Development of a Decision Support Tool for Day-to-Day Planning of Operations and Maintenance Logistics for Offshore Wind Farms

PhD Thesis

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Abstract

The offshore wind industry has grown rapidly in the past decade. Hundreds of turbines are being built in the North Sea every year. Maintenance of offshore assets is often hindered by the weather, vessel limitations and resource shortages. Deciding which maintenance tasks to carry out on the day is challenging, particularly at large wind farms, where operators have hundreds of tasks to choose from. Once the tasks have been selected, the assignment of technicians to vessels and vessels to turbines is decided, usually by human decision makers.

In this thesis, methodologies for O&M decision support were developed. Formulation of the problem solved in this thesis was assisted by an offshore wind farm operator to ensure applicability of the developed solutions in the real world. Firstly, a maintenance task prioritisation approach was proposed. Secondly, a tool for optimisation of vessel routes was developed. Given a set of vessels of varying specifications and a set of turbines with a range of maintenance actions to be completed, the tool computes and visualises effective vessel routing policies.

The outputs of the task prioritisation model can be used as inputs to the vessel routing optimiser to improve the quality of policies generated by the latter. This was illustrated in two case studies, which provided an in-depth analysis of the outputs of both models. The case studies have shown that considering uncertainties when planning vessel routing can yield up to 14% increase in the number of maintenance actions completed once the uncertainties have realised (compared to a policy which did not take uncertain inputs into account).

Additionally, the tool was tested during a visit to an offshore wind farm operations centre. It was shown that given the same choice of maintenance tasks and vessels, the tool exactly matched the policies created by human decision makers.

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I would like to thank the industrial partner (who cannot be named for confidentiality reasons) for supplying operational data and enabling me to visit their wind farm.

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Finally, throughout this journey I was supported by my friends, family and Zuzanna – thank you so much for your help.

Contents

Definitions, Abbreviations and Mathematical Symbols

Definitions

Accessibility – the proportion of time a wind turbine can be accessed for a given duration of a maintenance window (which in turn can be defined as the sum of transfer time, defined below and maintenance time). Access is possible when the significant wave height and wind speed at a turbine do not exceed the maximum allowed values.

CAPEX – Capital Expenditure – the costs incurred by a project before any revenue is generated.

Class 1 & Class 2 vessels – informal nomenclature used by some wind farm operators to distinguish between the improved capability vessels and standard CTVs (Crew Transfer Vessels). Generally, Class 2 vessels are standard CTVs while Class 1 vessels are modern, faster CTVs with improved crew transfer capabilities in high waves. Examples of Class 1 & 2 vessels were provided on page 159.

Cluster – in the context of offshore wind vessel movement planning, a cluster is a set of wind turbines requiring maintenance. All turbines in any given cluster are visited by the same vessel.

Crew-hours – hours of work done by each crew of technicians; used as an indicator of the amount of useful work completed by a given policy. Used rather than man-hours due to variable crew size depending on the task.

Critical path – for a single cluster of turbines, once the order of visits has been determined, a task is said to be on the critical path if it has no slack time associated with it. For example, if a task was to take longer than expected, the policy duration (as defined below) will be delayed by the same amount of time. On the contrary, a task is said not to be on the critical path if an increase in maintenance time does not result in the same increase of policy duration.

Levelised Cost of Energy (LCoE) – is the average price per unit of energy produced, which must be earned for a project to break even over its lifetime. It facilitates comparison of cost of producing a unit of electrical energy using different technologies. LCoE can be calculated by dividing the discounted total project costs (capital and operational) by the value of electricity produced over the lifetime of the project.

Logistics – "The part of supply chain management that plans, implements, and controls the efficient, effective forward and reverse flow and storage of goods, services and related information between the point of origin and the point of consumption in order to meet customers' requirements" definition adapted from [1].

O&M – Operations and Maintenance – encompasses all activities undertaken to maintain wind turbine electricity generation.

O&M Planner – the person, or team of people, responsible for creating daily O&M plans at an offshore wind farm.

OPEX – Operational Expenditure – funds required to run the project once revenue generation has begun. In the context of the offshore wind industry, this typically refers to costs associated with O&M.

Policy – (in the context of planning vessel routing) – a vessel dispatch plan, specifying the assignment of vessels to turbines and the order in which vessels visit individual turbines.

Policy duration – time between vessel leaving and returning to the O&M base

Probability of correct fault diagnosis – Pd(i) – occasionally, the operator may not be confident about the type or extent of work required on a faulty turbine. Pd(i) is a user input; setting it to 0.9 means that the user is 90% confident that the fault can be repaired in the expected time given the assumed amount of resources. This value can be used to influence low-risk policies, discouraging visits to turbines which may have been incorrectly diagnosed.

Route – a set of ordered wind turbine visits.

Sail day – a day when vessels can safely leave harbour and access the turbines to transfer technicians.

Time window – is the amount of time technicians and vessels have for carrying out maintenance, in a single day. Time window begins and ends with all technicians and vessels at the O&M base. In this thesis, it was assumed that time window constitutes the time limit; i.e. the maximum policy duration (defined above).

Transfer time – the time required to transfer technicians, tools and spare parts from a vessel onto a turbine and vice versa.

Utility – value associated with a maintenance task, describing the relative benefit associated with completing that task on the given day, compared to other tasks.

Weather day – also known as no sail day – a day when it is unsafe for vessels to leave the harbour, or attempt transfer of technicians onto turbines, due to weather conditions.

Wind farm operator – person, company or entity responsible for day-to-day management and control of wind farm activities.

Vessel routing – concerns deciding the route a vessel will take in terms of the turbines visited and the order of turbine visits. Not to be confused with the problem of deciding the route of the vessel between base and the wind farm (depending on the local sea conditions)

Abbreviations:

ALNS – Adaptive Large Neighbourhood Search

AI – Artificial Intelligence

BoP – Balance of Plant

CAPEX – Capital Expenditure

CBM – Condition-Based Maintenance

CDF – Cumulative Distribution Function

CMMS – Computerised Maintenance Management Systems

CMS – Condition Monitoring System

CTV – Crew Transfer Vessel

GA – Genetic Algorithm

GWO – Global Wind Organisation

HMM – Hidden Markov Model

HSMM – Hidden Semi-Markov Model

KPI – Key Performance Indicator

LCoE – Levelised Cost of Energy

LNS – Local Neighbourhood Search

MCDA – Multiple-Criteria Decision Analysis

MTBV – Mean Time Between Visits

MTTR – Mean Time To Repair

NN – Neural networks

OEM – Original Equipment Manufacturer

OPEX – Operating Expenditure

PDF – Probability Density Function

PPE – Personal Protective Equipment

RUL – Remaining Useful Life

SHM – Structural Health Monitoring

SMDP – Semi-Markov Decision Process

SOV – Service Operations Vessels

SWATH – Small Waterplane Area Twin Hull

VEGA – Vector Evaluated Genetic Algorithm

WT – Wind Turbine

Mathematical symbols:

Chapter 3

A – number of actions available to the operator

a – individual action identifier

a_N – “do nothing” action identifier

C – cost matrix for the SMDP model

D – reward matrix on the last day of SMDP simulation

H – significant wave height

Oa – optimal action array (per time stamp, per state)

R – reward matrix for the SMDP model

S – number of SMDP states

s – individual SMDP state identifier

T – transition matrix for the SMDP model

U – utility value of taking an action

V – value of an SMDP state

Z – planning horizon (in days)

γ – discount factor

τ – individual time step identifier

Chapters 5 and 6

B – crew & spare parts transfer time (between turbine and vessel)

c – cluster identifier

Cf – cost of fuel (in £ per day)

Ch – cost of vessel hire (in £ per day)

Cr – cost of wind turbine repair (in £)

E – speed correction factor

$F_{WT1\text{-}WT2}$ – distance between wind turbines WT1 and WT2

Ge – slack time at the end of the day

Gc – critical path slack time

Gn – non-critical path slack time

i – wind turbine identifier

J – total number of vessels used in a given policy

j – vessel identifier

K – expected duration of maintenance action

L – load in kg (i.e. spare parts and tools) required to carry out a maintenance action

Lc – total load in kg (i.e. spare parts and tools) required for all turbines in a cluster

M – number of technicians required to carry out a maintenance action

Mc – total number of technicians required for all maintenance actions in a cluster

P – probability of successfully maintaining all turbines within a cluster

Pt(i,j) – probability of successfully transferring the crew onto turbine i using vessel j

Pd(i) – probability of successful task completion, given the condition monitoring signal received from the turbine

Pr(i) - probability that repairing turbine i takes less time than the time available for a particular repair

P_x – weighted probability of completing maintenance on all turbines within a cluster

Q – number of turbines assigned to a cluster (or a vessel)

U_{mean} – mean of utility values of all maintenance actions to be carried out on a given day

W – time window (in hours)

V_{cs} – vessel carrying capacity (spare parts and tools)

V_{ct} – vessel carrying capacity (technicians)

V_v – vessel cruise speed

X – maximum time a maintenance task can take without breaching the time constraint

Y – risk aversion factor

α – gamma function shape parameter

β – gamma function scale parameter

Γ – gamma function

η – maximum number of turbines in a cluster

φ – task slack multiplier

ε – number of vessels (clusters) in a policy

λm – random number determining the duration of maintenance action

λt – random number determining whether crew transfer is possible

λd – random number determining whether a turbine has been correctly diagnosed

Ω – cluster's value

$\Omega_{y=0}$ – cluster's value, excluding the probability calculation

Chapter 1. Introduction

Vertical axis windmills built around 200 BC at the Persian-Afghan border are regarded as the first documented example of a stationary device which harnessed power of the wind [2]. The technology has come a long way since then; instead of grinding grain or pumping water, modern wind turbines convert the kinetic energy of moving air into electricity.

Wind power, as a renewable source of energy, is increasingly seen as an alternative to fossil fuels. In 2015, installed wind capacity reached 432 GW worldwide, which constituted around 7% of the total global power generation capacity [3]. In years 2000-2015, wind power accounted for one third of all new power installations in the European Union [4].

Despite these developments, it is feared that future development of onshore wind will be thwarted by scarcity of appropriate on-land installation sites, visual and environmental impact, concerns on noise and the use of land [5]. The sea, on the other hand, offers large, continuous areas on which major projects can be undertaken [6]. Constructing wind farms offshore mitigates the impact of electricity generation on human societies. Due to higher average wind speeds, offshore wind farms can achieve significantly higher capacity factors [7].

Offshore wind constitutes less than 3% of the total wind power capacity worldwide [3]. The first commercial offshore wind farm, Vindeby, was constructed in the Baltic sea off the Danish coast, in 1991. In little over 25 years, the technology has progressed from a small scale pilot project to playing an important part in the European Union's energy mix.

Offshore wind power is not without its disadvantages. Operations and Maintenance (O&M) costs associated with offshore wind farms are around double compared to onshore [8]; they constitute up to 30% of the total life-cycle cost [9]. Subsea foundations and cables, are more expensive to manufacture and install, making the capital costs of an offshore wind farm around twice that of an onshore farm [8].

Furthermore, repairs on an offshore turbine may not be possible in strong winds or high waves, due to vessel limitations and Health & Safety Rules. Restricted access to wind turbines in poor weather is one of the possible reasons for increased offshore failure rates, which have been shown to be up to 8 times higher for certain components [10]. Lower accessibility (as defined in Definitions Section) and higher failure rates have an impact on the wind turbine availability, contributing to increased cost of energy of offshore wind.

Contrary to new onshore wind developments in the UK, offshore wind still relies on government subsidies. This may change in the future: researchers argue that Levelised Cost of Energy (LCoE, defined in Definitions section) of offshore wind can be reduced by around 40% by 2026 [11]. This reduction is expected to be achieved despite the rise in capital expenditures (CAPEX), which has occurred in the past 15 years, as turbines were built in deeper waters and further offshore [11].

One of the key factors driving the cost of offshore wind power down is the increase in turbine size, as it can lead to cost savings in substructure, installation, O&M and grid infrastructure, as shown in Figure 1.1 [9]. Although the cost of turbine increases with rotor size, this may be party mitigated by a reduction in component costs due to economies of scale and increased efficiency and experience of the supply chain.

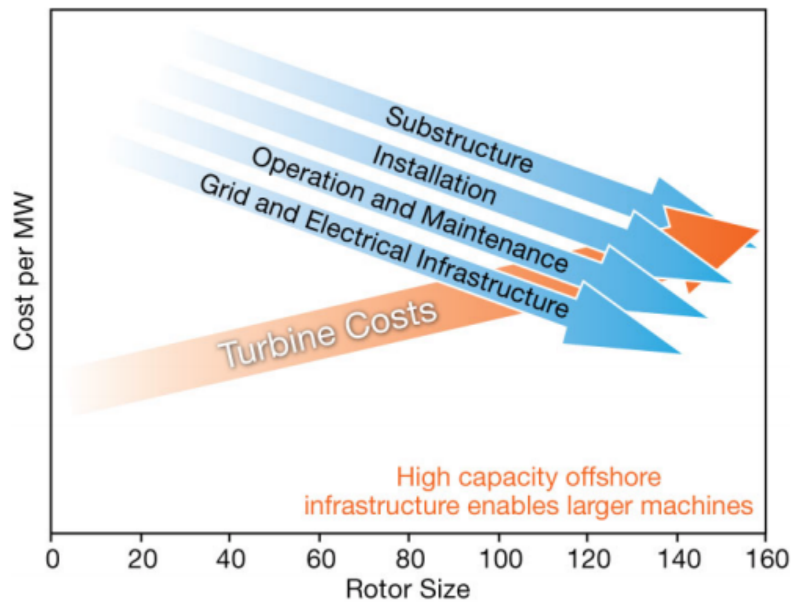

Figure 1.1. General trends in costs vs. rotor size [9].

A definition of O&M was provided in [12], stating that it comprises of two, distinct streams of activity. “Operations” refers to activities contributing to the high level management of the asset, while “maintenance” is the up-keep and repair of the physical plant and systems. A recent (2014) LEANWIND report [13] stated that significant O&M cost savings can be made through learning and technological innovation. The report produced numerous recommendations for offshore O&M cost reductions, which included:

a) Multi-functional vessels adaptable to a wider variety of tasks
b) Novel vessel designs or access system technologies to increase transfer capabilities in high waves (increased accessibility of turbines)
c) Decreased transit time between O&M base and wind farm (faster vessels)
d) Reducing vessel's motion which incurs sea sickness, which has a detrimental effect on maintenance crew operational efficiency
e) Improved weather prediction

Application of recommendations a-d on existing wind farms would likely require development, or purchase, of novel vessels, which take time to build and can be costly. Alternatively, an attempt can be made at improving the current systems and processes. This view is supported by a report by Offshore Renewable Energy Catapult [14], in which improvements of asset management strategies through the use of decision making tools was deemed one of the key priorities for the industry. Increasing the effectiveness of maintenance scheduling and vessel routing has the potential to both improve wind turbine availability and decrease the costs associated with offshore O&M.

In the context of offshore wind farm O&M, the term "logistics" encompasses a variety of activities, ranging from supply chain management, spare part management, vessel fleet management, and scheduling and routing vessels. Logistics constitute up to 18% of the total life-time costs of offshore wind farms [1]. According to Poulsen & Hasager [1], logistics is the "overlooked frontier in the quest for lowering the LCoE of offshore wind".

Planning maintenance at offshore wind farms is a complex process. Wind farm operators need to ensure the availability of resources required to carry out both planned and unplanned maintenance. Each day, planners need to prioritise maintenance tasks and decide on the assignment of technicians to tasks. Then, technician teams are assigned to vessels and the order of turbine visits is decided. As shown in Appendix A. Calculating the Number of Possible Vessel Routing Policies, there are more ways to solve this problem than there are stars in the observable universe. There are very few, if any, decision support tools which would facilitate making those decisions in the real world (as discussed in Section 2.1). Optimisation algorithms supporting day-to-day offshore wind farm decision making may enable operational cost decreases, increased efficiency and minimisation of human error.

1.1 Research Aim

This PhD project was initialised with the following **research question**:

"How can current wind turbine O&M systems and processes be improved through more efficient utilisation of resources to reduce the Levelised Cost of Energy (LCoE[1])?"

The research that followed combined with interviews with the members of industry revealed a clear research gap (as discussed in Section 2.1). A need was identified for methodologies capable of supporting operational (day-to-day) decisions regarding scheduling maintenance tasks on offshore wind farms. Definition of the research gap enabled specifying the **research objective**:

"The objective of research is to develop methodologies for supporting operational logistical decisions on offshore wind farm, which are suitable for practical application and aim to reduce LCoE through efficient use of resources."

In order to achieve this research objective, the following steps were taken:

- Research into the practicalities of planning offshore wind farm O&M and identification of the focus of the proposed decision support tool (Chapter 2)
- Literature review on the existing methodologies which could be applied in the proposed tool (Chapters 3 and 4)
- Development, testing and validation of the proposed methodologies for offshore wind farm LCoE reductions (Chapters 3, 5, 6 and 7)

Research goals and requirements are discussed in detail in Sections 2.3 and 4.3.

[1] As defined in Definitions Section.

1.2 Thesis overview

This thesis described the development and validation of a decision support tool for offshore wind farm O&M planning/vessel routing. The tool comprises of two key models: an SMDP prioritisation model and a vessel routing optimiser, with the outputs of the former being used as inputs to the latter. An overview of the two models, including their inputs and outputs is shown in Figure 1.2. This thesis is divided into eight chapters; their contents and novelty was described in the following sub-sections.

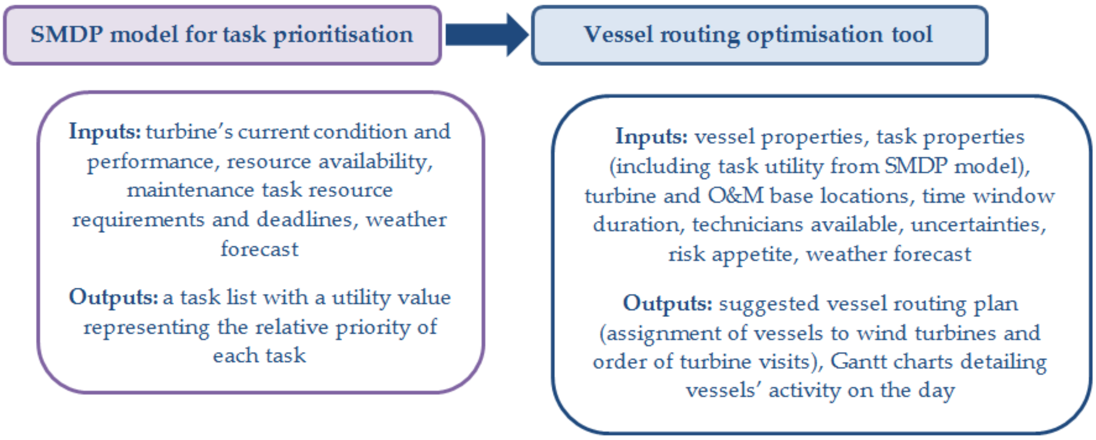

Figure 1.2. Visualisation of the inputs and outputs of the models developed in this thesis.

Chapter 2

Chapter 2 described the practicalities associated with planning offshore wind farm O&M. A research gap was identified at the start of the chapter. An attempt was made to scope the real world problem, including relevant constraints and factors to be considered when modelling. This was achieved through a review of relevant scientific papers and industry reports. Where no literature could be found on certain topics, gaps in the knowledge were filled through informal interviews with an offshore wind farm operator.

Chapter 2 was summarised with a list of requirements a decision support tool should have in order to be applied in a real world, which influenced the methodology choices made in latter chapters of this thesis.

Chapter 3

Chapter 3 focused on the problem of task prioritisation for offshore wind farms. A literature review was conducted to identify the factors and constraints which need to be taken into account when prioritising wind turbine maintenance tasks. Since the literature review did not identify a method which could be directly applied to the problem at hand, a novel approach for task prioritisation was developed. The proposed solution, based on a Semi-Markov Decision Process (SMDP), assigns a numerical value to a task's priority. The factors taken into account when assigning a task priority value include deadlines, wind and wave forecasts, turbine performance and future resource availabilities. The proposed SMDP method was applied to two case studies to evaluate its effectiveness. The results of the SMDP case studies were used as inputs to the tool developed in Chapter 5.

Chapter 4

Chapter 4 provided an in-depth literature review of approaches for solving the Vehicle Routing Problem (VRP); a well-researched area with numerous similarities to the problem faced daily by wind farm operators. An attempt was made to find a methodology applicable to the problem described in Chapter 2. Solutions developed for other industries have been considered, but none were deemed suitable for the problem at hand. A review of publications in the offshore wind domain was also conducted. In the end, it was determined that a novel methodology should be developed to solve the problem of offshore wind farm vessel routing. The knowledge gathered in the process of reviewing the literature was summarised as a set of requirements which a vessel routing optimiser should meet (Section 4.3).

Chapter 5

Chapter 5 described the development of a decision support tool for offshore wind farm vessel routing. The proposed approach consisted of a sub-problem solution approach (decision flowcharts, described in Section 5.2) and a master problem solution approach (a novel heuristic method, described in Section 5.3). Uncertain factors, such as the expected maintenance task duration, were modelled through incorporation of a risk aversion factor into the value function (as described in Section 5.2.3). The user can specify the impact uncertain inputs have on the policy generated by the tool by defining a risk aversion factor. A methodology for evaluating the policies generated by the tool using a Monte-Carlo approach was developed and discussed in Section 5.4.

Chapter 6

To demonstrate the capabilities of the tool described in Chapter 5, it was applied to two case studies (continuation of the case studies presented in Chapter 3). In depth analysis of the tool's outputs for the Winter Day and Summer Day case studies is provided in Sections 6.2 and 6.3 respectively. It was shown that a 14% increase in the number of maintenance actions completed can be achieved by including input uncertainties in the optimal policy calculation.

Chapter 7

Chapter 7 described the process of validating the proposed tool. The tool consists of three key parts: task prioritisation module, sub-problem and master problem solution approaches. Validation of those three approaches is discussed in Sections 7.2, 7.3 and 7.4 respectively. The entire tool was then applied to a real world case study, as discussed in Section 7.5. Comparison of the proposed tool's capabilities against other models in the field and against previously specified requirements are discussed in Sections 7.7 and 7.8 respectively.

Chapter 8

Chapter 8 summarised the work done in this thesis, with the tool's limitations and future work discussed in Section 8.3.

1.3 Contributions

The key contributions arising from the work done in this thesis include:

1. Development of the SMDP model for task prioritisation, which has the potential to be used in a variety of engineering sectors. In the published literature, this is the first attempt at quantification the relative utility value of carrying out offshore wind turbine maintenance tasks.
2. Development of a new heuristic algorithm, which outputs are comparable with the outputs of a commercial solver (for problems with 10-20 turbines).
3. Development of a novel methodology for incorporating uncertain inputs into a decision support tool. Quantification of the benefits arising from consideration of input uncertainties.
4. Application of the proposed decision support tool to a real world case study at an offshore wind farm. Definition of the real world problem from the point of view of a large (100+ turbines) offshore wind farm operator.

The publications and presentations associated with the above contributions are outlined below.

SMDP model for task prioritisation

Publication: Dawid, R, McMillan, D, Revie, M, "Time Series Semi-Markov Decision Process with Variable Costs for Maintenance Planning", *Risk, Reliability and Safety: Innovating Theory and Practice: Proceedings of ESREL 2016 (Glasgow, Scotland, 25-29 September 2016) p. 1145-1150.*

Dissemination: Oral presentation at European Safety and Reliability Conference (ESREL), 25-29 September 2016, Glasgow, UK.

Novel heuristic method

Publication: Dawid, R, McMillan, D, Revie, M, "Heuristic algorithm for the problem of vessel routing optimisation for offshore wind farms", *The Journal of Engineering 2017 (13), p. 1159–1163.*

Dissemination: Oral Presentation at the 6th International Conference on Renewable Power Generation (RPG), Wuhan, China, 19–20 October 2017.

Offshore wind farm vessel routing model

Publications:

- Dawid, R, McMillan, D, Revie, M , "Development of an O&M tool for short term decision making applied to offshore wind farms", WindEurope Summit, Online Proceedings, 2016. Available at: https://pure.strath.ac.uk/portal/files/56450691/Dawid_etal_WES2016_Development_of_an_O_M_tool_for_short_term_decision_making.pdf Accessed on: 2/11/2018

- Dawid, R, McMillan, D, Revie, M, "Decision Support Tool for Offshore Wind Farm Vessel Routing under Uncertainty", Energies Journal 11, 2190, 2018. Available at: http://www.mdpi.com/1996-1073/11/9/2190/pdf Accessed on: 2/11/2018

Dissemination: Oral presentation at EERA DeepWind'2017 Conference (18-20 January 2017) in Trondheim, Norway.

Industrial collaboration: An offshore wind farm operator provided data and expert knowledge, aiding the development of the decision support tool. However, due to data sensitivity issues, the operator wishes to remain anonymous.

Chapter 2. Planning Real World Offshore Wind Farm O&M

The aim of this chapter is to provide an outline of the practicalities associated with organisation of maintenance at offshore wind farms. Through a combination of literature review and interviews with wind farm operators (who did not wish to be named), this chapter attempts to:

1) Outline decision support tools for offshore wind, in an attempt to find a research gap (Section 2.1)
2) Familiarise the reader with the practicalities associated with real world maintenance of offshore wind turbines (Section 2.2)
3) Identify key challenges associated with planning maintenance (Section 2.3)

2.1 Models for Offshore Wind Farm Decision Making

The decisions made by wind farm operators can be broadly split into three categories, as proposed by Shafiee [15]:

a) Strategic decisions (planning horizon: 5 to 25 years) – which are often made at the beginning of the project. They include location of the O&M base location, type and layout of the wind turbines used
b) Tactical decisions (planning horizon: months to 5 years) – which include charter strategy for jack-up vessels, additions/removals from vessel fleet, upgrades to the O&M base, planning yearly annual service campaigns
c) Operational decisions (planning horizon: days to a month) – which include planning and prioritising on-the-day O&M actions and defining short term staffing requirements (i.e. how many technicians are required)

According to a report prepared by ORE Catapult, improvement of O&M operations through the use of decision making tools is a priority for offshore wind [14]. Shafiee [15] provided an exhaustive literature review of models for maintenance logistics organization for offshore wind energy. In total, 102 publications were referenced, of which 48 were classified as models supporting strategic decisions, 30 for tactical decision support and 24 models focusing on operational decisions. O&M and transport logistics were both in identified in a list of the top 10 areas within offshore wind planning, in which the need for decision support tools was the greatest [16].

Shafiee & Sørensen [17] proposed a framework for classification of asset management approaches. This publication also contained a review of papers published on the wind turbine maintenance optimisation approaches. The paper's conclusions contained two important points quoted below:

"Although many good maintenance optimization methods have been developed in literature, there still remains a big gap between academic models and application in practice. Many of the works have been published for mathematical purposes, whereas only very few number of industrial cases (~6% of the total publications) have been presented."

"Uncertainty in weather conditions and sea state is a major factor which can affect the accessibility in a wind farm. Meteorological conditions have so far seldom been considered as a stochastic input"

To the author's knowledge, there is no commercial tool for day-to-day planning of O&M activities and vessel routing/scheduling[2]. Interviews with experts (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators) revealed that most wind farms do not use operational decision making support tools. Out of the three decision making planning horizons outlined in a-c), operational decisions received the least attention in literature, as shown in Figure 2.1.

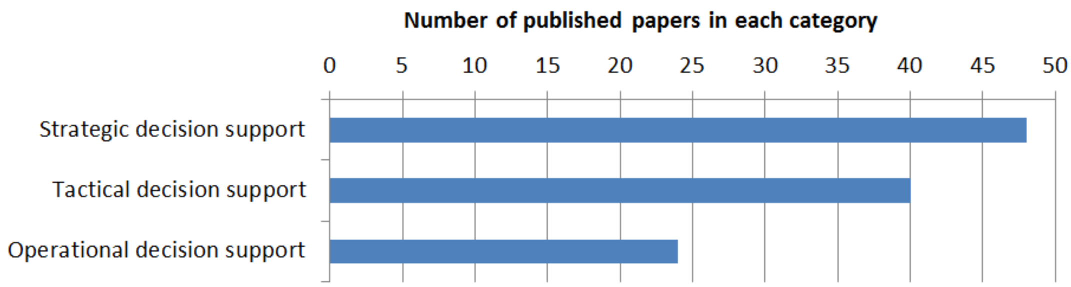

Figure 2.1. A breakdown of research in the offshore wind domain by decision horizon (from [15]).

2.1.1 Economic Case of Operational Decision Support Tools

As discussed in the previous section, most wind farms do not use decision support tools for day-to-day operations. Is it possible that the potential gains, which could be achieved by optimising daily wind farm O&M, are insufficient to justify investment in this area? To answer this question, a crude calculation quantifying the potential benefits of improved efficiencies in wind farm O&M planning is shown below.

Potential benefits of more efficient organisation of work are outlined in Table 2.1. Working on a conservative assumption that improvements in O&M work organisation can bring a 1% reduction in vessel use, 1% reduction in staff cost and 0.1% of increase in power capture (due to reduced lost revenue), the yearly revenue of a 500MW wind farm could be increased by over £250,000. Note that the aim of this

[2] Review of scientific publications on this topic is provided in Section 4.2.6.

crude calculation purely to illustrate the order of magnitude of potential benefits of improvements in the short term O&M decision making. A tool capable of achieving the above cost savings would likely be in high demand among offshore wind farm operators, provided it was sufficiently versatile to be applied to different sites without major alterations.

