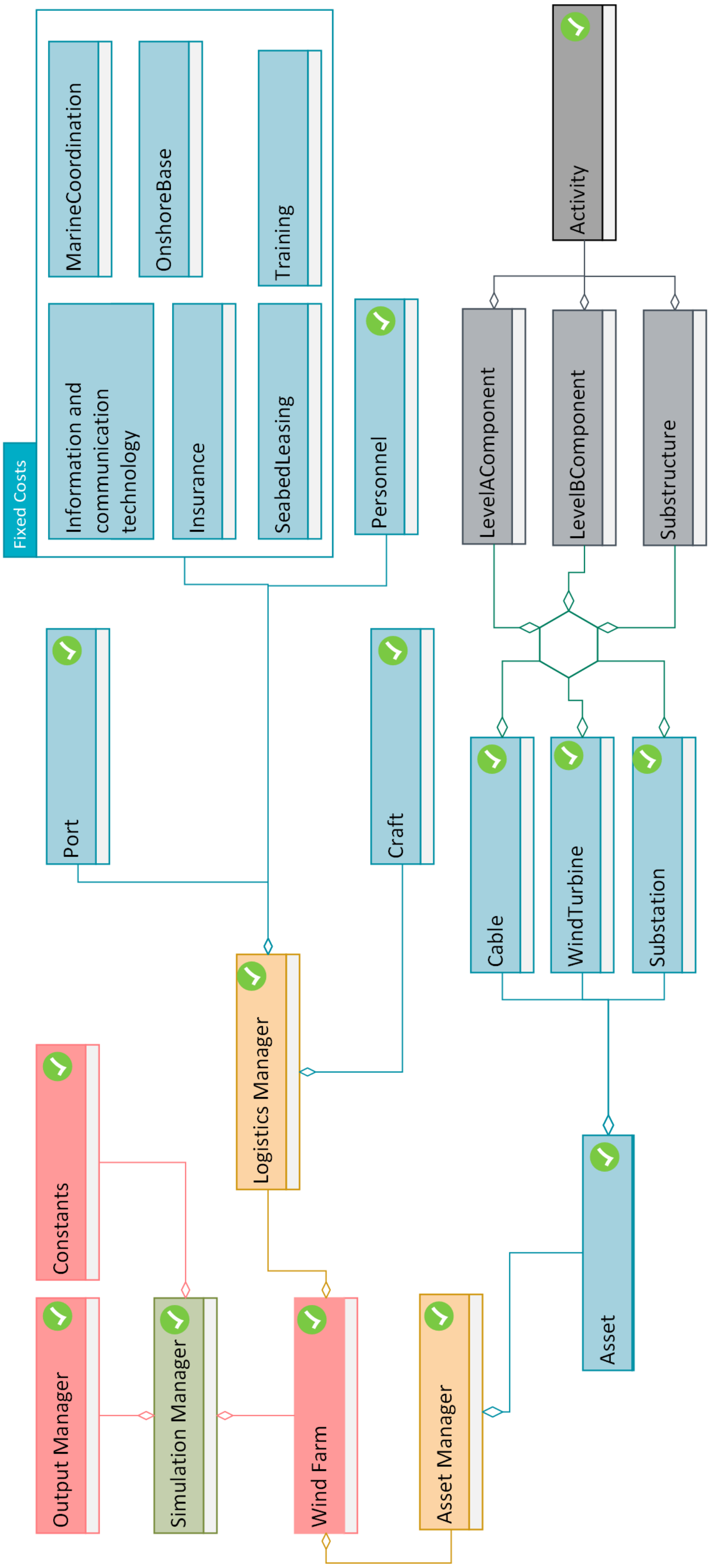


Figure 3.4: COMPASS class diagram

The level of complexity is different in different O&M simulation tools. Some tools such as Strath-OM and WavEC look at the wind farm as a whole, on the other hand tools like NoWIcob, Shoreline, UoE/JFMS and COMPASS look at each offshore asset individually. The granularity of O&M modelling may differ from tool to tool. Some model the whole farm, other model each asset, other split each asset into components. Higher granularity allows to capture the full complexity of O&M and model the interaction between activities, vessel movement between assets and combination of activities (also referred to as merging activities in this thesis).

Section 2.3 has demonstrated that some activities can be combined together while other have to be done in isolation. Section 2.3.9 has shown that there are restrictions in terms of number of personnel allowed on turbines which can limit the number of activities that can be performed on a turbine at any one time. Vessels also have limited personnel carrying capacity. None of the models presented in Table 3.1 are capable of capturing these limitations. Section 4.4 of this thesis will demonstrate a functionality that was developed in COMPASS to combine activities together where possible.

Section 2.3 has demonstrated that some activities may only be performed on a portion of assets. It has found that some activities may allow the turbine to keep operating before or during the maintenance campaign. Current O&M simulation tools are not capable of capturing that. Section 4 will show the developments in COMPASS that allow to capture this behaviour.

Section 2.4 has shown that activity duration is not constant. WavEC and WOMBAT aim to capture some of this variability via modelling personnel shifts and activity interruption due to weather (discussed further in Section 5.3). The approach taken in this thesis is data-driven. CFD function derived in Section 2.4 allow to model the variability in maintenance duration stochastically using a method demonstrated in Section 4.3.

3.5 How existing tools are fitted to capture current O&M strategies.

Chapter 1.4.2 shows that SOV became a popular O&M strategy in the past years. Out of the tools presented in Table 3.2 some have demonstrated some ability to model SOVs, these are O2M, ECN O&M Calculator and Shreline Design, however the simulation logic used in these tools is not openly available because these tools are commercial. Some SOV modelling ability has existed in the initial COMPASS model however it has been since upgraded through this research work to capture daughter crafts, accommodation limitations and picking up of personnel from turbines by these SOVs and their daughter crafts. Section 4.6.1 demonstrates this logic. COMPASS is now the only known non-commercial tool that is able to model SOVs with daughter crafts and recognise the accommodation on board of an SOV.

Two models have the TTP option are the OPERA and WES O&M tools. These tools were specifically designed for wave energy converters. These tools assume that all major operations on wave energy converters would require towing the devices to port. WOMBAT and WAVEC tools is also have an option to model TTP operations. This will be discussed in more detail in Section 5.3. Most of the other models have not reported the modelling TTP operations in their documentation. Some commercial tools, specifically ECUME-I, Mermaid, ForeCoast Marine and Shoreline Design may be able to model TTP operations however the exact details of the methods and assumptions they use are unknown.

UoE/JFMS tool has been used in one study to compare fixed-bottom offshore wind O&M with floating wind O&M that uses the TTP strategy, however the methodology used for modelling TTP operations is limited (Rinaldi et al., 2020).

There is an ongoing work at the FOW CoE at the ORE Catapult that investigates these strategies further. In order to accommodate this analysis this thesis develops a functionality for modelling TTP operations in COMPASS. It captures all the important steps of the process that have not been demonstrated in existing studies. In takes into consideration the changing weather limits for different parts of the process and calculates the waiting time at the quayside and the corresponding costs.

3.6 How existing tools are fitted to capture multi-rotor technologies.

Out of the listed O&M models, only one has demonstrated its application on multi-rotor turbines. Recent study modelled the O&M of multi-rotor systems using the Strathclyde University offshore wind OPEX to find an optimal CTV fleet for a farm with 1, 10 and 40 multi-rotor systems (McMorland, Pirrie, et al., 2022). There were however a few drawbacks of that work. Firstly, the multi-rotor system was modelled as two turbines put in the same location, meaning they are not seen as a single asset by a simulation software. Other O&M simulation tools may be able to use the similar approach to model twin turbines. In reality, there will be components that multiple rotors will share, such as a foundation or a transformer, so it is important to model the synergy between rotors and shared components. Additionally, that work also assumes that in the case of a failure on one turbine, the other turbines stay operational. Although this is a valid assumption for that study, other companies such as that of Hexicon AB and EnerOcean developed twin turbine concepts that use a passive yaw system, i.e. the turbines align with the wind by the use of a single point mooring. Therefore to cover all possibilities, there should be two operational options - one when all turbines switch off in the case of one turbine failure and another where other turbines stay operational.

Section 4.10 demonstrates the logic developed in COMPASS as part of this research work to capture multi-rotor turbine O&M. This logic is integrated in COMPASS i.e. it works alongside all other developments including TTP.

3.7 How existing tools are fitted to capture cable failures.

O&M simulation tools that either mention or model cable topology to some extent are NOWIcob (Bakken et al., 2017), DTOceanPlus tools (Correia da Fonseca et al., 2021) and WOMBAT (Hammond & Cooperman, 2022). NOWIcob models the wind turbines in such a way that each turbine is connected to the substation via a cable, if a cable fails, it leads to a disconnection of exactly one turbine from the grid. This method would only work for a star connection. Its functionality has not been demonstrated.

According to the WOMBAT tool developers, WOMBAT can model a string connection, but not other types connection.

DTOceanPlus is the most advanced package of tools when it comes to cable topology. DTOcean tools model it by generating a set of lists for each asset representing every possible connection to the onshore or OSS. The method is documented in text, but the code is not provided and neither any application example is given. It is however expected that these lists are either generated by multiple *for* loops from a list of two-asset connections provided by a user (such as "Wind turbine 1 is connected to Wind turbine 2") or have to be provided by a user in their final form. Because the code itself is not available, it is difficult to judge the flexibility of this method. It can certainly be used for simple string and ring connections but whether it is applicable to complex cases such as that of the Triton Knoll wind farm (see Figure 1.5) remains unknown.

The main drawback of this method is that it is not memory efficient. It requires the same information to be stored multiple times. For instance, the connection for Wind Turbine 1 (WT1) could be described in a list [WT1 CB1, WT2, CB2, SS1] where CB is a cable and SS a substation, and for WT2 as [WT2, CB2, SS1], hence the memory about [WT2, CB2, SS1] connection in this case is stored twice. WavEC O&M tool developers have also used the DTOcean method for modelling cable connections.

Section 4.7 develops a new Python-based method in COMPASS for capturing the effect of a cable failure given a cable topology design. This method is easily-implementable into O&M simulation tools, it is compact in terms of the script required, memory efficient and is highly flexible in terms of the variability of cable topology designs it can model. The methodology can also be used as a stand-alone method for assessing cable topology redundancy in the future.

Chapter 4

O&M Simulation Tool Development

Chapter 1 of this thesis summarised the O&M trends in offshore wind energy and highlighted how COMPASS development could meet the demands of current industry trends. Section 2.3 provides the lists of O&M activities that are expected to happen on a wind farm throughout its lifetime. Sections 2.3.10 and 2.5.2 also showed that some assumptions are often made in O&M simulation tools are not justified. These findings drove the development of COMPASS features that are discussed in this section.

4.1 Input variables

4.1.1 O&M activity attributes

As highlighted in Section 2.3 O&M simulation tools require detailed inputs. Table 4.1 contains the attributes of each activity in COMPASS. Some attributes are optional, others are required. The units for each attribute are presented there together with an example. Attributes highlighted in bold are the ones that were added during the development of COMPASS as part of this research work.

Percent of assets and final year attributes were added following the review of O&M activities presented in Section 2.3. It was found that some activities may only happen in the first couple of years, other activities such as subsea component inspection and seabird monitoring equipment inspection are expected to be performed on the certain portion of assets rather than on all assets.

Final year was also added following the findings in Section 2.3. It captures additional activities that may happen on certain components in the first year or two of turbine lifetime such as an extra visit to inspect turbine components or subsea anodes.

Similarly, consumables lead time was also added to capture the time it takes to prepare and deliver spare parts. This variable can also be used to represent supply chain delays. Currently this value is set as constant however future research may turn it into a time-dependant or stochastic variable to represent the change in demand depending on the time of the year.

An option to add more than one craft type was added. Some activities may require a combination of vessels rather than just one vessel type.

Sections 4.2, 4.3, 4.5, 4.4 discuss rate variability, duration CDF, switch and merge attributes in more detail.

Table 4.1: O&M activity inputs. Newly added or adjusted activity attributes are highlighted in bold.

Input	Optional or required	Units	Default	Example
Planned	required	TRUE/FALSE		FALSE
Percent of assets	optional	%	100	90
Rate	required	#/year		1
Rate variability	optional	string	none	Gearbox rate
Final year	optional	year	lifetime	5
Risk consequence	required	#		2
Risk probability	required	#		4
Equipment costs	required	£		10 000
Consumables costs	required	£		200 000
Consumables lead time	optional	h	0	72
Task duration	required	h		48
Duration CDF	optional	string	none	Gearbox CDF
Downtime	required	h		24
Switch	optional	TRUE/FALSE	FALSE	TRUE
Merge	optional	TRUE/FALSE	TRUE	FALSE
Urgency	required	High/Medium/Low		High
Personnel 1 type	required	string		technician
Personnel 1 number	optional	#		2
Personnel 2 type	required	string	none	engineer
Personnel 2 number	optional	#	0	3
Craft 1 type	required	string		tug
Craft 1 number	required	#		2
Craft 2 type	optional	string	none	ctv
Craft 2 number	optional	#	0	1
On Site	optional	TRUE/FALSE	TRUE	FALSE

4.1.2 Vessel attributes

Additionally, the user is required to specify the following vessel attributes:

- Lease type: ad hoc, long term or summer only
- Port assigned
- Minimum contract duration (if ad hoc)
- Annual charter cost (if long term)

- Mobilisation and demobilisation costs
- Time it takes to mobilise this vessel (lead time)
- Cost per day (if ad hoc)
- Speed
- Significant wave height (H_s) limit during transit
- Significant wave height (H_s) limit during personnel transfer
- Personnel capacity
- Time allowed to spend offshore (may be used to replicate personnel shifts or limited fuel capacity)
- Offshore location (applicable to SOVs only)
- Port return frequency (applicable to SOVs only)

Currently all of the above vessel characteristics are set as fixed values throughout the lifetime of a wind farm. In reality, some of these characteristics may depend on the vessel demand on the market. In particular, charter costs and mobilisation time may change depending on vessel demand. Vessel demand may increase in summer when weather conditions are more favourable to undertake any offshore projects. Such increase in demand can cause a temporary rise in vessel costs and lead to longer lead (or mobilisation) time.

4.2 Failure rate variability

Section 2.5 demonstrated that in the context of major operations there is not enough evidence of a bathtub curve. In fact it has been demonstrated that the change in the rate of major operations may be driven by the duration of a warranty agreement. Sources discussed in Section 2.5 also found that the frequency of forced outages and CTV visits varies throughout the years with a peak in the first year of operation but also in years 7-8 and 12-13 according to SPARTA (2022).

The observed FR variability patterns may be difficult to model using a function. This thesis suggest using a user-defined rather than function-defined FR variability. Having a user-defined FR variability is a simpler and a more accessible method. It gives more freedom to the user to assess various FR variability patterns without sacrificing computational time. The new development in COMPASS allows the user an option to specify the FR at each year of turbine operation in terms of % of the average FR. This list can be defined in the inputs (Rate variability in Table 4.1) and then converted to a Python list such as that below, representing 10 years of lifetime:

[0, 200, 100, 50, 200, 50, 100, 100, 100, 100]

This way if the user wants to model an increased FR in the first years of turbine operation they can do it by setting the expected percentage increase in the first years of operation. On the other hand if the user wants to capture the effect of a warranty agreement observed in Section 2.5 then they can do so by setting a high percentage in years 4-5. This approach also makes it less computationally intensive because this FR variability list is short and can be defined in advance before the simulation starts.

4.3 Maintenance duration model

Section 2.4 showed just how much variability there is in major operation durations. This section proposes a new way of capturing the variation in activity duration.

The following logic will be applied in COMPASS once a failure is modelled using the Monte Carlo method:

- Find the required logistics available i.e. vessels and personnel required for this task.
- Get the expected duration of a task from the simulation inputs (Task duration in Table 4.1). Analysts can use P90 values presented in Section 2.4.
- Find a suitable weather window for that operation using the expected duration.
- Generate a number between 0 and 1.
- Select the duration of an operation based on the generated value and the appropriate CDF (Duration CDF in Table 4.1) as demonstrated in Figure 4.1.
- Use that duration to capture the energy losses and the costs of vessel and personnel hire or any other KPIs that may be affected.
- Occupy the vessels and personnel for the generated operation duration.

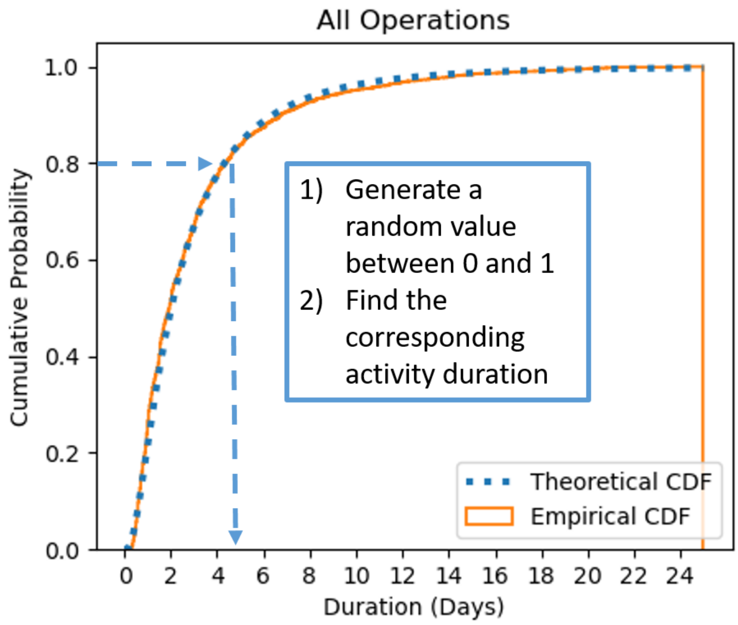


Figure 4.1: Steps describing the stochastic duration modelling based on CDF.

Section 5.5 demonstrates how COMPASS applies this functionality via a case study.

4.4 Merging activities

4.4.1 Activities on a single turbine

Section 2.3 presented the list of all activities that are expected to happen on each wind farm asset during its lifetime. It may happen however that in certain years multiple scheduled activities can be due on a single asset. It may also happen that an unscheduled maintenance can appear in summer when scheduled inspections are due. In certain scenarios activities may be combined together and can be performed either by the same team of technicians and in the same trip. Most O&M simulation tools look at these activities individually neglecting the possibility of combined activities (often referred to as opportunistic maintenance in the literature). This research developed a function in COMPASS capable of merging activities together. COMPASS user can specify per each activity whether merging of this activity is allowed or not (Table 4.1).

There are two main restrictions for combining the activities considered in this function:

- Vessel capacity i.e. how many people can physically fit into the vessel that is used for the activity.
- Personnel limit on the turbine (see Section 2.3.9)
- O&M activity restrictions (if it has to be done in isolation from other activities)

There are also three strategy questions that need to be asked when combining the activities:

- Would the tasks be done in parallel or in series?
- How should the vessels be combined?
- How should personnel be combined?
- How can the timing be combined?

The answers to these questions would depend on the strategy that a wind farm operator may choose and the types of activities. In order to accommodate that, several settings were added to the function. COMPASS user can choose between two options for combining the personnel: "sum" and "max". If option "sum" is selected, then COMPASS will assume that activities are performed in parallel by two distinct teams. If option "max" is selected, then COMPASS will assume that activities are done in series and will try to find the overlap between the personnel requirements for each. The same logic is applied to vessels. Figure 4.2 demonstrates this logic.

In the case of vessels the same rule applies. The default option is "max", because it is expected that the same vessel will be used if activities are combined together.

A lot of the maintenance activity time can be attributed to pushing-on the vessel, transferring technicians, checking that the equipment and consumables meet the required standards. In the case if large vessel is involved, then a significant time can be spent on dynamic positioning and jacking-up. Due to these factors, combining time required for activities can be challenging. It was observed in the data discussed in Section 2.4 that in the case of major operations, when multiple components are involved the time does not necessarily double. It is hard to estimate exactly by how much the duration of an operation would increase if multiple activities are combined together. Currently there is not enough data to make these estimates.

Current default setting in COMPASS is set so that in case if several activities are combined together the duration of all activities will be the maximum of the durations of these activities. If one activity requires one hour and another activity requires six hours, then the total duration will be calculated as six hours. This is especially feasible in the case if activities are done in parallel and "sum" is selected for personnel. This way two teams can be working on the set of activities in parallel.

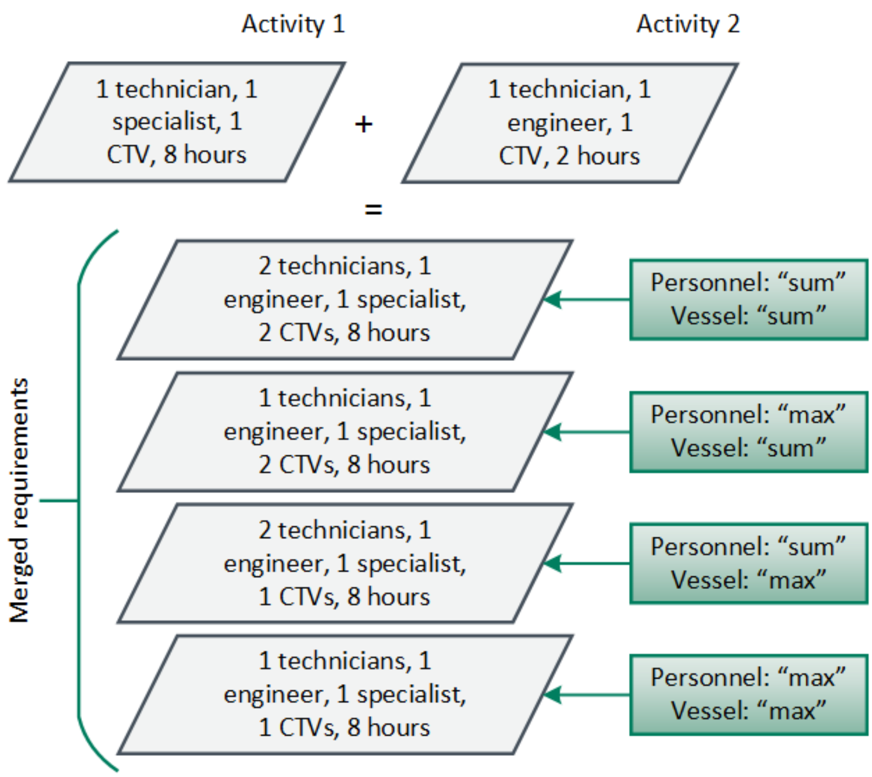


Figure 4.2: An example showing the merging of two activity requirements in COMPASS with different merging settings.

4.4.2 Activities on multiple turbines

Combining activities together is also relevant in the context of multiple turbines in a farm. It was observed in the data in Section 2.4 that scenarios where a JUV arrives to perform operations on multiple turbines is quite common. This strategy has two main cost and time benefits: JUV (or any other vessel) would need to be mobilised only once and demobilised only once, that vessel can travel between assets without returning to the port. Without access to the most of the O&M simulation tools presented in Section 3.2 it is difficult to tell what tools have the capability to capture these scenarios. Figure 4.3 illustrates the logic applied in COMPASS.

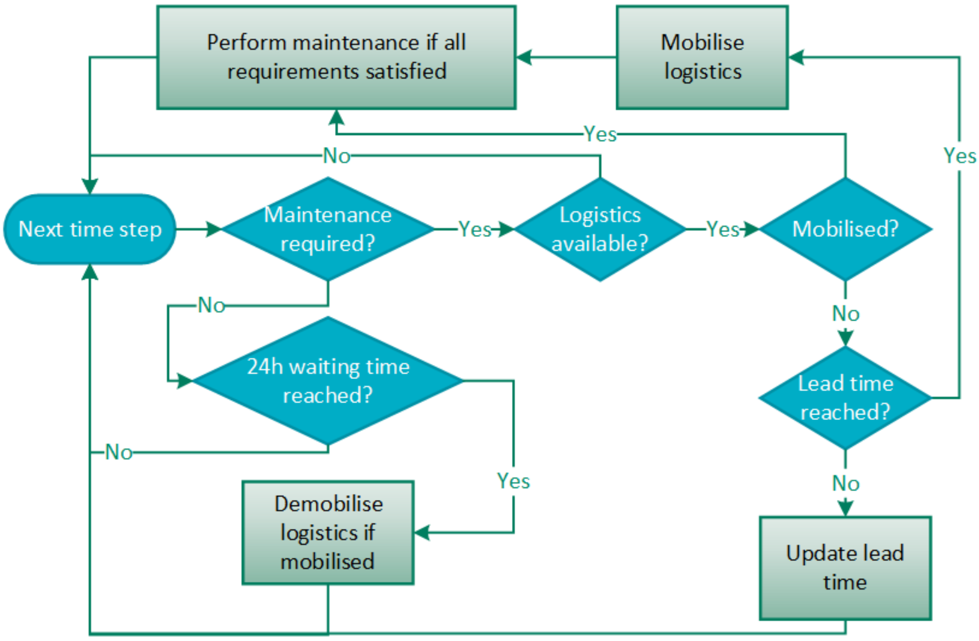


Figure 4.3: Mobilisation logic diagram

The 24-hour waiting window shown in Figure 4.3 was built into COMPASS to allow for activities on other assets to finish and give an opportunity for a mobilised vessel to move from one asset to the next, otherwise it may prevent the current vessel from arriving to these assets. Some activities may require more than 24 hours. Future work should take that into account, changes should be made to identify which assets require the current vessel and how much time is left until the end of the current activity. 24-hour waiting window does not have any associated costs in COMPASS i.e. unless the vessel is used on the day, the day rate will not be applied.

It is also a common occurrence that multiple planned maintenance activities are initiated on turbines at the same time. In this case a vessel is allowed to move from turbine to turbine until its vessel offshore time limit is reached. This limit is set in the inputs. For small vessels such as CTVs this limit is about the same as the shift duration (i.e. 8-12 hours). Future work can investigate these limits further particularly in the context of vessel charging. This limit could be defined by the battery capacity or the amount of fuel on board.

4.5 Asset switching on and off

There are several reasons why a wind turbine could stop producing power:

- Wind speed is outside the operational limit of that wind turbine
- Failure was not anticipated by the condition monitoring system and therefore happened unexpectedly causing the abrupt stoppage of electricity generation.
- The regulations for the current maintenance activity require the device to stop or disconnect from the grid.
- Request was made by the network grid operator to balance the network grid.

As was found in Section 2.3, not all activities require the turbine to be switched off during the activity. For example, some paint campaigns can be performed while turbines still operate.

Two additional attributes were added to the activity class in COMPASS that allow to model whether an activity causes the turbine to stop:

- Downtime: This variable defines whether the asset would turn off due to the unexpected failure.
- Switch: This variable defines whether the asset would need to be switched off during the activity taking place at an asset.

The majority of failures can be predicted quite early either using sensors installed to track the condition of different components or during the regular planned inspections. According to SPARTA observations 95% of blade repairs are likely to be part of a planned campaign (SPARTA, 2022). It is therefore important to have the downtime option because it allows to define whether this is an activity caused by an abrupt failure or an activity that is triggered by an alarm in the system or an inspection indicating the worsening of a turbine condition. In the former case the turbine is likely to continue operation until the activity occurs. In reality, there will be a limit for how long a turbine can continue its operation, i.e. the remaining life. It is also possible that an asset can operate at a reduced capacity until the issue is resolved. These scenarios are not yet captured in COMPASS and will form a part of the future work.

On the other hand, according to one of the experts interviewed in Section 2.3 transformer failures are unpredictable and do lead to an abrupt turbine outage. In fact transformer failure can cause a surge that can put the rest of the turbines in the ring or a string connection out.

Users can now change the Downtime and Switch attributes to represent the outcome expected in the case of failures and maintenance.

4.6 Vessel model upgrade

4.6.1 SOV modelling

Unlike CTVs, SOVs can stay offshore for much longer, default duration in COMPASS is 2 weeks. At the end of that period an SOV would be required to return to port to recharge. Unlike CTVs, SOVs can also stay at a turbine for longer than the duration of a single shift. Personnel from SOV can perform an activity in several shifts. In the case of a CTV, long activities would require several visits. SOV has a much larger accommodation capacity than a CTV would, up to 75 technicians can fit on an SOV (Hu & Yung, 2020). Figure 4.4 shows how SOVs can be modelled in COMPASS.

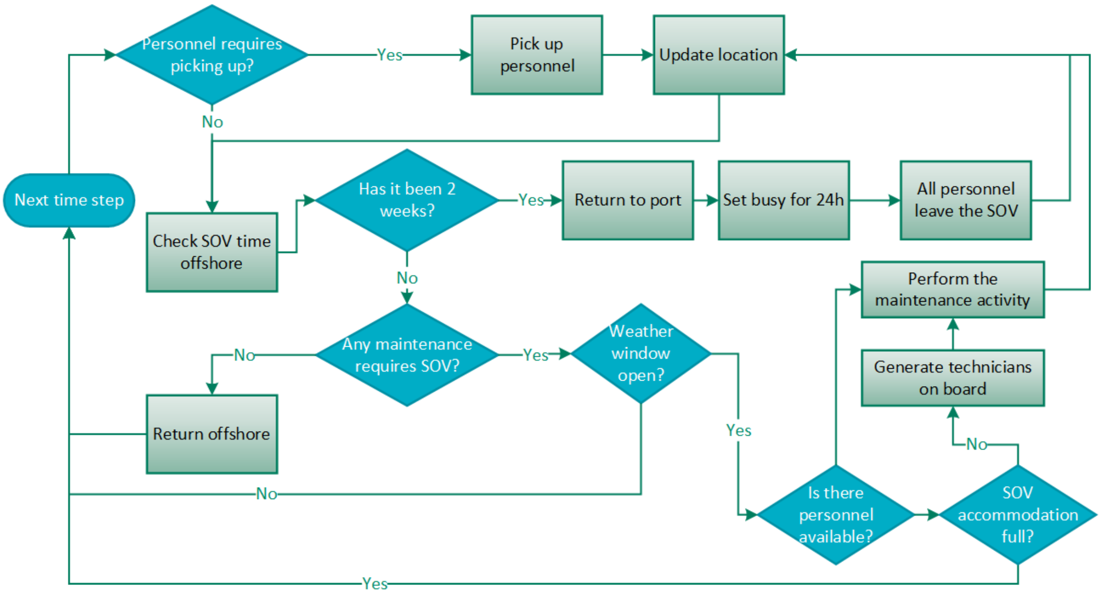


Figure 4.4: SOV modelling logic in COMPASS

Personnel are generated on an SOV on demand up to its accommodation capacity. They then occupy the SOV until the vessel returns to port and personnel generation restarts. If SOV accommodation is filled, no more personnel on board can be generated.