Table 2.1. Summary of potential benefits of day-to-day decision support tools.

Cost saving	Yearly cost/revenue for equivalent 500MW offshore wind farm	Estimated benefits
Reduced vessel use	**£2.5 million annually** including charter and fuel cost (from [12])	**1% cost reduction £25,000**
Reduced number of technician man-hours	**£2.4 million annually** assuming 30 technicians at a salary cost of £80,000 pa	**1% cost reduction £24,000**
Increase in wind turbine availability, leading to increased revenue	**£218 million annually** assuming energy price of £103/MWh (from [3]) and capacity factor of 48.3% - average capacity factor for Danish offshore wind farms in 2017 (from [4])	**0.1% revenue increase £218,000**

This section demonstrated that operational offshore wind farm O&M decision support tools received the least attention of the research community. There is a clear lack of models which have been applied to industrial cases. An O&M optimiser applicable to the real world problem could bring substantial cost savings to the offshore wind industry. Published operational decision tools for offshore wind are reviewed in the following section.

2.1.2 Operational Decision Support Tools for Offshore Wind

A comprehensive review of various decision support tools for offshore wind was conducted by Hofmann [18], who identified 49 different commercial and non-commercial models for different stages of the wind farm life cycle. One of the key conclusions of this paper was that most decision support models focus on the wind farm life cycle and long term planning – only one model out of 49 was explicitly defined as operational (or short term) decision support tool.

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[3] £103/MWh comes from taking an average of the Contract for Difference prices for wind farms auctioned off in the UK between November 2014 and September 2017. Source: [201]

[4] Source: http://energynumbers.info/capacity-factors-at-danish-offshore-wind-farms accessed on 23/05/2018

In their work, Hofmann [18] named commercially available software, including SeaPlanner by SeaRoc and WONDER by Deutsche Windguard. These systems can make wind farm operators job easier by facilitating technician movement tracking, logging maintenance, accessing SCADA data and visualising current operations. However, these commercial software packages lack the capability to optimise O&M by prioritising maintenance tasks or ordering turbine visits. Details of the commercial decision support tools such as the constraints they consider and methods they use are scarcely available. It is therefore difficult to evaluate the capabilities of the commercial products. While it is possible that some wind farm operators use in house scripts for decision support, it is often not in their best interest to share the details of the models and publish their capabilities.

Most publications on models for operational decision support for offshore wind focus on the problem of task scheduling [15]. In the real world, this process involves deciding the tasks to be carried out on the day or in near future. The choice of tasks depends on a number of factors, which include:

- Resource availability (vessels and technicians)
- Weather forecast (wind and significant wave height)
- Types of maintenance actions to be completed (deadlines, lost revenue if action is not completed, time or resources required to complete maintenance action)

Zhang et al. [19] proposed a Genetic Algorithm approach for optimising preventive maintenance actions at a small (25 turbines) wind farm. Actions are planned so that maintenance takes place during periods of low wind and taking into account the wake effects. Besnard et al. [20] showed that significant cost savings can be achieved by using the opportunistic maintenance approach to carry out preventative tasks while on a turbine carrying out a corrective action. Byon et al. [21] used discrete event system specification (DEVS) to simulate wind farm O&M activities, concluding that condition-based maintenance can lead to increased turbine availability compared to scheduled maintenance.

Additionally, there are five publications on optimisation of vessel routing for offshore wind farms [22]–[28] (methods used in those papers are discussed in Section 4.2.6). However, published work in this domain fails to take uncertain inputs into account (the impact of uncertainties on the operational decision making is discussed in Section 2.2.7). Only one of the papers published in the offshore wind O&M optimisation field has been applied to a real world case study [27].

The general trend emerging from this literature is that most authors focus on a part of the problem (e.g. condition based vs. scheduled maintenance, benefits of opportunistic maintenance, solution of vessel routing problems without prioritising tasks or taking uncertainties into account). Research should be focused on development of a holistic approach, capable of supporting a wider scope of decisions, instead of solving operational sub-problems separately.

Furthermore, some researchers argue that most academic models are not applicable to the real world problems. According to van Horenbeek, Pintelon & Muchiri [29]:

> *"The gap between academic models and application in a business specific context is still the biggest problem encountered in the field of maintenance optimization."*

The research gap in the field of operational O&M planning is a decision support tool applicable to the real world problem. Currently, no published methodology is capable of supporting decisions on both task prioritisation and vessel routing, while taking uncertainties on inputs into account. The following sections aim to describe the real world problem in more detail to identify constraints to be modelled and requirements which a method for planning O&M and vessel routing should meet.

2.2 The Problem of Day-To-Day Planning of Offshore Wind Farm Maintenance

Wind turbines need regular maintenance to generate power. The responsibility for carrying out O&M activities on turbines under warranty lies with Original Equipment Manufacturer (OEM) [30]. Once the warranty expires, the owner/operator decides whether to take on planning and execution of the O&M activities themselves, or to subcontract the OEM/third party company. In this thesis, "wind farms operator" refers to the entity currently responsible for planning wind farm O&M activities – including ensuring maintenance is done promptly and efficiently. The wind farm ownership structure was briefly discussed in Appendix C. Wind farm Ownership Structure.

An overview of the problem of operational planning of O&M for offshore wind farms is provided in Section 4.1. This section aims to provide a more detailed overview of the real world considerations wind farm operators need to take into account when planning O&M.

2.2.1 Planning Horizon in the Context of Vessel Routing

Rolling horizon, as defined by Sethi & Sorger [31], is often used for decision making in a stochastic environment. The term horizon refers to the number of future time periods which are considered when planning maintenance. A plan for the entire horizon is made at each iteration. Plans are continuously updated as new information becomes available (e.g. realisations of uncertainties or updated forecasts).

Offshore wind farm O&M planners tend to operate on a 3-7 day rolling horizon [15]. A detailed plan, including vessel assignment and the order of wind turbine visits is always created for the following day (day 1 of the rolling horizon). Plans for days 2-7 tend to be less detailed, as they are heavily dependent on the work completed on day 1.

The rolling horizon approach suits the problem of offshore wind farm maintenance planning. Detailed plans for days 1-2 cover the actions to be taken, technicians who carry them out and vessels used for transportation. Beyond that, resources and manpower required in the following week are estimated and secured to ensure technicians will be able to complete required actions. Creating detailed vessel routing plans for days 3-7 would likely be counterproductive, as by the time real world uncertainties realise, the plans, in most cases, would be outdated.

In some cases, certain aspects of offshore wind turbine O&M can be planned over a month in advance. For example, summer annual service campaign may be planned in the winter. This can involve pre-allocating resources to particular turbines, at particular dates. However, unforeseen circumstances may mean that those plans need to be revised. Similarly, plans to charter a jack-up vessel may be made months in advance, to avoid high spot-market hire prices for this type of vessels.

The need to create a detailed maintenance plan a day before it is to be implemented puts a lot of stress on the O&M planners. Interviews with offshore wind farm operators (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators) revealed that if a change of circumstances (e.g. turbine failure) occurs towards the end of planner's shift, they may be required to do overtime to create a plan of action for the following day. Working under pressure and on a tight schedule is likely to increase occurrences of human error, potentially leading to increased O&M costs.

2.2.2 Types & Characteristics of Maintenance Actions

Maintenance actions can be divided into preventative and corrective actions. Corrective maintenance involves taking action once a component has failed. Preventive maintenance involves either periodical services or Condition-Based Maintenance (CBM). The latter approach utilises CM data analysis to estimate the condition of the component and plan maintenance accordingly to avoid expensive failure. Comprehensive modelling by Andrawus et al. [32] has shown that CBM approach is the most effective approach for wind turbine O&M.

A number of researchers have shown the benefits of implementation of Condition Monitoring Systems (CMS) on wind turbines [33]–[36]. CMS usually consists of various sensors, which monitor the condition of a component and means of transferring that information to a processing unit. Additionally, modern wind turbines are equipped with SCADA systems, which can also aid prediction of incipient faults [37]. An overview of CMS for wind turbines is provided in Section 3.2.1.

Many modern wind farms are equipped with Computerised Maintenance Management Systems (CMMS), which facilitate CBM. CMMS monitor data coming from CMS; if parameters (such as component temperature/vibration) exceed pre-defined thresholds, system user is automatically alerted [38]. The alarm system is designed to analyse multiple data sources to provide maintenance planners with the most likely cause of parameter deviation, enabling them to plan appropriate actions to prevent failure. CMMS are described in more detail in Section 3.2.2.

Despite wind farm operator's efforts to prevent failures, some inevitably occur. A breakdown of failures by component is shown in Figure 2.2. To restore power generation, repairs of failed components are usually prioritised over preventative maintenance actions. Interviews with wind farm operators (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators) revealed that high priority tasks are usually the first to be started on the day, to maximise the time available for repairs.

If a vessel carrying multiple troubleshooting/repair teams were to break down, or if technicians got sea-sick and had to return to port, all corrective actions assigned to teams on that vessel would not be completed. To prevent this, technician teams assigned to corrective tasks are usually allocated on different vessels. This approach reduces the risk of having multiple failed turbines at the end of the day, as in an event of vessel failure at most one troubleshooting team won't complete their tasks.

A comprehensive study of offshore wind farm O&M data reported failure rates of 8.3 component failures per turbine per year [10]. Assuming failures are distributed evenly, an operator of a hypothetical offshore wind farm with 100 turbines would experience an average of 2.3 failures a day. Wind farm operators need to have resources (spare parts, technicians and vessels) on stand-by to promptly restore wind turbine generation on affected turbines.

The resources required to carry out corrective actions vary depending on the component and severity of failure. Generally, inspections and minor repairs are carried out by teams of 2, while medium-major repairs are conducted by 3-4 technicians [39]. Interviews with wind farm operators (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators) revealed that the number of technicians required to carry out a given task is not always fixed – certain maintenance actions are best carried out by 3 technicians, but can also be completed by 2.

There are also significant differences in the volume and weight of spare parts required for different corrective actions, affecting the choice of vessel assigned to carry out the task. Most repairs can be serviced by Crew Transfer Vessels (CTVs) (discussed in Section 2.2.3). Spares are transferred onto the wind turbine (for example using a davit crane) and then into the nacelle if required (using the internal lift). Components required for some major replacements may be too heavy/large to be transported by a CTV. Generator and blade replacements are usually conducted using jack up vessels [30].

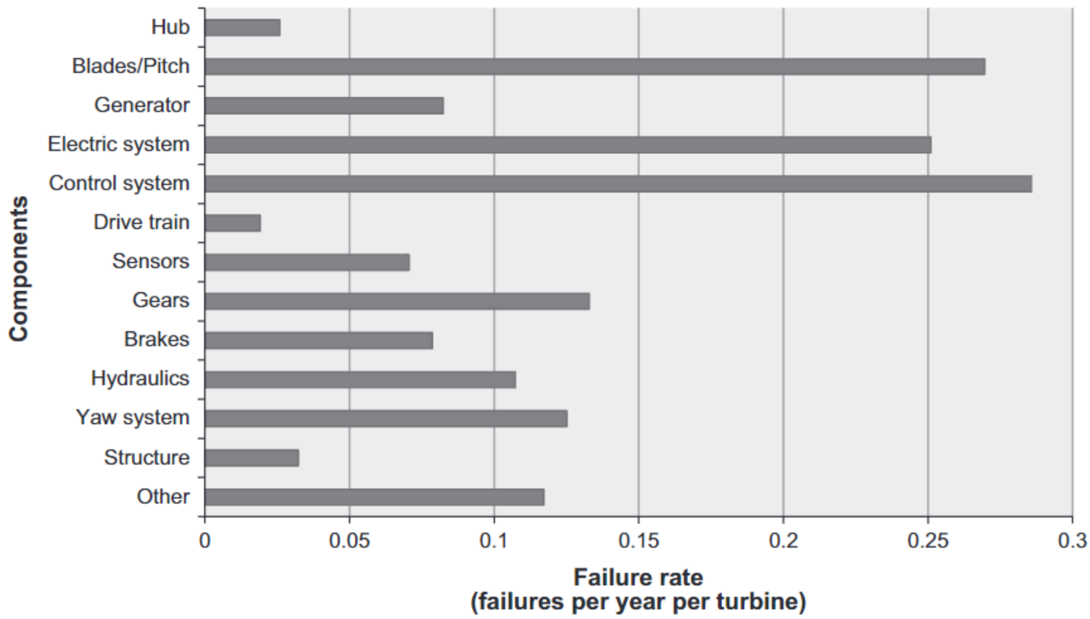

Figure 2.2. Breakdown of the wind turbine components by failure rate (adapted from [40]**)**

There are also significant differences in the time required to complete different corrective actions. For example a minor repair on yaw brake pads can be executed two technicians in 30 minutes [15] (not counting getting the technicians to the nacelle). On the other hand, major repairs in the hub can take over 40 hours [10]. Replacements of major components such as blades and gearbox can take hundreds of hours to complete, however, such events are very rare [9].

Note that the reported repair times often do not include the time required to transfer crew and equipment onto the turbine or the time required to move equipment from the bottom of the turbine to the nacelle. Interviews with wind farm operators (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators) revealed that vessel-to-turbine base and turbine base-to-nacelle transfers take approximately 20 minutes each. In this thesis, the time of repair includes the time required to climb/take a lift to the nacelle, but does not include the time required to transfer from the vessel onto a turbine (the latter is considered separately as "transfer time").

In addition to corrective actions, there are many preventative actions which are completed at offshore wind farms on daily basis. These include inspections, retrofit campaigns and annual services.

Statutory inspections are a legal requirement to ensure work equipment such as lifts and cranes are safe for use. They are undertaken by qualified engineers who follow a set procedure in accordance with suitable frameworks. Statutory inspection intervals depend on the type of equipment; it usually ranges from 6 months for lifts/tower hoists and 12 months for cranes, anchor points and emergency equipment [41].

Ad-hoc inspections of mechanical/electrical wind turbine components may also be carried out, for example if a component is underperforming. Visual inspections or crack detection sensors can provide the wind farm operator with a better understanding of the component's level of deterioration, allowing them to make informed decision about future maintenance requirements for the component. Various inspection techniques, such as ultrasonic testing, thermography and radiographic inspection were outlined in [42].

Most offshore wind turbines undergo annual service, which combines preventative maintenance actions on multiple components into a standardised procedure. Annual servicing can take as long as 60 hours [39], which can translate to approximately 7 days (depending on the procedures used/wind turbine manufacturer recommendations etc.). In the North Sea, annual service campaigns usually take place in the summer, when average wind speeds are at their lowest [43]. This minimises the lost revenue, as the turbines undergoing annual servicing do not generate any power. Summer is also the best time to carry out any retrofit campaigns, in which certain components are replaced/refurbished to increase safety/turbine efficiency. Annual services and retrofit campaigns are often carried out by supplementary teams of specialist staff and external service providers [43].

In summary, different maintenance actions are characterised by:

- Type of action (corrective vs. preventative), which in turn affects task priority
- Spare parts required, their weight/volume, affecting the choice of vessel (jack-up or CTV)
- Time required to complete maintenance
- Statutory or internal deadlines
- Health and safety considerations

When planning offshore wind farm maintenance, it is important to take those factors into consideration.

2.2.3 Vessels Used for Offshore Wind O&M

Crew Transfer Vessels (CTVs), as shown in Figure 2.3, are used for transportation of equipment and technicians to carry out most wind turbine maintenance tasks. Typical CTVs used in offshore wind are capable of carrying up to 12 technicians (due to the health and safety regulations discussed in Section 2.2.5), they can operate in significant wave heights of up to 1.5m [12]. Cruise speed of a standard monohull CTV is around 20 knots (37km/h) [44]. Vessels capable of higher cruise speed reduce the time spent travelling to site, increasing the time available for maintenance.

Figure 2.3. CTVs remain in place during crew transfers by pushing on against the transition piece [5].

Catamaran and Small Waterplane Area Twin Hull (SWATH) vessels are becoming increasingly popular among wind farm operators; they enable turbine access in significant wave heights of 1.5-2.5m [45]. Although some vessels may be approved for transfers at Hs equal to 2.5m, interviews with offshore wind farm operators suggest that transferring crews in such conditions poses a significant health and safety risk, and it is generally avoided. Properties, advantages and disadvantages of the aforementioned vessels have been discussed in more detail in [46].

Wind turbine accessibility (as defined in Definitions Section) is season-dependent (as discussed in Section 2.2.8); higher significant wave heights during winter hinder crew transfers. Some wind farms experience almost as many weather days (days with no access to the wind farm due to weather) as accessible days; for example, Barrow offshore wind farm had an average accessibility of 52% between 2006 and 2008 [47].

[5] Adepted from: http://www.owjonline.com/news/view,exclusive-maib-investigates-fire-on-crew-transfer-vessel_49130.htm. Accessed on: 18/06/2018.

It was shown that vessels with motion-compensation capable of crew transfers in 2.5m Hs can decrease waiting time to carry out minor maintenance actions by 53% [48] (compared to a standard CTV capable of transfer in 1.5m significant wave height).

Most offshore wind farms require multiple CTVs to carry out all their maintenance. The relationship between size of wind farm and the number of CTVs used is shown in Figure 2.4. The largest offshore wind farm in the world (at the time of writing) – London Array, utilises up to 8 CTVs to carry out maintenance [49], offering significant scope for optimisation.

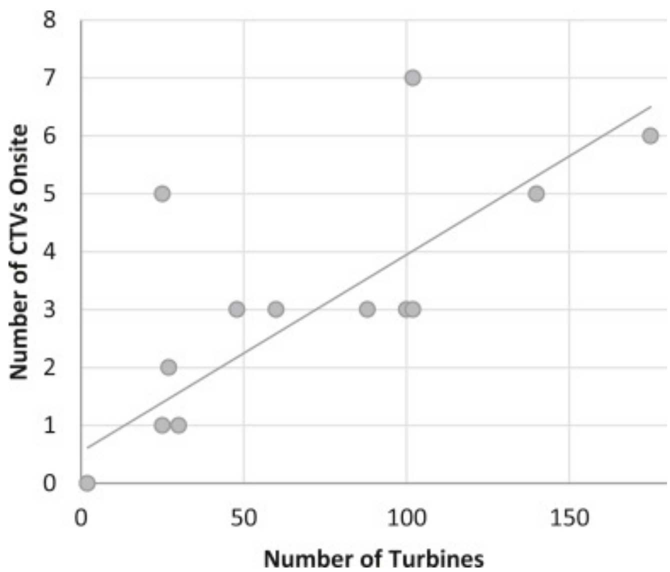

Figure 2.4. Number of CTVs required for maintenance actions vs number of turbines [50]**.**

Alternatively, helicopters can be used to transport technicians to the turbine. They are characterised by a high speed of transit (up to 135 knots – 250km/h [51]), leaving more time for repairs. However, helicopters tend to have limited carrying capacity for crew, tools and spare parts compared to CTVs. For example an EC135 helicopter, which was the first to be selected for offshore wind support by the Civil Aviation Authority, is capable of carrying 4-6 technicians [12]. Their use is limited by high winds and poor visibility. Operational data from Gwynt y Mor wind farm in the UK suggests that helicopters do not guarantee increased accessibility [52], recommending focussing on CTV improvements instead. The report also discussed additional limitations associated with the use of helicopters.

Major repairs, such as gearbox or blade replacements, are carried out using jack-up vessels, as pictured in Figure 2.5. They are capable of lifting heavy components, such as blades or generator and provide a stable base for crane operations by using the sea bed to elevate above the sea level. Detailed characteristics of different types of jack-up vessels have been discussed in [13]. The mobilisation time on a jack-up vessels can be lengthy and depends on the season/current market [53]. Chartering jack-up vessels is very expensive; daily rates on the spot market can exceed £250,000 [53], providing a clear incentive for the wind farm operators to limit their use of the jack-up vessels.

Figure 2.5. Jack-up vessels used for major component replacements [6].

As near shore sites in the North Sea are becoming scarce, future wind farms will be built further offshore [1]. Some of the future offshore wind farms in the UK will be located over 100km from shore. For example the distance from shore to Hornsea Project Three Offshore Wind Farm will be 132.9 km[7]. For reference, the average distance to shore for European wind farms in 2016 was 44km [54]. Travelling to and from farms as distant from shore as the Hornsea Project Three using a standard CTV would take up a significant part of the available time window, restricting the number of maintenance actions which can be carried out (approx. one way travel time to Hornsea Project Three for a standard CTV: 3.6 hours).

It was found that wind farm availability drops drastically for wind farms located 80km or further offshore [55]. Ensuring effective O&M at far-from-shore sites will require a Service Operations Vessels (SOVs) (also known as walk-to-work vessel [56]).

[6] Adepted from: https://www.windpoweroffshore.com/article/1214101/specialised-vessels-cut-costs. Accessed on: 18/06/2018.

[7] Data from http://www.4coffshore.com/windfarms/hornsea-project-three-gb-uk1k.html accessed on 18/06/2018.

SOVs provide overnight accommodation for technicians, eliminating the need for daily travel between O&M base and wind farm. Walk-to-work vessels can be equipped with motion-compensating gangways, which enable crew transfers in higher significant wave heights. SOVs have significantly larger carrying capacity (can accommodate up to 60 technicians[8]). However, SOVs are still an immature solution (partly due to large cost); they are not widely used as default maintenance vessels at offshore wind farms [30].

2.2.4 Costs Associated with Offshore Wind Farm O&M

Project costs can be split into Capital Expenditure (CAPEX) incurred at start of the project and Operating Expenditure (OPEX), incurred during the asset's operational lifetime (both defined in Definitions section). The general consensus in the scientific community is that offshore wind farm O&M costs constitute approx. 25-35% of the total project expenditure (i.e. CAPEX + OPEX) [26], [44], [57], [58]. In monetary terms, this can be as much as £290,000-£430,000 per turbine, per year [51]. In comparison, O&M costs of onshore wind projects only constitute 5-10% of the total expenditure [58]. Reasons for this significant difference include:

- Harsher offshore environment, causing increased failure rates
- Lower accessibility, due to weather/vessel restrictions on access
- Increased travel time and costs (i.e. vessel hire)

The cost of logistics[9] (vessel hire, fuel, planning etc.) ranges, depending on the source and definition of the term "logistics", from 11-32% of total OPEX [1], [51], [59]. Jack-up vessel hire can constitute up to 25% of total OPEX [51]. Other significant expenditure includes parts & consumables (approx. 15% of OPEX) and technicians' salaries (8% of OPEX) [51].

A summary of published offshore wind farm O&M costs is shown in Table 2.2. While many of the costs shown in Table 2.2 will differ from wind farm to wind farm (or depending on other factors such as vessel specifications), the table shows the orders of magnitude of different day-to-day O&M costs. Major failures of expensive components can cost over 60 times more than the revenue a turbine generates in a day. The operators are heavily incentivised to make sure failures of blades/gearboxes/generators are kept to a minimum.

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[8] From https://www.4coffshore.com/windfarms/siemens-gemini-sov-christened-nid4093.html Accessed on: 18/06/2018.

[9] Term "logistics" was defined in Definitions section.

Table 2.2 also sheds some light on the justification of the real world O&M decision making trade-offs. In the winter, it is not uncommon to wait an average of 5 days for an 8-hour weather window in the North Sea [48]. Neglecting to restore generation on one of the turbines during a winter sail day (as defined in Definitions section) means an average of £20,000 lost production (5 days times £4,000 lost generation). The potential cost saving of using one fewer vessel on a single day is approximately £3,000 (from £2000 saving on vessel hire and £1000 saving on fuel). It is clear that in the winter, most operators will be incentivised to maximise restoration of wind power generation (or prevention of new faults) rather than attempt to cut costs by using fewer vessels. Further discussion on the drivers of offshore wind farm O&M policies is provided in Section 2.2.6.

Table 2.2. Comparison of reported offshore wind farm O&M costs.

Cost	Monetary value	Source
Jack up vessel charter (on the spot market, including mobilisation)	£250,000 per day	[53]
Major generator repair	£200,000[10]	[60]
Technician wages	£80,000 per technician per year so approx. £9,000 per day for a medium sized wind farm[11]	[39]
24 hours of turbine downtime	£4,000	[41]
CTV hire costs	£1,500-4,000 per day per vessel	[61]
Operational cost of structural health monitoring system	£1,150 per day (for a 100 turbine wind farm)	[57]
CTV fuel cost	£12 per km travelled so up to £1,000 per vessel per day	Interview with an offshore wind farm operator

Wind farm operators may prefer to schedule maintenance actions for periods of low winds to minimise lost revenue. However, this approach is not common in the winter, as the potential benefits stemming from lost revenue reductions (thousands of pounds) are insignificant compared to the potential revenue losses incurred if a turbine ceases to generate power due to insufficient maintenance (tens of thousands of pounds).

[10] Value converted from USD to GBP based on 5/07/2019 exchange rate of 0.8.

[11] Assuming 261 working days in a year and 30 technicians per wind farm.

Which day-to-day O&M costs should be considered in the short term O&M optimisation process?

Cost minimisation is a widely used optimisation objective in various scientific publications on O&M optimisation. However, in the context of on-the-day decision making, many costs do not need to be considered, as they do not affect the choice of policy.

Take cost of repair as an example; when researchers in the field refer to the costs of repair (i.e. Dinwoodie et al. [39]), they usually mean the cost of spares. In most cases, this cost is unavoidable. Naturally, such costs can be delayed, but the benefit of doing so would be insignificant compared to the revenue generated by the turbine, if it was operational. It can be argued that the difference between spending £10,000 on a repair today, vs. doing so in 3 days' time is too small to be considered in modelling.

However, costs of failures which can be prevented should be included in the modelling. Take topping up lubricant as an example – neglecting to carry out this maintenance action can lead to a costly component damage. The cost of repair of this damage should be included in the analysis, to incentivise and prioritise the service action preventing failure.

If a model only considers costs over a short time horizon, the "optimal" action may be to never carry out certain maintenance actions. Take planning an expensive repair in the next few days as an example; the costs associated with this action may outweigh any revenue the turbine could have produced in that time. Yet it is obvious that the repair should be carried out promptly to restore generation. In this case, maintenance should be incentivised either by specifying a sufficiently high reward for the action or by taking into account the revenues produced by a turbine in a longer time horizon (e.g. a year rather than the original planning horizon of a few days).

If a vessel is chartered on a long term basis, the hire cost does not need to be considered when planning next day's maintenance. The operator will suffer the cost regardless of whether the vessel sails or not. However, if the operator plans to hire vessels on the spot market, charter rates can be highly variable and should be included in modelling.

2.2.5 Health & Safety Considerations

The purpose of this section is to familiarise the reader with some practical Health & Safety consideration which influence the process of planning maintenance of offshore wind turbines.

When assigning technicians to tasks, the maintenance planner must ensure that technicians have all relevant qualifications to complete the task. First and foremost, technicians must have an up-to-date Basic Safety Training certification provided by GWO (Global Wind Organisation – a certification body). Basic Safety Training certification is viewed as a universal seal of competence for offshore wind technicians; it consists of:

- GWO Working at Heights and Rescue – includes correct use of PPE (Personal Protective Equipment) and evacuation devices
- GWO First Aid – covers identification injuries, correct use of lifesaving first aid and use of first aid equipment
- GWO Sea Survival – focuses on the risks of hypothermia and drowning, outlines correct procedures for safe transfer from vessel to turbine and vice versa
- GWO Manual Handling – includes rescue techniques, procedures for lifting heavy objects and injured personnel
- GWO Fire Awareness – outlines procedures for dealing with fire and correct use of firefighting equipment

In addition to the basic Health and Safety training outline above, certification is required to carry out work on certain wind turbine components (e.g. work on certain electrical components requires high voltage competency training). As most Health & Safety certificates expire after 2-3 years, technicians are required to take refresher courses.

UK regulations only allow offshore wind turbine maintenance during daytime [62]. Dalgic et al. [62] have shown that significant O&M cost savings could be achieved by implementing a day-and-night working shift pattern. However, the cost savings would have to be substantial to offset the operational risk associated with carrying out O&M at night-time.

There are constraints on the access to certain parts of the turbine; for example for safety reasons, no work can be carried out in the hub if wind speed exceeds 12m/s [36].

Health & Safety considerations also influence the assignment of vessels to tasks. Quoting a RenewableUK report [63]:

"The selected vessel must be capable of operations within the expected prevalent conditions with a safety margin to allow for changes in environmental conditions"

Ultimate responsibility for the well-being of vessel passengers lies with the vessel master, however, they are obliged to work closely with marine coordinators to ensure health and safety standards are adhered to [63].

Transfer of crew form vessel to turbine should only be undertaken if both the vessel master and maintenance technicians are satisfied with the sea conditions. Some vessels may be equipped with vessel motion monitoring systems, which can aid the decision on whether to transfer crew. A Transfer Assistant (who is not part of the crew transferring onto a vessel) supervises the transfer, ensuring all crew wear appropriate PPE and observing for potential hazards. Upon transfer completion, vessel master must report to the marine coordinator the names of transferred crew and the location at which they were picked-up/dropped-off. Vessel-to-vessel transfers are discouraged [64].

Idle vessels may be required to hold a certain position in a wind farm, so that in the event of emergency, all manned locations are within 20 minutes reach of an idle vessel. Marine coordinators may permit idle vessels to loosely moor to wind farm structures [64].