Users can assign some O&M activities to require daughter crafts. In these cases a daughter craft will be first sought to perform that activity (but when it is unavailable the alternative option automatically becomes an SOV). Daughter craft then picks up the personnel and returns to the SOV.

4.6.2 Personnel limitations offshore

Those O&M simulation tools that model personnel activity usually do that by modelling personnel shifts. This is done by breaking down an activity into two or more activities if that activity exceeds the shift duration. COMPASS does not take into account personnel shifts the same way. Every activity in COMPASS is set as continuous. This is currently a limitation which was not addressed in this work primarily due to the lack of understanding around how activities can be broken down. It is not known whether an eight-hour activity can be performed in two four-hour visits or four two-hour visits etc.

From the discussions with experts in Section 2.3 it was also understood that the possibility to break down an activity may depend on the type of that activity. Breaking down an activity into shorter activities can increase the number of weather windows available for that activity however Section 5.4 demonstrates using a specific site that this increase is not significant when compared to the impact of the wave height limit for vessels.

WOMBAT, the tool included in Table 3.1, models shifts and sends vessels with personnel back to shore at the end of a shift. It is assumed in that model that a turbine will remain non-operational during the waiting time until the start of the next shift. This significantly impacts the EA outputs as will be demonstrated in Section 5.3. There is currently no evidence of this in real O&M that would support this method.

Review of major operation data performed in Section 2.3 and the discussion with experts in the same section showed that major operations are primarily continuous with very few exceptions when a component is brought onshore for refurbishment and later returned back to the turbine.

In the case of minor activities or planned maintenance this is more likely to happen because these activities often require vessels such as CTVs that cannot stay offshore over night. With SOVs becoming a more popular O&M strategy particularly for distant offshore wind farms, modelling activity interruption due to shifts is less of a necessity. If an activity requires multiple shifts then that can be done by the exchange of personnel between the turbine and the SOV during the activity without the need for the SOV to return to port.

Existing O&M simulation tools report very little on how personnel drop off and pick up offshore is modelled. Michael Welte et al. (2018) has discussed dropping off and picking up teams in the context of vessel routing and scheduling but it did not consider the interaction between personnel shift duration and vessel routing or O&M activity duration and vessel routing. Bakken et al. (2017) has implemented the vessel routing similar to that discussed in Michael Welte et al. (2018). Two options are considered there: "parallel tasks" and "non-parallel tasks". In the case of parallel tasks a vessel can drop off personnel at the first turbine and move to the second. It will then pick up the personnel at the second turbine followed by the first turbine. In the second option vessel will stay idle at the first turbine until the maintenance is complete and only then move to the next turbine. Unlike the existing methods COMPASS connects the personnel pick-up with the end of personnel shifts. Personnel that have exceeded the certain time threshold will be picked up and returned to their origin (port or SOV). Those that have not finished their shift will be allowed to move on to other tasks.

This COMPASS feature is important as it interacts with the merging logic described in Section 4.4.2. As demonstrated in the high-level COMPASS logic in Figure 3.3 and in SOV modelling logic in Figure 4.4 picking up personnel is prioritised over all other simulation functions to ensure that personnel is not spending more time offshore than allowed.

Figure 4.5 shows the logic diagram representing the computational logic used in picking up personnel from a farm. When personnel is generated it is assigned to either a port or an SOV depending on which activity they have started from. If an activity requires an SOV, then contractors will be generated on that SOV, therefore their origin will be that SOV. If an activity requires any other vessel then personnel generated for that activity will be assigned to the port that this vessel originates from. COMPASS will iterate through origins and compare these origins with the origins of available vessels. When an available craft with the same origin is found it will pick up the personnel and return them to their origin. For those personnel whose origin is an SOV they can be picked up by a daughter craft (if that SOV has one) if that SOV is not available. SOV returns to its offshore location once personnel is picked up. Personnel clock restarts the moment they reach the origin.

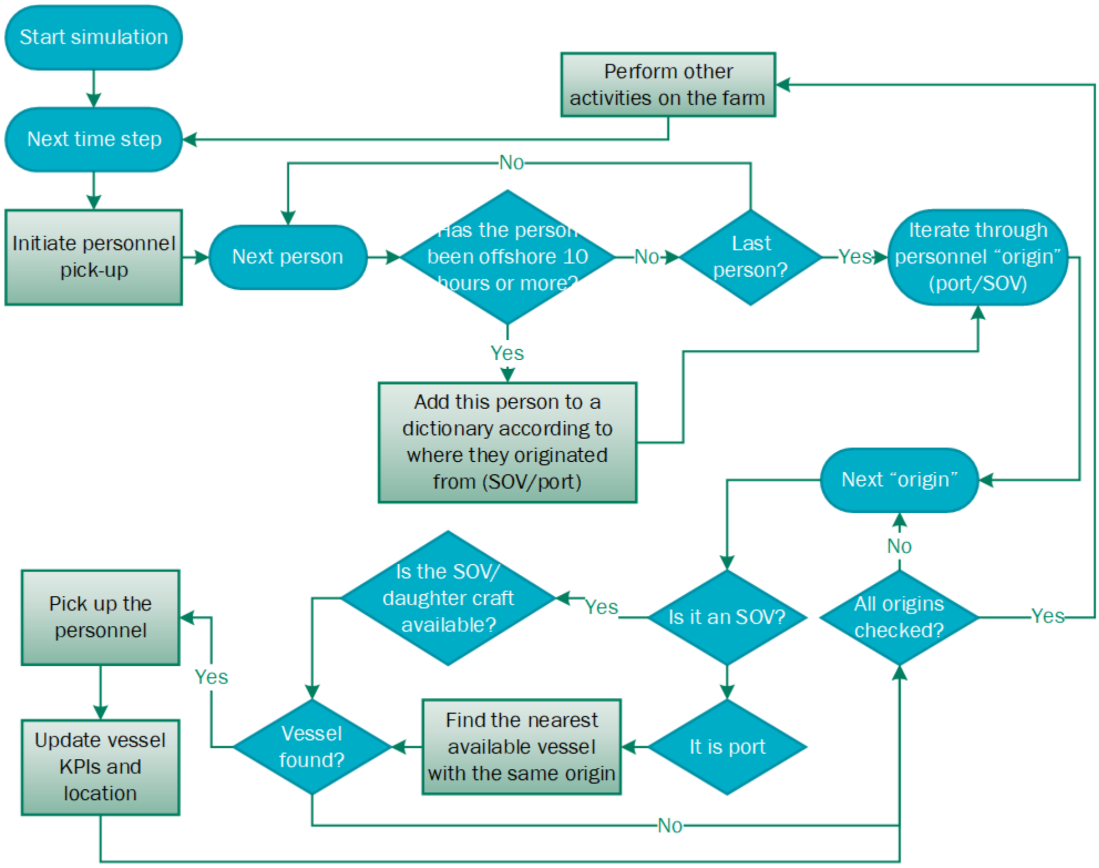


Figure 4.5: Computational logic behind picking up personnel in COMPASS.

COMPASS keeps record of the offshore locations of personnel. The tool will then calculate the total distance required to travel to pick up the personnel and taking into account the speed of the vessel involved it will calculate the time for which the vessel will be unavailable. COMPASS will set vessels that pick up personnel as unavailable so that they cannot be used to perform any other activities.

Picking up personnel is an important feature because it limits the availability of vessels to perform other tasks, makes the vessel transit distance estimation more accurate. There are however some limitations that still exist in this method:

- RAS are currently modelled the same way as personnel. Future work should include creating a separate class for robotic systems.
- Different assets may be operated by different teams. For example, OEMs may have one team of personnel responsible for turbine maintenance while wind farm operators may have another team maintaining cables and substations. Whether these teams can share vessels can change from project to project however it could make an interesting strategy assessment case.

Apart from the time limitation there is also a space limitation for personnel. For those activities where a vessel stays next to the turbines the limit can be set higher than for those where it does not, assuming that part of the team stays on the vessel itself while the other part of the team is working in the nacelle.

4.6.3 Vessel limitations offshore

Vessels in COMPASS have a time threshold added for several reasons:

- It may happen that all personnel is picked up by another vessel. If the vessel return to port is not triggered by returning the personnel then it is triggered by this time restriction.
- To represent the fuel/charge limit.

Vessels also have a personnel capacity on board and an accommodation capacity (if an SOV). For example a typical CTV limit for the number of technicians on board is 12. Maintenance activities will be merged together only until that capacity is reached.

4.7 Weather window check

Maintenance procedure can be broken down into three stages: vessel arrival to the site, maintenance (or drop-off of personnel) and vessel leaving the site. O&M simulation tools usually use a single weather limitation for the whole duration of such operation, however in reality vessel limitations would depend on the type of an activity that it is performing. If the user applies the vessel transit limitation for the entire duration of an operation then there is a risk of underestimating the weather downtime due to transit limitations usually being higher than the personnel transfer wave limits. On the other hand if the user applies the personnel transfer limit for the entire duration then there is a risk of overestimating the downtime due to weather constraints. Personnel transfer limits are normally stricter that the transit limits on vessels. For example, on a CTV the transit limit may be 2.5 m while the wave height limit for personnel transfer may be 1.75 m or even 1.5 m.

Weather window check in COMPASS is now split into three consecutive checks. One for the transit of the vessel to the location of the turbine, another for the transfer of personnel to the turbine and the last one for the transit of the vessel back to the port. This is necessary to make sure that the vessel and personnel can safely return back to the port.

In some occasions the vessel will not stay at the turbine for the entire duration of the operation. In this case the "transfer" weather window is still checked for the entire duration of the operation. This is needed to ensure that personnel are able to leave the turbine at any point during the maintenance activity. Figure 4.6 summarises the described logic.

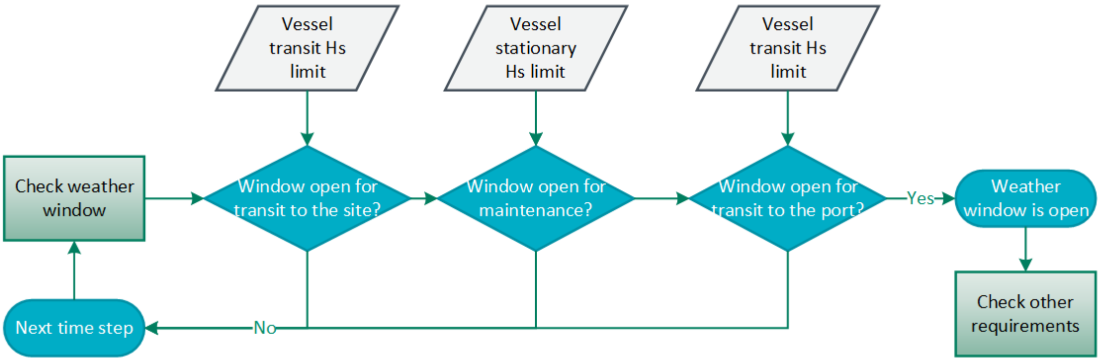


Figure 4.6: Weather window check performed for each maintenance operation.

If the three consecutive weather windows are open, only then the activity would be initiated. In the case if at least one condition is not met, COMPASS will move to the next time step and record current time step as Wait on Weather (WoW).

4.8 Cable topology

This work provides a more efficient and compact method for modelling cable connections which has no limitations on the type of cable topology and requires minimal user input. Rather than building in a complex code that consists of several loops that are hard to manage and may require additional coding if cable topology is changed, this work shows that cable topology can be modelled using a readily available Python package NetworkX that suits the purpose. In the documentation NetworkX is described as *"a Python package for the creation, manipulation, and study of the structure, dynamics, and functions of complex networks"*. This is the first study where this package is used for modelling wind farm cable topology. The main advantage of this package is in the set of functions that it contains.

At the start of any simulation the cable topology is initialised using the function `add_edge()`. This function feeds on two nodes that are connected. One by one each cable is added to the total network according to the input in Excel. Then once the simulation starts the following functions are of particular use when cable and substation failures occur:

- `remove_node(substation/turbine)` is used to model substation failure or temporary turbine disconnection during the towing procedure.
- `add_node(substation/turbine)` is used to model substation repair (i.e. going back to the operational mode) or floating turbine re-connection.
- `remove_edge(turbine 1, turbine 2)` is used to model cable failure between turbine 1 and turbine 2
- `add_edge(turbine 1, turbine 2)` is used to model cable repair between turbine 1 and turbine 2

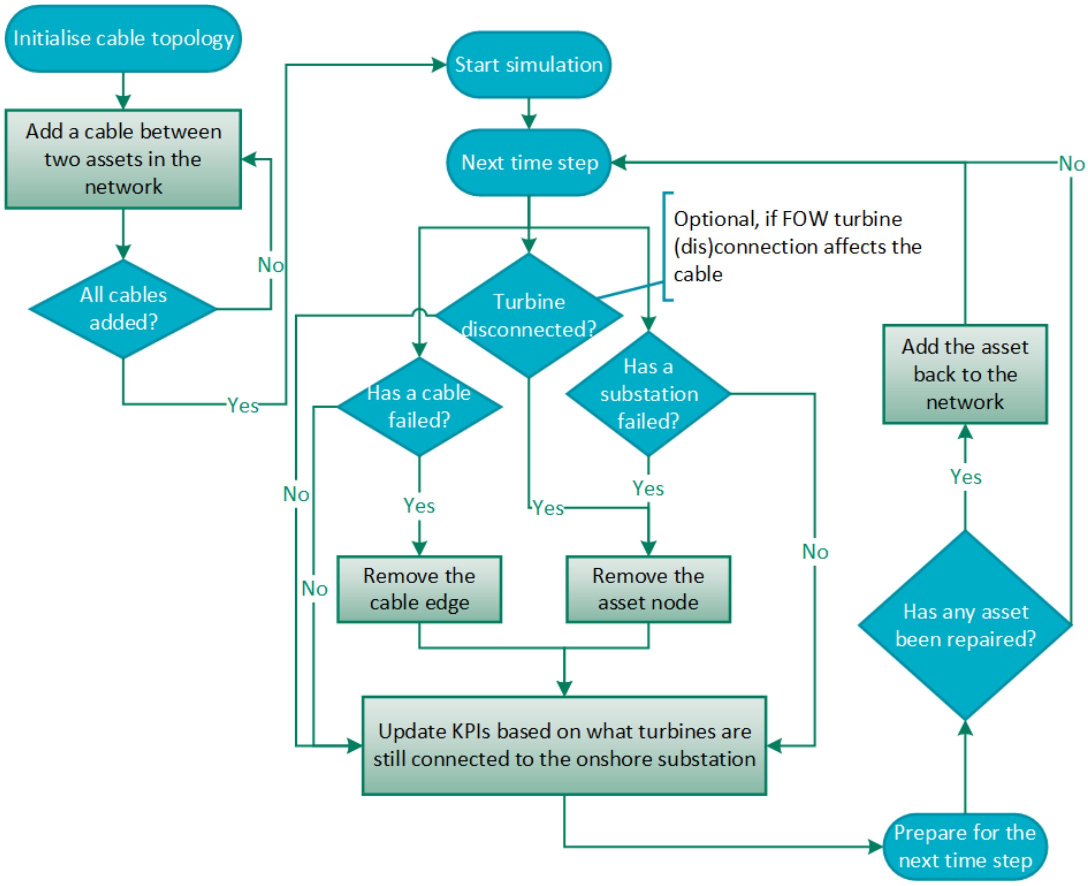


Figure 4.7: Cable and substation failure and repair modelling in COMPASS

- `has_path(turbine 1, onshore substation)` is used to check if there is still a cable path between turbine 1 and the onshore substation

Figure 4.7 demonstrates the logic in COMPASS designed to capture the effects of cable and OSS failures and repairs.

In order to model a ring connection with a varying cable thickness the method described can be updated in the future. Python package NetworkX allows to add an attribute to each edge and node. Such attribute could be the power carrying capacity of that cable or node. When the cable topology is initiated or when a cable is repaired, `add_edge(turbine 1, turbine 2)` could be updated with an attribute `capacity = 75 MW` for a cable that can only enable an export of 75 MW. Another attribute could be a transmission loss in terms of percentage that could be applied on each cable. This would allow for estimating transmission losses and calculating the overall energy output more accurately.

There is an optional feature designed for FOW (as seen in Figure 4.7). When floating turbines are disconnected from cables and moorings for towing, this disconnection may cause a temporary interruption to power transmission. Principal Power have designed a technology that can overcome this but the information about other floating technologies and their disconnection methods is currently not available (Principal Power, 2022). COMPASS user can now specify in the inputs whether TTP of the turbine causes cable disconnection or not.

4.9 Towing to port for maintenance

The towing process has been broken down into several steps:

1. AHTS arrival at the site
2. Disconnection of the turbine
3. TTP
4. Maintenance in port
5. Tow the turbine to the site
6. Connection of the turbine

Sea Impact have recorded these TTP operations the same way they recorded JUV interventions. Sea Impact tracked the two maintenance events involving TTP that happened on the Kincardine FOW farm in Scotland, UK. According to Sea Impact, there were some additional, preparation steps prior the AHTS arrival, they were likely to have been associated with cable and mooring disconnection. These activities happened in isolation from the sequence presented above. They are not captured in this research work, however it may be beneficial in the future to model activity sequencing. This was suggested previously in this thesis with regards to cable repair and replacement activities. It may also be beneficial for modelling unplanned activities resulting from planned inspection campaigns.

COMPASS user must define On Site input as FALSE to allow for TTP operation. Figure 4.8 describes how TTP logic works in COMPASS in more detail.

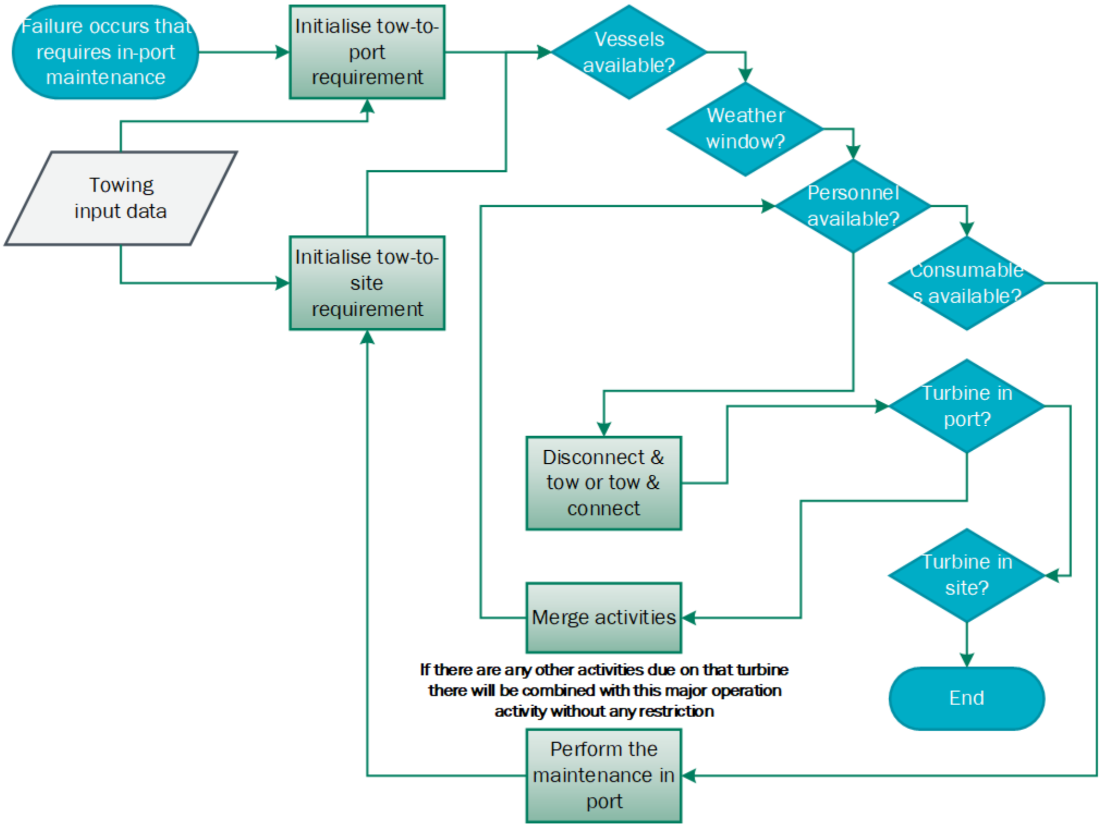


Figure 4.8: Logic diagram describing the simulation of the TTP operation in COMPASS.

The user must also define the following:

- Towing vessel type and number
- Towing H_s limit
- Towing speed
- (Dis)connection time
- Personnel type and number required

Section 4.7 described how the weather window check is split into three stages: transit to the site, maintenance and transit to the port. In the case of the TTP operation COMPASS will apply the same computational logic but with different inputs.

It will first check if the weather window is available for the transit to the site. The length of the open window will depend on the speed of the towing vessel and the distance to the site. Next, COMPASS checks if the weather window is open for the duration of the disconnection procedure. Lastly, COMPASS checks whether the weather window is open for the duration of the towing operation itself. The weather limit for the towing activity is defined separately from the vessel inputs as it depends on the turbine design and its towing requirements rather than the vessel that is towing it. Figure 4.9 presents the logic used for the weather window check for TTP operations in COMPASS. The weather window check process is reversed in the case if the turbine needs to be towed back to the site.

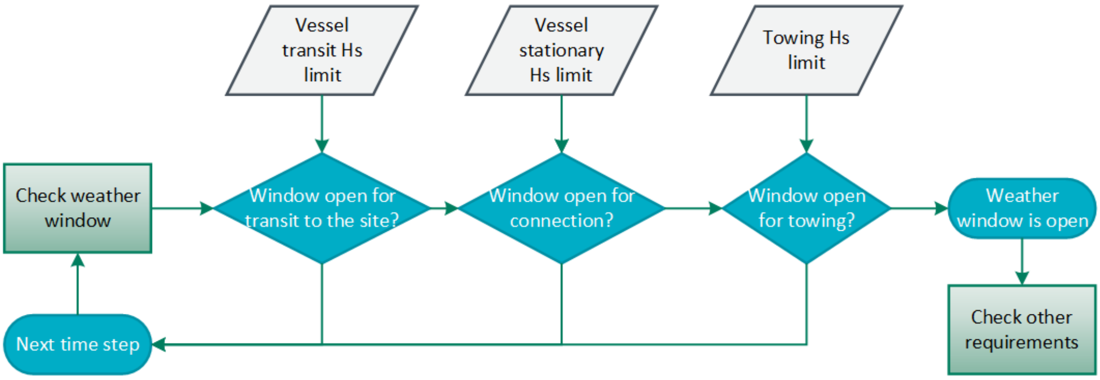


Figure 4.9: Weather window check performed for the towing operation.

COMPASS keeps record of the amount of time that the turbine has spent at the port quayside, the corresponding costs and WoW resulting from waiting for a suitable weather to be towed back.

4.10 Twin turbines

Flowchart shown in Figure 4.10 explains how twin turbine maintenance is modelled in COMPASS. Unlike the Strathclyde O&M simulation tool used in the multi-rotor O&M study mentioned earlier in this thesis, COMPASS models twin turbines as a single structure rather that two turbines put in the same location (McMorland, Pirrie, et al., 2022). This allows turbines to have shared components, such as dynamic cables or a semi-submersible substructure. Unlike the simulation tool used in the existing study COMPASS also has more than one option for the dependency between turbines in case of failures. The preferred option can be picked by a user depending on what type of system they are modelling.

COMPASS turbine setting "One Off All Off" defined as TRUE will cause all turbines to switch off in case of a failure, the same option set as FALSE will let the other turbines in the system to continue operation in the event of a failure. This is designed to allow for a passive yaw system where turbines on the substructure face wind direction by the means of a single point turret mooring system. Such system has been demonstrated in a laboratory environment in FlowWave (Mujahid Elobeid, 2023). Passive yaw system cannot operate if one of the turbines goes off.

There is no limit for the number of twins on the shared platform, however the larger the number of twins the longer the computational time will be because COMPASS will treat each twin individually when computing maintenance activities for them. Higher number of iterations leads to longer computational times.

Another assumption is made that personnel that arrived by a maintenance vessel can walk between turbines to continue planned maintenance, hence a service vessel does not need to move between turbines. For this reason planned maintenance activities are automatically combined for the twin turbines. It is not yet clear whether a HLV or an SOV would need to adjust its position in the case when large parts are involved, that cannot be carried safely by personnel.

The logic shown in Figure 4.10 was integrated in COMPASS in a way that allows for simulating the TTP process for floating twin wind turbines. If one turbine on the shared platform requires a major operation in port, then the whole structure will be towed to port i.e. COMPASS recognises the connection between the turbine and tows the whole asset (without the moorings and cables) to the maintenance port.

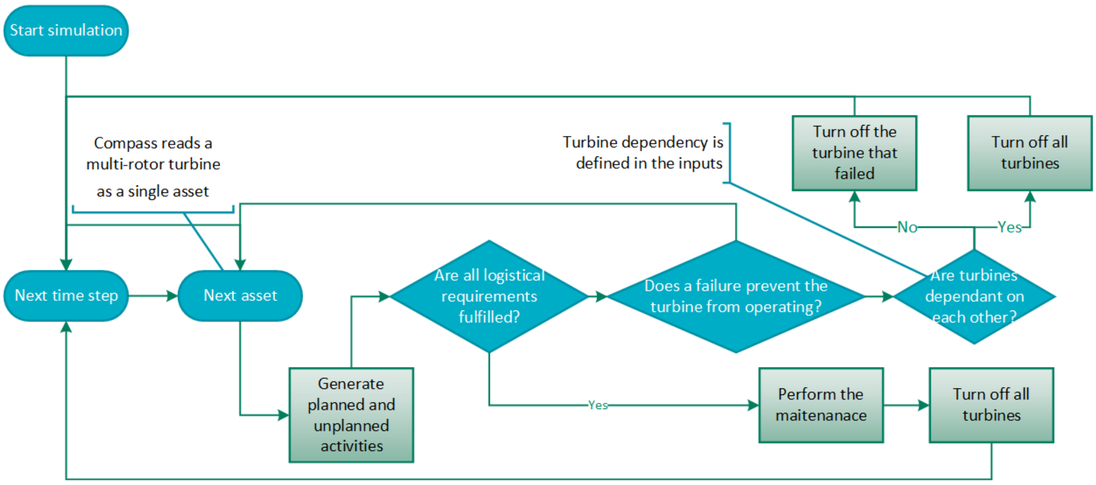


Figure 4.10: Computational logic used in COMPASS for modelling twin turbine maintenance.

4.11 Computational speed improvements

Simulations in the version of COMPASS existing prior to this research work were very limited to small wind farms and very few simulation runs due to the extensive computational time it required. Simulations would slow down when a modelled wind farm would reach summer time where a planned maintenance campaign would be initiated. Computational time is a limitation in time-step-based simulation tools which becomes more of an issue in tools like COMPASS where the tool complexity is gradually increasing with additional features. This issue has not been discussed in detail in any of the previous research studies.

Deterministic models calculate outputs based on average values and scaling factors. These models are fast but cannot capture the intricacies of O&M activities. The speed of deterministic models thus comes at a price of reduced accuracy. Capturing the changes in O&M strategies in deterministic models is also difficult and may involve a lot of assumptions. This section offers some solutions for increasing the computational speed of time-step-based O&M tools.

Although speeding up the simulations was not the objective of this work it became a necessity to enable realistic simulation times for case studies generated in Section 5.3. The list below is the suggestions for improving the computational speed of O&M models.

1. Use a CProfiler to profile the code and get information about where it spends the most time. This option is only applicable to Python-based tools however other programming languages can offer other profiling solutions. This can act as the first step in identifying what needs to be changed. CProfiler was integrated into COMPASS and can give a useful insight into what classes and methods COMPASS spends the most time in. Table 4.2 shows an example of the output from the CProfiler analysis sorted by cumulative time for the first 20 most intensive code activities.
2. Avoid iterating through Pandas DataFrames. Generally DataFrames are useful for processing and visualising tables in Python but not at the scale required for O&M simulation. Functions such as itertuples() and iterrows() slow down the simulation.
3. Avoid copying or editing Pandas DataFrames. As can be noticed in Table 4.2 pandas-related functions are computationally intensive. Particularly anything to do with generating a large DataFrame (like copying or converting a dictionary to a dataframe) will be time-demanding.
4. Operate with lists and dictionaries where possible.
5. Set conditions to skip certain computational steps where possible. For example, if no activities have been generated then the checks for available logistics can be skipped.
6. Write outputs to a file rather than store them within one object. Hour-by-hour operation is now an optional output in COMPASS. It contains the status of each asset, vessel and personnel at each timestep. Storing such output in a DataFrame can lead to overloading the Random Access Memory (RAM) and slowing down the simulation. To overcome this the hour-by-hour outputs can be written into a file at each timestep (i.e. long-term memory).

Table 4.2: CProfiler output example from simulating a wind farm in COMPASS. The top 20 script activities are listed according to the cumulative time or cumtime. Time per call is also listed as percall.

cumtime	percall	filename:lineno(function)
1173.727	1173.727	{built-in method builtins.exec}
1173.727	1173.727	SimulationManager.py:6(<module>)
1172.201	1172.201	SimulationManager.py:24(__init__)
1153.365	1153.365	SimulationManager.py:677(run_time_domain_simulation)
1153.364	1153.364	..\WindFarm.py:243(run_time_domain_simulation)
641.576	0.024	..\WindFarm.py:447(generate_maintenance_activities)
442.61	0	..\WindFarm.py:567(check_asset_activities)
160.327	0.002	..\WindFarm.py:636(merge_activities)
130.71	0	..\Assets\Activity.py:86(get_failure_rate)
99.386	0	..\pandas\core\frame.py:441(__init__)
91.082	0.001	..\pandas\core\internals\construction.py:237(init_dict)
85.174	0.003	..\Assets\AssetManager.py:1019(next_step_setup)
70.485	0	..\pandas\core\generic.py:5560(copy)
69.499	0.001	..\pandas\core\frame.py:1230(from_dict)
61.908	0	..\pandas\core\internals\construction.py:60(arrays_to_mgr)
58.085	0	..\pandas\core\indexes\base.py:293(__new__)
57.846	0.001	..\Computing\WindFarm.py:837(check_asset_logistics)
56.964	0	..\pandas\core\frame.py:2869(__getitem__)
55.349	0.005	..\Logistics\LogisticsManager.py:930(is_full_window_open)
52.199	0	..\pandas\core\internals\managers.py:786(copy)

These changes were implemented in COMPASS and proved to be effective. Most of these are Python-specific but in many cases there are alternatives to these solutions in other languages.

The individual impact of each change proved difficult to track because the changes were committed in bulk to the main COMPASS version, there were also updates of Python versions and PyCharm editor (which was used during this research work) versions that occurred throughout the course of this research work. Table 4.3 compares the time it takes to run the `run_time_domain_simulation()` function of the latest version with the computational time of the historical COMPASS versions. The results are based on simulating one year of operation of the same generic wind farm with 54 fixed wind turbines and 9 vessels using the same processing set-up. All simulations were run with Python 3.11.3 using PyCharm Community Edition 2023.1.2 and a single CPU core.

In Table 4.3, "Version 1" represents the version of COMPASS existing prior the start of this research. In "Version 2" some changes were introduced that reduced the simulation time by a generous 96%. The primary one was the writing of the hour-by-hour outputs into an external file so that it is not stored in RAM. Another change got rid of some Pandas DataFrame iterations. "Version 3" is the latest version with all other efficiency-related modifications added. This latest version includes all the added features described in this chapter. Despite the complexity that was added to COMPASS, the changes listed in this section allowed to reduce computational time by at least 40% compared to "Version 2". Computational time can be reduced by another 15% if the full hour-by-hour output is not generated. This output is only necessary for verification and debugging, as will be discussed further in Section 5.2.

Version	1	2	3	3
Commit date	18/02/2021	01/03/2021	24/03/2023	24/03/2023
Commit time	18:01	13:41	11:45	11:45
Full hour-by-hour output	✓	✓	✓	✗
Elapsed time (seconds)	4735	280	166	141

Table 4.3: Time it takes to run a simulation of a one-year-long operation of a generic 54-turbine wind farm with different historic COMPASS versions.

4.12 Simulation convergence

The fact that the Monte Carlo method is used in the software for modelling random failures means that each simulation will produce a different set of random numbers resulting in varying outputs from simulation to simulation. In order to get a good estimate of the range within which OPEX and other KPIs will lie, simulations need to run multiple times. The higher the number of simulations, the more representative the output values become of the whole population. The level of confidence in results is determined by a convergence study. The aim of the convergence study is to check whether enough simulations were run to get the representative KPIs.

Convergence can be performed on different volatile outputs depending on what outputs are of interest. Common outputs are EA and costs. Several measurements of central tendency can be used to evaluate the outputs such as mean, median or confidence interval (CI). Existing O&M analysis studies report only the mean from their simulations. Whether or not to calculate the CI depends on what is measured and why and the level of uncertainty in the outputs that is seen acceptable.

95% CI bounds in this thesis were calculated either using Student's t-distribution or normal distribution, the former is commonly used when a number of samples (simulations in this case) is low (< 30). If time and computational effort allow to run more simulations then normal distribution can be used. CI can be calculated using Equation 4.1

$$CI_{95\%} = \mu \pm MOE \tag{4.1}$$

Where MOE is the Margin Of Error calculated using Equation 4.2.

$$MOE = t_{95\%,n-1}\frac{\sigma_n}{\sqrt{n}} \tag{4.2}$$

In Equation 4.2, μ is the mean value of the sample, t is the confidence level value which varies with the confidence level and number of samples (simulations), σ is the standard deviation of the sample population and n is the sample size. The value of t can be calculated numerically, however in this study `CONFIDENCE.T()` or `CONFIDENCE.NORM()` function were used in Excel (for t-distribution and normal distribution respectively) to calculate the 95% CI using built-in t values.

Convergence was evaluated for mean and CI values. It was evaluated by measuring by how much each additional simulation changes μ or CI output. For example, μ would be calculated for the results from 10 simulations and then recalculated for 11 simulations and the relative change would be measured as Equation 4.3 demonstrates, where V_n is the output value after n simulations.

$$\textit{Relative change}_{n+1} = \frac{V_{n+1}}{V_n} \tag{4.3}$$

If the value stays close to 1 for several simulations then it indicates that additional simulations do not add an extra value. Choosing the acceptable relative change value depends on the desired accuracy and available computational time.

What is measured can play a role in convergence. Mean values typically converge faster than the CI, CI convergence can also depend on the selected bounds, whether it is 95%, 75% or less, the smaller the bounds, the faster the convergence. Depending on the type of simulations, some values can be more volatile than others. The acceptable level of convergence is case-specific and should be decided based on the impact that it can have on the outcome. Relative change of the output values should be lower than the difference in these outputs from two O&M strategies under comparison, otherwise it can impact the selection of the optimal strategy. That is, if the cost of one O&M strategy is 5% higher than the cost of the other, then enough simulations are required to keep the relative change in the mean cost output under 5%.

Because of the stochastic nature of simulations convergence depends on the number of simulated events. Number of simulated events will increase with increased number of simulations, increased FR or an increased number of assets in the simulation.

Chapter 5

O&M Tool Verification

5.1 Existing Verification Techniques

Verification and/or validation is necessary to build confidence in the results of simulations, to showcase that it is functioning as it was designed to function, and to identify the areas where potential improvement could be made. This thesis adopts the definitions of verification and validation from Dinwoodie et al. (2014) and Michael Welte et al. (2018) that are based on Sargent (2010). Verification of a simulation model is defined as ensuring that the computerized model is implemented according to the specifications of an underlying conceptual model of the system. Validation of the computer model is defined as ensuring that the model is sufficiently accurate for its intended applications. Validation of O&M simulation tools against existing wind farm operation is challenging due to several reasons:

- Sensitivity of wind turbine failure data: wind farm operators avoid sharing the failure information about their turbines to protect their reputation.
- Most O&M simulation tools are stochastic. This means that for any farm, they produce a possible range of outputs for this farm. This could be a range of costs, TA, vessel usage etc. If an existing farm is considered there will only be one value for the costs, availability and other outputs.
- Most wind farms are under 10 years old and have not experienced a full range of O&M scenarios.

Not all tools reported in Table 3.1 follow the same definition of verification and validation. Two models from Table 3.1 were not compared with real life scenarios or benchmarked against existing tools, instead, the validation was performed by an expert reviewing the model. ECN O&M Access tool has been reviewed by GL Wind (Dewan & Asgarpour, 2016). Similarly, Integrated Decision Support Tool (TU Delft) was reviewed by an expert from a wind farm developer Vatenfall (Koopstra, 2015) via an interview. Neither of the models revealed the process of their expert review or any of the tool criteria by which they were evaluated. It is also not clear how much access these experts had to the documentation of these tools and the code itself.

Benchmarking one simulation tool results against the other is a more accessible option compared to validation. This method also eliminates any specialist bias. Five of the O&M simulation tools presented in the Table 3.1 have been benchmarked against each other in two separate studies. One study compared the Strathclyde, NOWIcob, UiS Sim Model and ECUME simulation tools (Dinwoodie et al., 2014). All of the tools were discrete event, time-sequential modelling tools using the Monte Carlo simulation method. These simulations assumed failures only on the generating assets i.e. wind turbines and did not include cable failures and their effect on the power output. The study focused only on fixed offshore wind. Rinaldi et al. (2018) has extended this work and compared the UoE/JFMS model outputs against the outputs of the tools presented in Dinwoodie et al. (2014). This process was performed in three stages:

- Calibration: Run a set of simulations and perform the initial comparison. Identify the differences and adjust the computation.
- Sensitivity analysis: Vary the inputs and run the simulations
- Comparison: Compare the results with other models.

The study showed the performance of the UoE/JFMS Model against other simulation tools using the base case from Dinwoodie et al. (2014) and four variations to the base case that were prioritised:

- increase in FRs
- reduction of the CTVs available
- the exclusion of all failure categories, leaving only major replacements
- the exclusion of major replacements and leaving the rest of the failure categories

Another study that is very relevant in the context of tool verification is Sperstad et al. (2017). The objective of this work was to test how well the selected tools align in the selection of the optimal O&M vessel fleet. NOWIcob, DSS for Vessel Fleet Analysis, Shoreline Design, ECUME-I and StrathOW O&M were the tools used in this study. Sensitivity analysis was performed on these tools by varying several parameters, changes in H_s and FR resulted in the highest impact on the vessel fleet ranking. The analysis showed that these simulation tools agree on which vessel fleet is the best for the scenario given in the study but they only partially agree on the overall ranking of the different vessel fleets. It was concluded that the differences were not the result of the simulation methods but were rather dependant on how optimistic or pessimistic the modelling assumptions were.

This chapter verifies the COMPASS tool in three ways: via creating an output option for observing full hour-by-hour operation, via benchmarking it against other tools inspired by the work presented in Dinwoodie et al. (2014) and Rinaldi et al. (2018) and via performing a set of case studies covering a range of scenarios. The aim of this approach is to build confidence in COMPASS outputs. Section 5.2 presents a section of the full hour-by-hour output available in COMPASS. Section 5.3 then runs the benchmarking study of three O&M simulation tools: COMPASS, WavEC O&M tool and WOMBAT (Hammond & Cooperman, 2022; WavEC, 2023). The study methodology is based on the previous study Dinwoodie et al. (2014) but the inputs have been updated. This study also takes a step further and looks at how three O&M simulation tools perform at TTP scenarios which has not been done before. Sections 5.4 - 5.7 then present a set of case studies that use COMPASS.

The purpose of these studies was not only to build confidence in the outcomes of COMPASS tool but to also demonstrate novel applications of it and address some of the questions around current technologies and O&M strategies. Wind farm layouts used in this chapter are hypothetical and do not take into account unexploded ordnance, environmental measurements or wake effects. The layouts were approximated solely for purposes of O&M simulation.

5.2 Hour by hour output review

With each development in COMPASS, the tool functionality was checked by running test cases with hourly output. Hourly output metrics are presented in Section 3.3. Full output is produced in Excel at the end of each simulation and shows hour-by-hour operation on a wind farm. The file can be used for ensuring that the code works as expected. The output file is large and contains thousands of cells reporting asset, vessel and personnel status and location, it is therefore only produced for the first year or two of wind farm lifetime. Figure 5.1 presents a screenshot of the full output capturing the twin floating wind turbine maintenance. It presents only a section of the full output showing hour-by-hour change in weather conditions and turbine status, availability and location.

Because of the complexity of this output there is a high chance of missing some errors. Simulating just one year of wind farm operation with full outputs means there are 8760 rows of data in the output file. Each row represents an hour of wind farm lifetime. The number of columns depends on the number of turbines, vessels, and personnel modelled. The larger the farm the bigger the output file gets. Future work includes developing a visualisation tool that would allow to track all these operations visually thus making it easier to verify the simulation outcomes.

wind_speed	wave_height	WTG_NE8_1_Location	WTG_NE8_1_Status	WTG_NE8_1_ActivitiesDue	WTG_NE8_1_Availability	WTG_NE8_1_Revenue
3.572271632	1.1135268	58.268,-1.2995	Awaiting Repair	Control and Protection System Control Light Repair	[0, 0]	0
2.094666901	1.0886824	58.268,-1.2995	Awaiting Repair	Control and Protection System Control Light Repair	[0, 0]	0
1.614777071	1.0650926	57.5028,-1.7742	Services Arrive	Control and Protection System Control Light Repair	[0, 0]	0
3.862630085	1.0448909	57.5028,-1.7742	Services Arrive	Control and Protection System Control Light Repair	[0, 0]	0
6.208529483	1.0271986	57.5028,-1.7742	Services Arrive	Control and Protection System Control Light Repair	[0, 0]	0
7.360568263	1.0093808	57.5028,-1.7742	Disconnecting	Control and Protection System Control Light Repair	[0, 0]	0
7.332252478	0.99193954	57.5028,-1.7742	Disconnecting	Control and Protection System Control Light Repair	[0, 0]	0
7.318051021	0.9760041	57.5028,-1.7742	Disconnecting	Control and Protection System Control Light Repair	[0, 0]	0
7.048643228	0.96057034	57.5028,-1.7742	Under Tow	Control and Protection System Control Light Repair	[0, 0]	0
6.766852086	0.94450927	57.5028,-1.7742	Under Tow	Control and Protection System Control Light Repair	[0, 0]	0
6.30331817	0.92869925	57.5028,-1.7742	Under Tow	Control and Protection System Control Light Repair	[0, 0]	0

Figure 5.1: A snapshot of an hour-by-hour operation of a hypothetical twin floating wind turbine as seen in the full output from COMPASS simulation. Turbine location gets updated to port location the moment that the services (vessels and personnel) arrive but port costs are only applied from the moment the turbine reaches the port. Availability figures are calculated separately for each turbine twin. There may be scenarios when one twin is working while the other is stopped.

5.3 Benchmarking COMPASS

5.3.1 Participating O&M models

Three O&M simulation tools were included into this benchmarking case study: COMPASS, WOMBAT and WavEC. These tools were included into O&M simulation tool review in Section 3.2. A more detailed description of each tool is given in Table 5.1.

Table 5.1: O&M simulation tools that were involved into the benchmarking study.

Model	Description
COMPASS	See Section 3.3
WOMBAT v0.8.1	Open source O&M simulation tool designed by NREL. The purpose of the tool is to understand the trade-offs of maintenance and technology strategies during the O&M phase of a wind farm. It operates by breaking down the wind farm lifecycle into time series and performing necessary computations at each time step. Both the code and the documentation are publicly available (Hammond & Cooperman, 2022).
WavEC O&M tool	WavEC's in-house O&M simulation tool was designed to support the project development of ORE farms and make informed decisions about O&M planning and logistics (WavEC, 2023). WavEC O&M simulation tool utilises some of the computational logic from the existing DTOcean+ design tools, which has been further improved withing the EU-SCORES project (Correia da Fonseca et al., 2021; EU-SCORES, 2023).

The process of benchmarking was performed via setting a regular communication with all model developers, agreeing on the common inputs to be used, running the simulations and then comparing and discussing the results. All simulations were run independently by model developers.

All three models are in the state of active development and get regularly updated and fixed when necessary. The results presented in this section are only valid for the versions of the models that have existed by September 2023. It is not the purpose of this section to rate the models but to identify the difference in computational logic and assumptions, understand its impact on the results and highlight the importance of benchmarking the tools for building confidence in the simulation outputs.

5.3.2 Wind farm overview

A wind farm was designed for benchmarking purposes only. Figure 5.2 shows the layout of the wind farm and its cable connections. Same layout and cable connection was used in all scenarios. Table 5.2 describes the characteristics of this wind farm and its turbines.

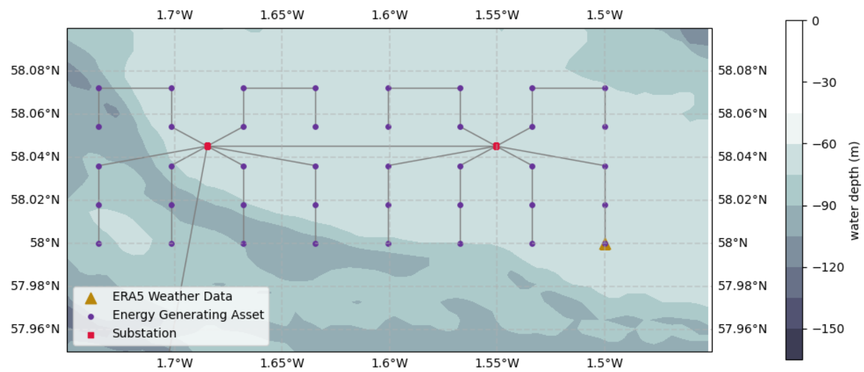


Figure 5.2: Farm layout with 2 substations, 40 turbines and 40 cables in a radial connection consisting of 12 strings.

Table 5.2: Wind farm characteristics used in cross-model verification.

O&M port	Fraserburgh (CTV/SOV)
Towing port	Peterhead
Distance to port	within a 45-55 km range
Number of turbines	40
Lifetime	20 years
ERA5 weather data point	58.00, -1.5 (100 m height)
ERA5 starting time	01/01/2000 00:00
Distance between turbines	2 km
Turbine capacity	15MW (NREL, 2020)
Array cable length	2.4 km
Foundation type	semi-submersible
Mooring line length	600 m

5.3.3 Vessel inputs

Table 5.3 contains the assumptions used to characterise vessels used in this verification study. It was not the purpose of this study to validate these assumptions. The purpose of this cases study was to benchmark the simulation methods used in each tool. Same vessel inputs were used in all three tools. The outputs are compared and discussed in Section 5.3.7. Six types of vessels were used: CTV, ROV support vessel (RSV), Anchor Handling Vessel (AHV), HLV, CLV and the AHTS.

Cases were broken down into two groups depending on how major operations are performed. There are two options considered in this study: in-situ maintenance and TTP. In the case of in-situ maintenance it is assumed that a semi-submersible HLV would perform the maintenance operation. In the case of TTP option HLV would not be involved and would be replaced with an AHTS that would perform the towing operation. All other vessels would stay the same.

In the case of towing the wind turbine, some time will be spent on disconnecting it from the cables and moorings and then connecting again once the operation is complete. The connection and disconnection times are assumed to take 12 hours. It was assumed that the cable remains connected during that time i.e. there is no disruption in power production from the rest of the farm. The use of the quayside during TTP operations was assumed to cost £130,000 per day.

This work considered only the H_s limit for the vessels however it recognises that wind speed and wave period can also significantly impact the operations.

Three types of charters were considered: long-term, summer and hired charters. In the case of a long-term charter a vessel is on a permanent contract and is always at the O&M port (when it is not doing maintenance work). Summer lease is similar but the contract is limited to summer months. When a vessel is hired it means that there is no long-term contract with this vessel and it may take time to bring it from a different location to the local port and mobilise it, therefore there is mobilisation time and cost associated with these vessels.

Table 5.3: Vessel characteristics

Vessel	CTV	RSV	AHV	HLV	CLV	AHTS
Number of vessels	3	1	1	1	1	2
H_s limit	1.5 m	2.5 m	2.5 m	2.0 m	2.0 m	3.0 m (transit), 1.5 m (tow)
Mobilisation cost (£)	0	0	325 000	325 000	500 000	200 000 (each)
Mobilisation time	0	0	2 weeks	2 weeks	2 weeks	2 weeks
Speed	20 kts	12 kts	12 kts	11 kts	20 kts	20 kts (transit), 3 kts (tow)
Seats	12	40	20	100	50	24
Day rate (£)	2 500 (each)	24 000	41 500	200 000	80 000	27 800 (each)
Time limit	1 shift	1 shift	no limit	no limit	no limit	no limit
Charter type	long-term	summer	hired	hired	hired	hired

5.3.4 O&M activities

O&M activity characteristics in this section were developed solely for the purpose of benchmarking the simulation methods of the selected tools. These inputs are partially based on previous work by Dinwoodie et al. (2014) and may not be fully representative of real life O&M. Section 2.3 however provides a more detailed guidance on wind farm maintenance activities that should be used in O&M simulation tools. Inputs in this case study were significantly simplified in order to fit the format of inputs of each tool used in the study.

Activities were grouped into minor activities, major repair, major replacement, subsea activities and annual service. Tables 5.4 - 5.9 summarise the assumptions associated with each activity.

The rates of minor activities were adjusted according to the rate of forced outages reported by SPARTA (2022). The rate was reduced by 85% as justified in Section 2.3 to account for remote reset. The rate was then split in the ratio 50/50 between shorter minor activities and longer minor activities.

Costs of minor activities were taken from Dinwoodie et al. (2014) and upgraded according to the cost ratio between 3 MW and 15 MW turbines taken from the ORE Catapult's cost model. It was assumed that some minor activities would take longer time than other. Table 5.4 and Table 5.5 summarise the assumptions associated with shorter and longer minor activities respectively.

Table 5.4: Minor repair activities assumed for the verification study.

System	Repair time (h)	Required technicians	Vessel type	Rate per turbine per year	Repair cost (£)
Rotor	4	2	CTV	0.9	4 200
Generator	4	2	CTV	0.57	4 200
Drive train	4	2	CTV	0.39	4 200
Transmission	4	2	CTV	1.815	4 200
Yaw	4	2	CTV	1.17	4 200
Central Hydraulics	4	2	CTV	0.57	4 200
Other	4	2	CTV	0.27	4 200
Substructure	4	2	CTV	0.5	4 200

Table 5.5: Medium repair activities assumed for the benchmarking study.

System	Repair time (h)	Required technicians	Vessel type	Rate per turbine per year	Repair cost (£)
Rotor	11	4	CTV	0.9	77 700
Generator	11	4	CTV	0.57	77 700
Drive train	8	4	CTV	0.39	77 700
Transmission	16	4	CTV	1.815	77 700
Yaw	5	4	CTV	1.17	77 700
Central Hydraulics	6	4	CTV	0.57	77 700
Other	6	4	CTV	0.27	77 700
Substructure	8	4	CTV	0.1	77 700

For major repairs and replacements, rates were also based on publicly available SPARTA review (SPARTA, 2022). Because there is no split between major repairs and major replacements in SPARTA, this benchmarking study assumes a split with a 50/50 ratio.

Replacement costs were taken from the Guide to an Offshore Wind Farm with an exception for electrical component costs (ORE Catapult & BVG Associates, 2020). Costs are not the focus of this study but they are one of the KPIs from the models and hence are required for comparison. Major repair was assumed to cost 20% of the major replacement. These and other assumptions associated with major repairs and replacements are provided in Tables 5.6 and 5.7 respectively.

Table 5.6: Major repair activities assumed for the benchmarking study.

Component	Repair time (h)	Required technicians	Vessel type	Rate per turbine per year	Repair cost (£)
Blade	24	10	HLV/AHTS	0.03	130 000
Electrical	24	10	HLV/AHTS	0.003	100 000
Gearbox	24	10	HLV/AHTS	0.009	210 000
Generator	24	10	HLV/AHTS	0.003	300 000
Main Bearing	24	10	HLV/AHTS	0.001	60 000

Table 5.7: Major replacement activities assumed for the benchmarking study.

Component	Repair time (h)	Required technicians	Vessel type	Rate per turbine per year	Repair cost (£)
Blade	48	15	HLV/AHTS	0.03	650 000
Electrical	48	15	HLV/AHTS	0.003	500 000
Gearbox	72	15	HLV/AHTS	0.009	1 050 000
Generator	96	15	HLV/AHTS	0.003	1 500 000
Main Bearing	96	15	HLV/AHTS	0.001	300 000

Table 5.8: Subsea repairs assumed for the benchmarking study.

Activity	Repair time (h)	Required technicians	Vessel type	Rate per year	Repair cost (£)
Mooring replacement	48	10	AHV	0.002/km	570 000 (mooring + anchor)
Array Cable replacement	48	15	CLV	0.006/km	200 000

Annual service is split into three parts: inspection of turbine components, inspection of the lifting and safety equipment and inspection of HV components. Annual service assumptions are provided in Table 5.9.

Table 5.9: Annual service activities assumed for the bechmarking study.

Activity	Repair time (h)	Required technicians	Vessel type	Rate per turbine per year	Repair cost (£)
Annual service (turbine)	16	3	CTV	1	5 000
Annual service (lifting & safety equipment)	4	3	CTV	1	5 000
Annual service (HV components)	8	3	CTV	1	5 000
Cable and scour survey	8	4	ROV	1	10 000
ROV inspection (moorings and cables)	8	4	ROV	1	10 000

It was agreed between the developers to model turbine failures so that once a failure on a turbine occurs it continues its operation. The turbine would then switch off once a maintenance starts. The turbine would not switch back on until the whole maintenance campaign is complete. This was done to narrow down the differences between the models.

In COMPASS there is an option to merge activities together, as described in Section 4.4. It was assumed that minor and medium activities can be combined together if there is an opportunity to do so. All major operation activities in COMPASS were set to be performed individually. Additional simulations were run in the TTP scenario where all activities have to be performed individually. Section 5.3.7 will show that in the TTP scenarios activity merging has an impact on the outputs, particularly in the case where FRs are high.

5.3.5 Sensitivity analysis overview

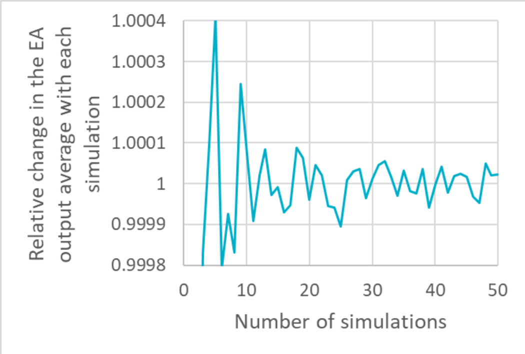
Two base case studies were designed: one where major maintenance would be performed using a HLV and another where a turbine would TTP for maintenance using two AHTS vessels. In both cases a sensitivity analysis was performed with the following changes to the original inputs:

1. No major repairs and replacements (modelled only once because two cases become the same when there are no major maintenance activities).
2. All FRs increased by 100% (annual service activities excluded).
3. Maintenance duration of all activities increased by 50%
4. H_s for vessels increased by 0.5m including the limit for TTP operations.

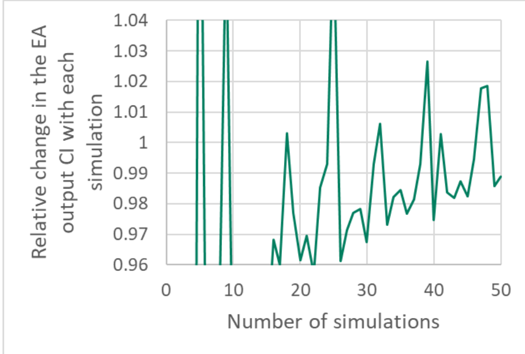
5.3.6 Convergence

COMPASS was run 50 times with each scenario. In this benchmarking study craft costs and EA are considered to be the most volatile outputs because they depend on many factors: weather, frequency of operations, opportunistic maintenance. Convergence study was performed on these two metrics. Convergence was calculated as discussed in Section 4.12. Although only the average output values were compared in this study, convergence analysis was also performed on the CIs of the outputs to demonstrate the slower rate of convergence in CIs. Figure 5.3 shows how COMPASS simulation results converge after 50 simulations. Even after just 10 simulations results converge to the level that is significantly lower than the difference between the outputs from the three models observed in the next section.

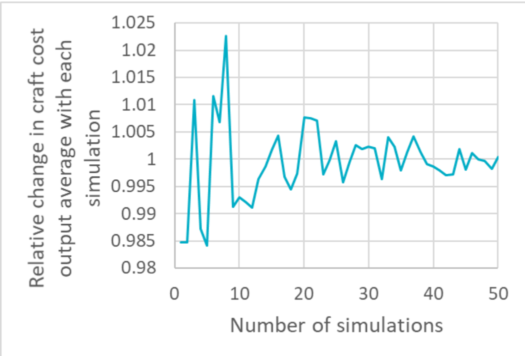
CI converges much slower than the mean value but varies within an acceptable range after 40 simulations. CI is not compared between the models in this study.



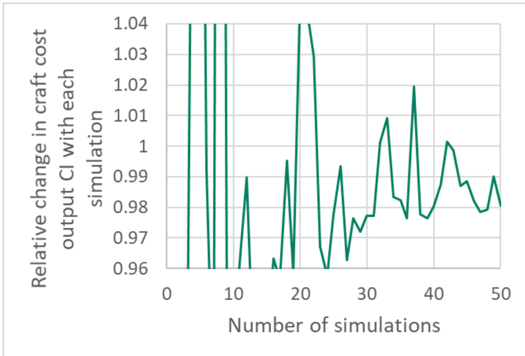
(a) Average EA convergence



(b) EA CI convergence



(c) Average craft cost convergence



(d) Craft cost CI convergence

Figure 5.3: Convergence of outputs from 50 simulations of the Case 1 "Base" case study. Values show the impact of each additional simulation on the average output. In this case running more simulations has very little impact on the average result. Relative change in the average output is too low to have an impact on the comparison between the models.

5.3.7 Results

Figure 5.4 shows the comparison of the total O&M costs resulting from the three models. All three models align very well in this metric and vary to the similar degree with the change in the inputs. Interestingly, although O&M strategy analysis was not the purpose of this study, it shows that all three models are consistent in selecting the optimal maintenance strategy. It can be observed in Figure 5.4 that all three models in this study agree on TTP scenarios to be more expensive than in-situ maintenance scenarios with current assumptions when same sensitivity analysis scenarios are compared.

O&M costs alone do not show the full picture, more metrics are required to benchmark the O&M simulation tools and understand the differences in methodology. The following paragraphs will show that despite the similarities in the total O&M cost outputs, the scale of differences in other metrics is much higher which is explained by the dissimilarities in some methods and assumptions used in the models.