To ensure no technician is accidentally left on a turbine at the end of the shift, before leaving the wind farm, the vessel master must confirm the location of all industrial personnel and passengers who were assigned to come back to base on their vessel [64].

Wind farm operators very rarely use vessels capable of transporting more than 12 technicians; such vessel would be classified as a passenger vessel, introducing numerous safety considerations and reducing operational flexibility [62].

2.2.6 Key Performance Indicators and Optimisation Objectives

Key Performance Indicators (KPIs) are quantifiable measures used to evaluate the performance of a project. One of the most popular metrics used by the industry to compare different wind farms is Levelised Cost of Energy (LCoE). LCoE can be defined as:

"The ratio of total lifetime expenses versus total expected outputs, expressed in terms of the present value equivalent" [1]

However, LCoE is a very broad metric, often heavily dependent on the site characteristic (e.g. mean wind speed). LCoE it is should not be used to evaluate the effectiveness of the O&M planning process. In the context of the problem of planning offshore wind maintenance, KPIs may be used to evaluate the quality of decisions made by planners. KPIs relevant to the problem at hand include:

1) Mean Time Between Visits (MTBV)
2) Mean Time To Repair (MTTR)
3) Percentage of reactive maintenance actions
4) Turbine availability
5) Man-hours worked by technicians/Turbines visited/Tasks completed
6) Operational Expenditure (OPEX)

Note that the wind farm operator would never choose to optimise their O&M plan for a single KPI. For example, availabilities of near 100% could be achieved, but the associated vessel and stand-by staff cost would be enormous.

Maximisation of **MTBV** increases the proportion of time technicians are doing useful work by reducing time wasted on crew transfer and getting to/from the nacelle. MTBV can be maximised by bundling tasks to be carried out at a turbine and completing them during a single visit (opportunistic maintenance). However, setting maximisation of MTBV as the sole optimisation objective would result in increased downtime or lead to preventable failures.

MTTR is a measure of how responsive the planners are to changing circumstances, but it is also heavily dependent on the skill of technicians and the weather.

Percentage of reactive maintenance actions as a proportion of all actions is one of the KPIs which the operators aim to minimise by keeping components well-maintained. High proportion of reactive maintenance can be costly; it is usually cheaper and more effective to prevent failure.

Wind farm operators aim to maximise the energy capture by minimising the amount of time a turbine is not operational (either due to a fault or due to maintenance being carried out). **Wind turbine availability** (i.e. the proportion of time when the wind turbine is functional)[12] is often used as a KPI in the offshore wind industry. Availability can be divided into time-based and energy-based.

Time-based availability is a measure of the amount of time the turbine was available to produce energy in a given period of time. Well-maintained offshore wind turbines can achieve time-based availabilities of over 97% [65]. However, if an increase in availability is achieved at a high O&M cost, the resultant profits may actually decrease [30].

Alternatively, **energy-based availability** takes into account the lost production in the periods of unavailability (method of calculating it was proposed in [66]). This method of calculating availability tends to favour the operator (rather than the service provider) as generally, turbines are unavailable when they cannot be repaired due to high waves, which often coincides with high winds. Analysis of a real wind farm data shows that time-based availability of 97% may correspond to an energy-based availability of only 89% [66].

Availability of a wind farm depends on the wind turbine failure rates and site accessibility. The latter can be broadly defined as a measure of the amount of time wind turbines can be accessed for O&M actions; a stricter definition was provided in [48]. Accessibility of a particular site will depend on local meta-ocean conditions, which are highly seasonal, and the capabilities of vessels available to the wind farm operator.

Availability is often used as a key metric in maintenance contracts [17]. Maintenance provider may be required to specify target/minimum turbine availability (97% was quoted as the industry standard by Conroy et al. [66]). If the actual availability is below the target, service provider may be liable to contractual penalties. While this type of contract encourages the maintenance provider to ensure high wind turbine reliability, it may result in a conflict of interest. For example, the owner/operator's preference is to carry most preventative maintenance during periods of low wind to reduce lost generation. The maintenance provider's interest is usually to reduce costs and reduce the complexity of the planning process, which can lead to scheduling tasks in advance and having roughly the same number of staff and vessels at hand regardless of the weather. Note: the relationship between the wind farm

[12] Availability = 1 – [Time unavailable/(Time available + Time unavailable)]

owner/operator and OEM/maintenance service provider is discussed in Appendix C. Wind farm Ownership Structure.

When planning maintenance actions for the following day, one of the objectives may be to maximise the amount of useful work done on the day. One of the ways of quantifying useful work is measuring the number of man-hours worked by technicians on shift. **Maximising man-hours worked**, in most cases, minimises the amount time lost on travelling between turbines and the time lost on ascending to/descending from the nacelle. Alternatively, the operators may want to **maximise the number of tasks completed**; however, not all tasks are equal. Completing a major repair is a far more important milestone than conducting an inspection. When faced with a high number of failed turbines, the operator's preference may be to restore generation on as many turbines as possible. This can be quantified by **the number of successful repair actions** carried out on the day. KPIs discussed in this paragraph all aim to maximise the operational efficiency (achievement of maximum amount of useful work given the limited resources).

OPEX is also a KPI relevant to the problem of planning day-to-day offshore wind farm maintenance. While there is a multitude of factors contributing to OPEX, the key costs in the context of offshore wind turbine maintenance are:

- Vessel costs (charter and fuel)
- Staff costs (technicians, planners, vessel skippers, management)
- Lost production
- Contractual penalties (i.e. for missing deadlines/targets)

Reported real world costs are provided in Table 2.2. Discussion on how some of the above costs affect the process of short term task prioritisation is provided in Table 3.1.

Recommended optimisation objectives

Following discussions with a wind farm operator, the key objectives relevant to the problem of planning offshore wind farm O&M are as follows:

1) Maximisation of the number of completed high priority maintenance actions. Note that this combines elements of OPEX minimisation (i.e. avoidance of contractual penalties) and availability maximisation (minimisation of turbine downtime)
2) Maximisation of the number of man-hours worked by technicians (maximisation of operational efficiency)
3) Minimisation of the number of unsuccessful maintenance actions, which also maximises MTBV and operational efficiency

4) Minimisation of avoidable costs (OPEX minimisation)
5) Maximisation of wind power generation (e.g. by delaying non-critical maintenance action during periods of high wind)

Application of a multi-objective optimisation approach may be required to generate policies while considering all of these objectives. The complexity of the problem and the presence of uncertainties make it impossible to state the exact value of carrying out a certain action today vs. carrying out a different action (or carrying out an action today vs. tomorrow). The process selecting/assigning weights to objectives/KPIs is subjective; it depends on the circumstances and the best interest of the decision maker (which differs whether it's maintenance provider or wind farm operator/owner). In this thesis, the author attempted to avoid the expression "optimal policy", because the real world problem has no single optimality criteria.

2.2.7 Uncertainties Affecting Day-To-Day Planning of Offshore Wind Farm O&M

The information available to the maintenance planner at the time of creating the vessel routing policy is not always 100% accurate. The process of planning real world wind turbine maintenance requires the decision maker to consider uncertainties, which can have a significant impact on the outcome of the policy. Interviews with the wind farm operators (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators) revealed three uncertain variables which the planners may need to consider in order to create an effective vessel routing policy:

a) Uncertainty on task duration
b) Uncertainty on the expected weather conditions at the wind farm (for example the forecasted significant wave height affecting crew transfer)
c) Possibility of failure misdiagnosis

Seyr & Muskulus [67] highlighted the importance of considering the uncertainty of weather conditions and duration of a maintenance task when planning offshore wind farm maintenance. Their paper has shown that not incorporating uncertainties on maintenance action time into the decision making process can lead to significant production losses. A literature review of approaches for optimisation under uncertainty is provided in Section 4.2.4. Zhang et al. [19] also stressed that considering weather forecast while planning offshore wind O&M is crucial.

Interviews with wind farm operators revealed that to avoid technicians having to work longer-than-12h shifts, tasks taking longer than expected are usually left unfinished (unless there is another task scheduled afterwards which can be delayed or cancelled). If a task takes a shorter time than expected, wind farm operators may make on-the-day modifications to assign an additional task to teams.

Depending on the weather forecast supplier, wind farm operators may have uncertainty bounds on values such as expected wind speed/direction and significant wave height. These values can be used to inform decisions on the assignment of vessels to tasks. As discussed in Section 2.2.3, vessels have different turbine access capabilities (in terms of the significant wave height). If the significant wave height forecast for a turbine which needs to undergo a high priority maintenance action is associated with high uncertainty, the operator would assign one of their most capable vessels to ensure maximum probability of transferring crew onto the turbine.

Uncertainty on the time of repair can be estimated by analysing past repair durations for the same task. However, in most cases, values such as uncertainty on task duration or probability of failure misdiagnosis are not quantified by the planners. According to interviews with the offshore wind farm operators, if the current decision making process is affected by factors such as high uncertainty on a particular task's duration, it is done subjectively, depending on the operator's "gut feeling" rather than based on a scientific procedure.

In summary, not including uncertainties in the process of planning offshore wind farm maintenance can lead to unsuccessful crew transfers, leaving unfinished tasks on turbines and last minute changes to the plan, which can introduce inefficiencies and increase maintenance costs.

2.2.8 Seasonality & Problem Size

The difficulty of the vessel routing problem increases with the number of turbines which require a maintenance action. Some sources reported estimated number of maintenance visits per turbine per year of 6 [13], or between 4 and 6 [68]. However, the actual number of times technicians access a turbine each year is higher, as the aforementioned studies do not include retrofits and Balance of Plant (BoP) tasks[13]. Annual service on its own can take up to 60 hours [10] (turbine dependent). Industry reported that offshore turbines require approximately 80 hours of maintenance a year [69] (which translates to roughly 10 full workdays).

It has been argued that the likelihood of turbine failure, is largest in the winter, due to higher wind speeds [13]. Accessing offshore wind turbines in the North Sea is most

[13] BoP tasks include the following: work on the transition piece (e.g. painting and inspections), maintenance/installation of equipment cranes, wind and wave measurement equipment, grid connection etc.

difficult in the winter (due to higher significant wave heights). A graph of the wait time to access a turbine with a minor generator fault, with a standard CTV, based on real data for a wind farm in the North Sea, is shown in Figure 2.6 (adapted from [70]). It can be seen that the difference between waiting time in the winter (here defined as lasting from beginning of November until the end of January) and other seasons is substantial. There is approximately 30% chance that the operator will have to wait for more than 4 days to carry out a minor repair in the winter.

A study by Fox & Hill [71] has shown that certain North Sea locations experienced up to 20 no-access days in January 2016. This can cause an accumulation of faults across the wind farm, resulting in shortages of maintenance assets (vessels, technicians, spare parts and consumables). The proportion of corrective maintenance actions is usually higher in the winter (due to service campaigns being planned for summer, reduced accessibility and higher failure rates in winter).

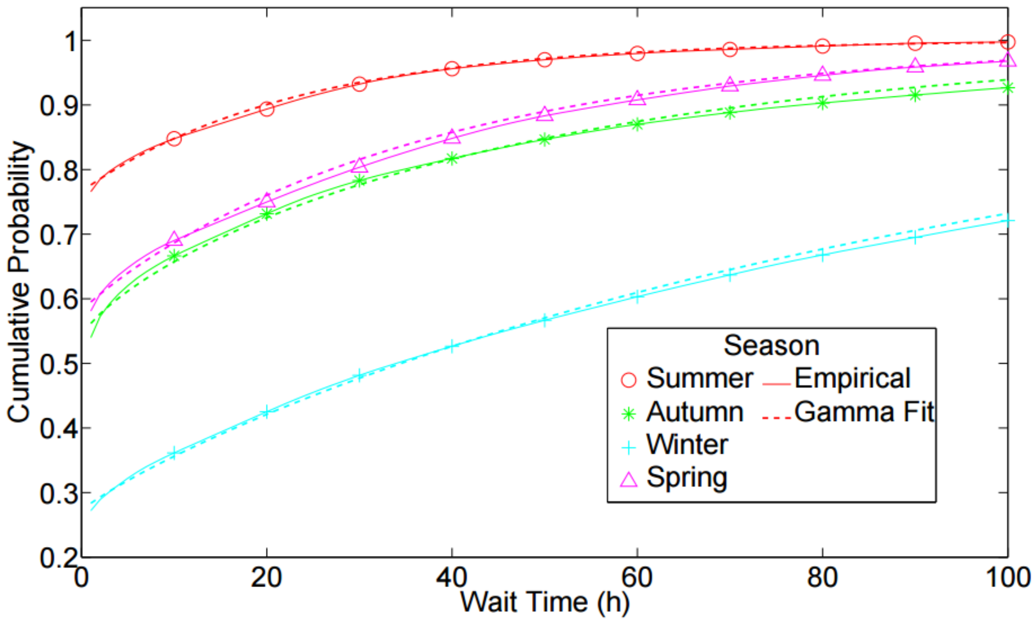

Figure 2.6. Cumulative probability of the waiting time to repair a minor generator fault [70]**.**

Winter is also the time of the year when the energy yield is the highest [13]. The combination of possible maintenance asset shortages due to multiple, accumulated faults across the wind farm, high uncertainty associated with winter weather, and threat of significant lost revenue puts enormous pressure on the maintenance planners. Evidence gathered during interviews with wind farm operators (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators) suggests that it is not uncommon for a large offshore wind farm in the North Sea to experience days with 20+ turbines requiring varying levels of maintenance action in the winter. The complexity of the problem wind farm maintenance planners face on such days is discussed in Example 2.1.

The problem is complicated further by the multiple KPIs (discussed in Section 2.2.6) and uncertainties the decision maker needs to consider (Section 2.2.7). Wind farm maintenance planners face this difficult task of creating a policy meeting all constraints on a daily basis. As the time to make the decision is limited, planners can only commit a small proportion of their time to policy optimisation.

Let us consider the following scenario: on a particular day, 20 turbines require a maintenance action. The operator has 5 unique vessels available. A decision needs to be made as to the assignment of turbines to vessels and the order in which turbines are visited. The number of possible policies (permutations of assignment of vessels to turbines and the order in which turbines are visited) equals $1.937*10^{25}$ (as shown in Appendix A. Calculating the Number of Possible Vessel Routing Policies). This is more than the number of stars in the observable universe[14]. This does not include the assignment of technicians to tasks, which would significantly increase the number of permutations.

Example 2.1. Problem size: mini case study.

[14] From: https://www.space.com/26078-how-many-stars-are-there.html, accessed on: 07/08/2018.

2.3 Summary of the Practicalities of Planning Offshore Wind Farm O&M

Accessing offshore wind turbines for maintenance is time consuming and uncertain. Many offshore wind farms face severe, seasonal access restrictions. It can be argued that the means of accessing the turbines, the number of assets that needs to be maintained daily and numerous constraints make the problem of planning offshore wind farm maintenance unique. Tools used in other industries cannot be easily applied to the problem of planning offshore wind farm O&M.

A research gap exists in operational decision support tools applicable to the real world problem of planning offshore wind maintenance (including planning vessel routing). Conclusions of Section 2.1 align with the feedback from wind farm operators, who confirmed the industry-wide need for operational decision support tools for maintenance planning. This chapter's key findings are summarised below:

1. Task priority depends on multiple factors, including type/characteristics of maintenance, deadlines, spare part availability etc. Task priority is a key factor in the process of planning offshore wind farm O&M; it should be quantified and included in the decision making process (Section 2.2.2)
2. Wind farms use vessels of varied characteristics, assignment of CTVs to tasks may depend on vessel capabilities (Section 2.2.3)
3. While maintenance costs vary significantly depending on the type of action, cost of spare parts/technician man-hours should not be considered when planning next day's vessel routing (Section 2.2.4)
4. Assignment of technicians to tasks depends on their Health & Safety qualifications (Section 2.2.5)
5. In the problem of planning day-to-day offshore wind farm O&M, there can be no single optimisation objective (Section 2.2.6)
6. Uncertainties on the weather forecast and duration of maintenance actions should be taken into account when planning offshore wind turbine maintenance (Section 2.2.7)
7. Many wind farms in the North Sea face an accumulation of corrective maintenance actions in the winter (due to reduced accessibility) which leads to increased problem complexity and increased need for an optimisation tool (Section 2.2.8)

Conclusions from this chapter influenced methodology choices made in Chapters 3 & 4. The resulting decision support tool is evaluated against points 1-7 in Table 7.11 (Section 7.8).

Chapter 3. Prioritisation of maintenance action using a time-variable Semi-Markov Decision Process

Section 2.2.2 outlined the breadth of maintenance actions carried out on wind turbines, which range from preventative, retrofits and statutory tasks to repairs. While all tasks are critical to smooth running of a wind farm, some actions are more urgent than others. To successfully plan offshore wind O&M, this "urgency" needs to be quantified. This chapter tackles this problem by proposing a methodology for prioritising maintenance actions.

Quantification of the incentive to carry out maintenance actions on a particular turbine, relative to others, is the first step in the overall process of improving the wind farm operational decision making. In Chapters 5-6 (description of the vessel routing decision support tool and the case studies) the utility value of visiting all turbines requiring maintenance is used as an input, enabling efficient resource allocation.

In this chapter, a literature review of models for diagnosis and prognosis was carried out. Effective maintenance task prioritisation relies heavily on knowledge of the underlying issue and the current state of the component, as shown in Figure 3.1. As frequent visual inspections of offshore wind turbine components are hindered by access difficulties, operators rely heavily on Conditioning Monitoring Systems (CMS) to diagnose the problem and estimate its severity.

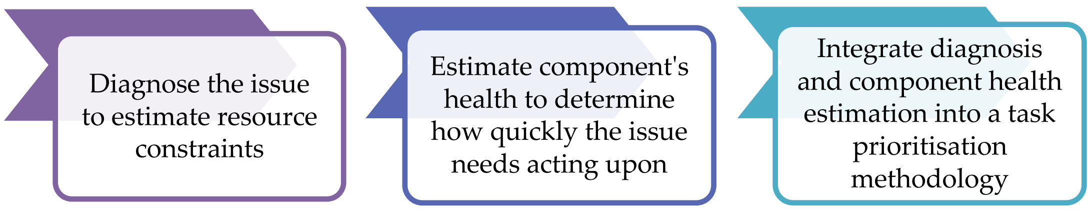

Figure 3.1. A comprehensive task prioritisation methodology relies on accurate diagnosis and health estimation models.

This chapter is structured as follows: the practicalities of task prioritisation for offshore wind turbines are outlined in Section 3.1. Having described the problem, literature is reviewed in search for a solution in Section 3.2. The proposed methodology is described in Section 3.3, with case studies and results presented in Section 3.4. Finally, Section 3.5 contains the chapter's concluding remarks.

3.1 Practical Problem Definition

Researchers in other fields may define vessel routing as deciding the coordinates of checkpoints a vessel must travel through on their planned routes to minimise fuel consumption depending on the wave height and direction (for example Petrie et al. [72] who developed an algorithm for cost-optimisation of vessel routes depending on weather constraints). Since this thesis is focussed on the combinatorial logistic problem, not the dynamic interaction of vessel's hull and waves, the latter problem is considered out of scope of this research. In the context of this thesis, vessel routing problem is defined as:

"The problem of choosing the assignment of vessels to turbines requiring maintenance and the order of wind turbine visits, in an attempt to maximise user specified KPI's."

It is also important to differentiate the problem of maintenance action prioritisation for offshore wind farms from the same problem in other engineering fields (such as other forms of electricity generation). It can be argued that the former problem is more challenging (due to the combination of factors a-f below). Decision support tools in this area can lead to significantly higher economic gains compared to prioritisation of maintenance actions in most other engineering domains for a number of reasons:

a) Relatively high failure rates of offshore assets, possibly due to harsh environment and higher wind speed [10].
b) Wind turbines consist of a broad variety of engineering components (electrical hydraulic, mechanical), each requiring different skills, tools and parts to maintain.
c) Significant amounts of time are spent daily on travelling to an offshore wind turbine, transferring crew and tools onto turbine and ascending to the nacelle. This limits the time available for repairs, while vessel capabilities restrict the amount of spare parts and tools which can be brought along for maintenance.
d) As discussed in Section 2.2.8, sea conditions often restrict the access to offshore wind turbines. For example, wind farm accessibility (as defined in Definitions Section) for some of the wind farms in the North Sea was reported to be below 15% in the winter [48]. Low accessibility can lead to an increased number of reactive maintenance actions required on a wind farm, hindering work organisation.
e) Maintenance decisions prior to long periods of inaccessibility can have a significant impact on LCoE. Interviews with wind farm operators

(summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators) revealed that failure to complete all necessary maintenance in this period can lead to turbines being inoperative for weeks.

f) Time to make a decision is constrained: maintenance tasks are usually prioritised a day before, however, if failures occur overnight, wind farm operators have less than an hour to readjust the priority list the following morning.

Interviews with an offshore wind farm operator revealed that on many days, the number of maintenance actions to be carried out exceeds the capabilities of technicians and vessels available. Inevitably, on days with resource shortages, carrying out all planned maintenance tasks is not possible. Effective maintenance task prioritisation can ensure that the effect of delaying certain maintenance actions minimises the impact on the wind farm KPIs, as discussed in Section 2.2.6.

First and foremost, O&M planners prioritise maintenance actions which ensure continuous running of turbines. This includes carrying out repairs on turbines which are not producing power, but also actions which prevent the turbine from failing in the near future. Wind farm operators may also be obliged to carry out turbine visits, which do not affect the turbine's ability to generate power in the short term. These include the annual service, statutory inspections and retrofit campaigns. Priority of these tasks generally depends on the proximity of formal deadlines and expected resource bottlenecks, which the operator has to consider. An overview of the factors affecting prioritisation of maintenance actions is provided in the following section.

3.1.1 Factors Affecting Prioritisation of Tasks on Offshore Wind Turbines

Practical considerations to be taken into account when assigning priorities to turbines which require a maintenance action are described in detail in Table 3.1. The subjective importance of each factor, defined by an offshore wind farm operator, is given in the first column of Table 3.1 (in brackets).

Definition of the practical problem provided the requirements a model needs to fulfil to aid maintenance task prioritisation in real life. A literature review was conducted to identify a suitable methodology for enabling automation of offshore wind farm maintenance task prioritisation.

Table 3.1. Outline of the factors affecting prioritisation of maintenance actions.

Factor affecting prioritisation (importance: 1 - high to 4 - low)	Explanation
Type of maintenance action required (1)	Carrying out repairs is generally prioritised over non-critical maintenance actions such as an annual service.
Deadlines (1)	Certain maintenance actions have hard or soft deadlines associated with them; for example all annual services need to be finished before late autumn/early winter, when access to turbines becomes difficult. Service providers may be bound by contracts obliging them to finish certain maintenance tasks by a set date.
Availability of resources (1)	Hiring external contractors is not uncommon on offshore sites (for example to carry out retrofits on multiple turbines). Often there is a limited time window when the contractors are available. The vessels themselves need occasional maintenance. Limited human resources may be available during festive periods.
Multiple maintenance actions on a turbine (2)	If maximisation of MTBV is a KPI on a given wind farm, higher priority may be assigned to a turbine on which a number of low-to-medium priority actions are required compared to a turbine with a more serious single fault. Interviews with offshore wind farm maintenance planners have also revealed that maintenance is often delayed if a turbine only requires one, non-critical maintenance action. Holding off maintenance until another action is required aims to increase the MTBV.
Wind speed forecast for the near future (3)	If the wind speed is expected to decrease significantly in near future, non-critical maintenance actions may be delayed, in an attempt to maximise revenue generated by the turbines.
Turbine's power output compared to others (3)	If a particular turbine consistently delivers a higher power output compared to others (e.g. due to upwind location), corrective tasks on that turbine will be prioritised over equivalent faults at other turbines to maximise revenue.
Future sea state forecast (3)	If the significant wave height is expected to increase significantly and remain high in the foreseeable future, reassessment of priorities may be necessary. Threat of limited or no access to turbines increases the priority of both corrective actions and maintenance which prevents turbine from failing in near future.
Repair probability (3)	Fault diagnosis is not 100% accurate; the level of confidence operators have on the maintenance action required varies depending on the quality and type of signals received from the CMS. Faults diagnosed with lower certainty may be assigned a lower priority to reduce the risk of technicians visiting the turbine and not being able to address the issue, due to misdiagnosis.
Repair cost (4)	The impact of the cost of repair on operational decision making for offshore wind is described in more detail in Section 2.2.2.

3.2 Literature Review

The aim of this section is to identify a methodology suitable for day-to-day prioritisation of maintenance actions on offshore wind farms. An outline of the key questions each section of the literature review aims to answer is provided in Figure 3.2.

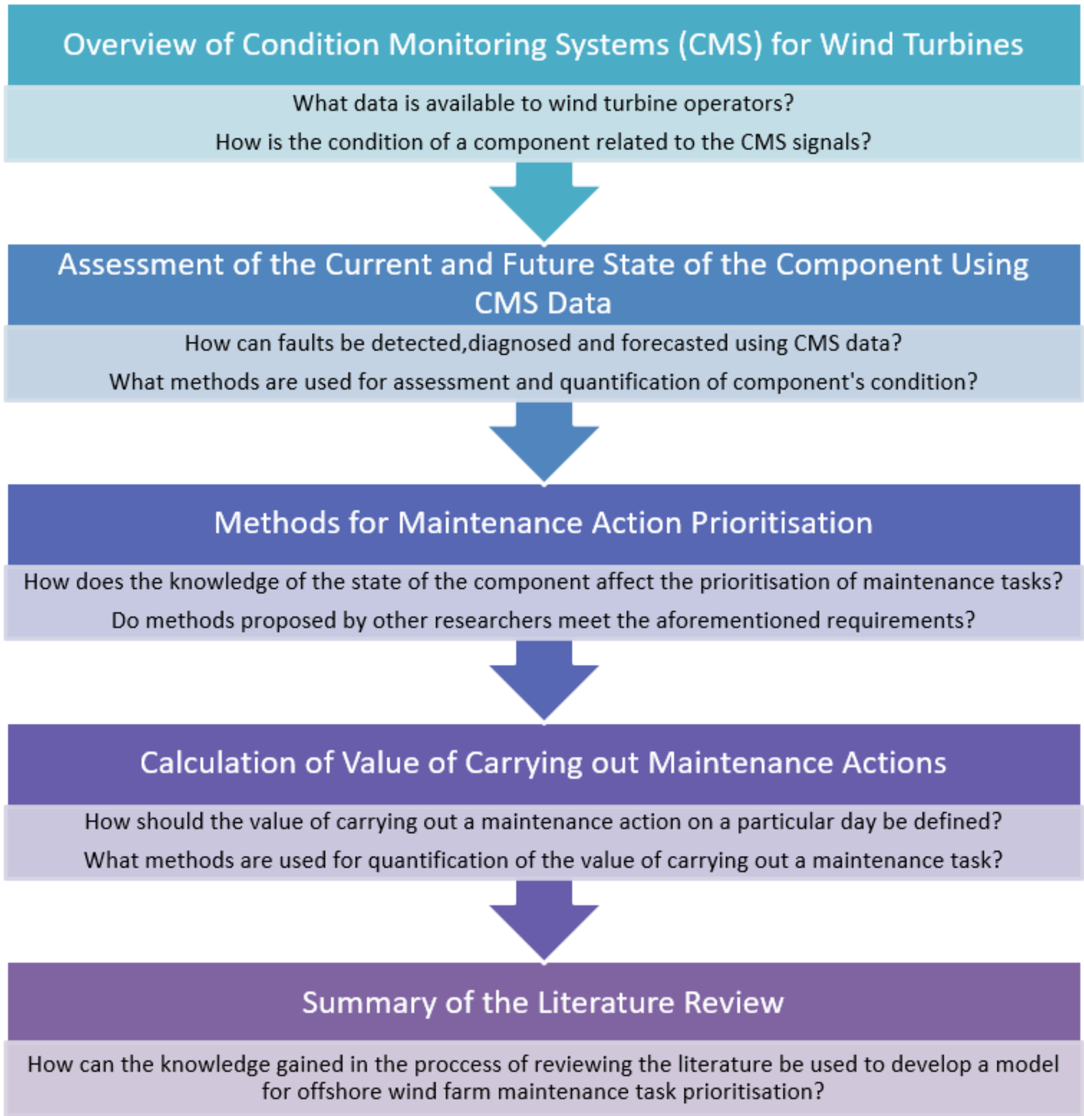

Figure 3.2. Overview of the Literature Review section.

The literature review begins by outlining the use of Condition Monitoring Systems (CMSs) in wind turbines (Section 3.2.1). This section provides an overview of the data collected by CMSs, which is one of the inputs to the task prioritisation model.

A review of methods used for assessment of the current state of an engineering component is conducted in Section 3.2.2. Knowledge of the level of deterioration enables the user to evaluate the extent of damage, quantify the need for resources (spare parts, tools and technicians) and estimate the time required to complete the maintenance task. Deterioration models are reviewed in Section 3.2.2, providing an insight into the consequences of not taking a maintenance action. Knowledge of the expected deterioration of a component enables the user to consider trade-offs of the costs associated with carrying out maintenance actions, revenues generated by the asset and the penalties for further deterioration if no action is taken. This is closely linked to estimating the Remaining Useful Life (RUL) of a component; approaches for RUL calculation were reviewed in Section 3.2.2.

Methods for prioritisation of maintenance actions are outlined in Section 3.2.3. Section 3.2.4 provides an overview of the methods of calculating the value of carrying our maintenance actions, which is a crucial input to the vessel routing optimiser described in Chapter 5. Section 3.2.5 contains a summary of the literature review and an outline of the recommended approach.

3.2.1 Overview of Condition Monitoring Systems (CMS) for Wind Turbines

Condition Monitoring Systems (CMS) consist of sensors, which monitor various parameters and data management software, which analyses the data extract value from it. As wind turbines grow larger in capacity and are located in more remote areas (including offshore), early detection and diagnosis of potential component failures is becoming increasingly important.

In general, CMS for wind turbines can be divided into SCADA (Supervisory Control And Data Acquisition) and purpose-designed systems. SCADA is a combination of software and hardware designed for operating wind turbines and providing the user with a range of parameters such as properties of the power output generated by the turbine (power factor, reactive power, current and voltages), temperatures of gearbox bearings and generator windings etc. Despite the fact that resolution of the data produced by SCADA systems is 10 minutes, which is considered, by some researchers, too low for accurate fault diagnosis [73], a significant amount of research was produced on methods of utilisation of data produced by SCADA, as discussed in Section 3.2.2.

A number of review papers were written on the use of CMS in wind turbines; trends in wind turbine CMS and fault diagnosis have been described in [60]. Requirements for modern wind turbine CMS, an outline of features and benefits of different commercially available systems and a description of a range of signal processing techniques used in CMS were provided in [73]. Classification of the state of the art condition monitoring approaches and an overview of future challenges of wind turbine CMS were discussed in [74]. Cibulka et al. [75] provided an overview of approaches for monitoring electrical, mechanical and fluid parameters in offshore wind turbines. An extensive technical report encompassing almost all aspects of CMS for wind turbines can be found in [76]. CMS are generally used to:

a) Detect problems before they occur and alert the operator in an attempt to prevent failure from occurring
b) Diagnose faults to identify the remedial action to be taken and ensure correct spare parts and tools are brought to the turbine
c) Forecast the remaining life of the component, enabling efficient planning of future maintenance strategy

Effective use of the CMS can lead to significant O&M cost savings, as failures can be prevented [60] & [76]. According to [77], key benefits of using a CMS include:

a) Avoidance of premature breakdown
b) Reduction of maintenance costs as inspection intervals can be increased
c) Improvement of the capacity factor, as given an early warning, operators can attempt to schedule maintenance during a period of expected lower wind speed
d) Support for further development of the monitored component, as the information provided by the CMS can lead to improved design

Naturally, the decision to invest in a CMS or not depends heavily on its performance [40], i.e. ability to detect issues early enough for the operator to deal with them and the number of false alarms. Research shows that for a CMS to be cost-effective, it must provide accurate diagnosis in around 60–80% of cases [36], however, this number will depend on the turbine used and site characteristics. Sufficiently early detection of a fault is also crucial; alarm triggered minutes before failure is of little value to the operator, who may not have sufficient time to apply the remedial action before failure occurs. The probability of CMS detecting a fault increases with time; the nearer a component is to failure the higher probability of detection, as shown in Figure 3.3.

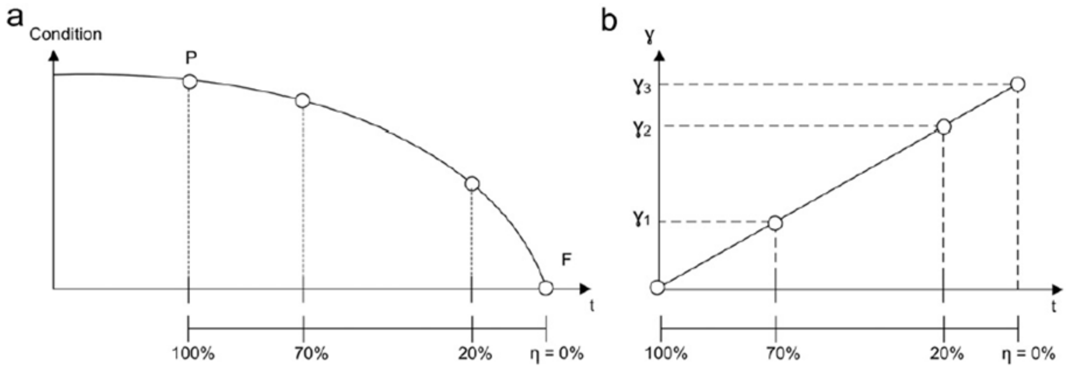

Figure 3.3. a) Illustration of the process of deterioration over time. b) detectability of a problem over time [33]**. Note: this graph is based on a mechanical component (gearbox) – deterioration and detectability of faults in electrical components may be significantly different.**

From part a) of Figure 3.3, four distinct zones can be identified: on the left the component is effectively in a brand new state. When the component's condition is between point P (100%) and 70%, operators may choose to slow deterioration down by preventative measures such as precision maintenance (for example alignment and balance for drive shaft or effective lubrication for bearings). Effective CMS will be capable of identifying faults in the third zone, with the component being between 70% and 20% of its original condition, at which point, the operators may choose to repair or replace the component before it fails. In the fourth zone, the component is nearing the end of its operational life.

Part (b) of the graph reflects how the probability of detection γ increases as the component's condition deteriorates according to [33]. The earlier CMS system is able to detect failure, the more value it presents to the wind turbine operator, as an attempt can be made to prevent or minimise the impact of component failure.

Data collected by CMS includes a broad spectrum of signals: vibration, acoustic data, temperature, pressure, oil analysis data, electrical parameters, pressure, moisture, humidity, weather and environment data [78]. Condition monitoring data provides the wind farm operator with an invaluable source of information; methods for analysing the data to assess the state of a component are described in the following section.

3.2.2 Assessment of the Current and Future State of the Component Using CMS Data

Various signal processing methods can be used to extract useful information form the stream of data coming from a CMS. The choice of approach often depends on the nature of the signal and the component being monitored. A comprehensive overview of signal processing methods was provided in [42].

Fault Detection

An extensive review of fault detection systems for wind turbines was provided in [77]. An outline of signal processing techniques for wind turbine fault detection, including Cepstrum Analysis, Fast Fourier Transform and Wavelet Transforms was provided in [42]. A review of the use of Artificial Intelligence (AI) in diagnostics of induction machines was conducted in [79]. Applications of AI methods, including Neural Networks (NN) and evolutionary algorithms, for diagnosis were also summarised in [78].

Analysing signals directly in the time domain is one of the simplest and cheapest detection approaches [80]. Thresholding is a commonly used method for wind turbine fault detection [81]. Once a given parameter is outside its normal operational values, an alarm is triggered, indicating a possible issue with the component. Thresholding using up-down counter technique was shown to be effective at detecting faults with minimal false alarms [81].

Trending time domain signals and monitoring their trend parameters such as peak, crest factor, kurtosis, and skew can provide an early warning on the forthcoming failure. Temperature trend analysis has been used to assess the condition of a wind turbine generator in [82].

Alternatively, signals obtained from CMS can be analysed in the frequency domain. This approach is particularly suitable for components containing rotational elements; as certain frequency ranges can be easily associated with faults which cause them, such as a defective bearing [42]. In commercial software for condition monitoring both time and frequency domain data are analysed [38]. Additionally, two independent studies on wind turbine gearbox fault detection were conducted in [83] & [84], both using time and frequency domain analysis to combine the advantages of both approaches. The former approach involved application of wavelet analysis to show that faults as small as chipping of a single tooth of a gear can be detected. The latter applied adaptive optimal kernel method for fault diagnosis of wind turbine planetary gearboxes; effectiveness of the proposed method was demonstrated through experimental and the in-situ signal analyses.

Research shown in [37] found that blade and drivetrain faults can be detected by using statistical techniques to find correlations between parameters recorded by SCADA systems. The importance of automatic interpretation of SCADA data to reduce its volume and condense it to key highlights to be shown to the user was stressed in [85], who proposed a NN approach capable of providing an early warning of gearbox and generator problems. NNs and clustering algorithms were used for wind turbine fault detection using SCADA data (albeit with additional sensors installed) in [86]. A comparison of three SCADA-based monitoring methods was provided in [87], showing that faults in major drivetrain components can be detected up to one year in advance, with high detection rates by using SCADA data alone.

Models for Fault Diagnosis

Detecting a problem with an engineering component does not always imply the knowledge of the underlying failure mode. Correct identification of the failure mode before scheduling maintenance is crucial, as it determines the remedial action to be carried out and therefore time, tools, skills and parts required to address the issue.

Diagnostic approaches of offshore wind turbines, which included model based (physics and statistical models) and signal processing methods such as Fourier Transform and wavelets have been discussed in a review paper focused on applications of condition based maintenance [75]. A brief literature review on the methods used for diagnosis of wind turbine drivetrain components was also provided in [88], with focus on monitoring generator’s terminals.

The use of Hidden Markov Models (HMMs) for diagnostics was reviewed in [89]. In HMMs, the observations (i.e. data from CMS) are used to calculate probabilities of the component being in certain states. States can represent normal system operation, individual failure modes or certain levels of degradation. The similarities between condition-based monitoring and speech processing (an area in which HMMs have been widely used) were highlighted in [90]. It was suggested that the techniques already proved in the speech recognition software could be successfully used in machine maintenance. A method for training HMMs using a Baum-Welch algorithm to diagnose the type of fault in large scale power transformers was proposed in [91].

Auto-Regressive Hidden Semi-Markov Models are an extension of HMMs. The former approach does not follow the standard Markov memory-less approach, it also relaxes the assumption of independent observations. It has been used in [92] for diagnosis of hydraulic pumps and shown good health state recognition rates.

A study on wind turbine gearbox diagnosis using a fuzzy expert system based on fuzzy logic was conducted in [93]. Fuzzy logic departs from the Boolean approach; instead it assigns a "degree of truth" value, which can help to interpret more complex systems in which multiple factors need to be considered to classify a fault. The approach proposed in [93] detects symptoms of degradation and anomalies using a set of 'IF' and 'AND' statements, derived from expert knowledge. For example:

IF Gearbox main bearing temperature is high
AND Gearbox thermal difference is high
AND Cooling oil temperature is normal
THEN Unbalance in the gearbox main shaft is quite certain [93]

The aforementioned approaches can be effective diagnosis tools when applied to real problems by an expert in the field or if they are incorporated in a commercial software package. Correct diagnosis of component failure or the root cause of an alarm signal is crucial for efficient organisation of maintenance activities on an offshore wind farm. Accurate diagnosis allows estimation of time and resources required to address the issue, which are necessary to create a detailed maintenance plan.

Modelling and Quantification of the Level of Deterioration

So far, methods of fault detection and diagnosis have been discussed. When prioritising maintenance actions, the ability to quantify the deterioration of a component using condition indices may enable improved decision making. Two turbines experiencing the same fault may be assigned a different priority when scheduling repairs due to factors such as asset's relative performance, accessibility, other maintenance required on the asset etc.

Making an informed estimation of the level of deterioration of a component can be achieved by the following approaches:

a) If significant data is present on component's past deterioration and failure rates, statistical methods can be used to model deterioration as a Markovian process, which include Gamma processes and Markov Chains
b) Past data can be used to estimate component condition's based on loading (i.e. S-N curves) or other measured quantities

c) If a reliable stream of condition monitoring data is available for the wind farm operator to analyse, quantifiable health index of a component can be created
d) Physical inspection can be carried out

A short review of the stochastic methods for deterioration modelling was provided in [29]. In the wind power domain, Markov models are the most widely used probabilistic method for deterioration modelling; the use of Markov models in the wind power domain was outlined in [89].

Markov chain is a random process, wherein a probability of transition between states only depends on the current state, not on the sequence of previous events [89]. At this point, a distinction has to be made between a Markov chain and Markov process (or a continuous time Markov chain). In a Markov chain, which is a discrete process, the probability of transition to a different state depends solely on the current state and not the historical data (although the model parameters themselves such as the transition matrix may be derived from historical data). This is also true in Markov process; however, the time spent in a state is exponentially distributed. The transition can occur at any instant of time, contrary to the Markov chain, in which the transition can only occur in a discrete time step. This makes Markov chains simpler to construct and compute, however, continuous time approach is considered a more accurate representation of the real life deterioration process. Continuous time Markov chains have been used to model wind turbine blade deterioration in [94].

Research conducted in [95] and [96] shows that HMMs have the potential for both diagnosis and quantification of deterioration. Authors of both papers proposed creating multiple HMMs, one for each failure mode, as shown in Figure 3.4. The HMM with the highest probability of being in a failed state was used to identify the failure mode. This approach is particularly useful for systems which have more than one likely failure mode, as is often the case with wind turbine components. Both studies were based on experimental data and the algorithms have also shown prognostic capabilities.

Semi-Markov models relax the assumption of constant transition probabilities, which is more representative of most engineering systems. They have been used in modelling deterioration of large infrastructure assets [97] and electrical transformers [98]. An approach based on Markov chains with time variable transition rates was proposed for deterioration modelling in a study of steel structures [99]. During inspections of steel structures, the state of a component was classified as one of seven pre-defined states (higher state numbers meaning a better condition). Years of inspections of multiple structures resulted in a significant amount of statistical data, which can be seen in Figure 3.5. As the steel structure ages, its state deteriorates. The average deterioration over time, along with confidence bounds are presented in Figure 3.5. Given a large enough pool of individual components, this data can be used to calculate the Markovian transition matrices, which define the probability of the component deteriorating to a lower state, given its current state and age. Markovian transition matrices can in turn be used to model component deterioration.

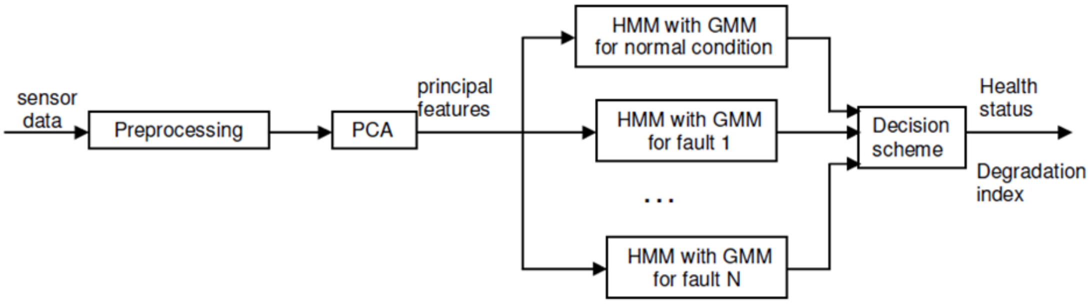

Figure 3.4. The use of multiple HMM chains for diagnosis and calculation of a degradation index [95]**.**

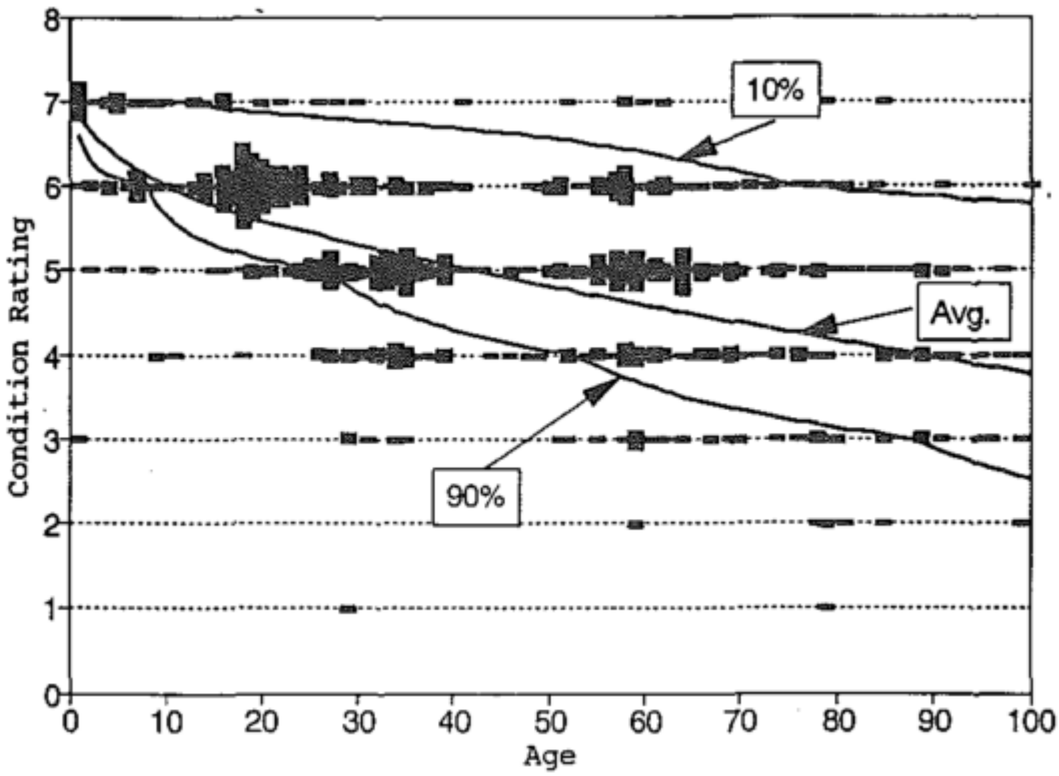

Figure 3.5. Deterioration of steel structures over time (discrete states) [99]**.**

One of the disadvantages of the discrete Markov chain approach is that the states, which are defined arbitrarily, may not be an effective representation of the deterioration process in complex cases. On the other hand, in the context of deterioration modelling, any continuous state space can be discretised, but not all discrete state spaces can be converted to a continuous domain. The versatility of discrete Markov chains lies in the ability to accept inputs in both continuous and discrete domains.

Alternatively Gamma process can be used to model gradual degradation of a component. A Gamma process can be seen as a special Markov process with a continuous state and time space with transitions occurring only in one direction [100]. According to [101]:

"The Gamma process is suitable to model gradual damage monotonically accumulating over time in a sequence of tiny increments, such as wear, fatigue, corrosion, crack growth, erosion, consumption, creep, swell, degrading health index, etc."

Gamma processes have been reviewed in [100] and [101]. Gamma processes are often used as building blocks in various inspection models, however, their application is restricted to components degrading in a monotonic process [100].

Health indices

If no large pool of failure and deterioration data is present, data generated by the CMS can be used to quantify the deterioration of a component. A list of seven desirable qualities for condition indices was provided by [102]. The authors stressed that quantities defining health of the component should be selected meticulously. For example, it was argued that while crack width may be used as a structural condition index, a more comprehensive measure of the overall component's health would be to consider crack width in a critical area of a structure and the level of intrusion of deterioration causing chemicals. According to [103], degradation of a component can be classified by one of three methods:

a) Subjective overall ratings, usually based on visual assessment
b) Overall index of degradation, an approach combining a number of indicators into a single value
c) Multidimensional description, an approach similar to b), except no attempt is made to produce a single index. Alternatively, if two or more parameters are known to be a sign of impending failure, they can be used to define a

multidimensional zone, alarming the operator and providing the suspected cause of the problem when signal enters the zone.

Out of the three approaches outlined above, only b) and c) offer a formal procedure of deterioration quantification which is not specific to the type of component analysed; examples of the use of health indices in industry and research domains are provided in the following paragraphs.

British regulator of electricity markets OFGEM (Office of Gas and Electricity Markets) used a health index scale to quantify the condition of power networks assets, which was used as a proxy for failure probability [104]. In oil analysis, number of wear particles present in the lubricant, water contamination and oxidation can act as indicators which can be combined into a single health index [105].

For simplicity and ease of use, some researchers choose to normalize the health index and divide it into distinct states, allowing the use of discrete state-based methodologies such as Markov models. An example in which the health index value was normalized to a range from 0 to 10 was provided in [106], with the scale divided into three parts: 0-4 representing deterioration with no significant impact on the component's performance, 4-7 being significant deterioration and 7-10 being states which pose significant risk of costly failure. A three state approach was also employed in [107]; a deep Bayesian network was trained to diagnose the system's state based on data from two sensors. The proposed methodology compared favourably with other classification methods.

A study on hydraulic pumps [108] used the amount of dust in oil as a health index. Three pumps were run in 4 distinct operating conditions: no contamination in oil reservoir, 20, 40 and 60 mg of dust in oil reservoir. Vibration signals were monitored during tests and used to train a Hidden Semi-Markov Model (HSMM), with each operating condition modelled as a distinct state. Fault recognition rates for the HSMM approach were up to 81% higher compared to HMM model.

In many mechanical and electrical system applications, it is common to assume a two state approach – working and failed states [109]. The use of health indices provides additional, quantifiable information on the components health, allowing modelling higher number of states and potentially enabling improved prioritisation of maintenance actions.

Forecasting Component's Deterioration and Estimating the Remaining Useful Life

While previous subsections focussed on methods for evaluating the current state of a component, this subsection explores the field of engineering prognostics. In the context of planning offshore wind farm maintenance, knowledge of the expected time before failure can be a useful metric for comparing priority of maintenance actions on different wind turbines.

Prognosis, which can be translated as "foreknowledge", is a term borrowed from Greek, now widely used in the context of predicting the future deterioration of engineering components. Discussion on the definition of the term "prognostics" in the context of CBM, was provided in [110] along with a review of various prognostic algorithms. A comprehensive review of the use of prognostics in machinery was provided by Jardine [78].

The use of machine prognostics in CBM was reviewed in [111]. A comprehensive summary of advantages, disadvantages and applications of major prognostic methods was provided. One of the key conclusions of this research was that most models in the field are limited to a specific domain and lack generality. The authors stressed the need for a general methodology, suitable for a wide variety of applications.

Approaches to prognosis can be divided into three categories: statistical, Artificial Intelligence (AI) and model based [78]. Data based and model based approaches are contrasted in Figure 3.6. Generally, model based methods are more computationally intensive, but often necessary when attempting to predict system's response in new operating conditions (or if no data on past performance is available). It was also argued that, ideally, a prognostic model should consist of elements of both data and physics-based approaches; as indicated by the links between the two in Figure 3.6. However, implementation and customisation of such approach to a range of components would be very time consuming. Typically, the choice of an approach depends on the amount and quality of past data and the confidence in predictive accuracy of a physics model in a given case [112].

The use of physics based models for components having multiple possible failure modes can be challenging, as each failure mode needs to be considered [100]. Given the abundance of data produced by wind turbine CMS, statistical and AI approaches are often favoured as they do not require detailed knowledge of the physics of failure. Data driven models are more versatile, as application of the same method to a wide range of components and failure modes is significantly easier compared to physics based models.

A review of offshore wind turbine fault prognostics methods was provided in [113], concluding with a set of recommended methods depending on the component in question. Out of the three approaches analysed (HMM, NN and particle filter method) HMM was applicable in the highest number of cases. HMMs were also used for real time failure prognosis in [114]. The authors created a belief rule base to incorporate expert knowledge and the influence of environmental factors into the model. HSMMs were also used to estimate RUL of bearings in [115], producing accurate results in case studies with real vibration data. However, the latter study was only shown to predict failure up to 10 hours in advance; such a short notice is unlikely to make a difference when prioritising offshore wind maintenance.

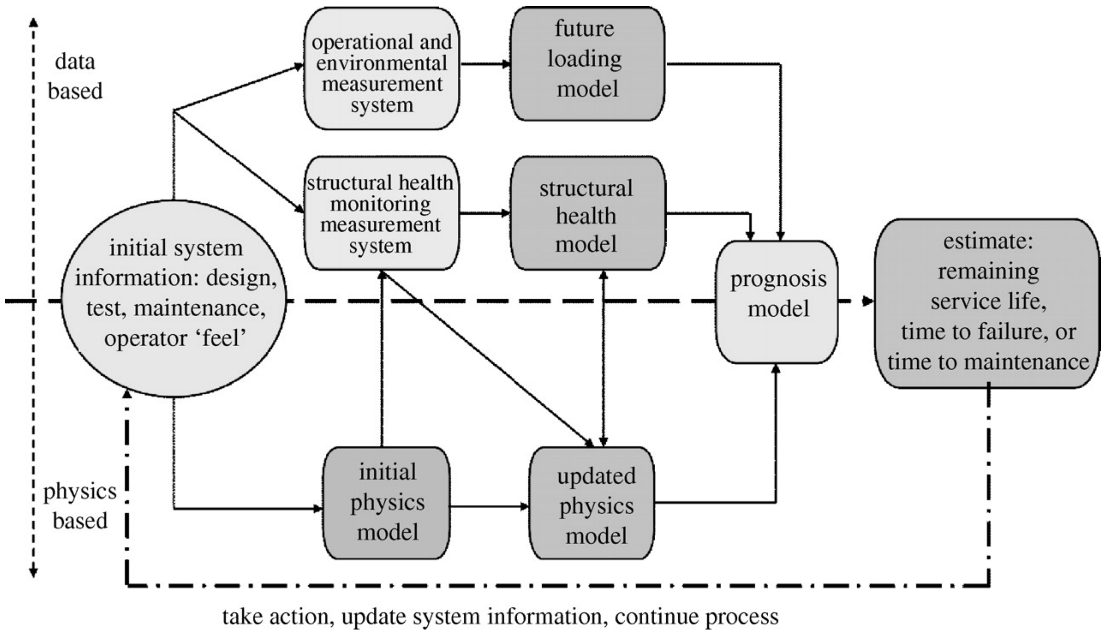

Figure 3.6. Damage prognosis: overview of data-based and physics-based approaches [112].

Bayesian networks are a graphical method of building models based on data or expert knowledge. An approach for estimation of the reliability of a wind turbine blade using maximum likelihood method and Bayesian statistics was proposed in [116]. Bayesian belief networks were also used for both diagnostics and prognostics in [117]; the proposed approach also allowed considering instrument uncertainties, which is one of the advantages of Bayesian networks. For example, if one of the sensors has failed and is providing false readings, a well-designed Bayesian network may be capable of recognising the possibility of sensor defect and providing a meaningful answer despite the fault.

Alternatively, AI methods such as NNs can be used for RUL estimation. A study focused on SCADA data analysis of wind turbines [118] investigated the use data mining algorithms in an attempt to predict failure of WT components. It found that NNs were capable of predicting the failure 60 minutes before it happened. Research conducted on wind turbine bearings has shown that analysis of temperature data using NNs can be used to predict the bearing failure up to 90 minutes in advance [119].

There are far fewer publications on prognostics compared to diagnostics [78] & [120]. The outline provided in this section focussed on approaches which may be applicable in prioritisation of maintenance actions for offshore wind turbines. For a prognostic model to be effective, it needs to be able to predict the component's condition sufficiently far into the future to facilitate preparation of spares and human resources [121]. Vast majority of the models reviewed in this section are unable to use data provided by CMS to effectively predict failure a day, or more, in advance.

In summary, the cost and difficulty associated with implementation of prognostics for a wide range of wind turbine components would not be justified by the benefits of the application of those systems solely for the purposes of maintenance action prioritisation. Given the current capabilities of the prognostics models, a more likely application would be to monitor critical wind turbine components such as the gearbox to provide an early warning of potentially expensive failures, allowing the operator to de-rate or shut down the component before damage is done.

3.2.3 Methods for Maintenance Action Prioritisation

Due to increased use of CMS in the wind domain, operators of large wind farms are often faced with a variety of alarms coming from multiple turbines. The operators are required to make a judgement whether a particular alarm warrants an immediate maintenance action. In addition to this, maintenance actions on offshore wind farms also include a plethora of non-critical activities, as discussed in Section 2.2.1. Given large scale retrofit campaigns, annual services, inspections and repairs, it is not uncommon for an operator of a 100+ turbine wind farm to be faced with 100+ different maintenance tasks which need to be carried out. In most cases, it will not be possible to carry out such high number of tasks in one day, due to real life constraints on time available, number and capability of vessels and technicians. This highlights the need for prioritisation of maintenance actions.

This section aims to review the approaches for prioritisation of maintenance actions, with focus on methods capable of answering the following question:

"Given a list of tasks with varying difficulty, resource requirements and different consequences of taking an action (or not taking it), how should the resources be allocated to maintenance tasks to ensure user-selected KPIs are maximised? "

A literature search for a methodology capable of answering this question **in the field of wind power**, did not provide any results. Interviews with offshore wind farm operators (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators) revealed the current practice is to divide the tasks into high and low priority tasks as shown in Table 3.2.

Table 3.2. Prioritisation of tasks: a pragmatic approach.

High priority maintenance actions	Low priority maintenance actions
• Turbines requiring a maintenance action to restore power generation • Turbines requiring a maintenance action to keep producing power • Maintenance actions which have to be carried out in near future due to deadlines and/or resource constraints	• Periodic/preventative maintenance actions • Retrofits • Inspections

The operators plan to carry out as many high priority tasks as possible given the resource constraints. Decisions on the priorities of individual actions within each section are made on a case-by-case basis using expert knowledge. This approach is crude and lacks consistency. In an attempt to improve on it and find a standardised method for offshore wind farm maintenance action prioritisation, literature search was extended beyond the wind domain.

Fwa & Chan [122] used NNs to prioritise repairs on highway pavements in an attempt to mimic the thought process of an engineer in charge of maintenance planning. However, the model developed only considers the state of the pavement, neglecting factors such as time required for repairs and availability of workforce. Li & Brown [123] ranked different maintenance actions according to their cost-effectiveness, which was based on the impact of component's failure and the repair costs. They proposed a weighted average system reliability index, which takes into account monetary cost, duration and frequency associated with interruption of service.

In the field of production line manufacturing, the problem of prioritising repairs has been tackled in [124] & [125]. Both papers used System Value Based method which was solved with a Genetic Algorithm (GA). The results of both these studies compared favourably with several other, commonly used maintenance prioritization policies such as: first-come-first-serve, shortest processing time first, longest processing time first, and static heuristic policy.