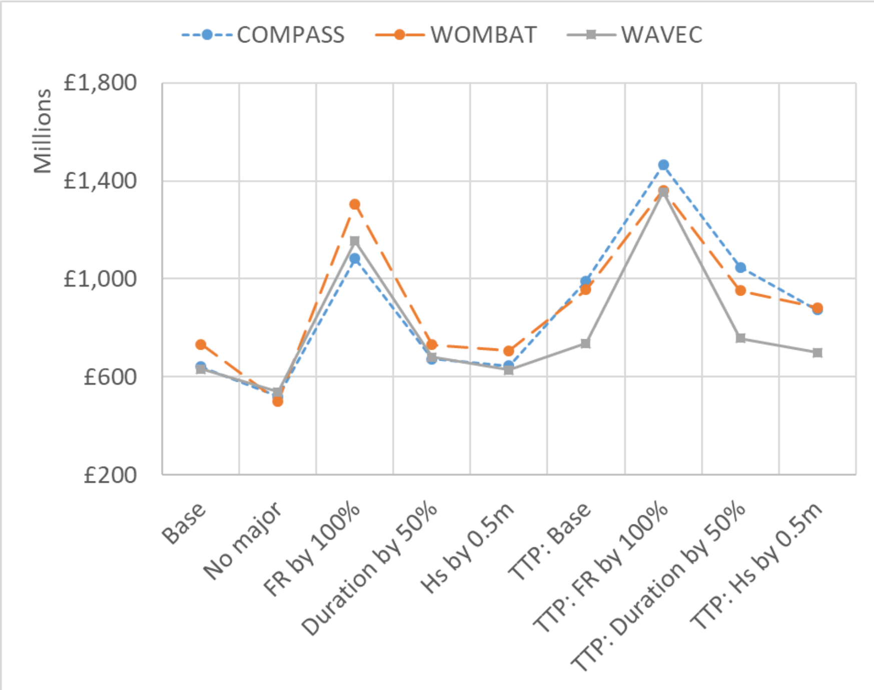


Figure 5.4: Total O&M costs

Figure 5.5 shows the mobilisation cost comparison between the models for the in-situ maintenance. The peaks and troughs of the results are aligned between the models for these scenarios. In the scenario with no major repairs the definition of a major repair was not specified explicitly, therefore different assumptions were made in different models. In COMPASS, in the "No major" scenario only those activities that require CTVs were left. In the WavEC O&M tool only major activities on the turbines were removed. WavEC O&M tool and WOMBAT results for this metric are almost consistently aligned and are consistently higher than COMPASS outputs. This is possibly due to COMPASS allowing for a 24-hour wait for a new activity for each vessel before it gets demobilised. Another reason is the fact that COMPASS does not compensate for the lost failure opportunity which will be discussed further in this section.

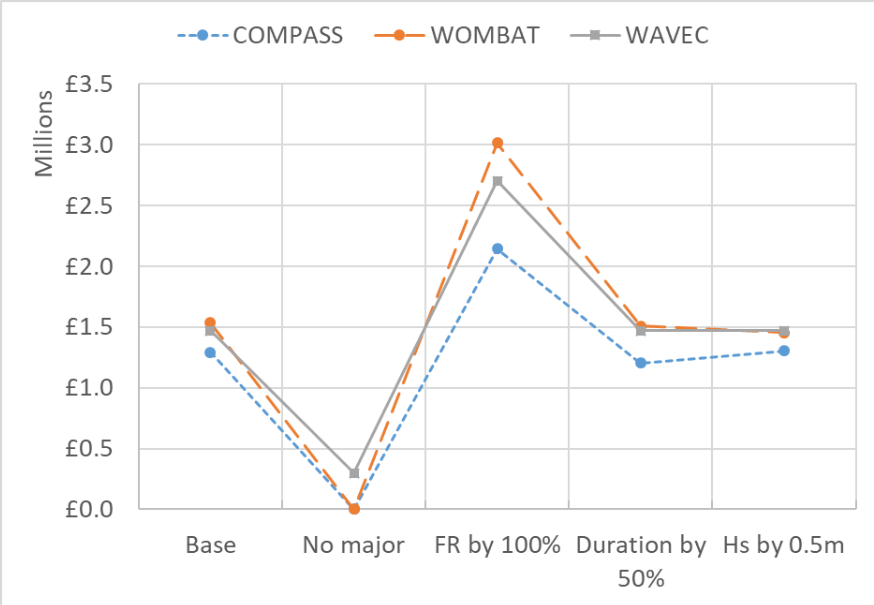


Figure 5.5: Total vessel mobilisation costs per year for the in-situ maintenance scenarios.

Figure 5.6 shows the mobilisation cost comparison between the models for the TTP maintenance. Vessel mobilisation costs are not applied in WOMBAT when AHTSs are required for towing. In COMPASS and WavEC O&M tool the logic remains the same as for any other case i.e. if the vessel is on hire, there is a mobilisation cost and a mobilisation time associated with it. This difference is reflected in the difference in results seen in Figure 5.6. Interestingly, COMPASS results are lower than those resulting from WavEC O&M tool in the increased FR scenario and the shifted H_s limit scenario. One possible explanation is the fact that COMPASS recognises when one activity happens after the other thus removing the need for additional mobilisation costs. When FRs increase there is a higher chance of multiple failures happening on the wind farm, hence more opportunities for the described behaviour. WavEC O&M tool mobilisation costs on the other hand are directly correlated to the number of asset failures defined in the inputs.

When H_s limit is lifted, COMPASS costs go down unlike WavEC O&M tool cost outputs which stay the same (because the number of asset failures stay the same). In COMPASS, AHTS vessels have a 24-hour waiting period described earlier in this thesis. Some maintenance activities in the inputs are 24-hour-long. When H_s limit is lifted there are more weather opportunities for an AHTS to return the turbine back to its site position straight after the maintenance on it is finished. This means that AHTS does not get demobilised and then mobilised again. It gets mobilised, and stays mobilised until the end of an operation.

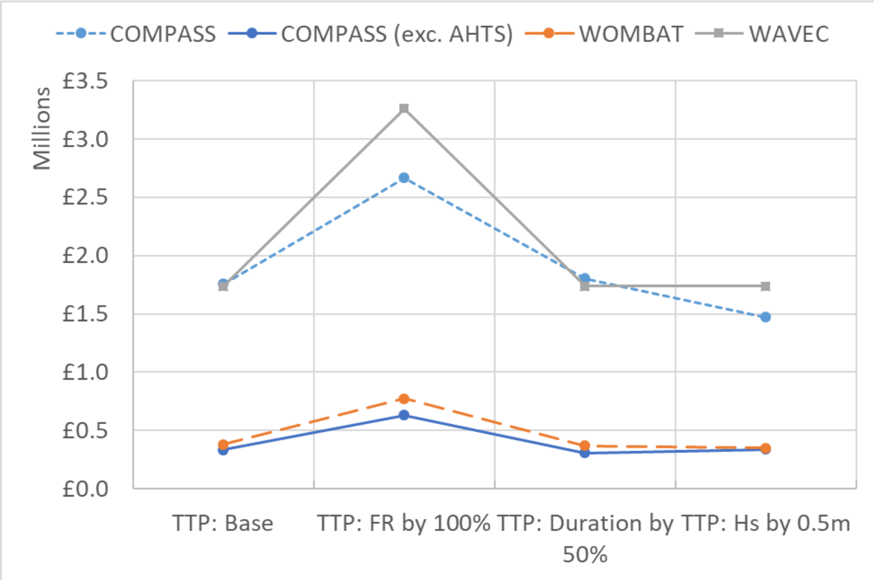


Figure 5.6: Total vessel mobilisation costs per year for the TTP maintenance scenarios.

When it comes to vessel hire costs, there is a significant variability in results. The main reason for this is the approach taken in the models for modelling activity interruption. One of these approaches is to do with how personnel shifts are modelled in WOMBAT. WOMBAT takes into account personnel shifts (assumed to be 12-hour-long for this study) and breaks down a maintenance campaign accordingly. If a vessel is offshore and a shift is over, that vessel will return to port and then resume the operation the next day. The same applies to weather, activities cannot resume if the weather conditions are not appropriate. Because the logic is applied on larger (more expensive) vessels such as HLV or CLV, it results in significant differences between the models when hire costs are compared. It can be observed in Figure 5.7 that when the shift duration is increased from 12 hours to 24 hours, the vessel hire cost drops. There may be other logic orders that have not been identified but which result in the dissimilarities between the results.

Interestingly, in WOMBAT and COMPASS the results are not as sensitive to the change in inputs in the TTP scenario as they are in the in-situ maintenance scenario. In the in-situ sceneario the hire rate of a HLV is 3.6 times higher than that of two AHTSs which explains why hire costs do not rise as much in the TTP cases as they do in the in-situ cases. WavEC O&M tool hire costs increase significantly with an increase in FRs. This is due to the WavEC O&M tool modelling the ongoing hire of the AHTS while it waits for the turbine to finish the maintenance in port. In COMPASS and WOMBAT this (waiting) AHTS hire cost is not applied. Additionally, in COMPASS there was no limit set for the number of turbines to be present at any one time in port. This means that several TTP operations may happen on the same day. This may also explain lower hire costs.

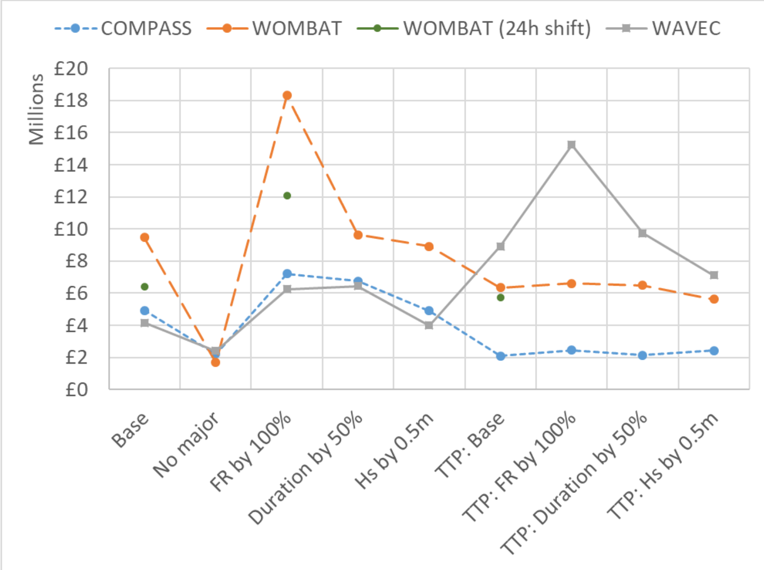


Figure 5.7: Total vessel hire costs per year for each scenario.

It was agreed between the participants to not model weather downtime associated with any maintenance activity. If a turbine requires maintenance it continues operating until the maintenance operation starts. This was done for the purpose of benchmarking. Neglecting weather downtime allows to narrow down the differences between the models that occur due to the differences in modelling logic. In reality, there may be some activities that lead to shutting down the turbine until it gets repaired, particularly minor operations.

Although this work does not model downtime prior to the maintenance campaign, all models measure WoW for each vessel, this metric was introduced in Section 4.7. It has not been previously used in model verification (Dinwoodie et al., 2014; Rinaldi et al., 2018). It is a measure of the average number of hours each vessel has to wait before starting the maintenance campaign. This work compares WoW for CTVs in Figure 5.8. COMPASS results are aligned with WOMBAT with some exceptions but are significantly higher than WavEC results. This is due to how WavEC computes this metric. Unlike COMPASS or WOMBAT, WavEC allows vessels to proceed with an activity even if a continuous weather window is not available. WavEC allows for an activity to be interrupted, hence WoW is integrated into the activity time rather than calculated separately. It uses a similar logic to that of WOMBAT with personnel shifts. Activity gets interrupted if the weather conditions worsen and then restarts again when the weather conditions improve.

The overall trend is similar in all three models in most cases with the waiting time increasing when the FRs or repair times increase and drops sharply when the H_s limit for vessels is shifted.

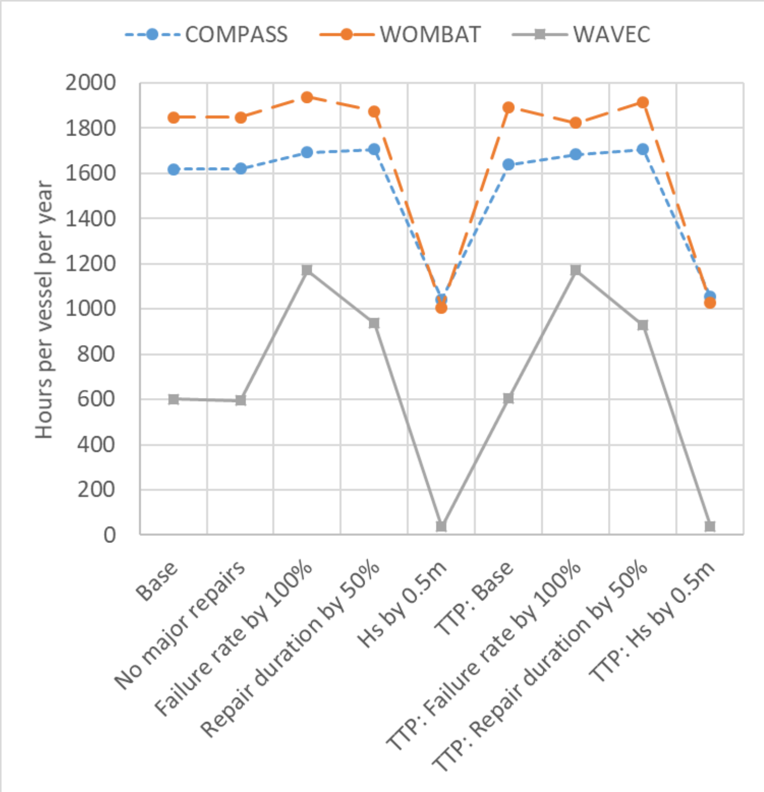


Figure 5.8: CTV WoW per vessel per year for each scenario.

COMPASS WoW results follow the similar trend to WOMBAT in most cases. The difference could also arise from the fact that WOMBAT takes personnel shifts into account.

Similarly to the vessel hire, EA turned out to be a metric with a significant difference between the models. Figure 5.9 demonstrates the EA results. COMPASS resulted in the highest EA values, followed by the WavEC O&M tool and WOMBAT results. The reason for these differences is partially to do with how activity interruption is modelled. In WavEC O&M tool this interruption occurs due to weather conditions, in WOMBAT activities get interrupted due to personnel shifts and unsuitable weather conditions. COMPASS on the other hand does not break down an activity into sub-activities and assumes they are always continuous and looks for a continuous weather window.

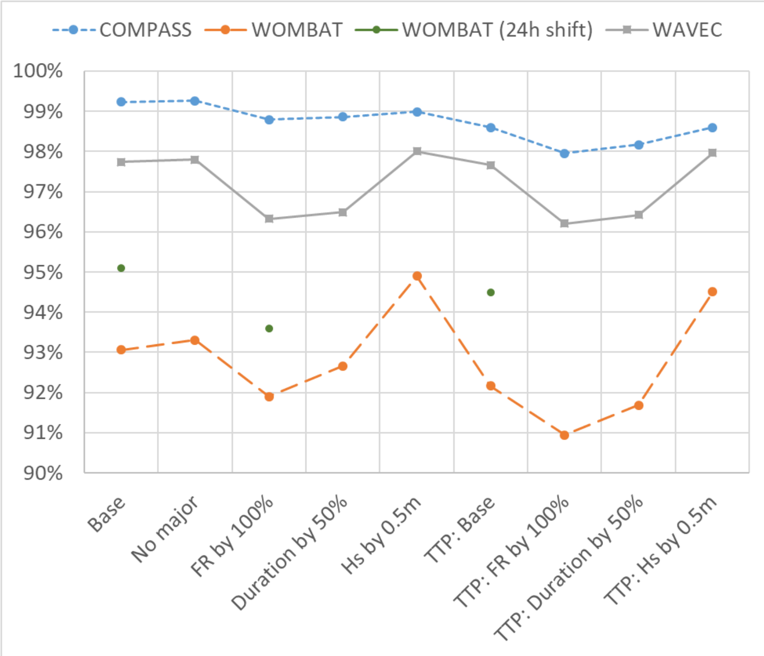


Figure 5.9: EA results for each scenario.

When personnel shifts are switched to the 24-hour period in WOMBAT, the availability output increases but it still does not align with WavEC or COMPASS results indicating that there are other computational differences in place. The difference may partially arise from the fact that the turbine switches off the moment the vessel leaves the harbour in WOMBAT while in COMPASS and WavEC this switching occurs the moment the vessel arrives to the turbine. Another reason is the frequency at which WOMBAT performs the weather window check. In COMPASS this check is performed at every simulated hour while in WOMBAT this check is applied every four days.

It is consistent between all three models that TTP scenarios result in lower EA values (with the given input assumptions). This shows that all three models are consistent in identifying the optimal strategy when it is evaluated in terms of EA.

Interestingly, Figure 5.9 also shows that the lower the average availability outcome from the model the more sensitive it becomes to the change in the inputs.

Counter-intuitively, the scenario with the shifted H_s limit for vessels resulted in lower EA in COMPASS compared to the "Base" case. This effect is not observed in other two models because the effect of activity interruption counteracts it. The effect is explained by the correlation between the H_s and wind speed. If the vessel H_s limit is shifted then rather than waiting for a milder weather, vessels go offshore in harsher weather conditions when there is a higher potential for wind turbines to generate electricity. Figure 5.10 supports this argument and shows the comparison between TA and EA. TA stays the same for scenarios "Base" and "H_s

by 0.5m" while EA decreases for the latter. TA also drops 0.7% compared to EA that drops by 0.4% when FRs are increased. It has been initially agreed for this benchmarking study that waiting time prior the start of an activity does not cause turbine downtime. In the "FR by 100%" case there are more turbine visits but they still happen when weather conditions are mild hence they do not impact the EA output as much.

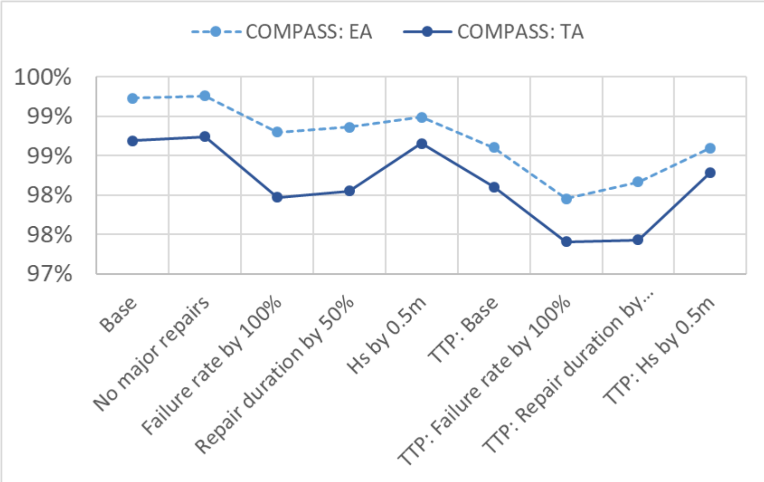


Figure 5.10: EA and TA results compared (COMPASS results only).

Figure 5.11 shows the number of unplanned visits modelled by each tool. Currently COMPASS does not count cable repairs into the total number of unplanned visits. This and the fact that some activities were allowed to be merged together resulted in lower number of visits modelled by COMPASS compared to other tools. Interestingly, there is a slight increase in the number of visits when the H_s limit is lifted. Presumably this is to do with the fact that the WoW decreases and hence the activities have fewer opportunities to accumulate. When activities accumulate they can be merged together. In this case they accumulate to a lesser extent and hence happen separately. This is also reflected in the slight increase in the mobilisation costs (see Figure 5.5). WavEC O&M tool takes a more deterministic approach at modelling the number of visits. In their case the number of visits is directly related to the number of asset failures and planned campaigns.

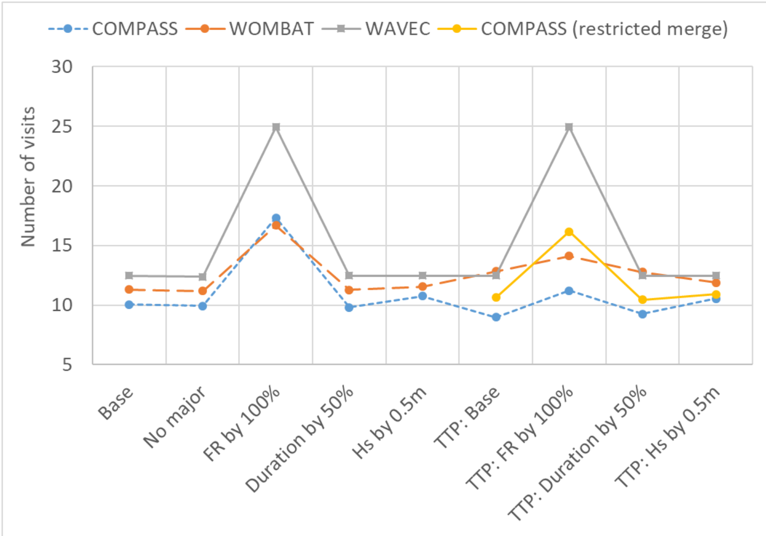


Figure 5.11: Average number of unplanned visits per turbine per year resulting from each scenario.

In the cases where turbines are towed to port for major maintenance the results for turbine visits match to a lesser extent. Interestingly, there is only a small increase in visits in COMPASS when FR is increased. There are two reasons for it. One is the fact that turbine waits for a suitable weather window for a longer time. Similar to the point discussed before this allows for activities to accumulate and be merged together. COMPASS simulations were run again with a restricted merge (i.e. all activities have to be performed in isolation) and a bigger peak was observed. Another reason is the current limitation of COMPASS that it does not compensate for the lost failure opportunity. When a turbine is undergoing maintenance or waiting in port it cannot generate failures. There is currently no function compensating for that i.e. increasing the failure probability in the steps following the maintenance. This results in a lower FR than what was set up by the user and becomes an issue when a FR is high and maintenance time is long. This is also the reason why mobilisation costs are consistently lower.

COMPASS measures KPIs associated with TTP operations. These are AHTS costs, quayside costs and AHTS WoW. There is currently not enough public data to conclude how quayside costs would be applied during the maintenance in port. COMPASS currently calculates the amount of time a turbine spends in port doing maintenance and distinguishes that from time when it waits to return back to site. The same quayside cost is applied to both times and the breakdown is shown in Figure 5.12. If costs are applied only on the maintenance time (work) then they align better with WavEC O&M tool results. WOMBAT does not capture the quayside usage and calculates the associated costs deterministically which align better with total and waiting costs from COMPASS. Additional research and data gathering is needed to understand how quayside costs differ for the working time and waiting time and what they include.

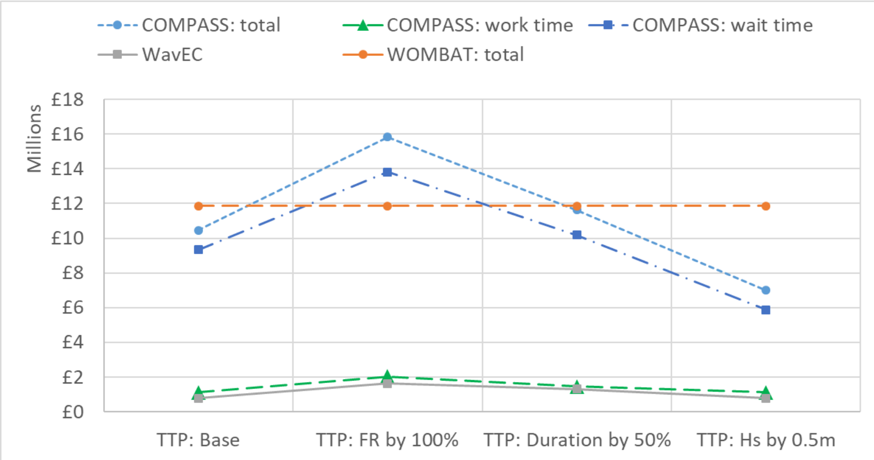


Figure 5.12: Quayside costs per year resulting from each TTP scenario.

Figure 5.13 shows how the AHTS WoW reduces (consistently in all three models) with lifting of the H_s limit. This results in a significantly lower AHTS mobilisation cost and quayside costs highlighting the importance of the H_s limit on towing operations. AHTS mobilisation cost reduces because rather than demobilising it (due to the time limit) and mobilising it again for the return-to-site operation, it gets mobilised only once for the entire campaign. It is likely there are some differences in the methodology that have not yet been identified that result in the difference in the scale of AHTS WoW between the three models. Consistent with CTV WoW results, WOMBAT results in the highest WoW and WavEC O&M tool in the lowest WoW outputs.

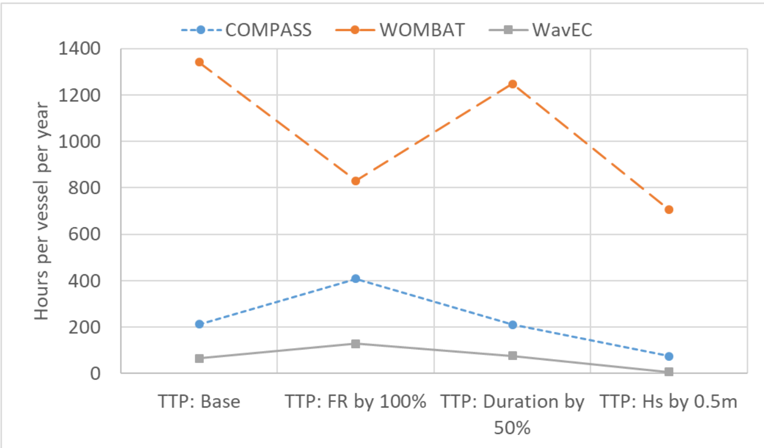


Figure 5.13: AHTS WoW per vessel per year resulting from each TTP scenario.

5.3.8 Benchmarking study discussion

One of the main purposes of O&M simulation tools is to compare O&M strategies. It is therefore expected from these models to pick up the change in the inputs and have it reflected in the outputs. All three models in this benchmarking study align in their response to varying the inputs when it comes to the most important metrics: total O&M costs and EA. That is, when FR increases, the costs increase consistently in all three models compared to the base case. When TTP is introduced, the costs increase in all three models and EA decreases (with the given assumptions). All three models have shown the sensitivity to the inputs but the scale of that sensitivity was found to depend on the methodology used which is different in all models.

This benchmarking study has found that it is particularly the way how O&M simulation tools model activity interruption affects the outputs. WavEC O&M tool models activity interruption due to weather, WOMBAT models this interruption due to both bad weather and personnel shifts. Currently COMPASS assumes all activities to be continuous. It is a desirable feature, but not for heavy-lift operations. Section 2.4 presented the estimation of heavy lift activity duration based on real-life data. The data captures the time of the arrival and departure of the JUV from each wind turbine. This time includes any shift changes and interruption due to weather. It is seen unnecessary to model activity interruption in COMPASS for heavy-lift operations because it is included in the input data. On the contrary, for other activities it could be a valuable feature and should be included into the future work. It is, however, important to perform an industry survey beforehand in order to understand the limitations around activity interruption.

This is the first study that benchmarks O&M simulation tools for TTP scenarios. Interestingly, all three models found that TTP scenarios result in higher costs and lower EA than in-situ maintenance scenarios (with the given set of cost assumptions). This output supports the ability of all three models to simulate O&M as intended. Consistently with previous verification studies, there is a significant difference between the outputs from the three models due to different methodologies used (Dinwoodie et al., 2014; Rinaldi et al., 2018; Sargent, 2010). Differences were particularly observed in the total hire costs and EA.

This work was found very useful for identifying and correcting software bugs in all three models. The results presented in this work are the results after these corrections were made. Because of the complexity of O&M simulation it is possible these errors could have been left unnoticed. It is therefore highly recommended to perform this kind of benchmarking prior to applying it in actual O&M analysis.

5.4 Case Study: SOV compared to an offshore maintenance base

5.4.1 Wind farm assumptions

The chracteristics of a FOW farm used in this case study are provided in Table 5.10 and the layout is shown in Figure 5.14.

Table 5.10: Characteristics of the case study floating wind farm

O&M port	Peterhead
Distance to port	100 km
Number of turbines	66
Lifetime	25 years
Turbine capacity	15 MW (NREL, 2020)
Water depth	100 m
ERA5 data point	58.5, -1.0 (100 m height)
ERA-20C data point	58.375, -1.25 (100 m height)
Average H_s (ERA5 data)	1.95 m
Average H_s (ERA-20C data)	1.82 m

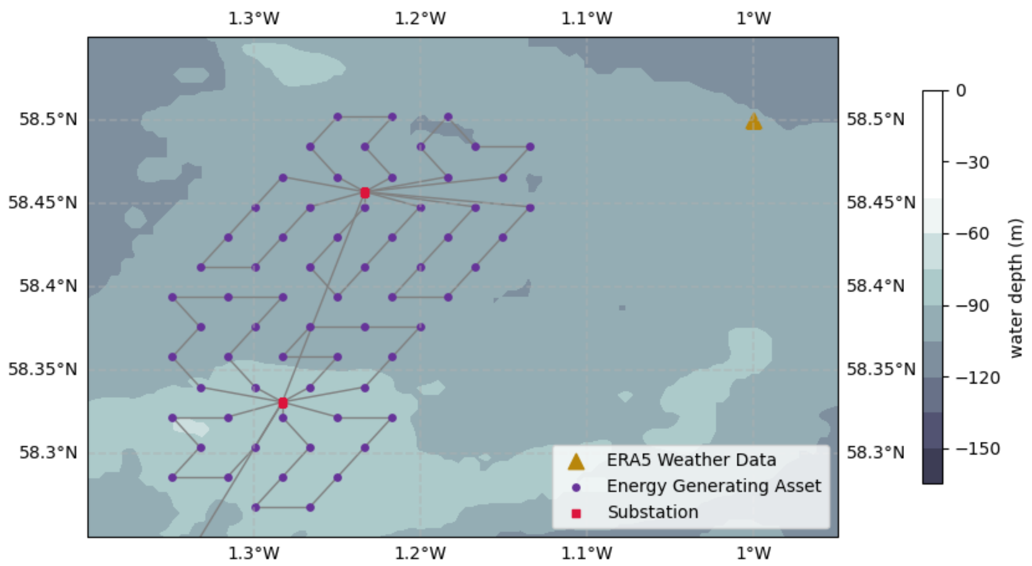


Figure 5.14: Hypothetical FOW farm layout

There are two OSSs connected to the onshore substation in Peterhead by two export cables. It was assumed that major operations in this farm are to be carried out offshore, on site using a semi-submersible HLV. This case study does not model TTP operations, the main focus of this study is the analysis of minor activities and planned maintenance that can be carried out by SOVs and CTVs. Major operations were not removed completely from simulation inputs assuming that they may interact with minor activities and planned maintenance by making turbines unavailable for certain periods of time. The use of CTVs based in Peterhead may be unfeasible for this site, given the distance. In this case study two scenarios were modelled: one with an SOV and another with 3 CTVs located at an OMB (attached to one of the OSSs).