Ambani [126] proposed a maintenance decision making methodology combining continuous Markov chain as a deterioration mechanism and a cost model which considers component costs and profits. Two prioritisation approaches were proposed; downtime prioritisation, which prioritises components which result in higher downtime and prioritisation of assets with the highest potential of decreasing the overall system profit. The latter was shown to perform better than the former; however, both approaches are very simplistic and not applicable to problems with additional constraints and uncertainties.

Khanlari et al. [127] argues that verbal expressions and rules deriving from expert knowledge, such as the aforementioned pragmatic approach, can be quantified using fuzzy rules. The proposed method prioritised repairs based on MTBF, MTTR, availability of spare parts and personnel. Naturally, a disadvantage of such approach is that it is highly subjective; interviews with different experts would likely lead to different outcomes.

A methodology for ranking maintenance activities by calculating the overall pavement serviceability index based on a combination of four health attributes using fuzzy set rules was presented in [128]. This, and similar health indices described in Section 3.2.2 are a crucial in the process of prioritisation of repairs, however in the context of offshore wind, the use of health indices alone is simply not sufficient. No methodology was found in literature capable of handling all, or most of the factors shown in Table 3.1.

In the author's opinion, the reason for scarcity of models applicable to the practical problem described in Section 3.1 is the specific nature of the problem. Many of the factors listed in Section 3.1, which drive the need for maintenance action prioritisation models, are unique to the offshore wind domain.

3.2.4 Calculation of Value of Carrying out Maintenance Actions

One of the key conclusions of Section 3.1 was that there is a need for a metric, i.e. a “value” or “utility”, which can combine the factors described in Table 3.1 into a single parameter. There are two key questions, which this section attempts to answer; in the context of offshore wind maintenance planning:

1. What is the purpose of calculating this value; how can it be used to inform decision making?
2. What is the definition of a value of carrying out a given maintenance action on a given asset?

The answer to the former question is straightforward: a value, which considers the majority of factors described in Table 3.1, would be a useful metric for ranking maintenance actions. It would aid decisions on:

a) Which turbines should be maintained or visited first
b) Which turbines should the more capable vessels or qualified technicians be assigned to
c) In an event of shortages of resources, which maintenance actions can be delayed until the following day

Additionally, calculating value of carrying out a maintenance activity can determine whether it is worth taking that action at all. It is the latter of the two questions that poses a challenge and cannot be answered in a sentence or a paragraph.

While it can be argued that repairing an asset presents a certain measurable value to its operator, definition of the value is not trivial, especially when uncertainties are present. It would seem that the simplest way to define the monetary gain of taking an action would be to subtract all costs associated with the activity from the revenue gained from taking the action. Even such a simple definition already begs numerous questions. What time horizon should be used to calculate the revenue gained from taking an action? The cost of electricity generated in the following week, month, or the entire lifetime of a wind turbine? Assuming the maintenance action has to be carried out sooner or later, does the cost of repair matter at all when it comes to task prioritisation (as discussed in Section 2.2.4)? What about factors difficult to quantify in monetary terms such as the probability of accessing a particular wind turbine in a given significant wave height?

Utility theory states that "although is impossible to measure the utility derived from a good or service, it is usually possible to rank the alternatives in their order of preference to the consumer"[15]. The utility of taking an action does not need to equal the monetary gain for the asset owner; it can simply be a quantity used to order different options. However, it is important that this quantity does take into consideration relevant factors, which affect the process of prioritisation. The utility, or reward, can be expressed using a dimensionless scale (i.e. from 0 to 100, where 0 is often the action of doing nothing, while 100 is the most desirable action), allowing ranking and comparing different actions.

Methods for utility quantification

Morton [129] criticised the use of interval scales (where all actions must be assigned a value between pre-defined boundary i.e. 0-100) as it can lead to rank reversals. Rank reversals occur if the order of prioritised tasks is changed when a task is added or removed, which is often seen as undesirable and counter-intuitive. It is recommended to use absolute scale or ratio scale; i.e. approaches which prevent rank reversal from occurring.

Multiple-Criteria Decision Analysis (MCDA) is a structured, multi-stage approach, which aims to find the preferred alternative of the decision-maker, based on their pre-defined criteria. The process is made up of several steps, ranging from structuring the problem, articulating the stakeholder preferences, evaluating options and making recommendations. MCDA aims to manage multiple, conflicting criteria to arrive at a logical decision [130]. Guitouni and Martel [131] categorised and briefly described a wide range of MCDA approaches used in a variety of fields. In the maintenance planning domain, the MCDA was used in [132]; the proposed approach involved engagement of a committee of experts, who rated different maintenance strategies on quantitative, weighted criteria, which the committee previously defined. However, the process of MCDA is time consuming and it would be difficult to streamline it sufficiently to be applied for day-to-day decision making for a wide range of wind turbine components.

A methodology described in [38] applied cost-based criticality combined with cost-benefit analysis for prioritising maintenance activities on assets. Utilities of different actions were calculated based on factors such as consequences and probability of failure, as shown in Figure 3.7. Utility was expressed in pounds (£), despite the fact

[15] From: http://www.businessdictionary.com/definition/utility-theory.html Accessed on 29/07/2017.

the figure is relative rather than absolute. All maintenance actions were ranked according to their utility, creating a prioritised list of activities. As shown in Figure 3.7, the proposed approach has a number of layers of complexity, which are necessary to consider the multitude of factors affecting prioritisation of maintenance actions. However, application of this methodology to the offshore wind domain would likely require an addition of a number of "branches" to the "decision tree" shown in Figure 3.7, which would consider external and internal deadlines, availability of resources, asset performance compared to others, wind and wave conditions.

One of the disadvantages of the methods reviewed in this section is their inability to consider the possibility that in some cases, it may be beneficial to delay carrying out a maintenance action until a later date. An example of this would be delaying a non-critical maintenance action on a wind turbine during a period of strong wind. Switching off the turbine to carry out maintenance on a day with low wind would result in reduced loss of revenue. For a methodology to be applicable for offshore wind maintenance action prioritisation, the capability to consider the benefits of delaying an action is a necessity.

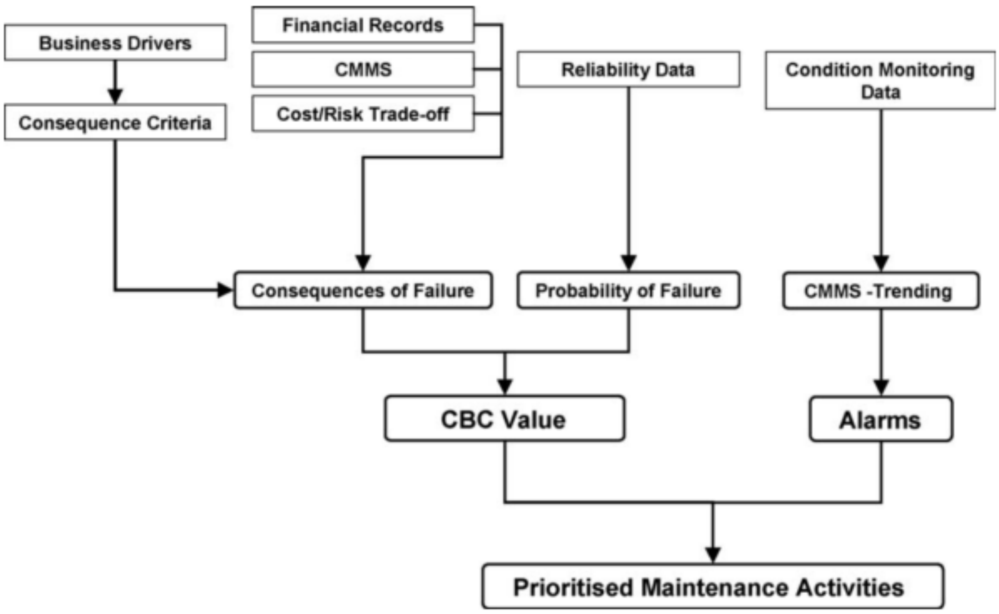

Figure 3.7. Cost-based criticality approach for maintenance activity prioritisation [38] **(CBC - Cost Based Criticality).**

The literature on methodologies for calculating values of maintenance actions is scarce. There is no evidence on the use of decision support tools for prioritisation of activities in offshore wind. Apart from the methodology proposed in [38], the research reviewed in this section severely lacks depth required for successful application to the real life problem.

3.2.5 Summary of the Literature Review

CMS are increasingly used in wind turbines in an attempt to gain detailed data on the current state of an engineering component, but also to predict the remaining useful life. The large volumes of data provided by CMS can be used to estimate current and future condition of a component. There are multiple ways in which this can be calculated and conveyed to the user:

a) Alarms
b) Diagnosis of the underlying issue
c) Health indices
d) RUL estimates

Versatility is the key to successful practical application, as monitoring techniques vary significantly depending on the component type, OEM, software package used for condition monitoring data analysis. Ideally, the model should accept a variety of input types, as well as constraints, which may change depending on the wind farm. Selection or development of a versatile methodology may enable successful application beyond offshore maintenance task prioritisation, potentially aiding decision making on onshore wind farms and in other sectors of the industry. For successful application in the offshore wind domain, the chosen method should also be capable of incorporating the majority of the factors described in Table 3.1 into the decision making process.

This literature review and interviews with wind farm maintenance planners (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators) revealed that currently, there is no structured framework, which would fit the aforementioned requirements for prioritising maintenance actions on offshore wind turbines. Despite the fact no suitable modelling methodology was found for that specific purpose, the literature review yielded some important insights:

a) There is a wide range of fault detection and diagnosis models suitable to a variety of wind turbine components. Models discussed in Section 3.2.2 can contribute to the process of maintenance prioritisation by providing accurate diagnosis and therefore expected resource and time requirements for maintenance action.

b) Literature on prognostics in the wind domain is limited. In other engineering fields, the models are rarely capable of providing a sufficient advance warning on component failure to aid the process of maintenance action prioritisation. The quality and quantity of the proposed approaches is insufficient to base any maintenance action prioritisation on it.
c) Literature on quantification of component's state or deterioration and calculation of value of a maintenance action is scarce, suggesting that real life decision making rarely requires quantification of incentives for carrying out a maintenance action.
d) Markov models were used across all sections of this review; from detection through diagnosis to prognosis. Due to their versatility, they have been applied to a range of problems. Markov models are relatively easy to compute.

Based on these conclusions, it was deemed that given the specific nature of the problem, a direct application of the methodologies reviewed in this section was impossible. Instead, the most suitable methodology should be selected and developed to fit the requirements; as discussed in the following sub-section.

Discussion of the modelling choice

Out of all the methodologies reviewed in Sections 3.2.2 & 3.2.3, Markov models seem the most versatile methodology. They have been applied for:

- Diagnosis of:
  - Faults in large scale power transformers [91]
  - Faults in hydraulic pumps [92]
- Modelling deterioration of:
  - Wind turbine blades [94]
  - Large infrastructure assets [97]
  - Electrical components [98]
  - Steel assets [99]
- Estimation of RUL in hydraulic pumps [106]
- Degradation and cost modelling of a multiple machine system [126]

Markov models are relatively easy to compute, even for problems with multiple health states and/or components. Markov chains can be easily converted to HMMs, which provide an effective framework for handling uncertainty. For those reasons, Markov models have been selected as the basis of the proposed maintenance action prioritisation framework.

The literature review identified a multitude of methods for diagnosis and some effective approaches for quantification of component condition, but there is a clear research gap in prioritisation models. It is recommended that practitioners apply one of the existing models for steps 1 & 2 of the overall decision making process shown in Figure 3.8. The outputs of these models should be used as an input into the proposed Markov-based prioritisation method, which will compute utilities of maintenance actions and generate a prioritised list of activities.

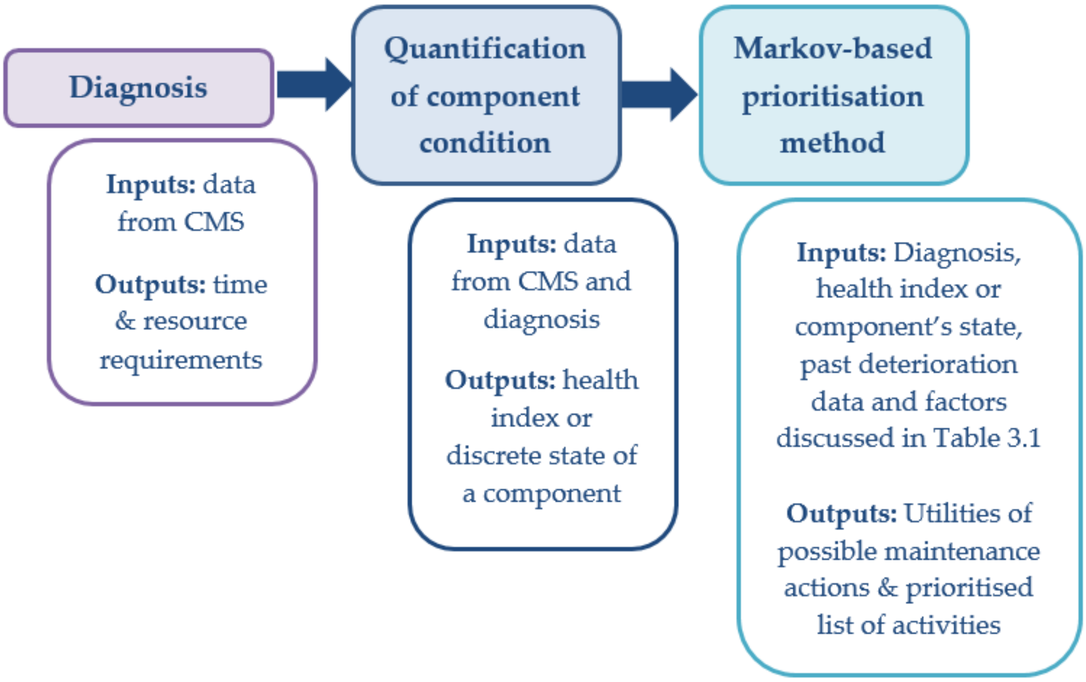

Figure 3.8. Proposed approach for maintenance action prioritisation.

Note that the proposed methodology eliminates the need for a prognostic model, which would be contained within the Markov model itself, provided past failure data can be obtained to calculate failure rates. Another advantage of using a discrete Markov model for prioritisation of maintenance tasks is that it is compatible with both discrete and continuous inputs (health index or state-based classification), enabling a choice of using either physics-based or data driven deterioration model.

3.3 Methodology for Calculating Maintenance Task Utility

As the proposed approach for task prioritisation was based on a Semi-Markov Decision Process (SMDP), it will be henceforth referred to as the SMDP model for task prioritisation.

First, let us define a planning horizon Z, which is the amount of steps, or days, the SMDP is set to run for. The value V of the component being in each of the states on day Z (the last day of the simulation) is equal to the final reward matrix D (Equation 3.2). Let S be the total number of the SMDP states for a given chain and s be the individual state identifier. A is the overall number of actions while a is an individual action identifier. Rewards and cost matrices: R and C respectively, are both three dimensional with a size of SxAxZ. Reward and cost matrices determine the financial rewards, or costs, of taking a given action at each time step. Transition matrix T, is a four-dimensional matrix which defines the probability of the system moving between states, depending on the action taken and the time step. Discount factor is denoted by γ.

Standard MDPs can be solved using Bellman equation [133]:

$$V(s) = \max_{a \in A} \left[R(s,a) + \gamma \sum_{s\prime \in S} T(s,a,s') * V(s') \right] \qquad (Equation\ 3.1)$$

where, s′ refers to the state to which the system will transition if action a is taken while the system is in state s. The standard solving procedure involves making an initial guess of the value matrix and solving the equation iteratively until convergence.

In the proposed approach, final reward matrix D provides the starting point for the first iteration (Equation 3.2). The iterative process consists of stepping back one day at a time to compute the value vector (value for each state) at the previous time step, until Z iterations are computed. The final iteration represents today's value vector. The modified Bellman equation is presented in Equation 3.3.

$$\overrightarrow{V_{\tau=1}} = \vec{D} \qquad (Equation\ 3.2)$$

$$V(s,\tau) = \max_{a \in A} \left[R(s,a,\tau) - C(s,a,\tau) + \gamma \sum_{s' \in S} T(s,a,\tau-1,s') * \begin{cases} D(s')\ if\ \tau = 1 \\ V(s',\tau-1)\ if\ t\ \neq 1 \end{cases} \right] (Eq. 3.3)$$

Note that τ in Equation 3.3 represents the iteration counter. As the simulation runs **backwards** in time, τ ranges from 1 (for day Z) to Z (today). As a result, s′ which denotes the next day's Markovian state, corresponds to τ – 1, as the next day would have been computed in the latest iteration. There are two differences between the standard version of Bellman equation (Equation 3.1) and the equation used in the model proposed here (Equation 3.3). Firstly, a dimension was added to the value, reward, cost and transition matrices – as in the proposed methodology, values in these matrices can vary over time. Secondly, a condition statement was added, indicating that user defined matrix D is used as a seed for state values on the first iteration.

Equation 3.3 enables calculation of the value of the turbine being in each of the user-defined Markovian states, at each time in the specified time horizon.

An overview of the proposed SMDP model is shown in Figure 3.9. A separate SMDP is created for each maintenance action, as cost and reward matrices vary depending on the type of fault. The aim of the SMDP is to calculate values for all states, for all days between now and the end of the time horizon. These values can be used to:

a) Determine the optimal action for each state, on each day. This can serve as prediction of future vessel and technician utilisation rates.
b) Rank all maintenance actions to be carried out on the day from the highest priority to lowest. This value will then be used as an input to the logistics model described in Chapter 5.

The proposed SMDP methodology is an attempt to capture all factors described in Table 3.1. However, the inputs to an SMDP are limited to those found in the modified Bellman equation (Equation 3.3). The aforementioned factors need to be captured within the three key inputs to the SMDP: the cost matrix, reward matrix and transition matrix.

An explanation of how the factors modelled, shown red boxes in Figure 3.9, are adapted to the three key inputs, shown in purple boxes, is provided in Table 3.3 .

Table 3.3. Factors affecting the priority of a maintenance action within the SMDP framework.

Availability of resources	**Effect on cost matrix:** If certain resources (i.e. vessels) are unavailable on some days in near future, the cost of using those resources on those days is set to a value sufficiently high to eliminate the possibility of the MDP selecting this action as optimal.
Properties of maintenance actions	**Effect on transition rate matrix:** If a certain maintenance action has a deadline by which it must to be carried out, the transition rates for that action are set to an identity matrix for all days succeeding the deadline.
	Effect on cost matrix: State of the component determines the cost associated with the maintenance action – highly damaged components are expected to cost more to repair than components featuring slight deterioration. The cost of resources such as vessels may vary over time; this variation can be modelled by specifying the expected cost of repair on each day throughout the time horizon.
Turbine accessibility	**Effect on transition rate matrix:** The transition matrix, originally defined by the properties of given maintenance action, is adjusted to include the expected probability of successful crew transfer from vessel to turbine. For example, under normal circumstances, taking action a in state s would result in transition to state s' with 100% certainty. If the wave forecast predicts 80% chance of successful transfer on a given day, the transition matrix will be modified to 80% chance of transfer to s' and 20% chance that the system will remain in state s.
Revenue generated by turbine	**Effect on reward matrix:** A baseline income from a turbine is initially defined. If a given turbine's power production differs significantly from baseline, for example due to its location and expected wind direction, the reward matrix is adjusted accordingly. If the wind speed is forecasted to change in future, expected revenues can be adapted. The state a turbine is in also dictates the amount of revenue it produces: i.e. a broken-down turbine produces no revenue.

Examples of the reward, cost and transition matrices, which were used as inputs to the SMDP, are shown in Appendix D. SMDP Case study Inputs.

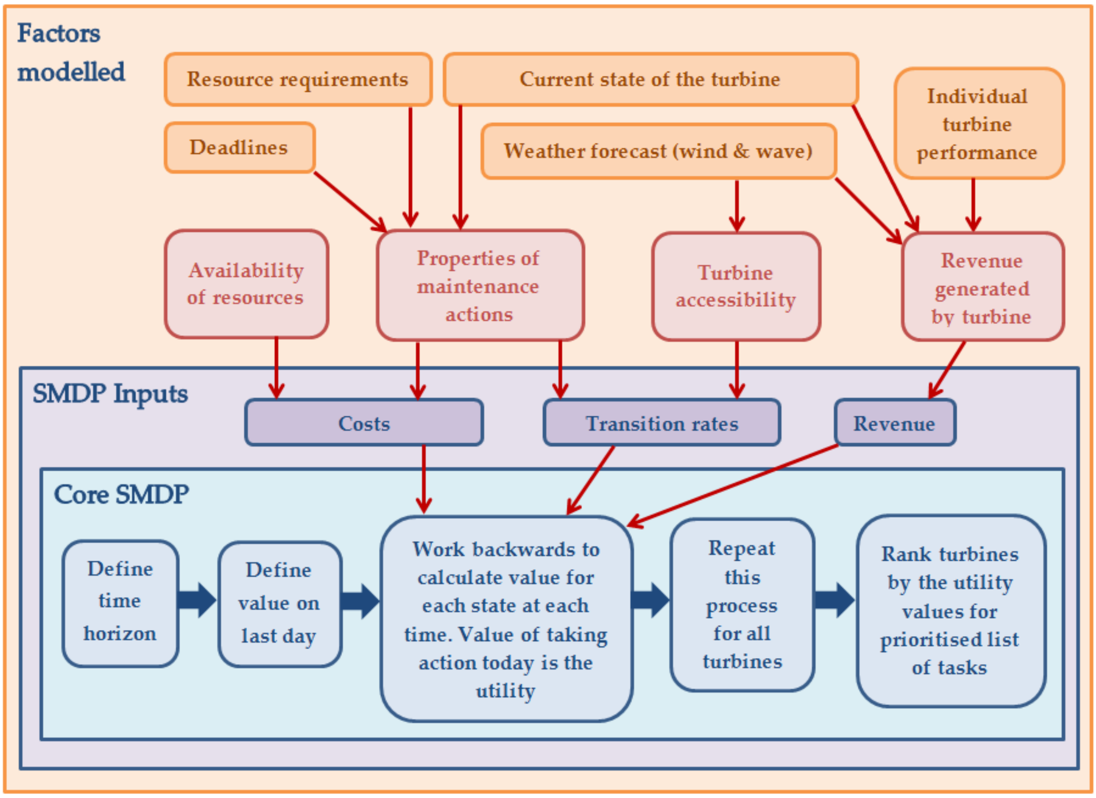

Figure 3.9. Overview of the proposed SMDP model.

3.3.1 Calculation of the Utility for Prioritisation of Maintenance Actions

The previous section described the use of Bellman equation for calculating the value of the component being in each of the states on a given day, depending on the action taken. Moore [38] has stated:

> *"Attention must be focused on those alarms that may have the gravest effect on the profitability of the organisation. To determine this, the maintenance manager must be able to balance the cost of performing maintenance activities against the cost of not performing them".*

In the approach proposed here, this balance was achieved by defining the utility of taking action 'a' today as the difference between value of taking an action and doing nothing, as shown in Equation 3.4.

$$U(a) = V(s_{\tau=Z}, a) - V(s_{\tau=Z}, a_N) \quad (Equation\ 3.4)$$

where $s_{\tau=Z}$ is the current state of the system and a_N is action of 'doing nothing'. Let us consider a simple case of a 2 state system (working and failed). By comparing taking an action to the consequences of not taking it, Equation 3.4 takes into account potential lost revenue. As the MDP works "backwards" to calculate values of each state, on each day, the utility of taking an action today encapsulates all possible outcomes of tomorrow and days beyond. This is illustrated in Figure 3.10; it was assumed that it is certain a maintenance action can be completed today, but there is uncertainty on whether sailing will be possible tomorrow. Hence, if 'do nothing' action is selected today, the risk of not being able to repair the fault tomorrow is included in the calculation. This is indicated by the orange arrows branching out on day 2.

By definition, the utility value of action 'do nothing' is always 0 (from Equation 3.4). Other actions, such as 'repair', can either have a positive utility, meaning choosing to carry those out is expected to add value to the overall state of the system, or negative, suggesting a given action should not be taken on that particular day. The magnitude of the utility value reflects the priority which should be assigned to a particular action.

In reality, negative utility of maintenance actions may occur in cases when there are additional costs associated with carrying out a maintenance action on a particular day. Alternatively, negative utility can be a result of a significant decrease in the expected wind speed in near future; carrying out non-critical maintenance actions on a 'windy' day will cause higher lost revenue compared to a day with low winds.

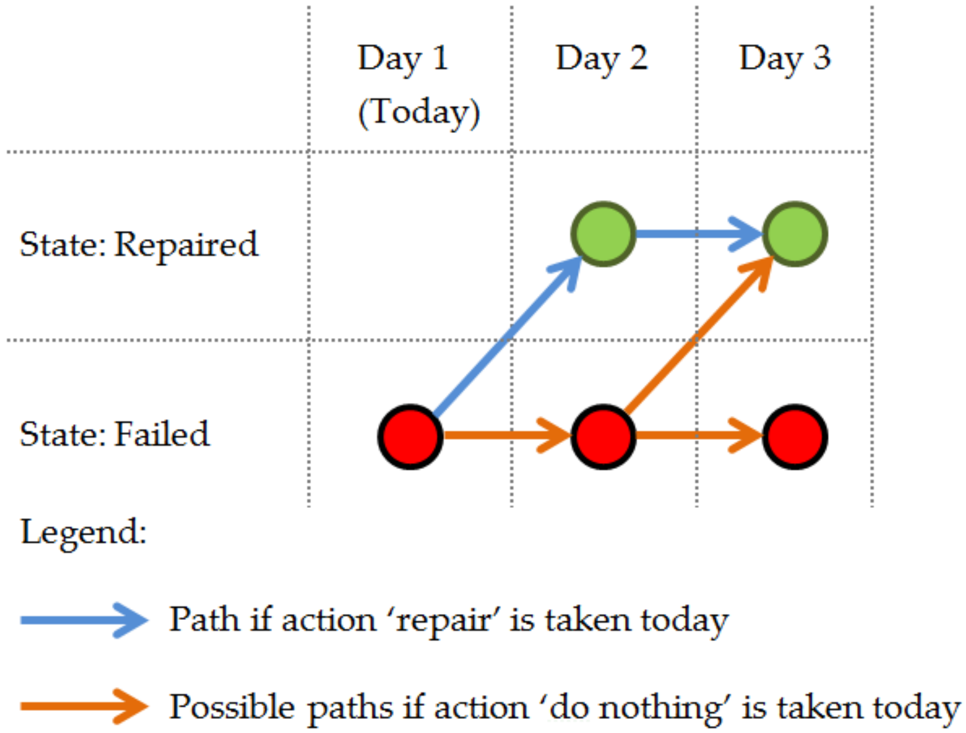

Figure 3.10. Possible outcomes of taking different actions today.

If more than 2 actions are possible for a given fault type, utilities for all actions can be calculated and compared against each other. The action with the highest utility would be wind farm operator's preferred choice.

Equation 3.4 allows calculating the utility of a single fault type on a given asset. However, there may be more than one maintenance actions required on a single turbine. If that is the case, two different scenarios are possible:

a) Both actions can be completed within the user-specified time window, on the same day
b) The time it would take to carry out both actions exceeds the time window

If a) is true, the utilities of all maintenance actions which can be completed within the time window are added. This approach clearly favours carrying out multiple repairs on the same turbine (i.e. opportunistic maintenance). It is more efficient than visiting the same turbine twice, or carrying out maintenance actions using two or more teams of technicians, as valuable time is saved on vessel-to-turbine transfers and climbing up and down the nacelle. To illustrate this, let us consider 2 different scenarios:

i. Two repairs (lasting 80 and 140 minutes, not including climbing up and down the nacelle) are carried out by the same crew on the same day
ii. The same two repairs are carried out on consecutive days

Assuming both maintenance actions take place in the nacelle, the total time required to complete repairs in each case can be calculated. Interviews with offshore wind farm operators revealed that each transfer from vessel to turbine (and vice versa) takes around 20 minutes. The time taken by hoisting tools and spares to the nacelle was also determined to be around 20 minutes. The total time taken to complete maintenance actions in both cases can be calculated using Equation 3.5.

$$2 * (\text{Vessel} - \text{turbine transfer time}) + 2 * (\text{Time to climb to nacelle}) + \text{Repair time} \qquad \text{(Equation 3.5)}$$

$$\text{i. Total repair time} = 2 * 20 + 2 * 20 + 80 + 140 = 300 \text{ minutes} \quad \text{(Equation 3.6)}$$

$$\text{ii. Day } 1 = 2 * 20 + 2 * 20 + 80 = 160 \text{ minutes}$$

$$\text{ii. Day } 2 = 2 * 20 + 2 * 20 + 140 = 220 \text{ minutes}$$

$$\text{ii. Total time for (ii)} = 160 + 220 = 380 \text{ minutes} \quad \text{(Equation 3.7)}$$

Comparing the results of Equations 3.6 and 3.7, the time saving due to carrying both repairs on the same day, by the same crew is 80 minutes. This can be seen as wasted time, as it is spent on transferring technicians, tools and spares to the nacelle rather than carrying out maintenance. Carrying out multiple maintenance actions on the same turbine, on one day aids maximisation of MTBV, one of the KPIs described in more detail in Section 2.2.6.

Let us now consider case b) from the previous page; wherein repairs of two or more different types, scheduled for a given turbine, cannot be completed in one day due to the time constraint. In this case, the values of individual maintenance actions can no longer be added together. Instead, the utility of sending technicians to such turbine is determined by the type of repairs. Let us divide all repairs into two types: corrective and non-corrective. The former is defined as an action which needs to be carried out to restore the turbine to the operational status (or prevent the turbine from failing in the short term). The latter is an action which, in the short term, does not affect the turbine's ability to generate power. This can include maintenance actions such as annual service or retrofits. If two maintenance actions can be carried out on a turbine on one day with the same team of technicians, the value of utility for that turbine will depend on the nature of those repairs:

1) If two or more actions to be carried out on a turbine are corrective, the utility of carrying out maintenance actions on that turbine is set to the lowest value of all the corrective repairs to be completed on that turbine.
   Example: Two corrective actions are required on a turbine: a repair, which on its own, has high utility and one which has a lower value. Repairing one of them will not make the turbine operational, as the other issue will persist, due to the technicians not having sufficient time to repair it. The utility for that turbine is set to the lower value of the two, as when ranking all turbines across the wind farm according to priority of visit, said turbine would come lower than a different turbine, which requires only the high utility corrective action.
2) In all other cases, i.e. if a turbine requires only one, or none corrective actions, the utility for that turbine is set to the highest value of all maintenance actions to be carried out on said turbine.
   Example: A turbine requires both a corrective and non-corrective actions. Given a choice between the two, the former action would likely be prioritised in real life, to restore turbine's ability to generate power. In the context of revenue generated, the fact that the turbine also required a non-corrective action is neither here nor there. Therefore, the utility of repairing a turbine with these two actions is set to the value of carrying out the corrective maintenance.

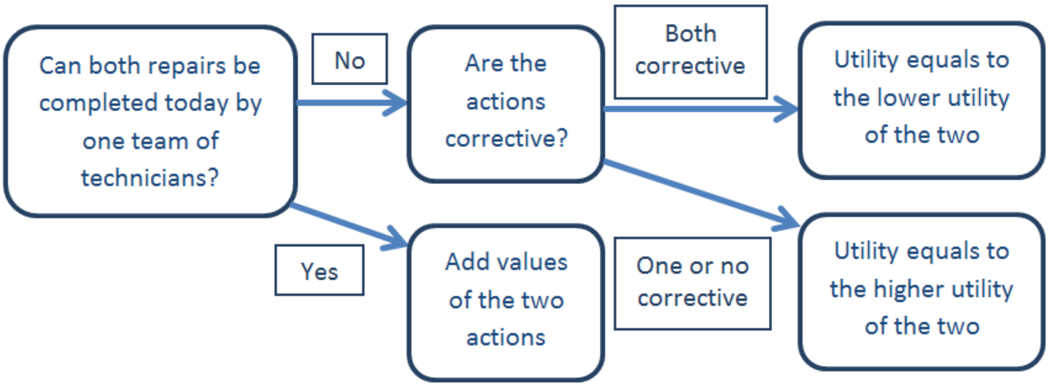

Figure 3.11. Proposed method for calculating the utility of visiting a turbine to carry out multiple maintenance actions.

Figure 3.11 contains the logic used in the proposed model, however, alternative logic flowcharts could easily be created and implemented depending on the user's requirements.

In summary, in the proposed method, utility of taking an action, which is expressed in monetary terms, represents the relative profit (revenue minus cost) generated by taking an action, compared to the profit that would be achieved if no action was taken. Defining the utility as such and using the proposed SMDP methodology enables considering all of the factors described in Table 3.1, which would not be possible if a simpler metric, such as actual revenue generated by a turbine, was used. Example 3.1 provides a case study to illustrate the nature of the calculated utility value.

The example shown in Example 3.1 illustrates how the proposed SMDP approach can be used to aid real life decision making. Frank calculated the utility of either action by contrasting the benefits of taking an action vs. costs of doing nothing. Comparing the utility values of the two actions allowed him to make an informed decision to maximise his profits. This simple example illustrates how easy it is to depart from using real monetary values when prioritising repairs. After all, the figure of £600 calculated in the latter case is not revenue produced by the mini-bus. It does not correspond to a value Frank will be able to gain or lose. It is the incentive, or utility of taking an action today.

Frank owns a coach rental business. He has to make a decision whether to take a mini-bus for its MOT (Ministry of Transport roadworthiness test) or repair a puncture on a luxurious coach. It is assumed that today, he can achieve either one or the other, but not both and that each action takes a full day to complete. Naturally, the coach generates more revenue than the mini-bus (£500 vs. £250 for the mini-bus). However, the MOT certificate on the mini-bus will expire on the following day; if service is not carried out today, Frank will have to pay a fee to tow the minibus to the testing centre. Frank should therefore consider whether the revenue generated by the coach tomorrow, if its tyre is fixed today, will offset the additional cost of towing the mini-bus to the testing centre tomorrow. Costs of both actions, along with expected revenues are shown in Table 3.4.

Frank decided to compare the action of fixing the puncture today (no revenue would be generated today, £500 of revenue tomorrow and thereafter) to not fixing the puncture today (no revenue today or tomorrow). It is clear that the incentive (or utility) of repairing the puncture on the coach in a 2-day horizon is £500.

Table 3.4. Properties and consequences of actions available to Frank.

	Repair puncture (coach)	MOT (mini-bus)
Cost of action today ǀ tomorrow	£0 ǀ £0	£0 ǀ £600
Revenue today if: action is taken ǀ no action is taken	£0 ǀ £0	£0 ǀ £250
Revenue tomorrow if: action is taken today ǀ no action is taken today	£500 ǀ £0	£250 ǀ £0
Sum (utility = difference between two values)	**£500 ǀ £0**	**£250 ǀ £-350**

If Frank chooses to take the mini-bus for its MOT today, neither cost nor revenue will be incurred today, but the mini-bus will generate £250 of revenue tomorrow and thereafter. If he chooses to do nothing, the mini-bus would generate £250 of revenue today, no revenue tomorrow and a towing fee of £600 would also have to be paid. Assuming a 2-day horizon, contrasting the effects of taking action and doing nothing in the case of the mini-bus yields £250 vs -£350, the difference being £600. Clearly, if Frank can only carry out one action today, it should be taking the mini-bus to the MOT test rather than fixing the puncture on the coach.

Example 3.1. A simple example of practical implementation of the SMDP methodology.

3.4 Task Prioritisation Using the Proposed Approach: Case Studies

To illustrate potential application of the SMDP methodology to a real life problem, two case studies are proposed. Given a set of offshore wind turbines requiring a range of maintenance actions, the model calculates utility of all actions, allowing prioritisation of wind turbine visits. The utility value obtained in the case studies shown in this section will be carried forward to Chapter 6, where it will be used as an input to the vessel routing optimiser.

3.4.1 Case Study Inputs

The two case studies discussed in this section are "summer day" and "winter day" case studies. The former contains a larger proportion of non-critical maintenance actions, while the latter features a higher number of repairs.

There are seven unique maintenance actions to be carried out, as shown in Table 3.5. The number of discrete Markov states for a task which takes less than one day to complete is two (state 1 being maintenance task completed/turbine fully functional and state 2 being turbine requiring maintenance). Some maintenance actions, such as wind turbine annual service can take multiple days to complete. For a 5 day service, there are 6 discrete Markov states (state 6 being service not started, state 5 being one day's maintenance done, etc.). For example, if a turbine requiring an annual service is in state 6 on day 1, five days of maintenance are needed for the task to be completed (one day per transition; i.e. state 6 to 5, 5 to 4 etc.). Carrying out the service on this turbine on day 1 will result in its state moving to state 5 on day 2.

Variable costs have been modelled for the annual service maintenance action; it was assumed that due to vessel limitation, this maintenance action cannot be completed on days 6 and 7. This was modelled by setting a cost of taking an action on those days to £1,000,000, effectively prohibiting the model from suggesting carrying out the annual service on those days.

Markovian deterioration of condition was modelled for the grease top-up action; if no maintenance is carried out when turbine is in state 2 (early warning) or 3 (severe lack of grease), turbine's condition deteriorates by one state on the following day until state 4 (turbine failure due to lack of lubricant) is reached, at which point turbine does not produce revenue and additional repair cost of £5000 is incurred. The transition matrix for grease top up maintenance action was provided in Appendix D. SMDP Case study Inputs.

It is expected that all repairs should be completed by the end of the time horizon (day 10), except for the high priority repair, which must be completed by the end of day 2. One of the practical reasons for such deadline could be the availability of external contractors, who are essential to carry out a given maintenance action.

The last column of Table 3.5 outlines the impact a maintenance action has on the power produced by the turbine on the day the maintenance is carried out. Assuming all maintenance activities finish around 4PM, taking medium repair as an example, the turbine will be producing electricity for 8 hours on the final day of repairs (State 2) and no power will be produced on days 1 and 2 of the three-day repair process (States 3 and 4).

Table 3.5. Inputs to the MDP model: Repair type properties.

Repair type	States	Variable cost	Condition deterioration	Repair result	Deadline	Power production hours on repair day
Manual reset	2	No	No	State 1	Day 10	8
Grease top-up	4	No	**Yes, 1 state each day (in states 2 & 3)**	State 1	Day 10	20 (States 2-3) 8 (State 4)
Retrofit	2	No	No	State 1	Day 10	20
Minor repair	2	No	No	State 1	Day 10	8
Medium repair (3 days)	4	No	No	**One state up**	Day 10	8 (State 2) 0 (States 3-4)
High priority repair	2	No	No	State 1	**Day 2**	8
Annual service (5 days)	6	**Yes**	No	**One state up**	Day 10	18

The SMDP models in both summer and winter case studies were run for a 10-day time horizon; which is sufficiently long to allow 5-day repairs to be completed. Due to the relatively short time horizon, the discount factor was set to 1. If the state of the system on day 10 is 1 (i.e. maintenance action completed/turbine is operational), a reward of £100,000 is granted. For consistency, this value is independent of the type of repair, its purpose solely to incentivise completion of the maintenance actions. Note that the magnitude of this number is not relevant as long as it is kept consistent for all maintenance actions (this ensures it has does not favour certain actions over others). If no deadline and final reward was present, the model would choose not to carry out non-critical maintenance actions such as retrofits.

In some cases, two different maintenance actions on one turbine may be required. It was assumed that the total duration of maintenance, including transfer of technicians and spare parts from the vessel to the nacelle cannot exceed 7 hours[16], if both actions are to be completed. Duration of all maintenance actions are defined in Table D.5 in Appendix D. SMDP Case study Inputs. Cost, reward and transition matrices used as inputs to the winter case study were provided in Appendix D. SMDP Case study Inputs.

There are three differences between the summer and winter case studies. Firstly, number and nature of maintenance actions required on turbines varies between the winter and summer case studies; these are outlined in Table 3.7 and Table 3.8 respectively. Secondly, the current and forecasted wind speed varies between the two case studies; the wind is expected to pick up in near future in the summer day case study. The reverse is true in the winter day case study, as indicated in Table 3.6. Thirdly, the probability of a sail day is lower in the winter day case study, as indicated in Table 3.6.

Once all inputs have been defined, the MATLAB-based model was run for both winter and summer case studies. Running simulations on a computer with an i7 3.4GHz processor and 8GB RAM took less than 0.2 seconds for each of the case studies (only one run for each case study was required). The prioritised task list for the winter case study produced by the SMDP model is presented in Table 3.7, which has been sorted by turbine visit priority in descending order.

[16] This number depends on shift duration and CTV travel time from O&M base to wind farm. In this case study, 11 h shift duration and approx. 90 minute CTV sail time from O&M base were assumed.

Table 3.6. Expected revenue produced by turbines in both case studies.

Winter Day Case Study			
	Today	Tomorrow	All other days
Revenue produced by a turbine	£9,600	£8,000	£8,000
Revenue produced by a high performance turbine	£10,560	£8,800	£8,800
Probability of a sail day	0.8	0.8	0.65
Summer Day Case Study			
Revenue produced by a turbine	£8,000	£9,600	£9,600
Revenue produced by a high performance turbine	£8,800	£10,560	£10,560
Probability of a sail day	1	0.9	0.8

3.4.2 Case Study Results

The "Recommended Action" column contains the suggested action to take on a given turbine, if only one action can be carried out on the day due to the 7h time limit. The values of all maintenance actions are expressed in monetary terms, for compatibility with the vessel routing optimiser described in Chapter 5.

As expected, the high priority repair tops the list, followed by two turbines requiring two maintenance actions, both of which can be completed on day 1. These are followed by two high performance turbines, capable of producing increased revenue compared to the other turbines. The utilities of the following seven turbines do not differ significantly; it is worth pointing out that grease top up in state 3 is ranked higher than in state 4. The model recognises that if no action is taken today, the turbine featuring the former alarm will deteriorate to the point of failure and an additional repair cost will be incurred.

Note that the additional repair cost does not affect the utility of grease top up in state 4, relatively to other, similar maintenance actions. Once the failure has occurred, the repair cost has to be paid regardless of the action chosen, as discussed in Section 2.2.4. The value for replenishing grease on turbines with early warning (state 2) is significantly lower – the model recognises that taking an action can be delayed until day 2 without significant consequences.

Finally, the utility of carrying out a retrofit on the winter's day is negative, as the optimal action is to wait until the following day to perform this action. If the retrofit was carried out today the turbine would be shut down during a period of increased wind speed. To minimise the lost generation, which is higher on day 1 compared to day 2, it is recommended to delay this non-critical maintenance action until day 2.

Table 3.7. Winter day case study. Maintenance actions prioritised using the SMDP approach, sorted from highest value repairs. Legend: numbers in brackets indicate MDP state. High Pr. - High priority repair, GTU - Grease Top Up, AS - Annual Service, Med - Medium repair.

Turbine ID	Fault 1	Fault 2	High Performance?	Recommended Action	Value (£ ,000)
68	High Pr.	-	No	Repair High Pr.	302.9
99	GTU (4)	Manual	**Yes**	Repair both	195.4
36	Manual	Minor	No	Repair both	175.6
85	Med (4)	-	**Yes**	Repair Med (4)	113.3
45	Manual	-	**Yes**	Repair Manual	96.6
42	Med (3)	-	No	Repair Med (3)	94.2
50	GTU (3)	-	No	Repair GTU (3)	92.1
19	Med (2)	-	No	Repair Med (2)	87.8
71	Minor	Med (3)	No	Repair Med (3)	87.8
3	Minor	-	No	Repair Minor	87.8
51	Manual	-	No	Repair Manual	87.8
92	GTU (2)	-	**Yes**	Repair GTU (2)	2.1
77	GTU (2)	-	No	Repair GTU (2)	2.0
21	Retrofit	-	No	Do Nothing	-2.1

In some cases (i.e. turbines 71 and 42), it may be possible that carrying out the same maintenance action results in different values, despite the fact that the utility calculated by the SMDP model of both maintenance actions is the same. The reason for this disparity is the logic presented in Figure 3.11, which assumes that the turbine with multiple faults should be assigned a lower priority than a turbine with a single fault.

Results of the summer day case study are shown in Table 3.8. Similarly to the winter case study, the top spot is occupied by the turbine requiring a high priority repair. The utility of this action is lower in summer than winter, as the probability of a sail day is higher in the former. Additional resources should be committed to addressing the issue on day 1 in the winter, due to the possibility that the turbine may be inaccessible on days 1 and 2, which would result in missing the deadline and forfeiting the final reward.

Table 3.8. Summer day case study. Maintenance actions prioritised using the MDP approach, sorted from highest value repairs. Legend: numbers in brackets indicate MDP state. High Pr. - High priority repair, GTU - Grease Top Up, AS - Annual Service, Med – Medium Repair.

Turbine ID	Fault 1	Fault 2	High Performance?	Recommended Action	Value
72	High Pr.	-	No	Repair High Pr.	241.9
55	Manual	Minor	No	Repair both	197.4
29	Med (3)	-	**Yes**	Repair Med (3)	127.6
84	Med (4)	-	No	Repair Med (4)	120.2
76	GTU (3)	-	No	Repair GTU (3)	108.7
96	Manual	-	**Yes**	Repair Manual	108.6
37	Manual	Retrofit	No	Repair both	103.4
56	AS (6)	Retrofit	No	Service AS (6)	101.6
89	AS (6)	-	No	Service AS (6)	101.6
4	GTU (4)	-	No	Repair GTU (4)	98.7
83	Med (2)	Retrofit	No	Repair Med (2)	98.7
48	Minor	-	No	Repair Minor	98.7
70	Manual	-	No	Repair Manual	98.7
91	GTU (2)	Retrofit	No	Repair both	15.4
81	GTU (2)	-	**Yes**	Repair GTU (2)	11.8
16	GTU (2)	AS (3)	No	Repair GTU (2)	10.7
40	GTU (2)	-	No	Repair GTU (2)	10.7
1	AS (3)	Retrofit	No	Service AS (3)	10.2
64	AS (3)	-	No	Service AS (3)	10.2
23	Retrofit	-	No	Retrofit	4.7

Conversely, the utilities of other maintenance actions are higher in the summer than in the winter case study. This is due to the assumption of higher mean wind speed in the summer (Table 3.6), meaning that on average, turbines in the summer case study produce more revenue.

Similar patterns emerge in both summer and winter case studies; turbines requiring a medium repair are assigned a high priority to ensure the 10-day deadline is met and to restart revenue generation as quickly as possible. High performance turbines are prioritised over baseline turbines with equivalent maintenance action requirements.

Comparing utilities for visiting turbines 40 and 91, it is clear that the SMDP model favours carrying out multiple repairs on the same turbine, contributing to MTBV increases. Unlike winter case study, the value of retrofit is positive, albeit low. As the wind speed is expected to increase in near future, non-critical maintenance actions are encouraged. Turbine 89, which requires an annual service, is ranked higher than some of the turbines requiring repairs. Duration of the former maintenance task in the case of turbine 89 is 5 days; the high utility is due to uncertainty of accessibility on days 2-10. If the uncertainty was removed, by setting a chance of sail day on all days to 1, the utility of all non-critical maintenance actions would be lower than the utility of visiting turbines requiring critical repairs.

While the magnitude of utility is an important output of the SMDP model, used as an input to the vessel routing optimiser described in Chapter 5, it is the ordered list of maintenance tasks is the focal point of this section. As a tangible, easy to understand output, it carries more importance to potential users of the proposed SMDP methodology than the magnitude utility values. The order of the prioritised list of tasks is logical given the assumptions made, it aligns with the pragmatic approach to task prioritisation outlined in Table 3.2.

3.4.3 Application of the Proposed SMDP Methodology for Short Term Resource Requirement Forecasting and Supporting Vessel Hire Decisions

Dawid, McMillan and Revie [134] proposed application of the SMDP methodology for determining the optimal maintenance actions for a single component over a 15-day time horizon. This was achieved by modifying Bellman Equation (as shown in Equation 3.8) to automate the process of optimal action selection:

$$Oa(s_\tau) = a \text{ such that } \max_{a \in A} \left[\begin{array}{c} R(s,a,\tau) - C(s,a,\tau) + \\ \gamma \sum_{s\prime \in S} T(s,a,\tau-1,s') * V(\tau-1,s') \end{array} \right] \quad (Equation\ 3.8)$$

where $Oa(s_\tau)$ is the optimal action to take in state s at time-step τ. The value of taking each action at each state and at each time step is calculated as it was in the SMDP method described in previous sections. To illustrate how the SMDP approach can be applied for forecasting resource requirements depending on the weather and vessel availability, a case study based on wind turbine gearbox is presented.

It is assumed that the condition of gearbox can be categorised as one of four discrete states: "brand new", "good", "bad" and "failed". The operator has the option of carrying out one of three actions on each day: replace, repair and do nothing. Replacing a component will restore it to the brand new state. Repair results in the component's state improving by one state (for example if component in a "bad" state is repaired, its condition is upgraded to "good" after the action is completed). Repair action is considered imperfect, meaning that there is a 10% chance of no improvement after the action is completed. A component in a failed state has to be replaced; repairing it will have no effect on its condition.

If the "do nothing" action is selected by the operator, there is a 2% chance that the component will deteriorate from state "brand new" to "good", 5% chance of deterioration from state "good" to "bad" and 15% chance of deteriorating from state "bad" to "failed". These arbitrary values describe the deterioration of a fictional component for the purposes of this case study. The deterioration probabilities populate the transition matrix. Costs of maintenance actions are outlined in Table 3.9.

There are two types of vessels available to the operator: a CTV used for repair actions and a jack-up vessel for replacement. Hire costs of each of the vessels are shown in Table 3.10. It is assumed that the CTV is capable of operating in significant wave heights up to 1.4m, while the jack-up vessel can be used in significant wave heights of up to 1.9m[17]. As discussed in Section 2.2.4, hiring a jack-up vessel on short notice can be very expensive, which is reflected in the first row of Table 3.10.

Table 3.9. Costs of actions (in £,000) for each state.

State/Action	Do nothing	Repair	Replace
Brand new	0	5	30
Good	0	5	30
Bad	0	5	30
Failed	0	N/A	30

Discount factor was set at 0.999 (per day) and the final rewards on day 16 were set at £150,000, £140,000, £50,000 and £0 for states "brand new", "good", "bad" and "failed" respectively.

[17] Each jack-up vessel has a maximum allowable significant wave height in which it can be jacked up. For example, Innovation jack-up vessel can be jacked-up in Hs of up to 2m: http://www.crist.com.pl/jack-up-vessels-and-barges,22,en.html Accessed on 5/07/2019.

Table 3.10. Time-variable hire cost of vessels (£,000). Jack-up hire cost includes mobilisation cost.

Days	CTV	Jack-up
Days 1-2	10	350
Days 3-9	10	150
Days 10-12	10	100
Days 13-15	10	80

The significant wave height forecast over the entire 15-day time horizon is shown in Table 3.11. It is assumed that the significant wave height is linearly correlated with wind speed, which determines the revenue generated by the turbine. The highest amount of revenue (in the 15 day time horizon) is expected to be generated on days 9-10, when the significant wave height is also at its peak. The revenue generated by the turbine on those days amounts to £10,000. Revenue on other days can be calculated using the formula found in Equation 3.9:

$$R(s,\tau) = \frac{H(\tau) * r_{2m}}{2} \qquad (Equation\ 3.9)$$

where r_{2m} is the revenue generated by a turbine when the significant wave height is 2 meters, H is the significant wave height. Naturally, a turbine with a failed gearbox is assumed to produce no revenue until the component is replaced.

Table 3.11. Forecasted significant wave height and vessel availability.

	Time (days)														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Wave (m)	1.1	1.2	1.3	1.4	1.5	1.6	1.8	1.9	2	2	1.7	1.4	1.3	1.2	1.1
CTV	Y	Y	Y	Y	N	N	N	N	N	N	N	Y	Y	Y	Y
Jack-up	Y	Y	Y	Y	Y	Y	Y	Y	N	N	Y	Y	Y	Y	Y

The key output of the model shown in Table 3.12 can be explained by analysing individual rows corresponding to four discrete states. If the gearbox is in a brand new state, action "do nothing" should be taken on all days. The model suggests carrying out repairs on days 1-4, even if the system is in a "good" state. This approach aims to reduce the probability of gearbox failure during a period of high waves (days 5-11), which would result in significant repair costs and potential lost revenue. Looking at the third row, it is clear that the optimal action is to repair whenever the sea conditions allow it, to prevent gearbox failure. Finally, when the gearbox has failed, it should be replaced in days 3-4 and 13-15. No replacement should take place on days 1 and 2 as the cost of hiring a jack-up vessel on such short notice outweighs the revenue which could be generated in that period. The same logic applies to days 5-15; it is more economical to delay the replacement action until day 13, as lost revenue lost during this period is less than the difference in vessel hire cost.

Table 3.12. The optimal actions depending on the day and the state of a component. Action 1 is "do nothing", 2 is "repair", 3 is "replace" [134].

	Time (days)														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Brand new	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Good	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1
Bad	2	2	2	2	1	1	1	1	1	1	1	2	2	2	2
Failed	1	1	3	3	1	1	1	1	1	1	1	1	3	3	3

The SMDP output shown in Table 3.12 provides the wind farm operator with an outlook of future resource requirements. The optimal actions in each state, on each day, would likely be similar for all wind turbine gearboxes on a wind farm. If the condition monitoring data suggests that a number of turbines are expected to experience a gearbox problem in near future, the operator should ensure sufficient resources and CTVs are present on days 1-4 to prevent gearbox failures. The decision to hire a jack up vessel for day 13 should also be considered, as volatility of the jack-up hire market may push prices up in near future.

The case study presented here was limited to 4 states and a single component. This can easily be extended to include more states and a variety of components, with no significant increase in computational time. The proposed SMDP methodology would benefit from integration with a prognostic model, capable of forecasting future deterioration of components on individual turbines. Combination of the SMDP model, a prognostic model, records of planned maintenance for the near future and accurate wind and wave forecast would likely prove a formidable tool for day-to-day maintenance task prioritisation and future vessel utilisation estimation on offshore wind farms.

3.5 Conclusions

Section 3.1 defined the requirements a maintenance task prioritisation methodology needs to fulfil for successful practical application to offshore wind farms. Literature review conducted in Section 3.2 found no publications offering a solution which satisfied all, or most, requirements. The information gathered surveying the literature influenced the choice of methodology: Semi-Markov Decision Process was selected as a versatile and computationally effective approach. The proposed SMDP model, described in Section 3.3, offers a structured framework for prioritisation of maintenance actions while taking into consideration:

a) A variety of maintenance actions with different properties
b) User-specified deadlines
c) Time-variable costs, which can be used to model availability of resources
d) Time-variable rewards due to wind forecast
e) Uncertainty related to future accessibility of turbines
f) Individual wind turbine performance
g) Multiple maintenance actions on a single turbine

To the author's knowledge, this has not been achieved in any other work in literature. The proposed SMDP approach provides a framework for prioritising repairs without utilising human judgement or expert knowledge, removing subjectivity from the decision making process and ensuring consistent results. One of the key advantages of this methodology is the ability to specify time-variable costs, rewards and transition matrices, providing the model with a capability to support decisions on whether to carry out a given action as soon as possible or wait until a later date.

The proposed method of task prioritisation will not result in rank reversal (described in more detail in Section 3.2.4), as addition or removal of turbines requiring maintenance does not affect the value of other repairs. The case studies, presented in Section 3.4 have demonstrated the model's ability to cope with a sizeable selection of different maintenance actions, yielding logical and sensible results. Validation of the SMDP model is discussed in Section 7.2.

The model captures some of the universal mechanisms used in real-life decision making as illustrated in Example 3.1. Section 3.4.3 demonstrated that the SMDP model can also be used for forecasting short term resource requirements and supporting decisions on jack-up vessel hire. While the methodology was designed for the offshore wind domain, failing assets, variable costs and rewards and constraints on maintenance actions are present in many engineering fields. In the author's view, this methodology is versatile enough to support decision making in a wide range of industries.

3.5.1 Limitations and future work

The proposed methodology has been developed specifically with short-term decision making in mind. If the SMDP model is to be applied for real life decision making, it may be necessary to integrate it with current systems used by wind farm operators to account for medium and long-term maintenance plans. Although the SMDP computational time is short, task list management and inputting data into the model can be time consuming. Integration with CMS and alarm management systems would facilitate application of the proposed method to wind farms with more than 50 turbines. Data integration is discussed in more detail in Section 8.3.3.

The number of maintenance tasks per turbine in the case studies was limited to 2; however, extending the model's capabilities to 4-5 maintenance tasks per turbine would not pose a significant challenge.

Chapter 4. Literature Review of Methods for Solving the Vessel Routing Problem for Offshore Wind Farms

Decisions on dispatching and routing resources between geographical locations are made daily in almost all industry sectors. Businesses face the challenge of optimising the movement of couriers, engineers, taxis, planes, vessels etc. Optimal route planning is a common logistical problem.

The word comes from Greek verb "logizomai", which means to think deeply and calculate consequences of actions. Oxford Dictionary defines logistics as "the careful organization of a complicated activity so that it happens in a successful and effective way"[18]. The aim of this chapter is to review methodologies for solving logistical problems in a variety of domains and select the most suitable approach for determining vessel routing for offshore wind farms. A large proportion of the literature reviewed in this chapter focuses on problems outside of the wind domain, as vessel routing for offshore wind farms has only been tackled by a handful of researchers.

This chapter is structured as follows: constraints and practical considerations of the problem at hand are outlined in Section 4.1. Section 4.2 contains the literature review of methods for solving logistical problems, with the findings summarised in Section 4.3, which also contains a brief overview of the chosen methodology.

4.1 Real-World Problem Description

The aim of this section is to familiarise the reader with the practicalities of planning vessel routing of offshore wind farms. This knowledge was gathered through informal interviews with operators of a major UK offshore wind farm (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators). This section expands on Section 2.2, which described the general challenges of planning offshore wind turbine O&M. Here, a more detailed analysis of the practicalities of planning vessel routing is provided.