5.4.2 Weather data

Two weather datasets were used for this study: ERA5 and ERA-20C, both are open-source global reanalysis data. ERA5 provides hourly data running until 2019 which can be retrieved from Copernicus (2018), it gets updated yearly based on new observations. ERA-20C data was retrieved from ECMWF (2010), it is only available until 2010 and provides data for every three-hour interval. ERA-20C data was linearly interpolated to fill in two-hour gaps. ERA5 data however has lower spatial resolution than the ERA-20C data, the respective resolution is 0.5 and 0.125 in both longitude and latitude. Figure 5.15 shows the comparison between the two datasets.

The data in the Fig. 5.15 was averaged over 25 years and 1990-2015 year span was used with ERA5 data and 1985-2010 year span with ERA-20C. It can be seen that peaks and troughs of the two datasets align well even though two datasets were retrieved for different coordinates. ERA-20C tends to model lower H_s resulting in 1.82 m mean H_s compared to 1.95 m for the ERA5. ERA5 reanalysis data gets regularly updated but ERA-20C has stopped its development. Nevertheless, both data sets were used in this study to see how the choice and the quality of data affects the outputs.

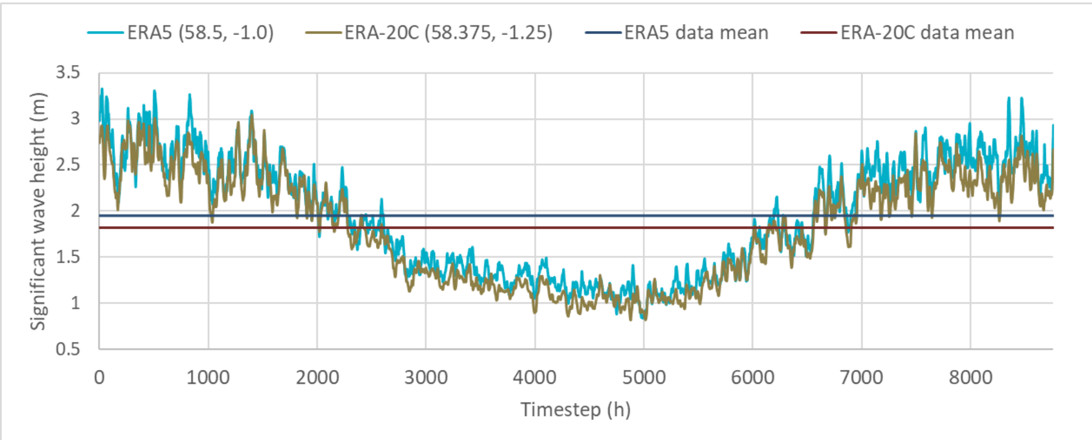


Figure 5.15: ERA5 and ERA-20C reanalysis data averaged over 25 years for each timestep

Figure 5.16 shows the number of opportunities in January to finish an activity that was derived based on ERA5 weather data. Currently activities in COMPASS are continuous meaning that the tool will look for a 12-hour weather window if a 12-hour-long activity occurs, however making that change may increase the number of opportunities to perform the task but may reduce the availability of the farm as was shown in Section 5.3. This would be the case if an activity requires keeping the turbine off until the full repair is complete. The effect of EA on the strategy comparison is demonstrated in Section 5.4.5.

Figure 5.16 shows that shortening the duration of an activity does not have nearly the same effect on the number of available weather windows in January as changing the H_s limit. Interestingly, the difference between vessel weather limits becomes less significant in the summer.

Figure 5.17 shows that in July (the month with the lowest average H_s) there is almost no difference in the number of weather windows for an eight-hour-long maintenance activity between a vessel with a 2 m and a vessel with a 4.5 m H_s limit. The choice of data also becomes less important in July for vessels with H_s limits over 2 m. In January, when the average H_s reaches its lowest there is a noticeable linear relationship between the H_s limit and the number of available weather windows. This means that for planned activities which most commonly occur in summer months, the choice of a vessel is much less important than for unplanned activities that may occur in winter as well as in summer months. The exception is vessels with H_s limits below 2 m. In both January and July the choice of such vessel can significantly impact the number of opportunities available to complete an eight-hour task.

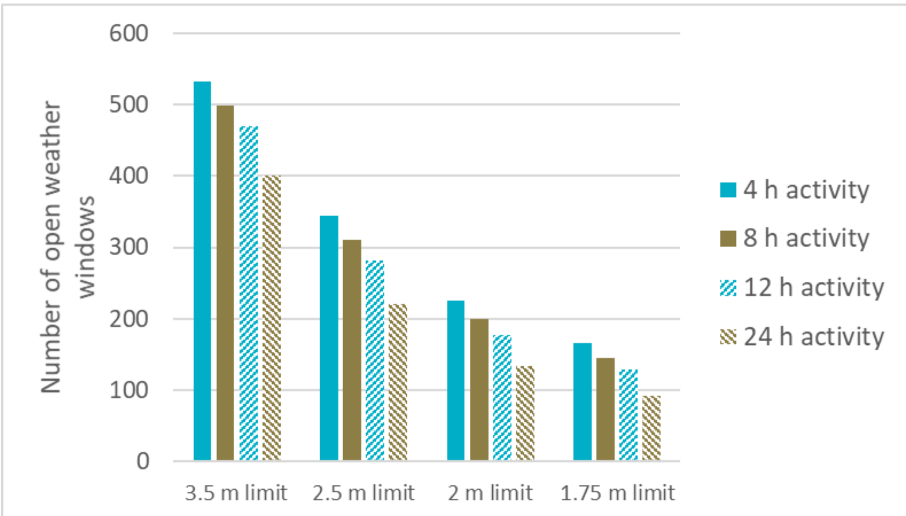


Figure 5.16: Number of weather windows for each activity duration in January for different wave limits (bottom axis)

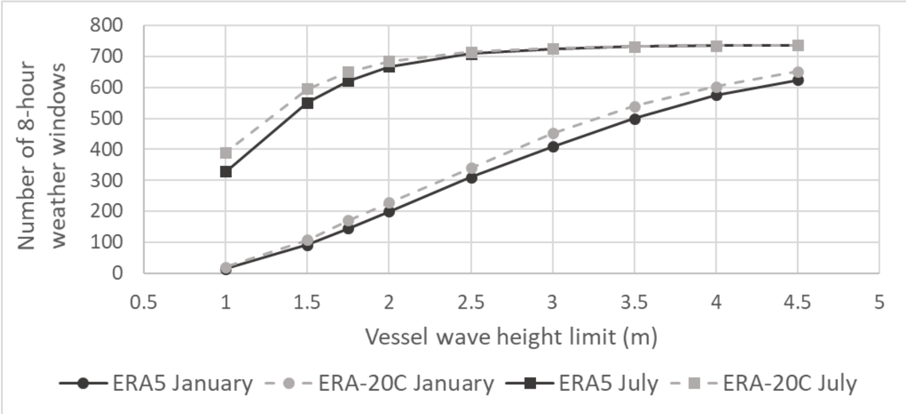


Figure 5.17: Number of open weather windows (opportunities) to perform an 8-hour maintenance activity for different vessel operating H_s limits. Data is shown for July, the month with the lowest average H_s in that area and January, the month with the highest average H_s. The difference between ERA5 and ERA-20C weather dataset is also shown.

5.4.3 Maintenance assumptions

Maintenance assumptions are summarised in Table 2.17. Data was based on values initiated in COMPASS prior to this research project. Data was updated with unplanned activities specific to floating turbines, their rates are listed in Table 5.11. It is considered however that using the data is sufficient to compare the strategies as long as the same input data is used in all scenarios.

The cost of replacing a dynamic cable was calculated using the coefficients provided in the COREWIND report for a 33 kV dynamic cable resulting in 385 £/m assuming the length of the dynamic cable is (2 $\times$ water depth (m)$\times$ 2.6) (Ikhennicheu et al., 2020). 33 kV is the maximum cable rating for which the cost coefficients were provided, however 66 kV may be more common in emerging projects.

Table 5.11: FRs and replacement costs of floating wind turbine subsea components assumed for this study

Component	**FR (per component per year)**
Hybrid synthetic mooring	0.0017 (per km)
Anchor	0.00012
Semi-submersible platform (structure damage)	0.018
Array Cable	0.003 (per km)
Dynamic Cable	0.003

This case study assumed one high level annual inspection with an RSV and one thorough inspection every five years with an anchor handling vessel. Marine growth removal every five years was also added as a regular activity.

5.4.4 Fleet assumptions

For the first strategy one SOV was used with one daughter craft and a capacity to accommodate 40 technicians. Depending on the SOV design, technician transfer limit can vary between 2.5 m and 4.5 m however 3-3.5 m are the most common limits according to Hu and Yung (2020). For this case study a medium size SOV was assumed having just one daughter craft. For the second strategy a fleet with three CTVs was assumed, all based at the OMB.

CTVs can be different in size and design and vary in their way of transferring technicians to the turbine. This makes it hard to come up with one representative value for the capacity and H_s limits. Although next generation CTVs may be bigger in size and be able to sit 24 personnel, most common CTVs have a capacity to transit 12 technicians. CTVs which could be installed on the OMB are expected to be smaller and hence the capacity of 12 was selected.

Current generation CTVs are expected to operate in 1.2-2.5 m waves (Stumpf & Hu, 2018), however with external consultation and interviews with ORE Catapult experts it was found that due to sea sickness and safety concerns as well as steeper waves far offshore, most CTVs travel in 1.5-1.75 m waves (Murrell et al., 2022). Future generation CTVs may have better motion compensating systems and designs to comfortably transfer personnel in 2.5 m waves. Due to this variability of wave limits two options were selected for this study with current generation CTVs and future generation CTVs. In total six scenarios were simulated in this study that are summarised in Tables 5.12 and 5.13.

SOV and CTV day rates were assumed to be £18,000 and £1,800 respectively.

Table 5.12: Characteristics of the OMB scenarios simulated in this study

Scenario name	OMB 1.75 m ERA5	OMB 2.5 m ERA5	OMB 1.75 m ERA-20C	OMB 2.5 m ERA-20C
Weather data source	ERA5	ERA5	ERA-20C	ERA-20C
CTV transit limit	1.75 m	2.5 m	1.75 m	2.5 m
CTV transfer limit	1.75 m	1.75 m	1.75 m	1.75 m

Table 5.13: Characteristics of the SOV scenarios simulated in this study

Scenario name	SOV 3.5 m ERA5	SOV 3.5 m ERA-20C
Weather data source	ERA5	ERA-20C
SOV transfer limit	3.5 m	3.5 m
Daughter Craft transfer limit	1.75 m	1.75 m

5.4.5 Results

Each scenario was run 20 times to minimize the error in the mean outputs. Convergence results can be found in Appendix D. Table 5.14 shows the results for the total OPEX of six scenarios which includes fixed costs, the costs of hiring the vessels and personnel costs as well as the average TA and EA resulting from each scenario over all years. The cost associated with building the OMB are not included in this table in order to compare OPEX only.

Previous studies have been used to benchmark the results of this case study (see Table 5.15). Results lie between the NREL minimum and maximum estimations (Musial et al., 2020) but are much lower than other estimations. All of these estimates are high level and were produced without using O&M simulation tools. COMPASS outputs on the other hand are case-specific and are produced by replicating the lifetime of a farm time step by time step.

Scenarios with SOVs resulted in the highest availability outcomes due to higher H_s limit but the drawback of this strategy is the higher OPEX due to significantly higher costs of hiring these vessels compared to CTVs.

In can be seen in Table 5.14 and later in Fig. 5.18 that the 0.13 m difference in wave means of two weather datasets ERA5 and ERA-20C affects the difference between results making the cases with ERA5 data more expensive. This difference is to do with the fact that vessels return to port more often with ERA5 data than with ERA-20C due to slightly worse sea conditions. There is also an effect of having lower time resolution in ERA-20C data which is linearly interpolated to model hourly data. ERA5 is hence more restrictive to the vessel logistics because it allows for fluctuations in H_s within each three-hour time span. EA however varies less than TA between scenarios with the same logistical setup and different weather datasets. This is to do with the fact that ERA-20C not only predicts lower waves in that location but also lower winds. It should be noticed however that TA results are more sensitive to switching from one dataset to another for cases with lower H_s limits for vessels.

Table 5.14: OPEX, TA and EA results from all six simulated scenarios.

	OPEX (£/kW)	TA (%)	EA (%)
OMB 1.75 m ERA5	46.21	92.1	89.6
OMB 2.5 m ERA5	46.67	94.2	92.8
SOV 3.5 m ERA5	49.01	97.1	97.2
OMB 1.75 m ERA-20C	45.13	92.5	89.7
OMB 2.5 m ERA-20C	44.63	94.4	92.7
SOV 3.5 m ERA-20C	48.57	97.3	96.9

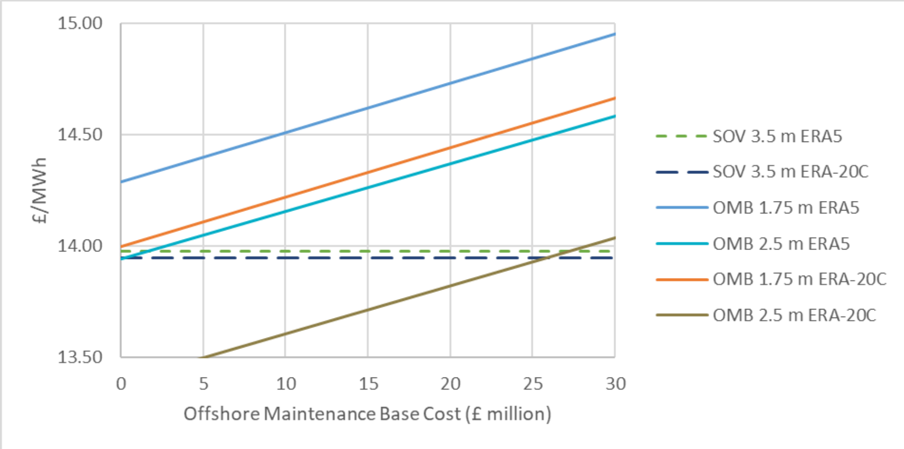


Figure 5.18: Six scenarios compared with varying the costs associated with the OMB

Table 5.15: O&M cost estimations from various reports for comparison with the results from simulations.

Reference	OPEX (£/kW)
(Myhr et al., 2014)	114
(James & Ros, 2015) (Commercial)	89
(James & Ros, 2015) (Pre-commercial)	139
(Musial et al., 2020) (min)	27
(Musial et al., 2020) (max)	59

DF formula presented in Equation 1.1 was applied on both the regular SOV hiring fee and the energy produced throughout 25 years of wind farm lifetime. For the OMB scenarios the cost of building the base was varied between £0 and £30 million in order to find the break-even points at which having the OMB would be cost effective. The discount rate was assumed to be 5.5% estimated by ORE Catapult (2021) for the first commercial-scale projects in UK. Figure 5.18 shows the results of this analysis.

For the cases with the OMB and low H_s limit, even when the capital cost associated with the OMB is low the lines stay above the SOV scenarios. The big difference between ERA5 and ERA-20C cases for OMB scenarios is to do with the fact that due to worse weather conditions vessels return to the port more often and hence their usage is longer in scenarios with ERA5 data. With ERA-20C data vessels can more often maintain several assets in a row without returning to port. Scenarios with high H_s limit i.e. 2.0 m for transfer and 2.5 m for transit are the only ones that have a section of the line below SOV scenarios.

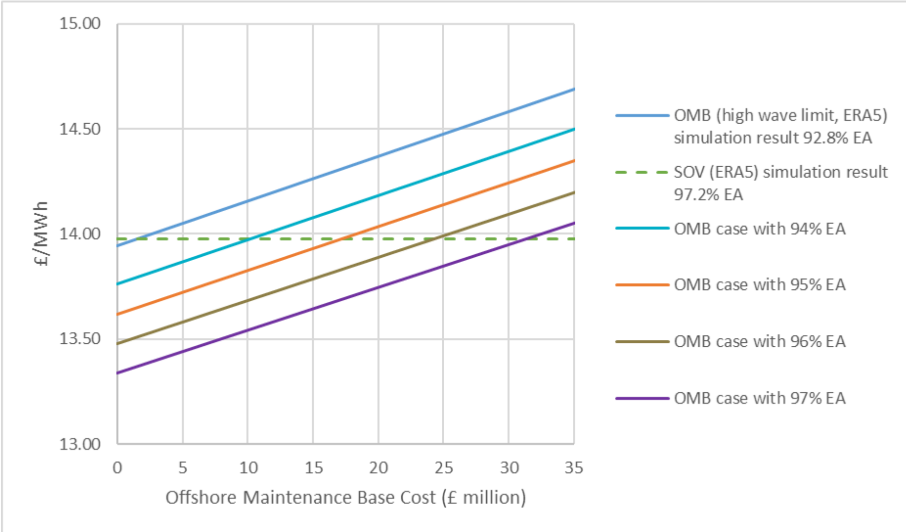


Figure 5.19: The effect of changing EA on the results

Figure 5.19 shows how this cost balance would change if OPEX stayed the same but EA increased for the scenario with the OMB, high H_S limit and ERA5 data. In the bottom four lines more energy is produced at the same cost which results in lower price per MWh. Even for the case with the highest availability presented in the graph the OMB would need to contribute less than £32 million to the total CAPEX which is unlikely if the OMB has a separate substructure. According to the report published by the ORE Catapult (Jump et al., 2021) a separate substructure of this size would cost at least £49.5 million.

Spare part storage capacity is not considered in both scenarios, however in the SOV case modeling the additional return to port would not affect the costs but would change the availability output. This is due to the assumption of a long-term SOV contract. However in the OMB case there would be an additional cost of helicopter or vessel delivery of a part if it is not available at the site.

5.4.6 Case study conclusion

This section demonstrated the application of COMPASS on SOV modelling and showed that having one SOV is a preferable strategy if costs and energy are taken into consideration unless the OMB shares its foundation with the OSS.

This case study modelled CTVs located at the OMB. It found that despite the higher number of vessels available in OMB scenarios the resulting EA was lower than in the single SOV scenario. In the most optimistic case, where CTVs would operate at $H_s = 2.5m$ the OMB scenario resulted in the maximum 92.8% reliability while maximum EA in SOV scenarios is 97.2%.

This case study also demonstrated that COMPASS captures the effects of weather data inputs and the lifting of vessel H_s limitations. It was found that where ERA5 data is used, vessels tend to return to port more often thus increasing the costs.

OPEX calculated using simulations were compared with other studies and correlate well with some of them, however most of the existing sources use high level estimates. The range of OPEX costs collected from different studies is too wide to evaluate the accuracy of the costs produced by COMPASS with confidence.

5.5 Case study: major operation duration variability

This section demonstrates how COMPASS can capture the variation in major operation duration. Section 2.4 estimated how the time it takes to finish a repair or replacement can vary using real operational data. Section 4.3 presented the computational logic developed in COMPASS to model the variability in maintenance duration.

Four major maintenance campaigns were modelled associated with four major components: gearbox, main bearing, blade and pitch bearing. These components were selected because of the significantly larger amount of data associated with them. Section 2.4 discussed the available data in detail. Section 2.4 produced CDFs for maintenance duration for each of these components. This study simulates two cases to demonstrate the newly-developed functionality and its impact on the simulation results.

In one case the planned duration is equal to the actual duration of the operation and the actual duration is modelled as a fixed value. In another case the actual duration is derived from a CDF as described in Section 4.3. Planned duration in both cases is based on the mean maintenance duration for each component, these figures are estimated in Section 2.4. This contradicts with the recommendation given in Section 2.4.7 to use P90 duration values as planned duration. The purpose of this particular case study was to keep the planned duration the same between the two cases and focus only on the comparison of a fixed duration maintenance with a variable duration maintenance.

5.5.1 Assumptions

For this case study an area in the north of Scotland was chosen because of its harsher weather conditions compared to some other sites in the UK. It was selected presuming that the weather conditions could have an additional impact on the difference between the two cases. Same turbine layout was used as in the benchmarking study (see Figure 5.2) but shifted to a desired location. Table 5.16 lists the wind farm and vessel assumptions used in this case study. The study focused solely on major operations of four components and ignored any other types of maintenance. For this reason, all vessels were removed from the fleet with an exception to one JUV. Table 5.16 lists the assumptions associated with that vessel. JUV mobilisation time was set to zero in order to focus on the impact of major operation duration alone.

Table 5.16: Assumptions used in the study comparing fixed and variable duration of major operations.

Distance to port	51 km
Number of turbines	40
Lifetime	20 years
ERA5 data point	58.00, -4.25 (100 m height)
Turbine capacity	15 MW (NREL, 2020)
Number of JUVs	1
JUV mobilisation time (days)	0
JUV hire cost per day	£200,000
JUV mobilisation cost	£900,000
JUV speed	20 knots
JUV Hs limit transit (transfer)	5 m (3.5 m)

Two duration modelling techniques were compared. One models the planned duration as equal to the actual duration of the operation and the actual duration is modelled as a fixed value. Another models the actual duration derived from a CDF as described in Section 4.3. Planned duration in both methods is based on the mean maintenance duration for each component, these figures are estimated in Section 2.4. Table 5.17 summarises the maintenance duration assumptions used in all scenarios.

FRs for the four components were also taken from Section 2.4. For sensitivity analysis additional scenarios were modelled with a Base FR (BFR) taken from Table 2.16 and a High FR (HFR), three times higher than the base one. In total four scenarios were modelled: one with fixed duration and BFR, one with fixed duration and HFR, one with variable CDF-based duration and BFR and one with variable CDF-based duration and HFR.

Table 5.17: Maintenance duration assumptions. Two approaches were used in modelling duration: fixed using a fixed value and variable using a CDF. Duration figures are based on the findings in Section 2.4.

Duration $\rightarrow$	**Fixed (hours)**	**Variable (hours)**	
Component $\downarrow$	Planned or actual duration	Planned duration	Actual duration
Gearbox	72	72	CDF
Main Bearing	130	130	CDF
Blade	51	51	CDF
Pitch Bearing	44	44	CDF

In all cases it was assumed that 50% of failures lead to an outage of a turbine while the other 50% do not i.e. in 50% of times a turbine would continue operating after a failure is detected and only stops working once a maintenance campaign starts. In real wind farms this split may be different. The aim of this split however was to capture the effect of any additional downtime due to waiting until the start of the maintenance campaign.

5.5.2 Convergence

As discussed previously multiple simulations are required to get an accurate estimate of O&M KPIs. Because of the additional stochastic variable it was decided to increase the number of simulations to 135 in the BFR case and 71 in the HFR case. Figure 5.20 demonstrates the convergence of the average JUV cost. This is the most volatile variable in this case study because it is highly sensitive to the duration of a maintenance activity. Figure 5.21 shows the convergence of the CI for the JUV cost outputs. CI is highly variable and hence converges slower than the average. Nevertheless, both figures show that convergence happens fast, reaching acceptable levels after around 20 simulations and after about 60 simulations the effect of any additional simulation on the final outcome plateaus. No significant difference was observed in the convergence of simulations with variable duration and fixed duration.

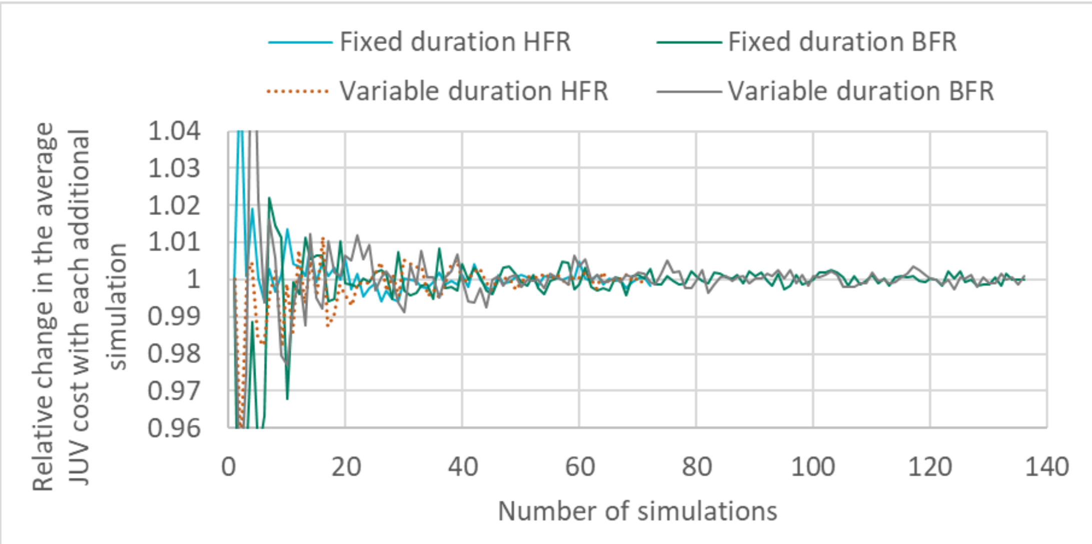


Figure 5.20: Convergence of the average JUV costs with each simulation

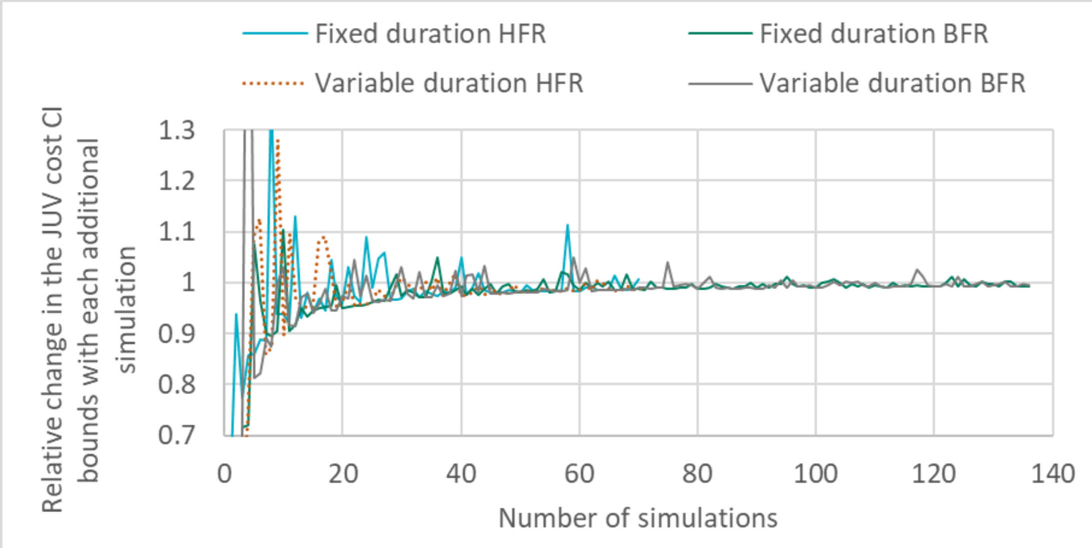


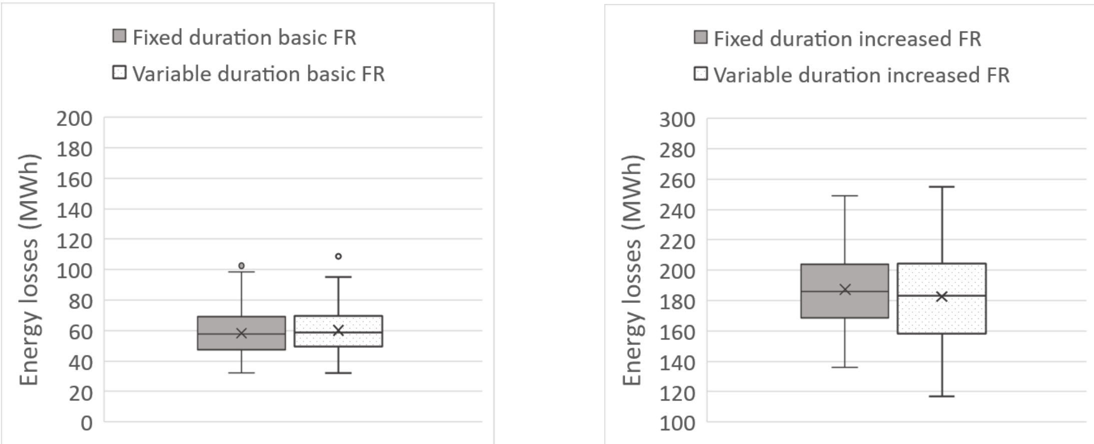
Figure 5.21: Convergence of the CIs for the JUV costs with each simulation

5.5.3 Results and discussion

Figure 5.22 shows the boxplots produced with the results from simulated scenarios. Energy losses presented there were calculated using the EA values calculated with COMPASS. Several observations can be made in these boxplots:

- Mean results are almost identical when the fixed duration case is compared with the variable duration case. This is because simulating a duration of a maintenance campaign using a CDF not only captures events where a maintenance took longer than anticipated but also those where it ended earlier. For example, a campaign that on average takes 2 days would occasionally take 1 or 3 days when simulated with a variable duration method. With a fixed duration method this campaign would always take 2 days.
- In the BFR case the boxplots are almost identical indicating that variable duration does not have a significant impact there.
- In the case of HFR the boxplot for a variable duration scenario is noticeably wider than that in the fixed duration scenario. This means there is a higher variability in the outputs from simulations with variable maintenance duration.
- Boxplots in Figure 5.22b representing HFR are at least 1.5 times wider than the cases in Figure 5.22a representing BFR scenarios. This indicates that a HFR leads to higher uncertainty around the energy loss output.
- In Figure 5.22b variable duration boxplot is shifted downwards compared to the scenario with a fixed duration. This is associated with a failure modelling limitation that has been discussed in Section 5.3. When a turbine is awaiting repair or undergoes maintenance no failures can be generated on it until it gets back to its operational state. COMPASS

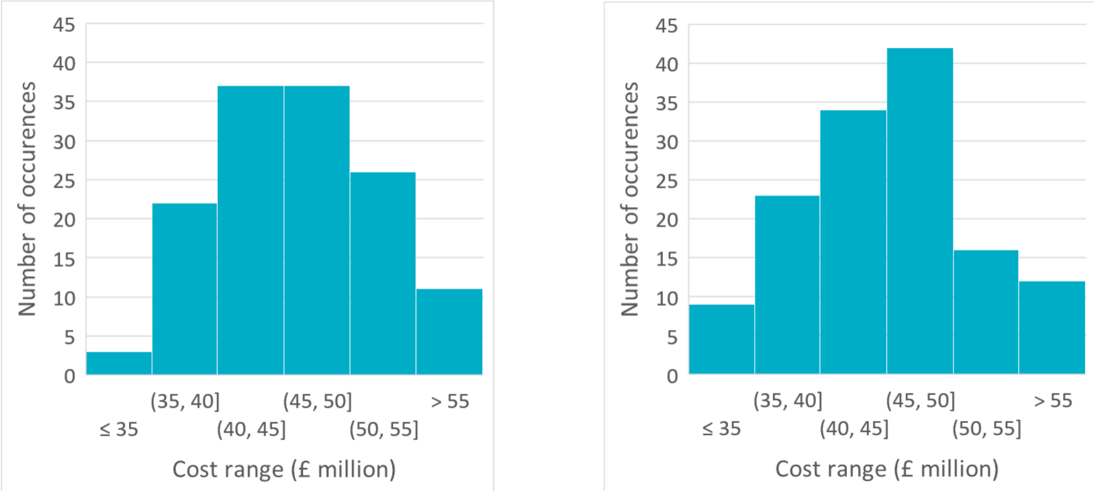
does not adjust FRs which leads to a lower FR in the simulations than what was set in the inputs. Due to the higher variability in the maintenance duration this effect becomes more apparent. Table 5.18 shows that there is fewer maintenance events modelled in variable duration case than there is in the fixed duration. If this tool behaviour was adjusted the boxplot for variable duration would shift towards a higher value.



(a) BFR **(b)** HFR

Figure 5.22: Energy loss variability resulting from each scenario.

Figures 5.23 and 5.24 present the variation in JUV hire cost in different scenarios. Figure 5.23 compares the costs for fixed and variable duration scenarios assuming the BFR. Figure 5.24 compares these scenarios assuming the HFR. As expected in the variable duration case the results shown in Figure 5.23b show higher occurrence of results for costs under £35 million and slightly higher for those above £55 million. The rest of the results are however more concentrated in the middle range than in the case of the fixed duration.

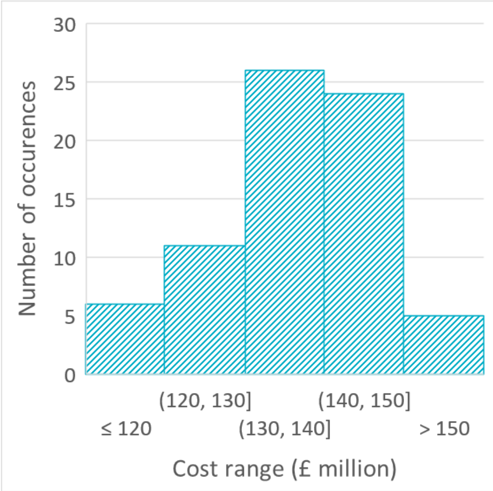


(a) Fixed duration

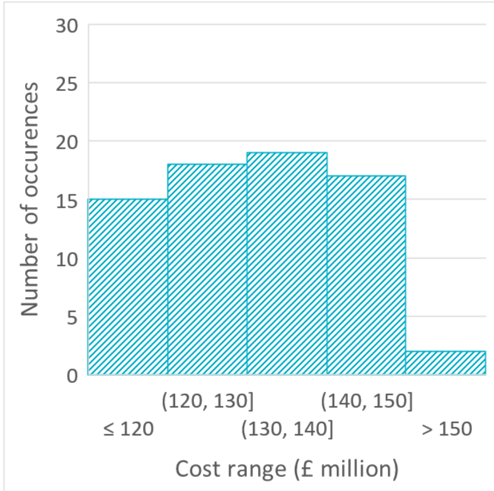
(b) Variable duration

Figure 5.23: JUV hire costs in BFR scenarios.

In the case of HFR the differences between fixed and variable duration scenarios become more prevalent. Figure 5.24a shows the results for the hire costs for JUVs assuming fixed durations. The results are concentrated within a £20 million range. This is not the case in simulations assuming variable durations. JUV hire cost results become more distributed in the cases with activities that can vary in duration. Unlike the fixed duration case where cost outputs are concentrated within a £40 million range, the likelihood of JUV hire costs being between £120 and £130 million is almost the same as £140-150 million. This indicates that in the case of HFR, the cost outputs assuming variable duration can be a more useful measure to assess the financial risk. These cost outputs will give a more realistic indication of spending on JUVs during the O&M phase of the project. These cost outputs can be useful for assessing financial risks and getting project insured. Average JUV costs in the variable duration case are lower than those in the fixed duration. The reasoning behind it is explained by fewer maintenance activities modelled in the variable duration case which has been discussed earlier in this section. If adjusted it is expected to see the shift in results in Figure 5.24b towards the right.



(a) Fixed duration



(b) Variable duration

Figure 5.24: JUV hire costs in HFR scenarios.

Table 5.18 provides a summary of outputs from four scenarios. What is noticeable in these results is the fact that mobilisation costs do not scale linearly with FRs. The ratio between the mobilisation cost in HFR cases to costs in BFR is 2.66 in fixed duration scenarios and 2.73 in variable duration. Although the FR increased by 3, the tripling of mobilisation costs is not observed. Because of the increased FRs there is a higher chance that multiple maintenance activities are required on multiple turbines in a farm at the same time. When it happens JUV moves from one turbine to the other without the demobilisation and mobilisation process.

Table 5.18: Summary of average outputs from four simulated scenarios.

Scenario:	**Fixed, BFR**	**Fixed, HFR**	**Variable, BFR**	**Variable, HFR**
Visits per turbine per year	0.076	0.231	0.076	0.226
EA	99.9%	99.7%	99.9%	99.7%
Total energy losses (MWh)	58	187	57	183
JUV hire costs (£ million)	46	138	45	130
JUV mob costs (£ million)	52	141	52	138
WoW for a JUV (hours)	3702	10481	3936	10264

Energy losses also increase disproportionately to FRs but unlike costs energy losses increase by a higher amount than FRs. In both variable and fixed duration cases energy losses have increased by 3.2 when FRs increased by a factor of 3. This is likely to do with the waiting time for the available JUV. Wind farm fleet consisted of just one JUV in all scenarios. In the case of increased FRs there is a higher likelihood of multiple activities to be due on multiple wind turbines in the farm but because only one JUV is modelled there is an increased waiting time until that JUV becomes available.

Overall Table 5.18 shows that average outputs for fixed and variable duration cases are quite similar. Figures 5.22, 5.23 and 5.24 showed that major differences arise when output distributions are compared.

Interestingly, four components investigated in this case study are the major contributors to major operations, particularly blades which is the most common component to require a JUV visit according to Section 2.4. This case study also assumed that half of the component failures are unpredictable which means turbines have to stop operating until the repair happens. Weather data point was chosen from the site where the weather conditions are harsher than in the currently installed wind farms around the UK. Despite these factors the EA results in this section are significantly higher than the average EA reported in SPARTA (2023) (which uses the term PBA instead of EA). Mean EA reported for UK wind farms in 2021/2022 is 95% (when grid curtailment is excluded) according to SPARTA (2023). The results from this case study indicate that major operations performed with JUVs are not the main contributor to the EA losses.

5.5.4 Case study discussion and further work

This case study shown that COMPASS can successfully model duration variability. It has demonstrated that the variability in maintenance duration results in a wider range of outputs for various KPIs, particularly when the FR is tripled. Despite that, the outcomes of this study have shown that mean KPIs stay almost the same irrespective of whether fixed or variable duration was modelled.

This case study also found that major operations modelled in this study do not result in significant downtime indicating that other O&M activities are the main cause of energy losses. The study has also demonstrated that mobilisation costs and energy losses do not scale linearly with FRs. The rate at which mobilisation costs increase is lower than the rate of increase of FRs. The rate at which energy losses increase is higher than the rate of increase of FRs.

Variation in duration of major operations was based on the data from Section 2.4 which takes into account only fixed offshore wind. In the case of FOW there is simply not enough data, only two major maintenance operations have been performed on floating wind turbines at the Kincardine wind farm at the time of writing. In both cases the turbines required towing to the port of Rotterdam where the maintenance was performed. These two maintenance campaigns indicate that it is likely that floating wind turbine maintenance campaigns will experience more duration variability than fixed. As was observed in Section 2.4 the probability of a maintenance campaign with a JUV to take over 20 days is less than 5% while both towing operations at the Kincardine wind farm took longer than that.

According to the Sea Impact database the first campaign took 57 days from start to finish, the second one took around a month. Such variation can make a big difference in terms of revenue losses. Without more data it is challenging to assess the variability of these campaigns. One option to overcome this is to generate data synthetically assuming a mean and an associated probability density function. Similar approach has been used before by Jenkins et al. (2022) for estimating major replacement rate distributions for offshore turbines. Jenkins et al. (2022) estimated 5th, 50th and 95th percentile for the replacement rate via conducting six interviews with offshore wind experts. Future work would require a synthetically generated CDF to model maintenance duration variability for floating wind turbines in COMPASS. The outcomes of this process could help wind farm developers assess the financial risks.

All scenarios in this section were modelled assuming that a planned duration is equal to the mean duration of the activities. Section 2.4 estimated the mean and the P90 values for the maintenance activities and has shown that P90 values are closer to those reported in the NtMs than mean. Using P90 values instead of mean could make it more difficult to find a suitable weather window and hence delay the repairs resulting in longer downtime.

More research is required to build enough understanding of how JUV contracts work. It is not clear whether there would be any cost penalty associated with JUV spending more time at a turbine than initially planned. Current work modelled JUV costs based on the number of days it spend working however it is not clear whether this cost increases when a maintenance project is extended.

5.6 Cable Topology Study

This section demonstrates how COMPASS can take into account cable topology when generating cable failures and calculate the EA of the wind farm accordingly. It also demonstrates the importance of having cable topology being included in the O&M simulation. This demonstration is performed via comparison of four cable topology designs simulated in COMPASS.

Each modelled wind farm consists of 40 wind turbines and 2 substations located in the North-East of Scotland. Each wind turbine is rated at 15 MW. Seabed conditions, wake effects, wrecks and unexploded ordinance were not taken into account neither in the process of turbine positioning nor in the cable topology selection. The aim of this section is to demonstrate solely the impact of cable failures on a generic wind farm.

COMPASS can be used to model the lifetime of a wind farm taking into account each turbine connection to the onshore substation. Cable topology modelling method was described in detail in Section 4.8. EA estimates resulting from simulations can then be used for estimating revenue losses and comparing them with the up-front project costs (CAPEX) that are required to add redundancy into the cable topology design.

5.6.1 Assumptions

Four cable topologies generated for comparison are shown in Figures 5.25-5.28. Figures 5.25 and 5.26 represent Design 1 and 2 respectively with 40 cables each, without any added redundancy. In both designs cables are connected in a string connection, but strings are shorter in the second case than in the first.

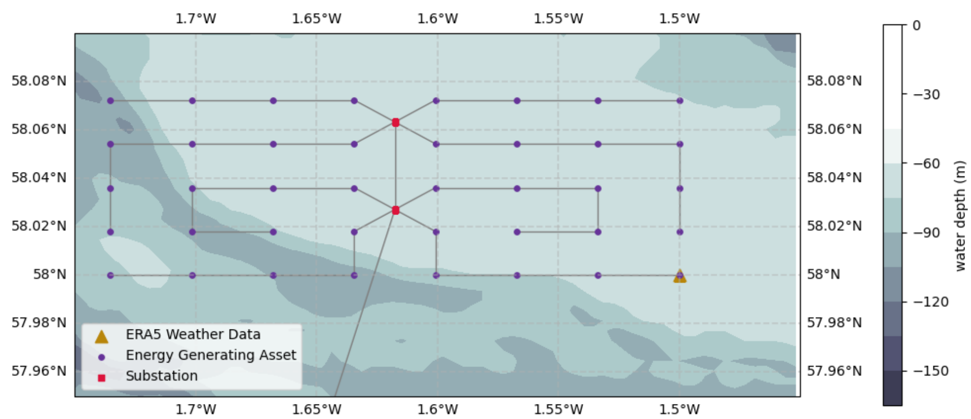


Figure 5.25: Farm layout with 2 substations, 40 turbines and 40 cables in a radial (string) connection consisting of 8 strings representing Design 1.

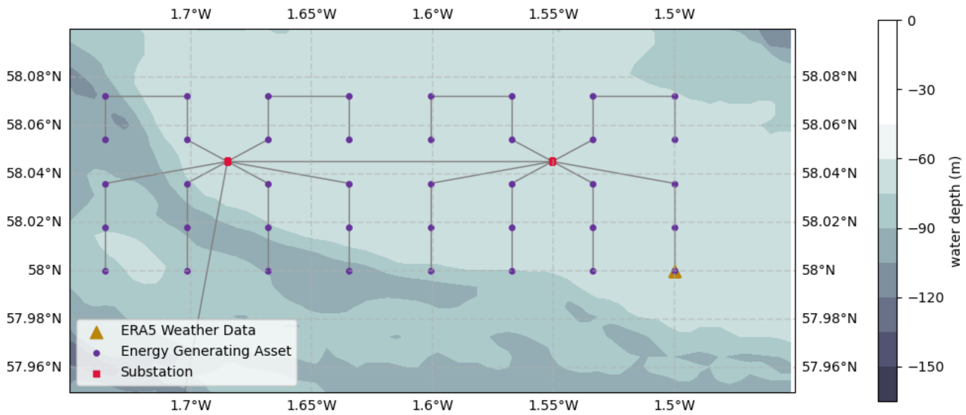


Figure 5.26: Farm layout with 2 substations, 40 turbines and 40 cables in a radial (string) connection consisting of 12 strings representing Design 2.

Figures 5.27 and 5.28 represent Design 3 and 4 respectively. Design 3 is identical to Design 1 but includes two additional cables that add some redundancy to the system. Design 4 is identical to Design 2 but includes six additional cables that add full redundancy to the system. In both scenarios sufficient cable thickness is assumed i.e. as long as there is a connection between a wind turbine offshore and the onshore substation this turbine is assumed to produce energy at its full capacity (in accordance with the selected power curve).

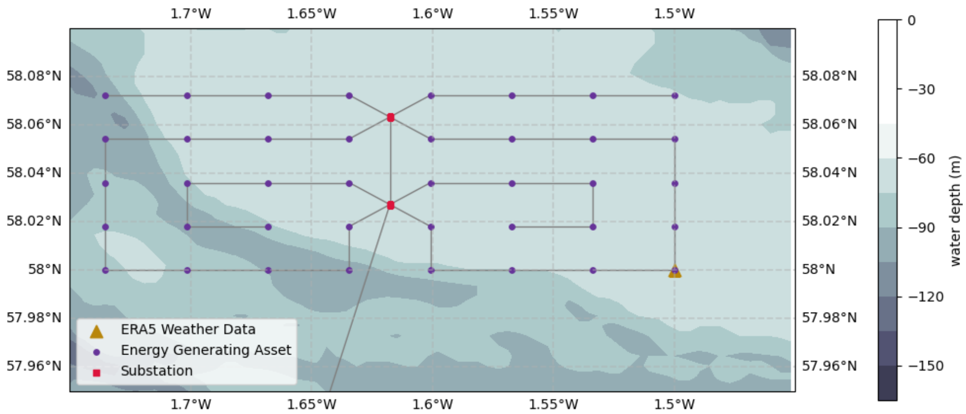


Figure 5.27: Farm layout with 2 substations, 40 turbines and 42 cables connected in a combination of a radial (string) and a ring connection representing Design 3.

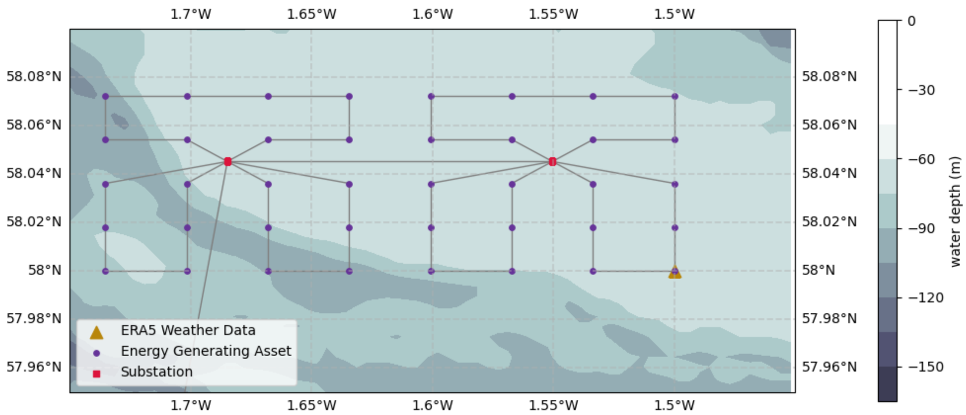


Figure 5.28: Farm layout with 2 substations, 40 turbines and 46 cables connected in a ring connection representing Design 4.

The following assumptions were made in O&M simulations using these four designs:

- Four FR scenarios were considered: 0.006, 0.012, 0.015 and 0.018 failures per cable per year. Lowest value is estimated based on the average cable FR reported in Warnock et al. (2017) and assuming a cable length of 2 km. Other values are added for the sensitivity analysis.
- Cable failure leads to a complete disconnection of the cable from the system (i.e. no amount of electrical energy can transfer through that cable).
- Discount rate is assumed to be 8% in most cases, but the discount of 4% is added for sensitivity analysis in specific cases.
- Two types of repair scenarios were studied: fast and slow. In the fast scenarios, CLV mobilisation time is 10 days and the duration of the cable repair is 48 hours. In the slow scenarios, CLV lead time is 30 days and the duration of the cable repair is 72 hours.
- Wind turbine, substructure and OSS failures are neglected. Export cable FR is set to 0 in all cases apart from the cable connecting two substations, its FR is the same as that of other cables.
- Power losses through the cables are neglected.
- Power curve for 15 MW turbines was obtained from NREL (2020).
- Table 5.19 shows the assumptions related to the CLV.

Port	Fraserburgh, Scotland
H_s limit during transit	5 m
H_s limit during maintenance	2 m
Speed	20 knots

Table 5.19: CLV assumptions

5.6.2 Results

Simulations with four designs were performed using COMPASS. In this study 50 simulations were run with each case. Convergence analysis resulted in the relative change in average revenue losses after 30 simulations to fluctuate within 3% from the baseline in all scenarios. This level of convergence is considered acceptable in this case study because 3% is not enough to impact the choice of the preferred topology.

Figure 5.29 provides the average EA values resulting from simulating the four cable topology designs in COMPASS assuming fast cable repair. EA results are much more sensitive to an increase in FR in less redundant designs. Design with long strings resulted in the lowest EA values and the steepest EA reduction with FR increase. As expected, this is followed by Design 2, 3 and 4. Increase in FR affects Design 3 and 4 significantly less than Design 1 and 2.

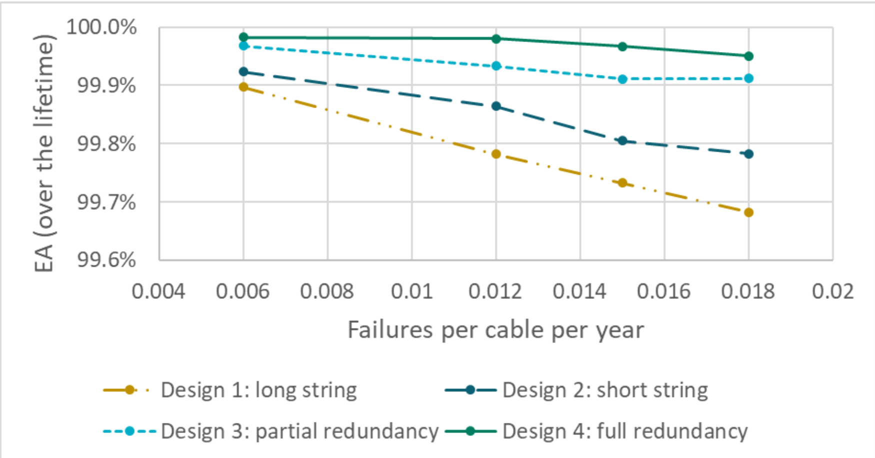


Figure 5.29: EA results with four different array cable topology designs and assuming fast repair.

Figure 5.30 provides the average EA values resulting from simulating the four cable layouts in COMPASS assuming slow cable repair. EA results are significantly more sensitive to the increase in FR than in the fast repair cases. Similar to fast repair cases, increase in FR affects Design 3 and 4 significantly less than Design 1 and 2. The difference between designs widens as the FR increases.

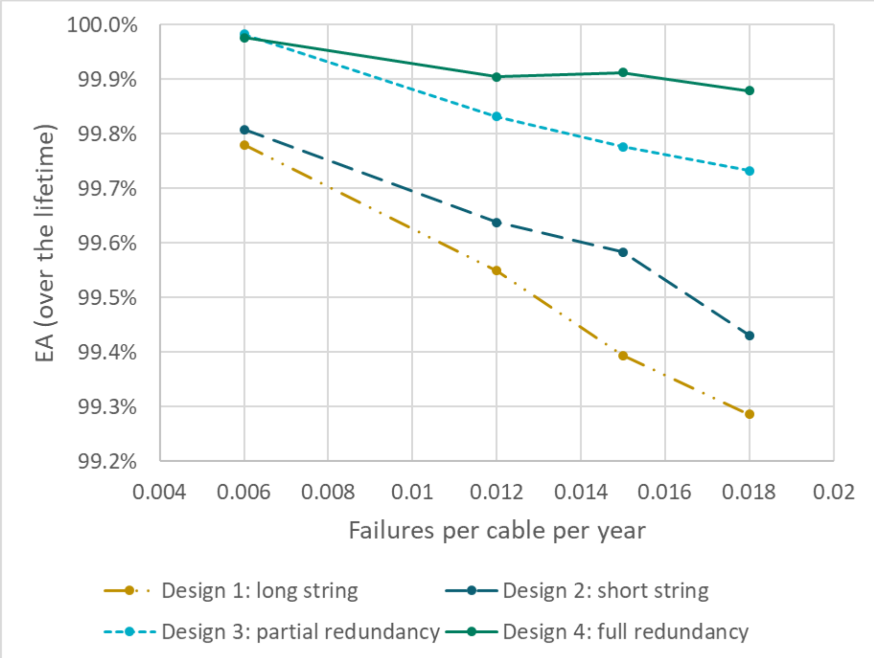


Figure 5.30: EA results with four different array cable topology designs and assuming slow repair.

Using the ERA5 weather data and 15 MW turbine power curve expected energy production E_e per year was calculated to be 3,387 GWh. Revenue losses were then calculated using E_e, EA results (Figures 5.29, 5.30) and assuming a fixed electricity price of 60 £/MWh and discounted using Equation 1.7 and the discount rate of either 8$\%$ or 4$\%$. Additional cable costs (those that are added for redundancy, 2 cables in Design 3 (partial redundancy) and 6 cables in Design 4 (full redundancy) were calculated assuming a cost per cable is £1.4 million, this price was informed by the ORE Catapult's Market Analysis and Insights (ORE Catapult, 2023c). The results of this cost analysis for fast and slow repair scenarios are shown in Figure 5.31 and Figure 5.32 respectively. Figures 5.31a-5.31d and Figures 5.32a-5.32d are based on the discount rate of 8%. Figures 5.31e-5.31f and Figures 5.32e-5.32f are based on the discount rate of 4%.

In all FR scenarios, Design 1 resulted in the highest revenue losses due to the lack of redundancy, it was followed by Design 2, 3 and 4 with Design 4 having the lowest revenue losses. An exception is in the slow repair scenario with FR=0.006 in which Design 3 and 4 result in the same EA. Despite the lowest revenue losses, Design 4 resulted in the highest cost overall in all scenarios, because of up-front costs associated with six cables added for redundancy. Design 2 is the most cost-effective in scenarios with low FRs (0.006 and 0.012 failures per cable per year) but it is marginally less cost-effective than Design 3 when FR is increased.

Figure 5.31 presents the results from the fast repair scenarios. Figure 5.31a presents the results from the lowest FR scenario. In this scenario up-front cable costs significantly outweigh the revenue losses. Design 4 is 4.0 times more expensive than Design 1 and 5.3 times more expensive than Design 2. Design 3 is 1.58 times more expensive than Design 1.

Figure 5.31b presents the results from the scenario with increased risk of cable failures and 0.012 failures per cable per year. Revenue losses are significantly increased in Designs 1, 2 and 3 but stayed almost the same in Design 4 due to added redundancy. Design 3 in this scenario becomes more cost-beneficial than Design 1.

Figure 5.31c presents the results from the scenario where cable FR is increased further, leading to higher revenue losses. Design 2 remains to be the most cost-effective scenario but the difference between Design 2 and Design 3 narrows. Design 4 in this case is still the most expensive case out of all due to high up-front cable costs.

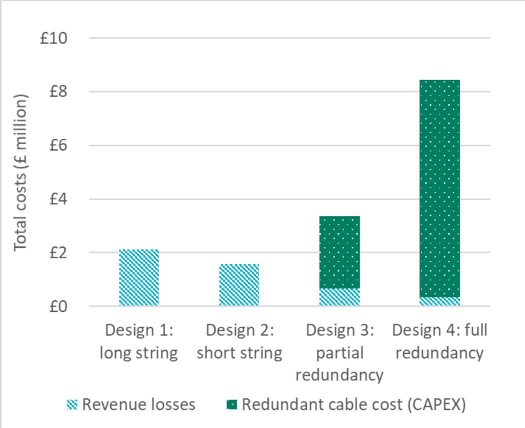
Figure 5.31d presents the results from the scenario with the cable FR of 0.018 failures per cable per year which is the highest rate out of all scenarios. Design 2 remains to be the most cost-effective scenario but it is only 0.2% different from Design 3.

Figures 5.31e and 5.31f show how the results would differ for the cases with the highest FRs if the discount rate was 4% compared to 8% used in previous figures. Lower discount rate results in higher revenue losses. In these cases Design 3 proves to be more cost-effective. This highlights the importance of the discount rate role in selecting the right cable topology design.

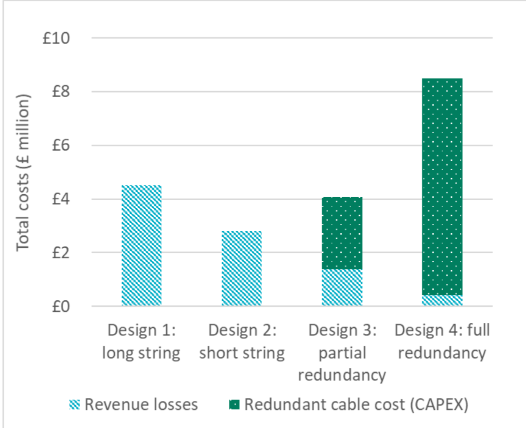
In the slow repair scenarios, revenue losses are significantly higher. This can be observed by comparing Figure 5.32 (slow repair) to Figure 5.31 (fast repair). In slow repair scenarios, Design 3 with partial redundancy is the most cost-effective one irrespective of the FR or the discount rate. Revenue losses are directly related to EA results. As the failure rate increases, the revenue losses increase as well with the biggest increase seen in Design 1 and 2 (no redundancy). Unlike fast repair scenarios, when the discount rate is reduced to 4%, both Design 3 and 4 become more cost-effective than the other two options in high FR scenarios.

Figures 5.32 and 5.31 show how COMPASS can effectively be used for comparing different cable topologies and analysing the impact of increasing the cable FR on the difference between the designs. This case study has shown that shorter cable strings can reduce the revenue losses. It has also shown than even partial redundancy can offer a cost advantage over a string connection, particularly when the cable FR is high.

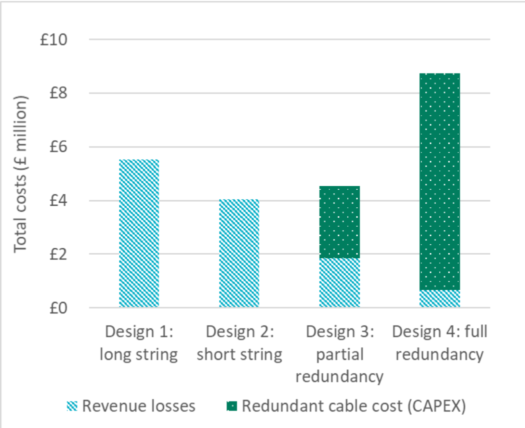
Other variables that can have a significant impact are the costs of any additional redundant cables and the electricity price. Finding out how much these variables can vary is beyond the scope of this analysis but should be included when a real wind farm cable topology is analysed. Nevertheless, COMPASS proves to be a useful tool for evaluating the cost saving advantage of one cable topology design over the other.