El-Thalji [135] provided a comprehensive review of the O&M practices of wind power assets, highlighting that the main issues in offshore wind maintenance lie with site accessibility and environmental factors. A LEANWIND report stated that a wind farm with two hundred 5MW turbines would be expected to require around 3,000 visits per year [13], which roughly translates to 8 visits a day, a proportion of which will be unforeseeable (i.e. unexpected failures). If a route plan is made a day early, it

[18] http://dictionary.cambridge.org/dictionary/english/logistics accessed on 15/08/2017.

is likely that it will need re-calculating by the following morning due to the fact that a number of issues would have arisen overnight. Therefore, planning horizon for vessel routing decisions is very short (1-2 days, as discussed in Section 2.2.1). According to the interviewed wind farm operators, the current approach to solving the problem does not involve any decision support tools.

The real world decision making process is outlined in Figure 4.1. Note that this represents the logic used by the interviewed wind farm operators. It begins by compiling a task list of maintenance actions to be carried out in the near future[19]. Planners then identify the high priority maintenance tasks – each of those is assigned a vessel and a troubleshooting team of technicians, who are skilled at carrying out repairs or other crucial maintenance tasks.

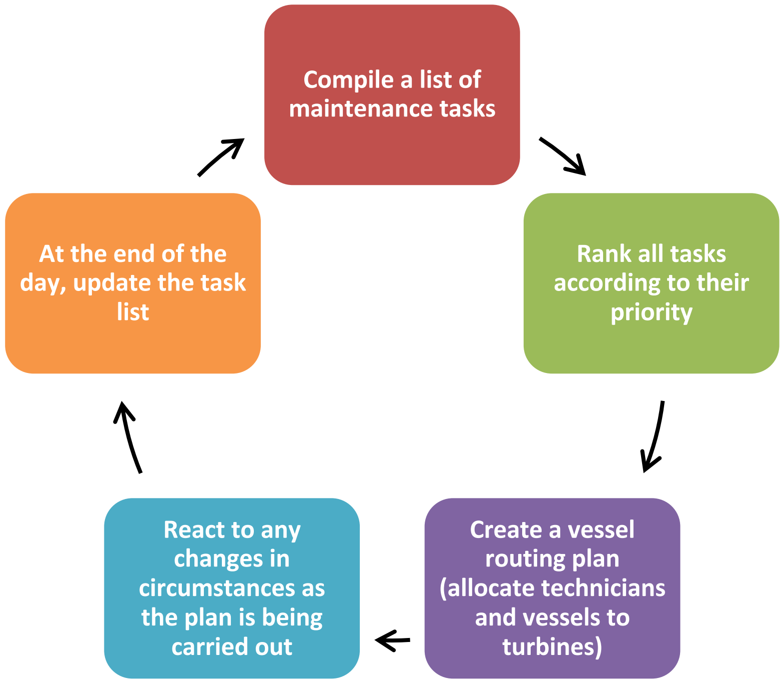

Figure 4.1. Outline of the vessel routing decision making process for offshore wind farms.

Each vessel which has been assigned a troubleshooting team is allocated additional maintenance tasks in the proximity of the turbine requiring a repair. The process is repeated until all technicians have been allocated a vessel, resulting in a list of

[19] At large offshore wind farms (100+ turbines) listing all tasks would be time consuming – there may be thousands of various tasks to be carried out in the near future. Alternative approach is to keep a prioritised list of 30-50 tasks. New tasks are then added as completed actions are crossed off the list.

maintenance tasks to complete on the day. The order of turbine visits is determined by the maintenance task duration – tasks expected to take longer are visited first to maximise overall time to complete the action.

A single wind turbine may require multiple maintenance tasks. If this is the case, an attempt will be made to complete all actions on one day, time constraint permitting.

When planning the vessel routing, wind farm operators aim to satisfy five key objectives (as discussed in Section 2.2.6):

1) Maximisation of the number of completed high priority maintenance actions. Note that this combines elements of OPEX minimisation (i.e. avoidance of contractual penalties) and availability maximisation (minimisation of turbine downtime)
2) Maximisation of the number of man-hours worked by technicians (maximisation of operational efficiency)
3) Minimisation of the number of unsuccessful maintenance actions, which also maximises MTBV and operational efficiency
4) Minimisation of avoidable costs (OPEX minimisation)
5) Maximisation of wind power generation (e.g. by delaying non-critical maintenance action during periods of high wind)

A summary of all factors, which the decision makers need to take into consideration when planning vessel routing for offshore wind farms is provided in Table 4.1.

This section presented the unique constraints and factors, which define the problem of scheduling vessel routing for offshore wind farm maintenance. The literature review presented in the following section aims to find a method capable of optimising vessel routing to achieve objectives 1-5) while taking into account most of the factors outlined in Table 4.1.

Table 4.1. Key factors to consider when planning real-life vessel routing for offshore wind farms.

Factors to be considered	Description
1) Maintenance action priority	As discussed is Section 2.2.2, stopped turbines and maintenance actions with nearing deadlines are examples of the high priority tasks. The higher the priority, the more likely that a task will be selected to be carried out on the day. Operators may choose to dispatch vessels to turbines with high priority tasks first, before other turbines are visited, to maximise the time on turbine. Maintenance action prioritisation is discussed in Chapter 3.
2) Properties of all maintenance actions	This includes the resources required to complete the maintenance action, as well as the expected task duration. The former needs to be considered if vessel's capacity is limited, while the latter is crucial when deciding the order in which turbines are visited.
3) Vessel properties and heterogeneous vessel fleet	Carrying capability of vessels in a fleet may vary; operators may choose to assign higher capacity vessels to tasks which require heavy spare parts, tools or an increased number of technicians. The vessel's speed and ability to transfer crews onto turbines in high waves can also vary depending on the vessel size and type. Operators tend to dispatch more capable vessels to turbines which are expected to experience higher waves. Using faster vessels to carry technicians to turbines with high priority maintenance actions can result in additional time for repairs, as less time is spent travelling.
4) Variable vessel speed due to acceleration/ deceleration (speed correction factor)	If the sea is calm, the vessel's cruise speed can be used to calculate the time taken to travel from the O&M base to the wind farm. However, when the vessel is travelling between turbines, the captain needs to traverse the wind farm. There may be restriction zones which the vessel cannot enter (for example due to blade work overhead). To allow for the above and for acceleration/ deceleration, a reduced speed should be used for calculations of time required to travel between turbines.
5) Time constraint & calculation of policy duration	The time between vessel leaving and returning to the O&M base (also known as the "policy duration") is limited by the maximum working hours of technicians and vessel crew. Scheduling too many maintenance actions in a day leads can lead to unfinished tasks, which was shown to be inefficient in Section 3.3. To achieve an accurate estimate of policy duration, it is important to consider factors such as the time required to transfer technicians and spare parts onto a turbine, the time required to ascend to the nacelle, expected duration of the maintenance actions and vessel travel time to/from wind farm and between turbines.

Factors to be considered	Description (cont.)
6) Wind turbine locations	Wind farm operators aim to maximise the amount of time technicians spend on maintenance by reducing the time spent on travelling between turbines. Assigning vessels to clusters of turbines located close to each other helps to achieve this.
7) Uncertainties	Uncertainties associated with planning offshore wind farm maintenance are described in detail in Section 2.2.7. Known uncertainties can, and should be included in the decision making process. Consider the following example: one crew of technicians was assigned to carry out maintenance tasks on two different turbines. If uncertainty on duration of both tasks is high, there is a risk that maintenance will take longer than expected. This may lead to the policy time limit being exceeded, meaning that one, or both tasks would not completed and would need to be attempted again at a later date. In this case, a better approach would be to assign these tasks to two different crews of technicians and schedule the policies so that tasks with high uncertainties are not on the critical path (discussed in more detail in Section 5.2.3).
8) Problem size	As shown in Appendix A. Calculating the Number of Possible Vessel Routing Policies, there are more ways to schedule visits to 20 turbines using 5 vessels than there are stars in the observable universe. It is a problem impossible to solve optimally without the use of state-of-the-art decision support tools. Problem complexity and size impact the computational time; this needs to be considered in the process of methodology selection.
9) Costs associated with maintenance	If a vessel is hired on a pay-per-use basis, the hire cost should be taken into account when making a decision whether to use the vessel. Operators aim to minimise the fuel costs by optimising the order in which turbines are visited and encouraging use of fuel-efficient vessels in policies involving increased travelling.
10) Technician skills and qualifications	Each technician has a unique skillset and background, potentially making them more or less effective at carrying out certain maintenance tasks. Some maintenance actions can only be completed by technicians with appropriate qualifications and training.
11) Previous day's assignment of technicians to vessels	Assigning technicians to the same vessel they were on the day before saves time, as their tools do not need to be craned between vessels (note that this constraint may be specific to the site where the tool was validated).
12) Time required to come to a decision	Operators take between 1-5 hours to finalise the vessel routing plan. If software was used to support decision making, computational time would be expected to be on the lower end of this spectrum, to allow for managing inputs to and outputs from the model.

4.2 Literature Review

A survey of literature on solving logistical problems in a variety of domains was conducted. Standardised logistical problems are described in Section 4.2.1, to familiarise the reader with the different problem categories. This was followed by a summary of review papers on solution methods for different problems, provided in Section 4.2.2. Literature focusing on solving the vessel routing problems in the offshore wind domain is reviewed in Section 4.2.6.

4.2.1 Categorisation of the Logistic Problems

In the field of logistics optimisation, the Travelling Salesman Problem (TSP) is one of the most studied problems, with multiple real world applications [136]. A travelling salesman needs to visit a collection of customers in different locations. Solving the TSP involves finding the shortest route in which all customers are visited. In a pure TSP, the only constraint is that the salesman needs to start and end their journey at the same point (depot). Some researchers proposed extensions of the TSP, such as TSP with multiple depots and salesmen; these were described in more detail in [137].

Vehicle Routing Problem (VRP), first introduced in [138], is a generalisation of the TSP, in which the vehicle returns to depot before visiting all customers. While TSPs are mainly concerned with finding the shortest distance between customers, VRPs introduce additional layers of complexity, such as vehicle capacity. Variations of the VRP include:

a) Capacitated VRP – each vessel has a limited capacity for carrying goods; at no point in the tour the vehicle is allowed to carry more goods than its capacity (for example: Alba & Dorronsoro [139])
b) VRP with heterogeneous fleet – vehicles can have different characteristics such as capacity and speed (for example: Dondo & Cerda [140])
c) Multi depot VRP – vehicles start and finish tours at multiple depots (for example: Dondo & Cerda [140])
d) VRP with Time Windows (VRPTW) – customers need to be visited at specified time (for example: Czech & Czarnas [141])
e) VRP with Pick-up and Delivery (VRPPD) – goods collected from customers are classified as either goods to be taken back to depot or goods to be delivered to another customer (for example: Ganesh & Narendran [142])

f) VRP with backhauls – customers can have both positive and negative demand, the latter meaning goods need to be collected from the customer and returned to depot (for example: Gajpal & Abad [143])
g) Stochastic VRP – includes uncertainties, for example on the customer demand, travel time or the time window (for example: Tas et al. [144])
h) VRP with Profits (VRPP) – each customer is associated with a profit which will be collected when visited by the vehicle. In this variation, not all customers need to be visited by the vehicles (for example: Li & Lu [145])

Categorisation of complex problems, such as the vessel routing problem described in Section 4.1, is very difficult. Most real world problems will feature a combination of the underlying assumptions of VRPs discussed in a-h). Instead, the research community has created a category specifically for problems with multiple, complex constraints named Rich VRPs (RVRPs). RVRP consists of real-life problems featuring uncertainties, multi-objective optimization functions and a variety of constraints on time, distance and more [146]. Rich VRPs, may be especially difficult to solve as they can involve compound[20] or antagonist[21] decisions [147].

4.2.2 Review Papers

This section aims to summarise the contributions and conclusions of review papers on VRP solution methods. VRP is a very well-researched problem; it has been defined as early as 1959 [138]. More recently, Laporte [148] provided a summary of 50 years of research into VRP solution methods in a landmark paper, which has been cited by over 700 researchers[22].

Laporte [148] noted that while there are algorithms capable of producing exact solutions to TSPs with thousands of customers, the best exact algorithms for the VRP can only tackle problems with up to 100 customers, with simple constraints [146][148]. As solutions to most real problems must be computed quickly, the algorithms used in practical applications are mostly heuristic. Vidal et al. [147], who conducted an extensive review on approaches used for solving VRPs, arrived at the same conclusion; only relatively small capacitated VRPs can be solved, consistently, to optimality.

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[20] Comprising of multiple steps: e.g. sub-problem and outer problem.
[21] For example problems with conflicting objectives.
[22] According to https://scholar.google.co.uk, accessed on 20/01/2019.

Laporte [148] divided all heuristic methods into classical and metaheuristics; the former tend to be purely constructive; they do not feature an improvement phase and their objective function does not deteriorate from one iteration to the next. Examples of classical heuristic methods include the savings algorithm, set partitioning heuristics and cluster-first, route-second heuristics. Metaheuristics can be considered improvement methods; many are hybrid approaches combining two or more algorithms in an attempt to improve the solution quality. Examples of metaheuristic methods include local search, variable neighbourhood search and Tabu search. Some metaheuristics were inspired by natural processes; these include Genetic Algorithms (GAs), Ant-Colony Optimisation (ACO), Particle Swarm Optimisation and Simulated Annealing (these were discussed in more detail in Section 4.2.3).

One of Laporte's [148] conclusions was that many successful metaheuristic methods are over engineered, suggesting that researchers should focus on producing simpler and more flexible algorithms, capable of handling a wide range of constraints, even if this meant a small loss in accuracy. He also highlighted the need to incorporate the dynamic and stochastic factors into VRP solution methods.

Vidal et al. [147] reviewed 64 VRP solution methods and categorised them according to the problem variation (as discussed in Section 4.2.1) and fundamental features such as neighbourhood properties (i.e. multiple and large neighbourhoods), use of hybridisation and problem decomposition. The authors provided useful tables allowing to easily identify the main characteristics of best solution approaches in a given problem category. Tabu search, genetic/evolutionary algorithm and iterated local search were the three most frequently used approaches. The use of these methods for solving various VRPs variations is described in Section 4.2.3.

Hartl [149], noted that the solution time of standard VRPs decreased significantly since the problem was introduced, due to both advancement in computing power and improved solution algorithms. However, since most classical VRPs can now be considered solved, researchers have turned to problems featuring complex, practical constraints: RVRPs. According to Prodhon & Prins [150], there are many practical problems where serving all customers is impossible. This makes finding the optimal solution more difficult compared to a standard VRP, as selecting the nodes to be visited adds another layer of complexity to the problem. Li & Lu [145] stated that one of the key shortages in existing literature is the lack of research on solution methods for VRPs with profits, wherein not all customers must be visited.

Caceres-Cruz et al. [146] provided a comprehensive survey of methods for solving RVRPs, an overview of the optimisation approaches is outlined in Figure 4.2. VRP and all its variations are considered NP-hard (Non-deterministic Polynomial-time hard) [146], meaning that in theory, finding a feasible solution is as hard as finding the optimal one in an NP problem [151]. In practice, it is impossible to guarantee the mathematically optimal solution for most RVRPs [146]. To categorise models for solving RVRPs, Caceres-Cruz et al. [146] defined 36 unique constraints. Out of the 36 constraints, 10 are applicable to the offshore wind maintenance planning problem as defined in Section 4.2.1; these are as follows:

1) Multidimensional capacity: the vessels can carry a limited amount of technicians and spare parts
2) Heterogeneous fleet of vehicles
3) Fixed fleet of vehicles: number of vehicles is limited
4) Fixed cost per vehicle: i.e. vessel hire cost
5) Variable cost of vehicle: vessel fuel cost
6) Duration constraint: maximum crew working time
7) Asymmetric cost matrix: costs of maintenance actions may vary for different turbines
8) Stochastic times: there is an uncertainty associated with maintenance action duration
9) Time windows: picking up technicians should be done after maintenance action is complete, unless the overall time limit does not allow completing the task.
10) Pick-up and delivery: each turbine is visited twice

The 36 constraints defined by Caceres-Cruz et al. [146] are insufficient to fully define the real world problem of scheduling offshore wind maintenance. Additional constraints for the real world problem, include asymmetric rewards for visiting customers, technician skill requirements to complete maintenance and previous day assignment of technicians to vessels.

According to the classification provided by Caceres-Cruz et al. [146], there is no model in literature capable of solving the RVRP for constraints 1-10) described above. Out of 55 models classified in [146], the approach with the most shared constraints, proposed by Vidal et al. [152], has only 8 constraints in common with the offshore wind problem (not including the additional constraints described in the previous paragraph).

The above analysis demonstrates that each real world problem is uniquely defined by a set of constraints, direct application of methodologies proposed by other researchers always requires further modelling work to accommodate additional constraints.

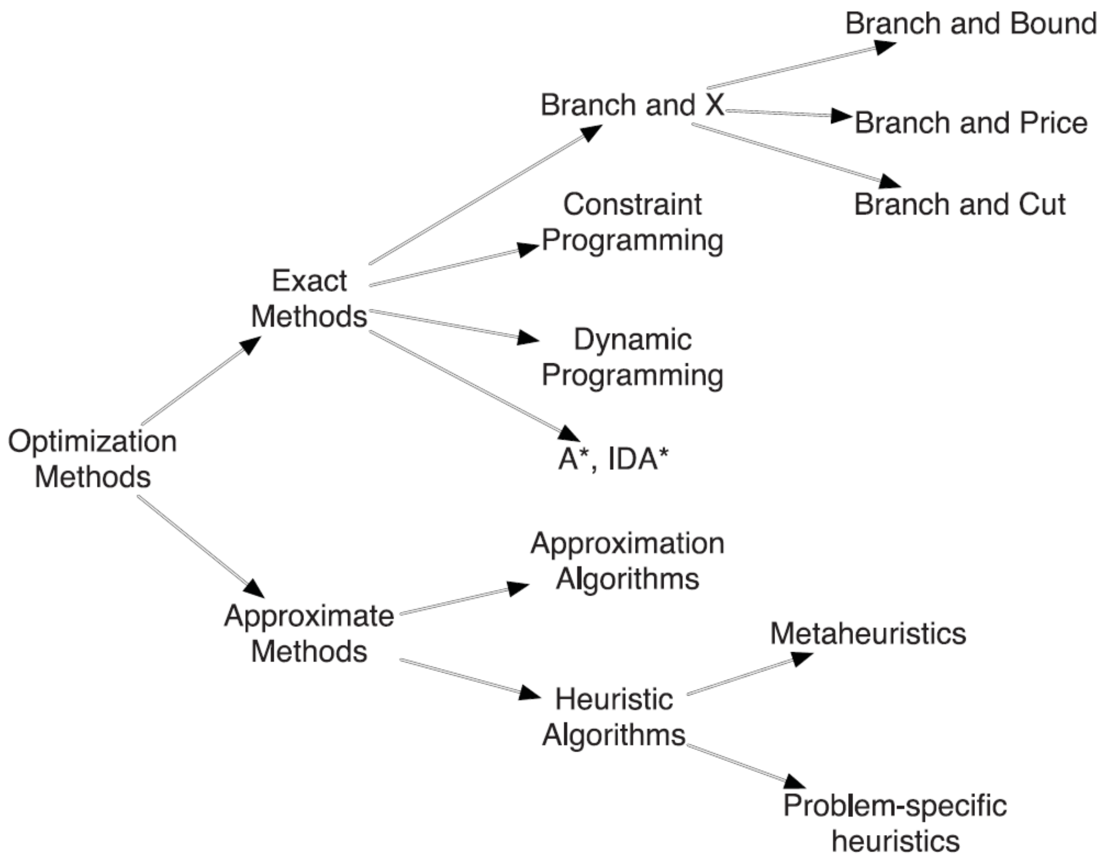

Figure 4.2. Classification of optimisation methods in the context of VRPs [146].

In recent years, multiple industries, including wind power generation, saw a rapid increase in novel telematics systems, which provide the asset operators with large volumes of operational data, as discussed in Section 3.2.1. Statistical analysis of the data can provide its user with useful stochastic information (e.g. time spent on turbine carrying out a maintenance task), which, if included in the decision making process, can lead to cost savings [153]. A new class of VRP was defined – Stochastic VRP (SVRP) to incorporate randomness from the aforementioned statistical analysis.

An SVRP features at least one stochastic variable, such as travel time, customer demand or service time. Berhan et al. [154] surveyed 49 relevant papers on SVRP solution methods and found that:

a) Less than 10% of papers contained a methodology capable of tackling stochastic service time (i.e. uncertain maintenance task duration, crucial factor in the problem of offshore wind maintenance planning)
b) Less than 20% of papers were based on real data
c) Single most common methodology used across all papers were Markov chains (in 12% of papers)
d) Majority of approaches focus on stochastic customer demand, capacitated vehicles and use cost minimisation as objective
e) Objectives such as maximisation of vehicle utilisation, number of customers to be serviced and revenue earned have been effectively untouched by researchers

Points a) & e) only reiterate the key message emerging from this section thus far: there are very few models in literature tackling problems similar to the offshore wind maintenance planning problem. There is also a clear lack of practical application of theoretical models in real-world problems.

Oyola et al. published a two-part study; first part [155] reviews the literature on various problems under the SVRP umbrella. A number of useful tables were provided, which categorise the different approaches by the probability distribution function used, recourse action and the evaluation method. The second part of the study [156] provided a detailed description of exact and approximate solving procedures used for SVRPs, including branch-and-cut, local search approaches and evolutionary algorithms to name a few. The authors identified Tabu search as the most widely used and effective SVRP solution method. It was noted that heuristic methods are more common than exact solution approaches, as the inherent difficulty associated with solving VRPs is exacerbated by the addition of stochastic elements is SVRPs, hindering successful application of exact methods. The authors expect that in the future, research into SVRP solutions will increasingly focus on simple methods, as some of the best approaches currently available are relatively easy to construct and solve. Overall, the two-part study provides an exhaustive literature review on VRP optimisation algorithms, clearly outlining the characteristics of different solution procedures. A number of the models referenced in [155] & [156] are discussed in more detail in Section 4.2.3.

In dynamic VRPs, additional information is revealed as the plan is being executed. Dynamic SVRPs are a relatively new research area, with potential application to the offshore wind maintenance planning problem, in which plans need often need to be changed as new information becomes available. In their review of stochastic and dynamic VRP solution approaches, Ritzinger et al. [153] have shown that models capable of handling dynamic events and stochastic information typically yield improved results compared to pure a-priori methods. This, however, requires a significant computational effort, limiting the size and number of scenarios which can be analysed using dynamic and stochastic approaches.

An overview of the different optimisation methods is shown in Figure 4.2. At this point, a decision to narrow down the search of literature is made; the following section describes focuses on the most popular heuristic approaches used to solve a variety of VRPs. This choice was motivated by the conclusions from key review papers in the field ([146] & [156]), who remarked that heuristic methods seem a more likely candidate than exact methods to solve complex VRPs. The focus of the investigation carried out in this thesis is on capturing multiple real-world considerations (such as uncertain maintenance time or uncertain weather), which add complexity to the problem. Heuristic methods have a significantly higher chance of obtaining feasible solutions to complex problems in reasonable computational time [146].

4.2.3 Overview of the Application of Heuristic Methods to the Vehicle Routing Problem

According to Cacerez-Cruz et al. [146], heuristics serve three main purposes:

a) Solving problems faster (compared to exact methods)
b) Solving larger problems or problems with many complex constraints
c) Providing more robust algorithms

Majority of approaches discussed in this section can be classified as metaheuristics, which were defined by Sorensen & Glover [157] as “a high-level problem-independent algorithmic framework that provides a set of guidelines or strategies to develop heuristic optimization algorithms”. Two major strategies are used in metaheuristics: diversification and intensification [158]. The former aims to generate solutions which are significantly different to each other, in an attempt to find a solution close to the global optimum. The latter focuses on finding new solutions which are similar to known, high value solutions, in an attempt to find a local optimum.

The following subsections present an outline of the notable heuristic approaches with the potential for application to the offshore wind farm vessel routing problem.

Local Search Methods

In a standard Iterated Local Search (ILS) algorithm, a feasible solution is iteratively improved by introducing modifications, such as swapping and/or adding removing locations to be visited. The search is usually terminated when a local maximum/minimum is encountered. The algorithm is easy to construct and compute, however, the outputs of a standard ILS were described as "often a fairly mediocre solution" [159]. In a standard ILS, the only way of escaping the local minimum is to start each iteration with a different configuration.

Large Neighbourhood Search (LNS) was applied by Ropke & Pisinger [160] to a VRP with backhauls. A neighbourhood is a set of solutions similar to the original solution (i.e. solutions which can be obtained by relatively simple modifications). The aim of increasing the size of neighbourhood is to attempt to escape local minima. The proposed approach is based on removal of nodes, or clusters of nodes, which result in large cost increases. As removal heuristic is varied iteratively, the search diversifies, or in some cases intensifies.

Tabu search method was first proposed by Fred Glover [161] in 1986. A shortlist of recent search history, called a "tabu list", is created and stored in short-term memory for a certain number of iterations. Tabu moves cannot be carried out, preventing cycling back to solutions which have been previously visited. This approach allows carrying out sub-optimal operations in order to escape local optimum.

More recently, Tabu search has been applied to VRP with backhauls in [162]. Initial policy is found by finding nearest neighbours for consecutive nodes to be visited by a vehicle. Once the maximum carrying capacity of a vehicle is reached, a new route is started. The policy is then improved, in order to minimise the total distance travelled by vehicles using a two-step process. First, solution improvement is carried out using Tabu search. Second, the policy is further improved using frequency based memory. The proposed approach produced higher quality vehicle routing policies compared to other algorithms for VRPs with backhauls.

However, despite the efforts of researchers referenced in this section, local search algorithms are generally prone to premature convergence, particularly if the state-space is large [163].

Evolutionary Algorithms

The most widely used Evolutionary Algorithm (EA) is Genetic Algorithm (GA). Inspired by genetic laws and natural selection, GAs cross over high quality solutions in order to generate new, improved policies. GA, which was first proposed by Holland [164] in 1973; it is now a widely used optimisation tool in a variety of fields.

Baker & Ayechew [165] conducted a study comparing the performance of GAs to Simulated Annealing (SA), described in the following section and Tabu search. They have shown that GAs are capable of producing close-to-optimal solutions to basic VRPs with few constraints, however, not as consistently as the Tabu search method proposed in Rochat & Taillard [158]. Computational effort required to achieve close-to-optimal solution using the proposed GA compared favourably with alternative approaches (Tabu search and simulated annealing). The approach proposed by Rochat & Taillard [158] was classified by the authors as a local search method, however, since creation of new solutions is driven by components of previous solutions, their methodology can be seen as a mix between a local search approach and an evolutionary algorithm.

Alba & Dorronsoro [139] applied a GA approach to capacitated VRP, improving upon nine best known solutions published in literature. It is another example of a hybrid approach, wherein the GA is supported by a local search method. Four years later, Vidal et al. [166] proposed a hybrid GA which combined the exploration breadth of genetic algorithm and improvement capabilities of local search method. In each iteration, the GA offspring is enhanced by local search procedures (education and repair). The authors pointed out that allowing a controlled exploration of unfeasible solutions can lead to improved algorithm performance. Notably, the algorithm developed by Vidal et al. [166] outperformed other published VRP solution methods by producing either best known or new best solutions in all benchmark instances.

All the publications reviewed in this section applied GAs to relatively simple VRPs with few constraints. GAs are rarely used for RVRPs and SVRPs – Caceres-Cruz [146], in their extensive survey of RVRP solution approaches, did not identify a single application of GA.

Swarm Algorithms

Nature inspired, global optimisation algorithms such as Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) are classified as Swarm Algorithms. Swarm refers to a group of agents, who follow a set of simple, user-defined rules. Interactions between the agents, which involve a degree of randomness, converge to produce efficient paths between nodes.

In ACO, agents are referred to as ants; they lay down pheromones along their path between randomly selected nodes. Relating the quality of a given path to the strength of the pheromone trail causes ants to converge on high value/low cost paths. This procedure is repeated until a termination criterion is satisfied. An example of ACO application to the offshore wind maintenance optimisation (Zhang [23]) is discussed in Section 4.2.6.

Bell & McMullen [167] applied ACO and Multiple Ant Colony Optimisation (MACO), to a set of standard problems. In MACO, each ant colony leaves a unique pheromone trail, which can either be used to create individual vehicle routes or to perform multi-objective optimisation. Bell & McMullen [167] have shown that ACO is capable of producing policies within 1% and 3.9% of the known optimal for a problem consisting of 50 and 100 nodes respectively. MACO significantly outperformed ACO in instances with 100 and 150 nodes, finding solutions within 6.45% of the known optimal.

Gajpal & Abad [143] used MACO to minimise the total distance travelled in a VRP with backhauls. Two types of ants are used: route ants, aiming minimise the route distance and vehicle ants, which aim to minimise the number of vehicles used. At each iteration, ant solutions are improved using two local search schemes (customer insertion/interchange and sub-path exchange). Their model produced five new best known solutions for the benchmark problem instances, outperforming other algorithms for VRP with backhauls available in the literature. The computational times of MACO, although reasonable (under 5 minutes in all test instances), were twice as long as LNS algorithm.

Particle Swarm Optimization (PSO) is a population-based global optimisation algorithm, first proposed by Kennedy & Eberhart [168]. This method is inspired by movement of social species such as fish or birds. In PSO, individual particles' movement is governed by both their past, highest value position and the best known global location. Over time, the swarm collectively converges on the optimal, or close-to-optimal solution.