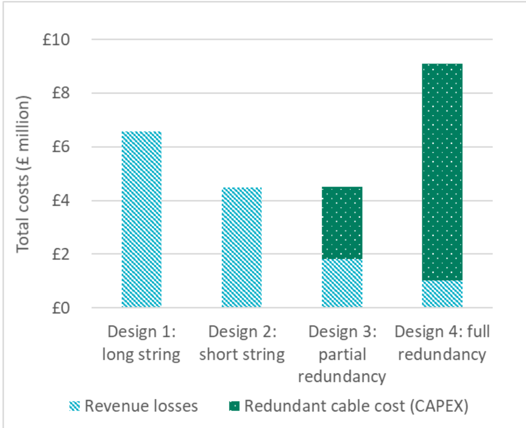
(a) Costs compared assuming **FR=0.006** and **8% discount rate**.



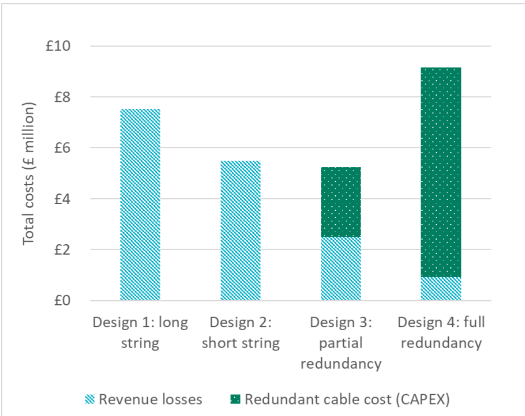
(b) Costs compared assuming **FR=0.012** and **8% discount rate**.



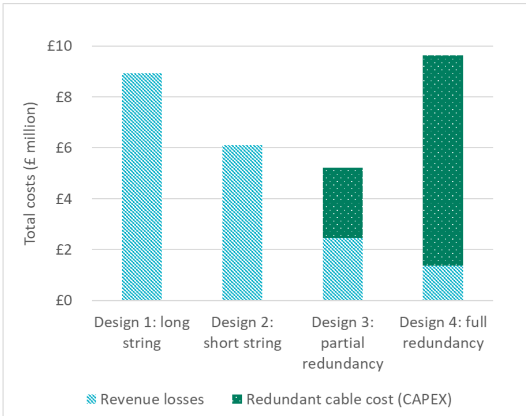
(c) Costs compared assuming **FR=0.015** and **8% discount rate**.



(d) Costs compared assuming **FR=0.018** and **8% discount rate**.

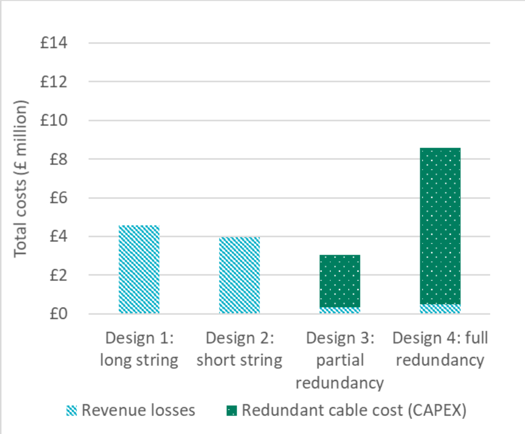


(e) Costs compared assuming **FR=0.015** and **4% discount rate**.

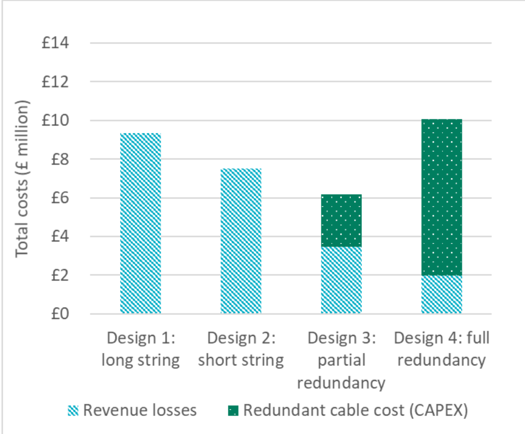


(f) Costs compared assuming **FR=0.018** and **4% discount rate**.

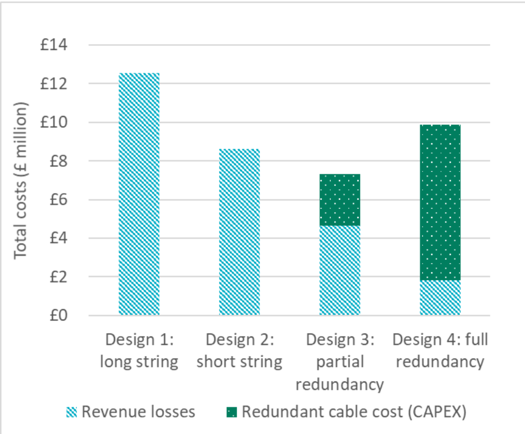
Figure 5.31: Revenue losses combined with additional cable costs (for redundancy) compared for the four FR scenarios with varying level of cable redundancy and two discount rate options assuming **fast cable repair**. Revenue losses in all figures were generated for a period of 20 years assuming the electricity price of 60 £/MWh. Redundant cable cost is assumed to be £1.4 million. FR is given in terms of failures per cable per year.



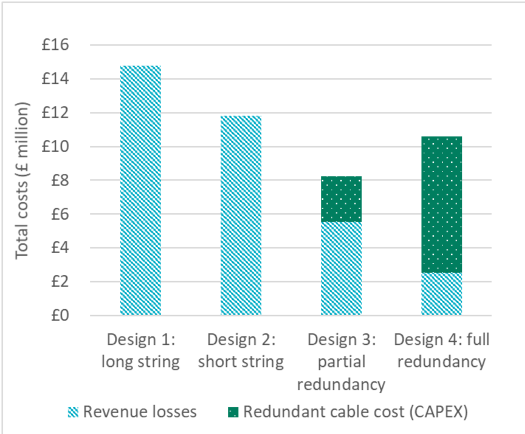
(a) Costs compared assuming **FR=0.006** and **8% discount rate**.



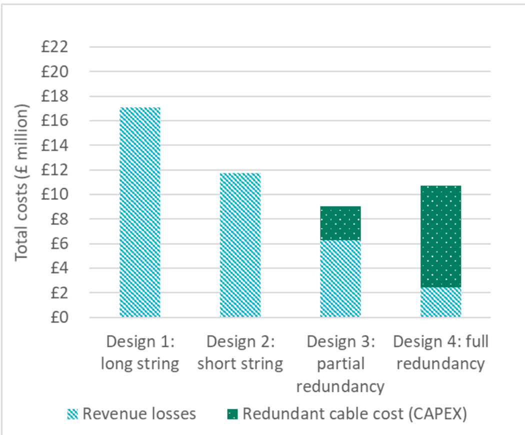
(b) Costs compared assuming **FR=0.012** and **8% discount rate**.



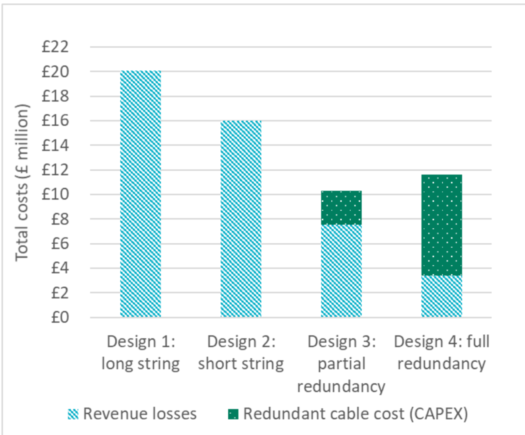
(c) Costs compared assuming **FR=0.015** and **8% discount rate**.



(d) Costs compared assuming **FR=0.018** and **8% discount rate**.



(e) Costs compared assuming **FR=0.015** and **4% discount rate**.



(f) Costs compared assuming **FR=0.018** and **4% discount rate**.

Figure 5.32: Revenue losses combined with additional cable costs (for redundancy) compared for the four FR scenarios with varying level of cable redundancy and two discount rate options assuming **slow cable repair**. Revenue losses in all figures were generated for a period of 20 years assuming the electricity price of 60 £/MWh. Redundant cable cost is assumed to be £1.4 million. FR is given in terms of failures per cable per year.

5.6.3 Case study discussion and further work

This section presented the first study that uses an O&M simulation tool to compare array cable topology designs. The feature developed in COMPASS has been explained in Section 4.8 and has proven to be effective in this study. Capturing cable failure impact on an ORE farm will lead to better estimates of EA.

This section demonstrated how the cost of added redundancy in a cable topology can be compared with the revenue losses in non-redundant cable topology designs. This study analysed four different cable topologies for a generic wind farm with 40 turbines. Commercial wind farms are usually much larger in size and have a more complex shape due to seabed limitations. Future work may include looking at more complex wind farms and cable topologies such as branch configuration and collector network. Picking a different offshore location or varying the cable vessel H_s limits may affect the results increasing the waiting time until the replacement activity can be performed.

Results have shown that even a small variation in EA results can lead to a significant difference in revenue loss estimations. This particular case study has shown that using shorter cable strings can reduce the revenue losses. Partial redundancy with long strings can be more cost-beneficial than the short string design, particularly in the cases where FRs are increased and where repair is slow (caused by longer mobilisation time and longer repair duration).

The study has also shown that adding full redundancy to the system can be expensive because of high up-front costs that are not discounted, unlike the revenue losses that are discounted through the wind farm operation years. This case study also demonstrated that the discount rate can impact the choice of the optimal cable topology.

It is important to use tools that are capable of capturing small variations in EA. Existing open-source O&M tools do not have the methods implemented that would be able to capture complex cable topology designs. Using COMPASS can help guide wind farm operators to selecting the most optimal cable topology. Future work may include looking at more complex wind farms and cable topology designs such as branch configuration and collector network.

Many variables can affect cable topology selection, which include cable cost, electricity price, discount rate, cable FR, cable repair duration, CLV lead time, CLV weather limits, cable thickness and power losses through cable. Some of these variables were analysed via a sensitivity study however future work should include a broader analysis.

Cable thickness and any cable losses were also not taken into account when calculating cable costs. Cable in ring scenarios (Design 3 and 4) is required to be thicker to be able to carry the load of additional turbines. Higher capacity cables are more expensive. Additionally, higher load on cables leads to higher power losses.

It is possible that cable FR varies throughout the lifetime. This study assumes that it is not the case and FR is the same throughout the lifetime of a farm. Higher FRs in the beginning of the lifetime would result in higher revenue losses due to the cost discounting.

5.7 Case Study: O&M of twin and single offshore wind turbines

This section demonstrates how modelling of a wind farm maintenance can have different results depending on whether a single turbine or a twin turbine is considered. COMPASS twin turbine modelling method has been explained in Section 4.10. This case compares the O&M metrics for two offshore wind farms with the same total capacity but different asset structure. One farm consists of twin turbines while the other farm consist of single turbines. Twin turbine concept used in this study is a single-point-mooring, passive-yaw system where two turbines share a substructure as shown in Figure 1.3a.

McMorland, Pirrie, et al. (2022) have performed an analysis on multi-rotor fixed offshore turbines using the Stathclyde OM tool but the tool has certain limitations covered in Section 4.10. The study performed by McMorland, Pirrie, et al. (2022) includes only the unscheduled minor repairs while this case study considers all types of maintenance activities. The multi-rotor system considered studied in McMorland, Pirrie, et al. (2022) consisted of 45 low-rated rotors on a fixed-bottom substructre. This section looks at larger turbines using floating semi-submersible substructures. McMorland, Pirrie, et al. (2022) considered an O&M fleet consisting only of CTVs. In this section regular maintenance will be performed by SOVs rather than CTVs, which is relevant for floating wind farms that will be installed further away from shore.

5.7.1 Wind farm assumptions

Two wind farms are considered in this study: one with 50 single 14 MW turbines and another with 35 twin 10 MW turbines. This way the total wind farm capacity is the same 700 MW.

In both scenarios, planned maintenance and minor operations are carried out using an SOV. SOV weather limits are assumed to be the same as in Section 5.4. Both scenarios assume the same number and type of mooring lines and anchors per substructure.

Wake effects are expected to be stronger between 14 MW turbines due to larger turbine diameter than for 10 MW turbines. Although wake effects are not modelled in COMPASS, the distances between turbines are expected to affect the transit times between turbines. Distance between turbines was assumed to be 10 times the rotor diameter. The assumed rotor diameters for 10 MW and 14 MW turbines were 180 m and 220 m respectively. Distance between 10 MW turbine rotors considering the assumptions made, would be expected to be 1.8 km (10 rotor diameters), however the distance between the centres of twin turbine foundations should be about 180 m bigger (1.98 km) considering that there are two turbines and not one, this calculation is demonstrated in Figure 5.33. Therefore the distance between foundations for twin turbines is rounded to 2 km and between single 14 MW turbines it is calculated as 2.2 km.

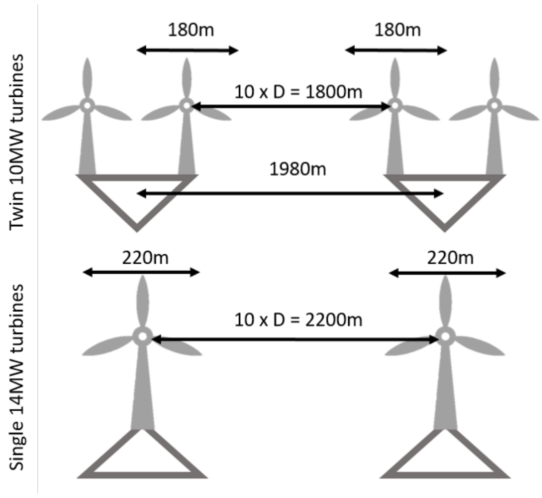


Figure 5.33: Distances between turbines and foundations.

Despite the increase in distance, the frequency and duration of maintenance activities for cables is kept the same in both scenarios. Turbine and approximated cable layouts for the two scenarios are shown in Figure 5.34 and Figure 5.35. COMPASS takes into account cable layout using the method described in Section 4.8. This is particularly important for this study because, although the capacities of the two farms are the same, the number of cables is higher in the case with 14 MW turbines.

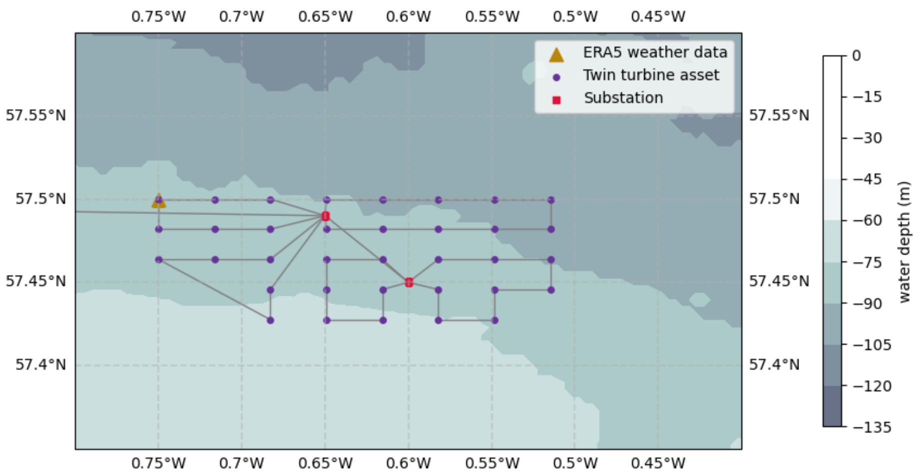


Figure 5.34: Floating wind farm layout with 35 twin 10 MW turbines

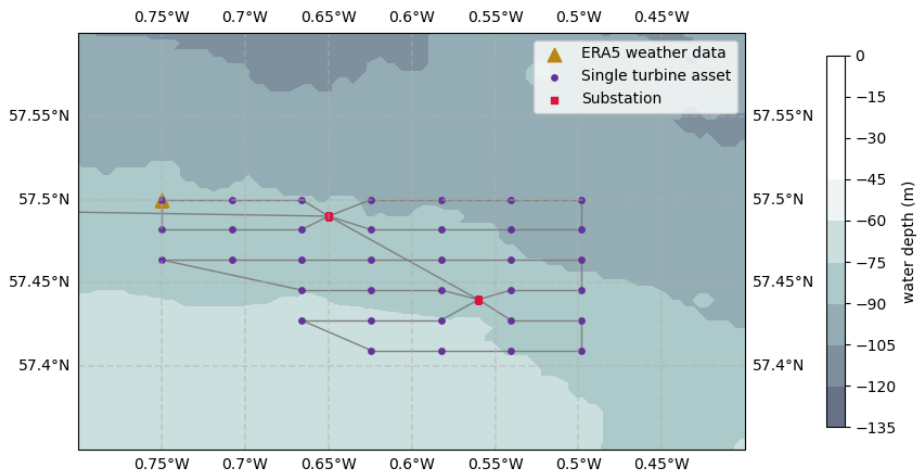


Figure 5.35: Floating wind farm layout with 50 single 14 MW turbines.

Table 5.20 summarises the farm characteristics used in this study.

Table 5.20: Characteristics of the 700 MW floating wind farm

Farm capacity (in all cases)	700 MW
Number of turbines	35 (twin turbines) or 50 (single turbines)
Distance to port	70 km
ERA5 data point	57.5, -0.75 (100 m height)
Lifetime	25 years

The power curve for a 10 MW turbine was taken from the NREL database (NREL, 2016). To model a 14 MW turbine power curve, the 10 MW turbine power curve was scaled such that cut-in, cut-out and rated wind speed are the same for both 10 MW and 14 MW turbines. Resulting power curves are shown in Figure 5.36.

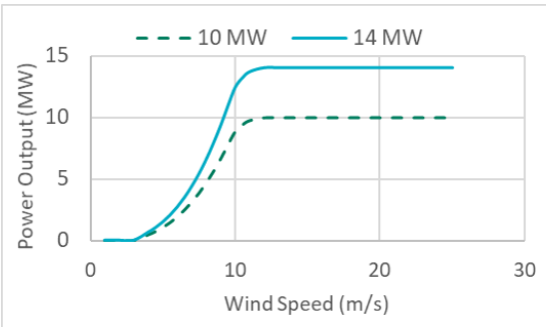


Figure 5.36: Power curves for 10 MW and 14 MW turbines. The power curve for a 10 MW turbine is based on NREL (2016), the curve for a 14 MW turbine is a scaled up version of a 10 MW turbine with a ratio 1.4:1.

5.7.2 O&M assumptions

Publicly available SPARTA (2022) review shows that the number of forced outages increases with the turbine rating. According to the source, the turbines rated below 3.6MW, between 3.6MW and 5MW and over 5MW experience almost the same number of forced outages per MW per month. It is not evident that turbine rating alone drives the forced outages up. In this case study FRs leading to minor repairs were scaled linearly with turbine rating. Future work could analyse the statistic reported in SPARTA (2022) in more detail to extract the effects of turbine age and weather conditions on the number of forced outages.

Section 2.5 results are currently inconclusive about the major operation rate increase with turbine rating. Major operation rate was therefore kept the same for 10 MW and 14 MW turbines. This study also assumes the same planned maintenance frequency for 10 MW and 14 MW turbines.

Activity input assumptions used in this study for 10 MW turbines are based on the original COMPASS inputs but modified according to internal expertise and SPARTA (2017). The summary of assumptions is given in Table 2.17. FRs for submerged components are the same as in one of the previous case studies presented in Section 5.4.

Spare part lead time assumptions for the 10 MW turbines in this study are the same as presented in Table 2.9 with exception for the gearbox and the generator which are assumed to take 4 weeks of lead time each. All spare part costs were scaled linearly with increase in power rating according to Fitch-Roy et al. (2013). Equipment costs were scaled linearly too.

Table 5.21 shows four scenarios that were simulated in this study. Case TW-2x10 represents a scenario with a farm with twin turbines rated at 10 MW each, cases named SL-14-0, SL-14-20, SL-14-40 represent scenarios with a farm with single 14 MW turbines. TW-2x10 case was taken as a base case for generating the inputs for 14 MW turbines. First, all inputs (FRs, maintenance durations, vessel and crew requirements etc.) were copied to make a new 14 MW scenario. Then consumables costs and FRs were adjusted assuming a direct correlation between these parameters and the turbine rating, forming the case SL-14-0. Spare part lead times and maintenance durations were then scaled up by 20% and by 40% in cases SL-14-20 and SL-14-40 respectively.

Spare part lead time scaling was assumed based on an expectation that the supply chain for larger components is restricted by port size and vessel availability thus increasing the time it takes for suitable parts to arrive. Further research is needed to validate this assumption.

Table 5.21: Differences between simulated cases. TW-2x10 represents a farm with twin 10 MW turbine and the rest represent farms with single 14 MW turbines.

Case name	FRs*	Spare parts costs	Spare part lead time and maintenance duration
TW-2x10	Base assumptions	Base assumptions	Base assumptions
SL-14-0	increased by 40%	increased by 40%	increased by 0%
SL-14-20	increased by 40%	increased by 40%	increased by 20%
SL-14-40	increased by 40%	increased by 40%	increased by 40%

**Rate increase was applied only on minor activities.*

5.7.3 Results and discussion

Results from the 30 simulations of each case described in Table 5.21 are summarized in Figure 5.37 and Table 5.22. As can be seen in Figure 5.37 cases SL-14-0, SL-14-20 and SL-14-40 (i.e. single 14 MW turbine cases) are all more expensive in terms of annual OPEX (calculated in £/kW) than the case with twin 10 MW turbines, with the lowest difference of 4.5% and the highest difference 5.3% compared to TW-2x10. The same figure shows that the highest TA output out of all scenarios is 91.7% which also belongs to the twin turbine case TW-2x10.

OPEX component of the LCOE ($LCOE_{OPEX}$) was then calculated to assess both the costs and the energy production in a single KPI. Table 5.22 provides $LCOE_{OPEX}$ calculated via dividing OPEX by the total energy output in each case.

If $LCOE_{OPEX}$ is compared, then the difference is even greater than that between the availability figures, with the minimum of 6.0% difference between SL-14 cases and the TW-2x10 case, favouring the latter. OPEX and $LCOE_{OPEX}$ presented in Table 5.22 and Table 5.23 do not include the quayside costs, however following paragraphs will discuss the impact of the quayside costs on this comparison.

Additionally, Table 5.23 provides the breakdown of OPEX. From this breakdown it can be seen that the biggest contributor to the differences between all cases are craft costs. In all cases, fixed costs make the biggest portion of OPEX, followed by craft, personnel, consumables and equipment costs.

As was expected with current assumptions, cases SL-14-20 and SL-14-40 are more expensive than SL-14-0 due to the increase in lead time and maintenance duration. This study found that a 20% increase in consumables lead time and maintenance duration caused a 1.6% increase in $LCOE_{OPEX}$ compared to the SL-14-0 case. Interestingly, 40% increase in the same parameters caused a 1.9% increase in $LCOE_{OPEX}$ which means that the change is not directly proportional to the increase in lead times and maintenance times.

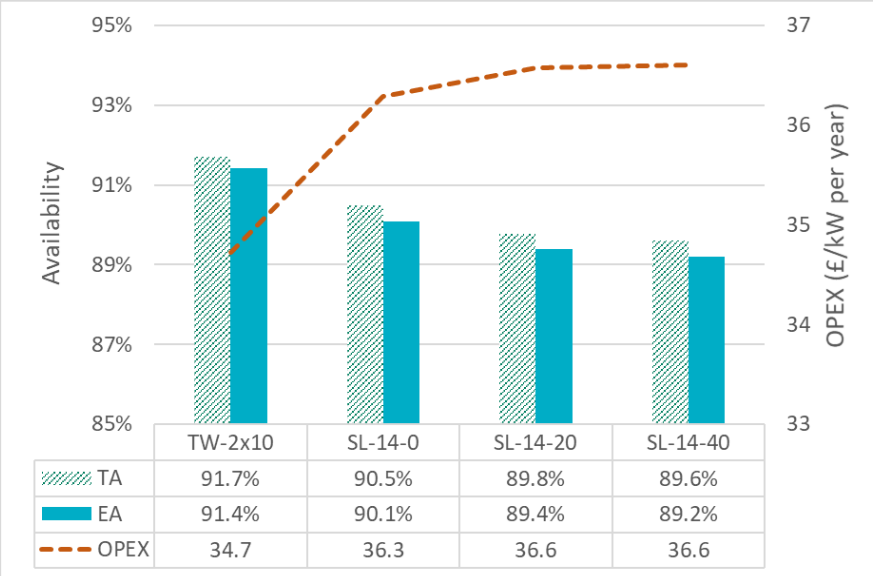


Figure 5.37: Availability and cost results of the simulated scenarios.

Similarly, TA decreased from 90.5% in case SL-14-0 to 89.8% in case SL-14-20 but then further decreased to 89.6% in case SL-14-40. Longer maintenance times require more waiting for a suitable weather window. During this waiting time, other failures may happen on other turbines. When a suitable weather window is found, activities would be done in a bundle hence resulting in more effective maintenance operations and vessel usage. This effect could explain the unexpectedly small difference between SL-14 case results.

Table 5.22: Annual O&M cost and energy output for each of four cases and the resulting OPEX

Case name	**TW-2x10**	**SL-14-0**	**SL-14-20**	**SL-14-40**
OPEX (£/kW per year)	34.7	36.3	36.6	36.6
Annual energy output (MWh)	3671	3616	3589	3581
$LCOE_{OPEX}$ (£/kWh)	6.62	7.02	7.13	7.15

Table 5.23: Total cost outputs from simulations of 25 years of farm O&M of each of four cases.

Case name	**TW-2x10**	**SL-14-0**	**SL-14-20**	**SL-14-40**
Fixed costs (£m)	285	285	285	285
Crafts cost (£m)	250	265	268	267
Equipment (£m)	1	1	1	1
Consumables (£m)	7	11	11	11
Personnel (£m)	65	73	76	77
Total O&M cost (£m)*	608	635	640	640

**Undiscounted.*

A summary of the SOV, CLV and AHTS vessel usage is provided in Table 5.24; these are the only vessels that are expected to affect the difference between scenarios. AHTS vessel and CLV usage are the main reasons for differences between scenarios in terms of costs. Because major repair rates were kept the same for 10 MW and 14 MW turbines (due to the lack of information on how they scale), AHTS vessels in case TW-2x10 are used more often. AHTS day rates, mobilization and demobilization rates are much lower that the rates for a cable vessel.

All vessel cost assumptions in this study were taken from the COMPASS vessel database. CLVs in this database have 96 times higher mobilization cost than that of a single AHTS and 20 times higher day rate than that of a single AHTS. CLVs are used more often in the cases with single 14 MW turbines (SL-14-0, SL-14-20, SL-14-40). Despite it being used much less than a AHTS vessel, its total cost is much higher due to higher vessel rates. Because there are 59 cables in SL-14 cases compared to 43 in the TW-2x10 case, the likelihood of failures is higher and hence that is reflected in the craft cost output and the CLV usage output.

Quayside costs were not included in the KPI comparison discussed earlier. Quayside costs would include the rental of the space and a crane for maintenance. COMPASS however tracks the quayside work time in terms of work days a year, these are shown in Table 5.24. From these outputs, a difference between twin turbine and single turbine case quayside use was calculated to be 4.3 days a year. Knowing the number of days the quayside is used it is possible to solve Equation 5.1 to find the quayside cost at which two scenarios TW-2x10 and SL-14-0 would break even.

$$\frac{D_{TW} \times C_{QD}}{E_{TW}} + \frac{\sum C_{SL}}{E_{TW}} = \frac{C_{SL}}{E_{SL}} + \frac{D_{SL} \times C_{QD}}{E_{SL}} \tag{5.1}$$

In Equation 5.1 D_{TW} and D_{SL} are the number of days that the twin turbines and single turbines spent in port respectively, C_{QD} is the quayside rate per day (the unknown), E_{TW} and E_{SL} are the total energy outputs from the twin turbine and the single turbine scenarios respectively, $\sum C_{TW}$ and $\sum C_{SL}$ are the sums of total O&M costs for the twin turbine and single turbine scenarios respectively which include fixed costs, consumables and equipment costs, craft costs and personnel costs and exclude quayside costs.

Solving Equation 5.1 for C_{QD} it was found that the quayside cost would need to be £371,500 per day in order for the TW-2x10 case to have the same OPEX as in the SL-14-0 case. Cranes hire for onshore turbines cost up to £41,000 per day, mobilisation cost is around 50% of that but offshore turbines are larger and hence the crane costs may be higher van Doornik (2023). There will be some costs associated with port usage but significantly lower than that of a crane. Therefore, even with quayside costs added TW-2x10 remains a more favourable case in terms of O&M costs, time and EA and OPEX. Larger, 14 MW turbines may require a bigger, more expensive onshore cranes.

Table 5.24: Vessel usage compared between the four cases.

Case name	TW-2x10	SL-14-0	SL-14-20	SL-14-40
SOV usage (days/year)	32.8	40.4	40.0	40.1
Cable vessel (days/year)	1.0	1.3	1.5	1.5
AHTS usage (days/year)	28.3	21.5	21.5	21.5
Quayside use (days/year)	20.8	16.5	18.2	19.5

5.7.4 Case study summary and further work

This case study demonstrated how COMPASS can be effectively applied to analyse twin turbine O&M. It compared O&M of a floating wind farm with 50 single 14 MW turbines and a floating wind farm with 35 twin 10 MW turbines.

Results of O&M simulations performed using COMPASS show that O&M costs for the scenario with single turbines are at least 4.5% higher than for the farm with twin turbines, with the assumptions used in this study. This difference increases to 5.3% if compared to a scenario where spare part lead time and maintenance duration of activities are 20% higher for 14 MW turbines. This study found that $LCOE_{OPEX}$ for the cases with single turbines is at least 6.0% higher in scenarios with single turbines than in the twin turbine scenario.

Despite more frequent TTP operations in the scenario with twin turbines, scenarios with single turbines were more expensive mostly because of the higher number of cables in the farm. In this case study O&M of twin turbines remains to be cheaper than that of single turbines with quayside costs up to £372,000 per day. This case study was based on several assumptions. Future research may provide more insight into how FRs and other O&M activity characteristics change with turbine rating. This would allow for a more detailed and justified comparison of O&M of wind farms with twin and single turbines.

Future research should investigate in more detail how turbine component costs change with turbine rating. Turbine size does not scale linearly with turbine rating, therefore the assumption that component costs would scale linearly is an oversimplification. Similarly, cable failure frequency and maintenance durations were assumed the same for all cases, however greater cable length in cases SL-14-0, SL-14-20 and SL-14-40 may increase the likelihood of cable exposure and failure. At the same time, array cable used in the TW-2x10 case would have to be higher rated and hence would be more expensive to replace.

There is a general lack of information on spare part management, more research should be done to understand what spare parts can be stored in a local O&M base, how much time would different parts take to arrive if they are not in the inventory and what variables lead times depend on. More research is needed to understand the supply chain constraints in the context of spare parts for maintenance.

Another constraint is that not all UK ports have the required draft and space for TTP operations and may not always be available for the major turbine maintenance operation. UK floating wind farms Hywind and Kincardine send their turbines for major maintenance to Norwegian fjords and Rotterdam port in the Netherlands respectively (KOWL, 2019; Statoil, 2017).

Chapter 6

Conclusion and Further Work

6.1 O&M activities and their characteristics

This research work has demonstrated that there is currently a gap between real and analytical O&M. It has shown that existing data on O&M activities are insufficient and contain information gaps (team size, activity duration, OSS and auxiliary equipment activities and other). It argues that some data available in the literature is limited to wind turbine capacity under 4 MW and small data pools. Such data may no longer be applicable to modern offshore wind turbines.

This research then found additional resources and analysed them to generate a set of inputs for O&M simulation tools that can be either used directly or act as a guide for selecting the values for O&M activity characteristics. These resources include MPDs, Sea Impact service, 4C Offshore service, NtMs and annual publicly available SPARTA reviews. This research also used some additional literature and consulted with offshore wind experts to fill in the missing gaps and combine certain activities together.

Through the review of the listed resources this research work was able to identify five activities related to cables, ten activities related to OSSs, eight activities related to substructures, five planned activities related to wind turbines, twelve minor unplanned activities related to wind turbines and TPs and multiple unplanned major operations on main wind turbine components.

This thesis provides the collected characteristics for each activity that can be used in O&M simulation tools. In particular, their rates, durations, vessel and personnel requirements. Some values either have not been found through this research or have a high level of uncertainty, especially those associated with floating substructures and cables due to the lack of information about these in the listed resources; further research is required on these.

This research particularly focused on the durations of major operations requiring HLVs. It has provided evidence that major operations can take longer than initially anticipated. This research then performed a statistical analysis on the data using R Studio and fitted probablity distibution curves into the maintenance duration datasets. It then developed a method for modelling this time variability in O&M simulation tools and demonstrated its use via a case study. The results have shown that maintenance duration variability affects the KPI ouput range but not the mean. This is particularly true when FRs are increased. Maintenance duration may be even more variable in FOW turbine operations.

This research also found that some O&M simulation tools assume that FRs are higher at the start of the wind turbine lifetime and at the end of it, stabilising in between. This research looked for the evidence of this and found that major operation rates do not follow this particular trend. Instead, it was found that there is a peak in operations in years 5-6 attributed to the warranty agreement between a wind farm operator and an OEM reaching the end at that time interval.

This research work has also found that the major operation rates associated with components other than blades tend to follow a 4-6 year cycle. Presumably it is associated with the repair of these components and the subsequent degradation. More data points over a longer time span may give more insights into these trends in the future.

6.2 O&M simulation tool development

This research work has found that FOW and multi-rotor technologies have shown the potential to turn into full scale commercial wind farms in the nearest future. This research work highlighted the significant cost and wind farm downtime implications of cable failures which may become a bigger issue with the development of FOW requiring dynamic cables and the development of higher-capacity wind farms requiring more substations.

This thesis presented a review of currently existing O&M simulation tools and the initial COMPASS structure. It found that most of the existing tools do not capture cable topology or capture it with significant limitations. It also found very little documentation of the methodology that very few O&M simulation tools use for modelling the TTP process required for FOW. This research also found that modelling multi-rotor turbines using existing tools has certain limitations. This research then addressed these limitations in the ORE Catapult's in-house O&M simulation tool COMPASS.

This research work developed a Python-based method for capturing the effect of cable failures and repairs on wind farm KPIs. It then demonstrated its use in a case study comparing four different cable topology designs. This is the first research study that used an O&M simulation tool to compare cable topologies with and without added redundancy.

This thesis has presented the development of other COMPASS features applicable to FOW. It has presented the logic diagrams used for modelling TTP, three-step weather window check and cable disconnection during the turbine disconnection for towing. This functionality was then demonstrated in two case studies. One where COMPASS was benchmarked against two other simulation tools and another where single-rotor and multi-rotor system O&M were compared.

This research work developed a computational logic for capturing the O&M of multi-rotor turbines with greater accuracy, recognising that two rotors are connected via a substructure. It then demonstrated its use on a case study comparing single-rotor and multi-rotor system O&M.

O&M simulation tool development in this thesis has also addressed the issue of combining O&M activities together, FR variability, picking up personnel offshore and setting up crew and time limits for vessels. This research developed an SOV modelling computational logic and demonstrated its use in a case study.

Following the development of new O&M simulation inputs this work identified some missing O&M activity attributes in COMPASS. These attributes were added to COMPASS in order to accurately represent O&M activities in a simulation. Some attributes already existed prior to this research work but needed a significant adjustment. These attributes are percent of assets covered by the activity, FR variability, final year at which the activity happens, spare part lead time, duration CDF, switch (on or off during the maintenance campaign), merge, optional second craft.

Unlike any other previous O&M simulation tool development studies this research work addresses the issue of long computational time. The issue grows as the complexity of the tool increases. The faster the simulations are the more O&M strategies can be simulated within a given time frame. Multiple modifications were made that allowed for reducing the computational time of COMPASS by more than 95%. Several ways for reducing the computational time were listed in this thesis and have proven to be effective.

6.3 Benchmarking against other models

Section 5.3 presented the case study where COMPASS results were benchmarked against two other O&M simulation tools: WOMBAT v0.8.1 and WavEC O&M simulation tool. The case study included several scenarios with various inputs. O&M simulation tool benchmarking studies have been done before but the study presented in Section 5.3 is the first to benchmark the tools for the TTP scenarios.

OPEX results from all three models aligned in their sensitivity to different scenarios, but other KPIs were also measured to understand the differences in modelling assumptions.

One significant difference was found among the three models. It was associated with O&M activity interruption. In COMPASS activities are modelled as continuous. In WavEC they get interrupted if the weather hits the vessel or activity limit and restarts again later. In WOMBAT activities also get interrupted due to weather but they also get interrupted due to personnel shifts. This resulted in the highest EA values in COMPASS and the lowest in WOMBAT with WavEC results in between. This difference significantly affected the vessel hire costs too.

There were other major differences associated with TTP operations. COMPASS and WOMBAT end the AHTS hire once it finishes its towing job. WavEC model on the other hand continues the hire of the vessel until the maintenance and towing back to the original site is complete. This results in significantly higher hire costs compared to WOMBAT or COMPASS.

There was also a difference in quayside cost estimations relevant to FOW scenarios. Currently there is a lack of understanding about how much these costs are and when they would be applied. COMPASS distinguishes between work time (when a turbine undergoes maintenance) and wait time (when it is waiting for a good weather window). Currently it applies the same quayside cost on both. WavEC only applies the costs on the work time. WOMBAT model takes a more deterministic approach on quayside and applies a generalised cost that does not change irrespective of the scenario.

6.4 Outcomes of several case studies

Several novel case studies were performed to assess different O&M strategies and demonstrate how COMPASS applies the features presented in this thesis. Each case study was limited to one location and a specific wind farm size.

Section 5.5 of this thesis demonstrated the use of variable operation duration modelling in COMPASS. It presented a case study which analysed how the variability of the duration of a major operation can impact the results of simulations. The study assumed a fixed offshore wind farm. It has shown that the mean KPIs do not change very much between the two options. It has shown however that the range of KPIs can change depending on which option is used. Option with variable duration and increased FR resulted in wider range of JUV cost outputs. That in turn can impact the financial risk assessment. More research is needed to understand the impact of delays on JUV costs. Based on the first two TTP operations at Kincardine, it is also expected to see more variability in maintenance duration in FOW farms.

Section 5.4 of this thesis presented another case study. In this study COMPASS was used to model an SOV with a daughter craft and an OMB with three CTVs. The case with an SOV resulted in an EA of at least 96.9% whereas the case with an OMB resulted in the EA of 92.7% in the most optimistic scenario. The case study found SOVs to be more cost effective than

OMB. SOVs are more expensive however than three CTVs but the up-front cost associated with building an OMB make an SOV a preferable scenario. OMB costs could be reduced if it shares its foundation with the substation or another offshore substructure. The case study was limited to one location and a specific wind farm size.

For the first time this thesis has shown how an O&M simulation tool can capture the impacts of cable topology design on the O&M KPIs of the wind farm. Four cable topology designs were compared: one with long strings, one with short strings, one with partial redundancy and one with full redundancy (ring connection). The case study has taken into account the up-front costs of any additional (redundant) cable. It has also performed a sensitivity analysis by varying the FR. The case study has found that the choice of the optimal cable topology design depends highly on the FR modelled. In the lowest FR scenario the designs with no redundancy resulted in the lowest costs. In the highest FR scenario the design with partial redundancy resulted in the lowest cost. As expected, the design with shorter strings was consistently lower in cost than the design with longer strings. COMPASS has proven to be an effective tool to measure these cost savings. It was also discussed that electricity price, discount rate and cable costs can significantly impact this assessment.

This research work developed a method for modelling twin turbines that share a substructure and demonstrated its use in another case study. The case study analysed one generic wind farm following four scenarios: one with twin turbines and three with single turbines but with varying the spare part lead time and maintenance duration. The analysis of simulations that were run in COMPASS showed that the scenario with twin turbines results in lower costs and higher EA, this is primarily due to the higher number of cables in the single turbine scenario. That in turn resulted in increased CLV costs and higher revenue losses.

6.5 Limitations and further work

6.5.1 Ever-changing field

Offshore wind farm O&M is an ever-changing field. New technologies arise with impressive regularity that have been developed to make O&M more efficient, minimising downtime, costs and carbon emissions. These technologies arise at different scales, some are related to vessels while other are specific to condition monitoring and repair. ORE technologies also evolve. This thesis considered large-scale floating wind farms and demonstration scale twin wind turbines a possibility in the nearest future but other technologies could also emerge. Although this is a positive change it is a challenge for O&M simulation tools because they need to either be built highly adaptable or undergo a continuous development. It has been observed in Section 3.2 that many of the existing tools are the outcome of numerous academic research projects but once each project finished the tool development discontinued or slowed down. This results in their limitations at modelling future ORE farms.

Building adaptable tools is challenging because it is hard to anticipate all possible ORE technologies and O&M innovations. It is also challenging to develop tool features that are capable of capturing the innovations without changing the scripts. For example, current strategy for floating turbine maintenance is TTP but it is possible in the future there will be specialised vessels or turbine-based cranes or other technologies that simplify floating turbine maintenance. There are countless RAS technologies as well that are hard to represent by a single logic loop in O&M simulation tools.

Continuous development is seen as a more feasible option. Keeping a skilled team of developers ensures that our tools stay updated and effective.

6.5.2 Data analysis

Section 2.4 presented the analysis of over 2000 major operations and estimated the duration of major operations for main turbine components. A significant variation in activity duration was observed. Probability distribution curves were fitted into the data in order to be able to incorporate them into COMPASS and capture duration variability. A more detailed analysis of the data could help with understanding what impacts the variation in activity duration, particularly what causes the activity to take longer than initially planned. Machine learning algorithms could be used to investigate if weather, turbine size, vessel type or OEM type or a combination of these have an impact on the maintenance duration. Similarly, machine learning could be applied to find if the same variables affect the frequency of major operations.

6.5.3 Inflation

This research project relied on pre-existing cost estimates for components, equipment, personnel and vessels. Some of these costs were taken from the pre-existing COMPASS versions, others were based on internal expertise at the ORE Catapult and existing literature. These cost assumptions may be out of date due to COVID-19 pandemic and Russia's invasion of Ukraine driving up the inflation. Further research is needed to revise the cost assumptions used in COMPASS. While strategy selection is often unaffected by costs due to like-for-like comparisons, accurate estimation of operational expenses (OPEX) relies heavily on cost assumptions.

6.5.4 O&M simulation

There are several limitations that COMPASS still has that have not been addressed during this research work. Many of these are present in other simulation tools too. These limitations are listed below with suggestions for future research and improvements.

Weather simulation: It is common to use historical reanalysis data in O&M simulation tools, the most common being ERA5 historical reanalysis data that was also used in this thesis. Global climate is currently changing very fast due to the continuous release of greenhouse gases into the atmosphere which inevitably leads to the change in wave heights and wind speeds around the globe. Different research institutions are currently looking into that problem and trying to predict how much change will be seen in the future but no dataset has been developed as of yet that could replace hourly reanalysis data that is currently being used and capture the effect of climate change.

Separating personnel and RAS: This work focused very little on RAS but there are many emerging technologies that will make O&M much simpler, safer and faster. These could potentially include drones and turbine crawlers capable of inspecting turbine components and autonomous ROVs. These technologies could potentially charge offshore as well. Because they operate differently from personnel and have more flexibility in operation it would be beneficial to have a separate class in COMPASS capturing RAS.

Activity interruption: Section 5.3 presented the results from benchmarking COMPASS against two other O&M simulation tools. One of the outcomes of that work was that activity interruption can have a significant impact on the results. Interruption is relevant when small vessels without any accommodation are involved, such as CTVs. Smaller vessels usually have much stricter weather limitations. Activity interruption can occur due to: daylight duration, shift duration and the change in weather conditions. It is necessary to understand better which activities can be interrupted and which have to be continuous. This can be done by speaking to the relevant specialists in the industry. With this knowledge activity interruption can be integrated into O&M simulation tools and then these tools could guide the farm operators to the optimal strategies around how it is best to split O&M activities.

Activity duration: Section 2.4 presented the analysis of over 2000 heavy lift operations and estimated the duration of major operations for main turbine components. A significant variation in activity duration was observed. Probability distribution curves were fitted into the data in order to be able to incorporate them into COMPASS and capture duration variability. Future work can delve deeper into the data to understand what impacts the variation in activity duration, particularly what causes the activity to take longer than initially planned. Future work should investigate if weather, turbine size, vessel type or OEM type or a combination of these have an impact on the maintenance duration.

Dependencies between activities: O&M simulation tools often model maintenance activities in isolation from each other. It has been observed in Section 2.3 that some activities result from the other. Often a repair follows an inspection or a survey. Some maintenance operations are a sequence of tasks each requiring a different vessel. Cable repair activities, paint campaigns are the examples of such. TTP activity also qualifies as a sequence of tasks (mooring and cable disconnection, preparation for towing, towing, maintenance etc.). A feature that could benefit current O&M simulation tool is the ability to capture a sequence of activities that are dependent on each other.

Cable topology method improvements: The method capturing cable topology that was presented in this thesis in Section 4.8 is the first ever method that has been demonstrated to capture the impact of cable failures in O&M simulation tools, applicable even on complex array cable layout designs. Its current limitation is its inability to take into account cable rating. Currently COMPASS always assumes that electricity can be transmitted to the grid as long as there is a path between a turbine and an onshore substation. It does not measure the maximum carrying capacity of the cables on the path. This can be effectively implemented in the future and enhance energy output and EA estimation.

Appendix A

Stochastic failure generation methods in Python

The following code can be used to analyse the time it takes to run different failure generation methods

```
    """
Compare the time it takes to run different stochastic
failure generation methods
Note: Please note that some inputs can be modified
"""

import numpy as np
import math
import random
import matplotlib.pyplot as plt
import statistics
import time

"""Please set the failure rate here"""
failure_rate = 0.1 # failures per hour
"""Please set the number of 1-hour timesteps here"""
num_timesteps = 30000


mttf = 1/failure_rate
timesteps = list(range(num_timesteps))
time_delta = 1
ttf_dict = {'Method_1': [], 'Method_2': [], 'Method_3': []}

# Method 1
def method_1(ttf_dict, failure_rate, time_delta, timesteps):
```

```
    ttf = 0
    for timestep in timesteps:
        random_val = random.random()
        probability_failure = 1 - math.exp(-failure_rate * time_delta)
        if random_val < probability_failure:
            ttf += 0.5
            ttf_dict['Method_1'].append(ttf)
            ttf = 0
        else:
            ttf += 1
    return ttf_dict

# Method 2
def method_2(ttf_dict, timesteps, mttf):
    timesteps_ignore = []
    for timestep in timesteps:
        if timestep in timesteps_ignore:
            continue
        random_val = np.random.exponential(scale=mttf)
        ttf_dict['Method_2'].append(math.ceil(random_val)-0.5)
        timesteps_ignore = list(range(timestep, timestep +
        math.ceil(random_val)))
    return ttf_dict

# Method 3
def method_3(ttf_dict, failure_rate, timesteps):
    timesteps_ignore = []
    timesteps_ignore_max = -1
    for timestep in timesteps:
        if timestep <= timesteps_ignore_max:
            continue
        random_val = random.random()
        ttf = -1/failure_rate * math.log(random_val, 2.71828)
        ttf_dict['Method_3'].append(math.ceil(ttf)-0.5)
        timesteps_ignore_max = timestep + math.ceil(ttf)
    return ttf_dict


print('The time it takes to run Method 1, Method 2 and Method 3 takes')
```

```
start = time.time()
ttf_dict = method_1(ttf_dict, failure_rate, time_delta, timesteps)
end = time.time()
print(end - start)
print('and')
start = time.time()
ttf_dict = method_2(ttf_dict, timesteps, mttf)
end = time.time()
print(end - start)
print('and')
start = time.time()
ttf_dict = method_3(ttf_dict, failure_rate, timesteps)
end = time.time()
print(end - start)
print('seconds respectively')


# Plotting
plt.hist(ttf_dict['Method_1'], bins = 30)
plt.show()

print(f'The mean time to failure according to the selected failure
rate should be {mttf}')
for key in ttf_dict:
    mean = statistics.mean(ttf_dict[key])
    print(f'{key} mean is {mean}')
```

Appendix B

Cable repair and reburial procedure steps

Cable reburial is performed in four stages:

1. Detection of cable exposure
2. Pre-works survey where required
3. Cable reburial via mass flow excavator, water jet trencher/jetting ROV, or plough or in the case of an inter-tidal section backhoe dredger (if high tide), or excavator (if low tide).
4. Post-burial survey

In the case of the cable failure the repair is performed in the following steps:

1. Pre-works survey if required
2. Physically disconnect cables from electrical system and cable protection systems (if required)
3. Pull cable out of seabed by the cable laying vessel or debury via jetting/air-lifting tool. Approximately 300m length of an export cable or platform link cable or the whole length of an inter-array cable (up to 4km length) subject to the nature of the repair;
4. Cut the cable
5. Lifting the cable ends to the repair vessel (For array cables it may be preferable to lift a whole length of a cable between two turbines, of up to approximately 2-4 km length)
6. Jointing a new segment of cable to the old cable
7. Lowering the cable (and joints) back to the seabed
8. Cable burial
9. Post-works survey (if necessary)

Appendix C

R Studio script for fitting probability distributions

The following code can be used to analyse the time it takes to run different failure generation methods

```
library(fitdistrplus)
library(readxl)
library("xlsx")

# Set seed for the repeatability of the results
set.seed(2)

sheet_names <- c("Main_Bearing_single", "All",
                "Rotor_Shaft_Bearing_single",
                "Gearbox_single", "Gearbox_stacked",
                 "Blade_single", "Blade_stacked",
                 "Pitch_Bearing_single")

dir_name <- "Durations_Data\\Activity_Durations.xlsx"

# Initialise the dataframe
df <- data.frame (row.names = "ID","Setup name","Log-normal mean",
                  "Log-normal sd", "Log-normal p",
                  "Weibull shape", "Weibull scale",
                  "Weibull p", "Gamma shape", "Gamma rate",
                  "Gamma p")


# Iterate through Excel file sheets and read the data
for (sheet in sheet_names) {
sheet_name <- sheet
```

```
all_activities <- read_excel(dir_name, sheet = sheet_name)
activity_v <- t(all_activities[,sheet_name])
activity_v <- c(activity_v)
v_len <- length(activity_v)

# Generate a list of indexes
indexes <- seq(1, v_len)

# Select the sample size
if(sheet_name == "All" | sheet_name == "Blade_single" |
    sheet_name == "Blade_stacked") {
  sample_size <- 200
} else {sample_size <- v_len}

# Take a random test sample
dist_index_sample <- sample(indexes, sample_size)
test_sample <- activity_v[c(dist_index_sample)]

# Open png file for the log-normal distribution
fig_name <- paste(sheet_name, "_lnorm_2.png", sep = "")
png(fig_name, width = 857, height = 657)

# Fit log-normal distribution
fit.lnorm <- fitdist(activity_v, "lnorm")
par(mar = c(2, 2, 2, 2))
plot(fit.lnorm)
m <- fit.lnorm$estimate[1]
s <- fit.lnorm$estimate[2]
location <- log(m^2 / sqrt(s^2 + m^2))
shape <- sqrt(log(1 + (s^2 / m^2)))

# Test the log-normal distribution
test_lnorm <- ks.test(test_sample, "plnorm",
            meanlog=fit.lnorm$estimate[1],
            sdlog=fit.lnorm$estimate[2])

# Close the file
dev.off()
```

```
# Open png file
fig_name <- paste(sheet_name, "_weibull.png", sep = "")
png(fig_name, width = 857, height = 657)

# Fit weibull deistribution
fit.weibull <- fitdist(activity_v, "weibull")
test_weibull <- ks.test(test_sample, "pweibull",
            fit.weibull$estimate[1],
            fit.weibull$estimate[2])
plot(fit.weibull)

# Close the file
dev.off()

# Fit gamma distribution
fit.gamma <- fitdist(activity_v, "gamma")
test_gamma <- ks.test(test_sample, "pgamma",
            fit.gamma$estimate[1],
            fit.gamma$estimate[2])
plot(fit.gamma)

# Open png file
fig_name <- paste(sheet_name, "_cullen_frey.png", sep = "")
png(fig_name, width = 857, height = 657)
descdist(activity_v, discrete=FALSE, boot=sample_size)
# Close the file
dev.off()

# Update the dataframe with results with distribution variables
df[nrow(df) + 1,] = c(sheet_name, unname(fit.lnorm$estimate[1]),
            unname(fit.lnorm$estimate[2]),
            test_lnorm$p.value,
            unname(fit.weibull$estimate[1]),
            unname(fit.weibull$estimate[2]),
            test_weibull$p.value,
            unname(fit.gamma$estimate[1]),
            unname(fit.gamma$estimate[2]),
            test_gamma$p.value)
}
```

```
# Print the DataFrame to view the results
print(df)
```

Appendix D

Simulation convergence

Each scenario was run 20 times to minimize the error in the mean outputs.

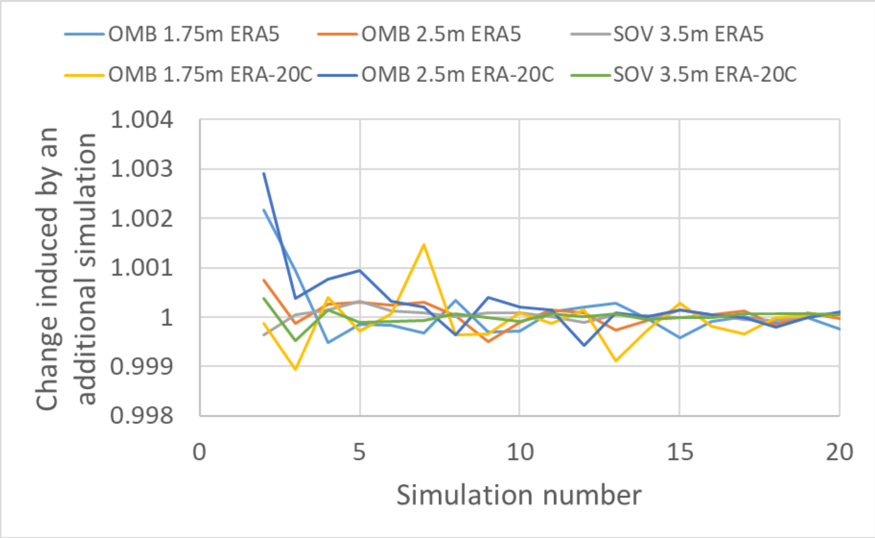


Figure D.1: Convergence of the average energy availability outputs

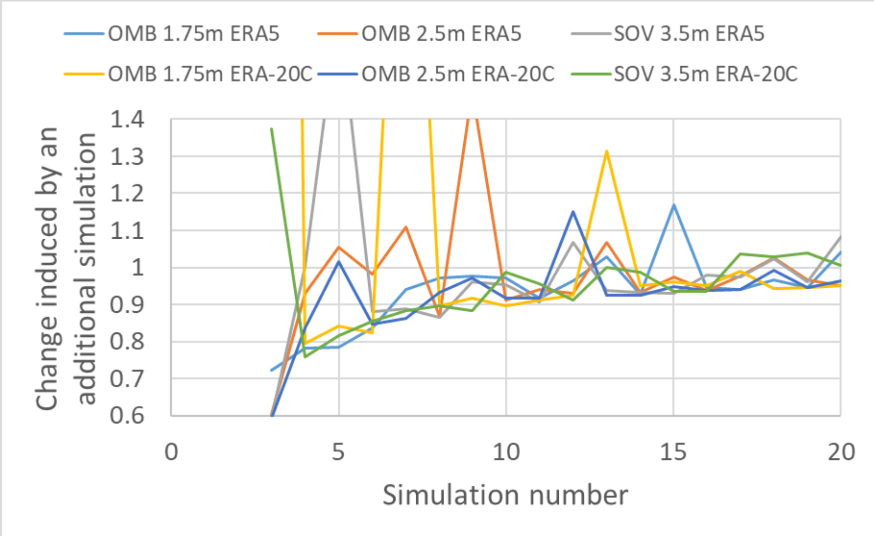


Figure D.2: Convergence of the margin of error for energy availability outputs

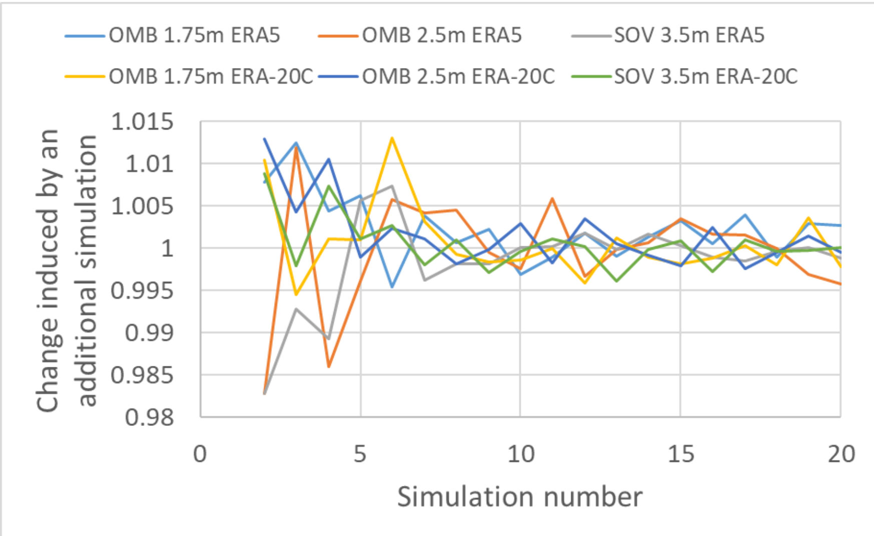


Figure D.3: Convergence of the average for logistics cost outputs

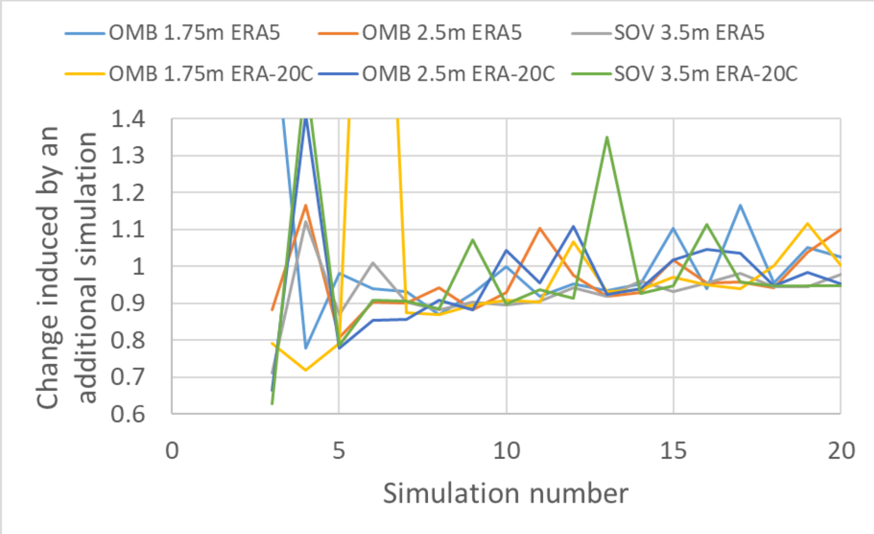


Figure D.4: Convergence of the margin of error for logistics cost outputs

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