While PSOs are most widely used for problems in which the optimal solution is a point or a surface, they can also be adapted to solve VRPs. Marinakis et al. [169] proposed an approach based on PSO combined with path relinking and local search. Their model was applied to a VRP with stochastic demands, wherein demands become known as the vehicle arrives at each customer node. Comparing their methodology to a GA and Differential Evolution Algorithm (DEA), the authors have shown that their algorithm outperformed both GA and DEA. However, an independent study conducted by Vidal et al. [147] have shown that better solutions can be achieved in shorter computational time, for example by using an approach based on adaptive memory & Tabu search [170].

In summary, one of the main advantages of ACO is that multi-objective optimisation can easily be implemented. However, the computational time required to produce close-to-optimal policies using ACO can be long, especially if applied to a problem with complex constraints. Both ACO and PSO perform best when used in tandem with a local search method. There are very few examples of swarm intelligence approaches being used in to solve RVRPs.

Simulated Annealing

Simulated Annealing (SA) is a metaheuristic based on the physical analogy of cooling metals. As temperature decreases over time, the probability of accepting worse-than current solutions decreases. Initially, high probability of accepting "bad trades" facilitates exploration of the state-space. Towards the end of the simulation, depending on the user-defined settings, the algorithm may only accept better-than-current moves, focusing on achieving the local optimum. The simulation is terminated when equilibrium is reached; i.e. when no improved solution is found in a pre-defined number of iterations.

Aksen [171] proposed a method based on SA for VRP with profits and time deadlines. However, the gap between the proven optimal and output of the proposed heuristic exceeded 5% in half of test instances. Parallel SA was used by Czech & Czarnas [141], wherein a number of SA processes are run in parallel, with the probability of accepting lower-than-current value solutions affected by the solutions found in parallel processes. Parallel SA approach improved upon a number of best-published results for benchmark problems.

VRPPD solution approach described in Bent & Hentenryck [172] comprised of two stages: first, SA was used to reduce the number of routes. Second, LNS was applied to explore sub-neighbourhoods selected by SA to find the local travel cost minimum.

The resulting algorithm generated new best solutions to benchmark problems found in literature. Cases with up to 600 customers were computed in reasonable time given the size of the problem (most runs took between 50 to 90 minutes).

Javid & Seddighi [173] proposed a simulated annealing heuristic, featuring three risk measurement policies (moderate, cautious and pessimistic). The authors demonstrated that incorporating risk into the model significantly lowers the total costs. This approach is particularly suitable for applications with high disruption risk. In the context of offshore wind, risks which may disrupt a policy include inability to transfer crew from vessel onto turbine or inability of crew to finish maintenance within the specified timeframe.

Cluster-first Route-second Approach

The two most common clustering techniques are route-first cluster-second and cluster-first route-second, as shown in Figure 4.3. Prins [174] provided an in depth review of route-first cluster-second applications to VRPs. In this method, a "giant" route is created and partitioned into smaller sizes depending on the vehicle's capacity.

In cluster-first route-second, the problem is decomposed into clusters of customers, whose requirements do not exceed the vehicle capacity. In TSP applications, clusters are usually generated based on the geographical location of customers. Then, order of visits within each cluster is optimised. Early applications of this method to capacitated VRPs include Fisher & Jaikumar [175] and Bramel & Simchi-Levi [176]. Constructive clustering approaches seem a natural choice for the offshore wind problem described in Section 3.1; cluster-first route second-approach mimics the process wind turbine planners follow to arrive at a routing policy.

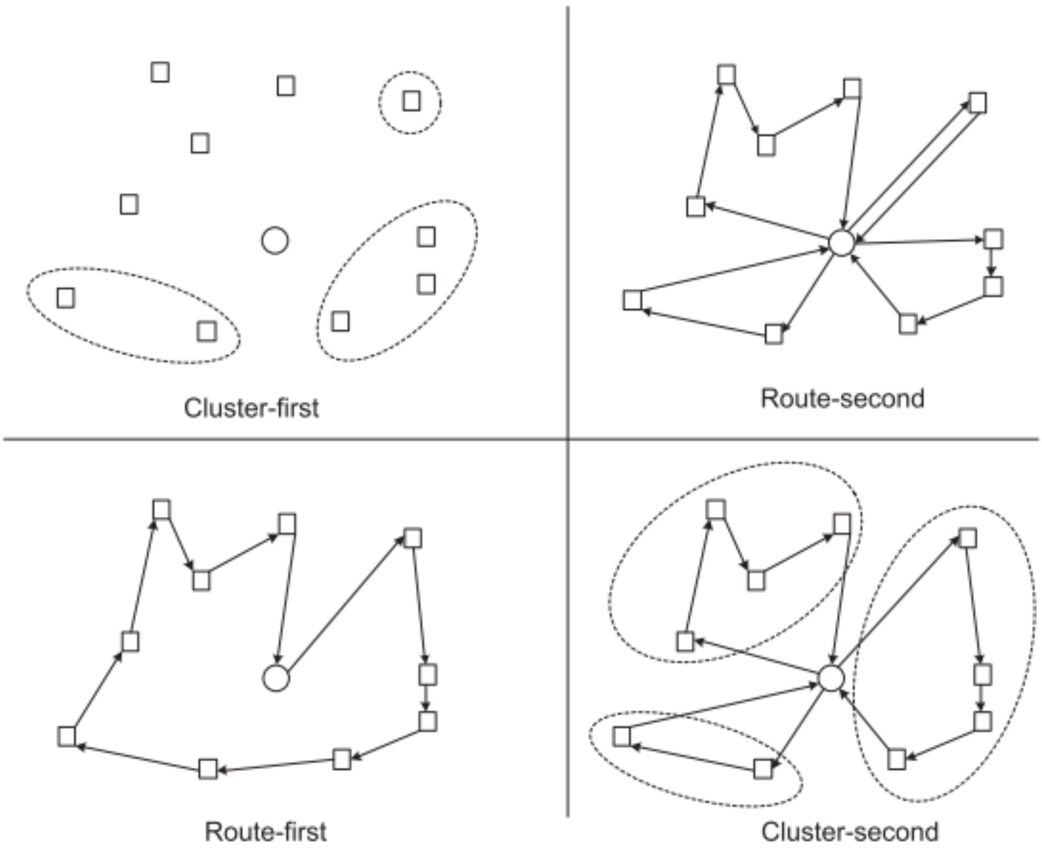

Figure 4.3. VRP solution approaches: cluster-first route-second and vice versa [174].

Dondo & Cerda [140] proposed a three-phase heuristic, based on cluster-first route-second method, for the multi-depot routing problem with time windows and heterogeneous vehicles. First, cost-effective clusters are generated. In phase 2, vessels are assigned to clusters. The last step involves ordering nodes within each cluster, determining the arrival times for each customer. Expressing the model in terms of clusters rather than individual customers reduces the computational time drastically. Tests on benchmark problems resulted in a number of optimal or near-optimal solutions.

Ganesh & Narendran [142] applied a multi-phase constructive heuristic to a vehicle routing problem with sequence-constrained delivery and pick-up. Initially, clusters are created based on customer's geographical locations. Order of node visits is determined by a Shrink-Wrap Algorithm, which maps the nodes on polar coordinates, sorting them by angle and distance to create routes. Each cluster is then assigned a vehicle. Constructed solution is input to GA, which uses crossover and mutation to produce offspring iteratively until specified number of iterations. This method produced some best known solution to benchmark problems.

Cluster-first route-second method is closely related to the procedure human decision makers follow to solve real-life routing problems [147]. This approach is very effective at dealing with highly constrained problems with few feasible solutions, as the ensuring that capacity constraint is satisfied is achieved at the first step of the process [147].

This concludes the review of applications of general heuristic methods for the VRPs. The following section provides an overview of the approaches used for optimisation under uncertainty, in the context of VRPs.

4.2.4 Review of Optimisation Approaches under Uncertainty

Review papers covering a range of SVRP solution methods are discussed in Section 4.2.2. Here, approaches for optimisation problems under uncertainty are discussed in more detail.

Robust optimisation is one of the methods of solving optimisation problems with uncertain inputs. Recent advances in robust optimisation have been discussed in [177]. This approach aims to arrive at solutions which are robust to input changes. However, it is based on planning for the worst-case scenario, assuming that uncertainty is the most unfavourable [177]. This can lead to low quality, pessimistic policies. Some researchers attempted to address this; for example Sun & Wang [178] proposed a robust optimisation approach for a VRP with uncertain customer demand and transportation cost, allowing the user to determine varying levels of risk acceptance, with their model calculating an optimal solution for each value of risk acceptance.

Some real world problems can be modelled by classifying the decision variables into two sets. The first set contains variables which are fixed before the realisation of uncertain parameters. The second set, contains variables which are determined once random events occur, allowing implementation of policy improvements. The second stage can be seen as a corrective measure, or recourse, hence the name of the approach: recourse programming [179]. An example of application of recourse programming was published by Haugland & Ho [180], who tackled VRP with stochastic demands.

Table 4.2. Comparison of solution approaches to VRPs with stochastic variables.

Authors	Assumptions	Solution method	Distribution used to model service /travel time
Li et al. [181]	Soft time windows Stochastic travel time Stochastic service time	Tabu search	Normal
Russell & Urban [182]	Soft time windows Stochastic travel time	Tabu search	Shifted gamma
Lei et al. [183]	Stochastic service time	LNS	Normal
Chen et al. [184]	Stochastic travel time Stochastic service time	Branch-and-cut Adaptive LNS	Normal
Tas et al. [144]	Soft time windows Stochastic travel time	Tabu search	Gamma
Gomez et al. [185]	Stochastic travel time Stochastic service time	Multispace sampling heuristic	Phase-type

Table 4.2 presents a comparison of VRP solution approaches with various assumptions and probability distributions used to model stochastic variables. In problems with soft time windows, customer visits outside of the soft time window are permitted, but penalised to discourage servicing a customer too early/late. In summary, Tabu search was the most common solution procedure for SVRP publications shown in Table 4.2. Normal and gamma distributions were used to model stochastic variables in most papers. Discussions with wind farm operators revealed that in the context of offshore wind turbine maintenance, a gamma

distribution with a long tail (positive skewness) would fit the real-world service time more accurately than normal distribution.

In the approach proposed by Gomez et al. [185], a multispace sampling heuristic was used. In the first phase, multiple solution spaces are sampled. The optimal combination of the sampled solutions is then assembled in the second stage. The latter phase is modelled as a set-partitioning problem and solved using a commercial solver. Having conducted benchmark tests using a variety of probability distribution functions (including Erlang, Burr and lognormal distributions) Gomez et al. [185] concluded that since most real world travel and service times have positive skewness, assuming normal distributions can lead to poor routing decisions.

4.2.5 Multi-Objective Optimisation

Many real world problems are characterised by conflicting objectives. For example, manufacturers design their products minimising cost while attempting to maximise quality. In non-trivial multi-objective optimisation problems, no single solution can satisfy all objectives.

Multi-objective VRP solution procedures have been reviewed by Jozefowiez et al. [186], who provided a comprehensive overview of papers on real-life multi-objective VRPs. The authors listed the most common VRP objectives, which include minimisation of distance travelled and time spent travelling, minimisation of cost and/or fleet size, maximisation of profit and/or quality of service. According to Jozefowiez et al. [186], the three key approaches for solving multi-objective VRPs are:

- Scalar techniques – a simple technique requiring definition of individual objective weights to calculate the solution's total weighted value. This method does not guarantee that all Pareto optimal solutions will be found. Examples of the use of scalar method include optimisation of emergency evacuation using a combination of vehicular traffic and mass transit in [187].
- Pareto methods – which directly notion of Pareto dominance, as discussed below.
- Alternative approaches – for example the Vector Evaluated Genetic Algorithm (VEGA) approach, first proposed by Schaffer [188]. In VEGA, solutions are produced iteratively using a GA. A set of non-dominated solutions[23] is saved at the end of each iteration as the current-best guess.

[23] Neither objective function can be improved upon without the other functions deteriorating

Pareto graphs are often used to visualise the solution state-space of multi-objective optimisation problems. Figure 4.4 shows the Pareto front made up of non-dominated solutions marked by full circles. Solutions on the Pareto front are all considered equally good. Once a Pareto front is generated, the decision maker' preference usually determines the chosen solution. Alternatively, this process can be automated; however, this usually requires further input from the decision maker. For example, in the approach proposed by Deb & Sundar [189], before the optimisation process commences, the decision maker is asked to define a reference point which will act as the optimisation goal. Once the Pareto front is generated, evolutionary multi-objective optimization is used to identify the Pareto region closest to the reference point.

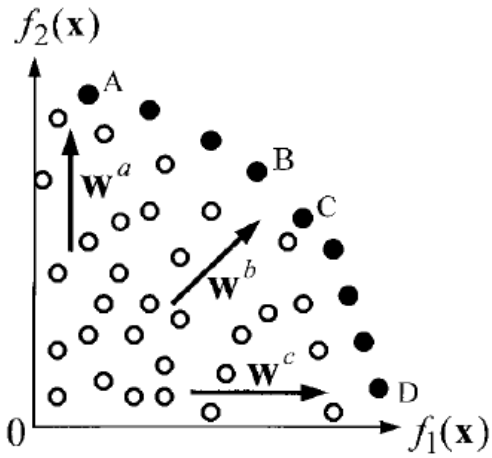

Figure 4.4. Pareto front made up of non-dominated solutions (full circles) and dominated solutions (empty circles). Adapted from Ishibuchi & Murata [190].

This section provided a brief summary of the most common approaches for tackling multi-objective optimisation problems. The following section provides an overview of the research conducted specifically on the vessel routing problem for offshore wind farm maintenance.

4.2.6 Literature in the Wind Domain

Researchers have only started working on the offshore wind farm vessel routing problem recently, with the first paper published in 2014. Zhang [23] proposed an approach based on Ant Colony Optimization (ACO), a metaheuristic technique, to solve cases with up to 28 turbines and 2 vessels. A summary of constraints considered in this, and other models discussed in this section is presented in Table 4.3. One of the key limitations of the model proposed by Zhang [23] is that it does not allow a team of technicians visiting more than one turbine on the same day. In practice, this may be encouraged for maintenance tasks of shorter duration as it increases technician utilisation rate.

In the same year, Dai et al. [22] published their work on short term planning of vessel routing. The proposed exact solution algorithm failed to find the optimal solution within the time limit even in cases with as few as 8 turbines requiring maintenance. Despite differing methodologies, the two aforementioned papers are solving the same problem with very similar constraints (see Table 4.3). Both approaches have only been applied to cases with two vessels, while large offshore wind farms such as London Array have as much as 8 CTVs at their disposal [49].

Stålhane et al. [24] proposed two alternative solution approaches to the offshore wind farm vessel routing problem; an exact, arc-flow model and a heuristic path-flow method. The latter approach is essentially an arc-flow decomposed using Dantzig-Wolfe method. It is capable of producing close-to-optimal results in reasonable computational time. The main difference between the problems solved by Stålhane et al. [24] and Dai et al. [22], is that the former calculates the downtime cost on a more detailed level. The authors did not indicate whether the proposed methodology could be applied to cases with heterogeneous vessels and time horizons longer than one day.

Irawan et al. [25] divided the problem into a master and a sub-problem. The master problem focuses on finding the optimal assignment of clusters to vessels so that the overall cost is minimised. In the sub-problem, the order of wind turbine visits is decided. Both problems were solved using constraint programming. Dantzig–Wolfe decomposition method combined with a mixed integer linear program was used to produce solution in a reasonable computational time. Numerous real-life constraints were considered and the model's outputs compared favourably to results produced by Dai et al. [22].

In the model proposed by Irawan et al. [25], the number of turbines per cluster can be limited to reduce computational time. This assumption is reasonable, as in most real life cases, it would be impractical to dispatch a single vessel to visit more than 8 turbines. In consequence, results of the case study with 36 turbines were not proven optimal, even though the solution method is exact. The computational time of the algorithm proposed by Irawan et al. [25] is highly variable; for example the time to solve a 24-turbine case study ranges from 2 to 58 minutes. They also demonstrated that significant cost reductions can be achieved if maintenance planning on multiple wind farms is done centrally, rather than generating separate routing policies for each individual wind farm.

To compute the results, Irawan et al. [25] used IBM ILOG CPLEX commercial software, which uses branch and bound and branch and cut algorithms. In the branch and bound method, a total enumeration tree is created. Computing the entire tree would take unreasonable amounts of time for most real world problems. Instead, if it can be proven that descendants of a certain node in a decision tree cannot improve on the current best solution, the branches resulting from that node are pruned. This systematic process reduces the state-space to a computationally manageable size. Branch and bound and branch and cut algorithms are exact methods, however, increasing the problem size increases computational time exponentially. Producing an exact solution for a problem consisting of 72 turbines required 40 hours of computational time [25] on a desktop computer, which is beyond reasonable in the context of decision support for offshore wind vessel routing (unless cloud computing or a supercomputer is used).

Schrotenboer et al. [28] proposed a heuristic method based on Adaptive Large Neighbourhood Search (ALNS) for solving the offshore wind farm vessel routing problem. They applied the ALNS model to benchmark problems proposed by Irawan et al. [25]. The proposed heuristic found near-optimal solutions in short computational time (under 10 seconds); a significant improvement compared to the exact method proposed by Irawan et al. [25].

In their publication, Schrotenboer et al. [28] did not describe the vessel routing problem and assumptions used; it can be assumed that the authors used Irawan's et al. [25] set of constraints. The focus of the Schrotenboer's et al. [28] publication was on the potential benefits of sharing technicians between O&M bases. A two-stage ALNS was embedded in a Monte Carlo model to investigate the impact of technician sharing in different scenarios. It was shown that sharing technicians across O&M bases can yield 7% cost savings as fewer vessel trips are required.

Table 4.3. Classification of vessel routing models based on 17 constraints. Note that the maximum no. of vessels and turbines refers to the highest values used in case studies, not an inherent model limitation. * variable cost only

Heuristic method	✓		✓		✓	✓	✓
Exact method		✓	✓	✓	✓		
Limited no. of technicians				✓		✓	✓
Applied to a real world case study						✓	
Time horizon >1 day	✓	✓		✓	✓	✓	✓
Heterogeneous vessels	✓	✓		✓	✓		✓
Fixed & variable vessel costs	✓	✓	*	*	✓		*
Multiple O&M bases				✓		✓	✓
Profit collection (rewards for actions)						✓	
Penalty costs (i.e. lost revenue)	✓	✓	✓	✓	✓	✓	✓
Uncertainties (i.e. service time)							
Variable vessel speed							
Vessel stays at turbine (some actions)	✓	✓	✓	✓	✓		✓
Time window limit	✓	✓	✓	✓	✓	✓	✓
2-d vessel capacity	✓	✓	✓	✓		✓	✓
Transfer time modelled			✓	✓	✓	✓	✓
Technician qualifications				✓			✓
Maximum no. of vessel	2	2	5	4	2	1	10
Maximum no. of turbines	28	8	8	36	25	9	60
	Zhang (2014) [23]	Dai (2014) [22]	Stålhane (2015) [24]	Irawan (2017) [25]	Raknes (2017) [26]	Williams (2018) [27]	Schrotenboer (2018)

Raknes et al. [26] formulated a mathematical model of the offshore vessel routing problem by defining over fifty constraints, which, for small problems, can be solved by commercial Mixed-Integer Programming (MIP) solvers (based on the branch-and-bound search). To enable application of their model to cases with 20-25 wind turbines requiring maintenance, Raknes et al. [26] proposed two rolling horizon heuristic methods, which iteratively produce solutions to MIPs by considering shorter planning horizons.

However, the proposed methodology is not suited to application to cases with a time horizon longer than one day. First, solving the model for two or more work shifts did not always produce a feasible result. Second, longer planning horizon increases the problem's computational difficulty, lowering the quality of results; the author concluded it is more efficient to consider only one period when deciding on routes and schedules for maintenance vessels. Interviews with offshore wind farm operators (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators) confirm that most real life routing decisions are made with one day planning horizon. While certain decisions should be made in advance – for example scheduling planned maintenance well ahead can aid resource management, the literature and practitioners (interviewed during the site visit described in Section 7.5) confirm that planning the vessel routing beyond one day is often counterproductive.

To reduce computational time, Raknes et al. [26] introduced symmetry-breaking constraints. As the order in which actions are completed is fixed by the model user, this decision is not subject to the optimisation process, potentially yielding sub-optimal solutions.

Both Irawan et al. [25] and Raknes et al. [26] modelled the problem using multiple linear constraints, which were input to and computed by commercial solvers. However, the method presented in the former publication was able to produce exact solutions to larger, more constrained problems in shorter computational time. The effectiveness of the approach proposed by Irawan et al. [25] is most likely due to splitting the problem into master and sub-problems.

Stock-Williams & Swamy [27] described a daily O&M planning tool developed by ECN (Energy research Centre of the Netherlands). Their approach, based on a Genetic Algorithm, handles both task prioritisation and vessel routing. Initial solutions are crossed over and mutated to produce new policies. Fitness of the newly created policies is evaluated, high quality solutions are re-inserted into the pool of candidate policies.

If maximisation of overall energy yield over the time horizon is chosen, the tool proposed by Stock-Williams & Swamy [27] prioritises corrective actions over preventative. If no corrective actions are required, the tool may recommend not taking any actions on a day with high forecasted wind speed, to maximise energy capture.

The tool was applied to a real world case study, based on Princess Amalia Wind Park in the Netherlands (120MW, 60 turbines). Day-to-day O&M at this site is carried out using a single vessel, and this was reflected in the case study, in which the optimiser only had one CTV available. This reduces the problem complexity significantly, as the issue of assignment of tasks to vessels does not need to be considered. Application of this tool to more complex problems may reduce the quality of results (or increase the computational time required to achieve quality results).

Having conducted an analysis of 153 days of maintenance records, Stock-Williams & Swamy claim that by following the tool's proposed policies (versus the decisions actually taken at by wind farm operators), energy yield could have been increased by 1.1%. However, this value seems very optimistic and is unlikely that such increase would be seen in reality. One of the reasons for this scepticism yields from in-depth analysis of the individual policy described in the paper.

On a particular day, there were service orders on 7 preventative and 2 corrective tasks. The tool's suggestion was to carry out both corrective tasks, while historic operational data shows that on that day only one corrective task was attempted. The authors' claim that this decision to carry out both corrective actions, rather than one, would have prevented 10MWh of lost revenue (based on historical weather data). However, it is highly unlikely that the maintenance schedulers (described by the authors as experienced) would not consider the option of carrying out both maintenance tasks in such a simple scenario with only 9 service orders for the whole wind farm. In reality, the reason for not carrying out the second corrective action would probably be lack of technicians with troubleshooting skills/qualifications or lack of spare parts. As the study did not have access to historical operational information such as qualifications of technicians on shift on a given day or spare part requirement/availability, the estimated increase in energy yield cannot be considered credible.

Ultimately, the tool developed by Stock-Williams & Swamy [27] stands out from the publications discussed in this section as the only tool applied to a real world case study. To the author's knowledge, it also has the best user interface. As ECN is a not-for-profit organisation, the tool can be adopted by wind farm operators with little or no licence fees.

To the author's knowledge, there are no other published research papers focusing on optimisation of offshore wind farm vessel routing; it is a relatively niche and young research area. As shown in Table 4.3, the constraints modelled by different researchers vary significantly despite the fact that they are solving the same problem. To date, no model in the offshore wind domain has tackled stochastic service times or variable vessel speed, which should be addressed in future research to ensure successful real-world application.

With the exception of Raknes et al. [26], researchers presented no graphs to visualise the policy. Only Dai et al. [22] provided an overview of the optimal order in which turbines were visited in different case studies. Lack of this information makes it difficult to compare and contrast policies generated by different approaches. Effective visualisation of the policies proposed by optimisation models (as shown in Figure 4.5) is a crucial part of the process of transforming a theoretical methodology into a practical decision support tool.

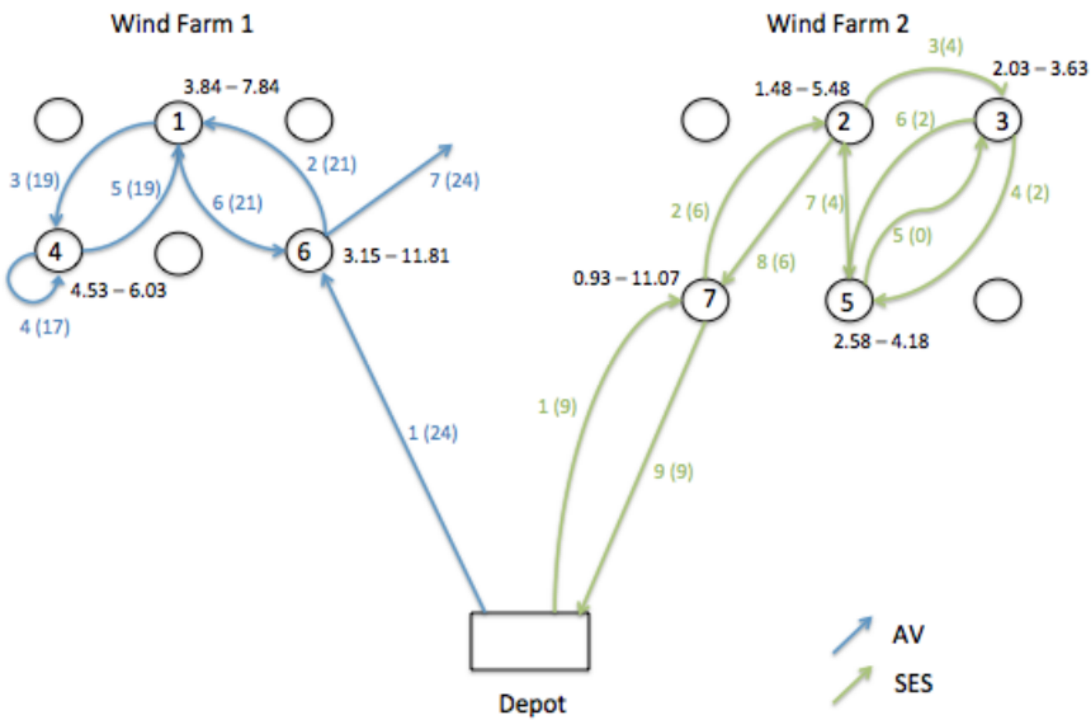

Figure 4.5. Visualisation of the vessel routing policy proposed by Raknes et al. [26]. **Numbers beside the arrows define the order of visits and number of technicians present on a vessel (in bracket). Numbers next to turbines denote the drop off and pick-up times. AV – Accommodation Vessel, SES – Surface Effect Ship.**

4.3 Summary of the Literature Review

This review failed to find publications which successfully solve a routing problem while considering factors described in Table 4.1. Caceres-Cruz et al. [146] demonstrated that an attempt can be made at defining a real-life problem using a set of 36 constraints, however, even such a large amount did not include all constraints relevant to the offshore wind vessel routing problem. Most approaches proposed for real world RVRPs are solving unique problems, hindering effective comparison of different solution algorithms.

In the wind domain, the literature on solution approaches for VRPs is scarce, with only seven publications; the most effective being the MILP model proposed by Irawan et al. [25]. One of the key messages from their work is that decomposition of the VRP into a master and a sub-problem is a common denominator in recent advances in VRP solution methods.

Outside of the wind domain, a number of comprehensive review papers focusing on VRP solution methods are discussed in Sections 4.2.3-4.2.5. One of the main conclusions from Section 4.2.3: Overview of the Application of Heuristic Methods to the Vehicle Routing Problem was that researchers are able to achieve improved results by combining different heuristic methods. This was demonstrated by:

1) Vidal et al. [166], who used a hybrid approach based on local search and GA
2) Marinakis et al. [169], who solved VRPs using a PSO with path relinking and local search
3) Bent & Hentenryck [172], who proposed an algorithm combining SA & LNS

with all three papers achieving best known solutions to benchmark problems. Based on the literature review and problem description (Sections 2.2 and 4.1 respectively), a research gap has been identified. The offshore wind industry would benefit from a model with the following features:

a) Capable of handling stochastic inputs i.e. uncertain service time, as recommended by Ritzinger et al. [153] and Shafiee & Sørensen [18]
b) One day planning horizon, as recommended by Raknes et al. [26]
c) Capable of solving heavily constrained problems with unserved customers, as recommended by Li & Lu [145]
d) The approach needs to be flexible, to handle a wide range of constraints, including problem-specific constraints, as recommended by Laporte [148]

e) Capable of using a measure of risk to produce a range of policies, i.e. moderate, cautious and pessimistic, as recommended by Javid & Seddighi [173]
f) Based on real data, as recommended by Berhan et al. [154]
g) Probability distribution of the uncertain service time should reflect the real-world distribution (i.e. positive skewness) to ensure high quality results, as recommended by Gomez et al. [185]
h) Capable of producing clear visualisations of the recommended policies, which according to practitioners is essential for successful real world application
i) Capable of modelling most factors discussed in Table 4.1
j) Capable of producing solutions in reasonable computational time (i.e. less one hour for problems with ~20 customers on a desktop PC)

Requirements a-j) will be used to evaluate the proposed methodology developed in latter parts of this thesis.

4.3.1 Discussion of the Modelling Choice

Based on the literature review conducted in Section 4.2, a comparison of exact and heuristic methods is presented in Table 4.4.

Table 4.4. Advantages and disadvantages of exact and heuristic VRP solution approaches in the context of the offshore wind farm maintenance planning problem.

Method	Advantages	Disadvantages
Exact methods	- Designed to find the optimal solution - Successful application in Irawan et al. [25]	- Highly variable computational time - Applications in literature utilised expensive commercial software packages - Modelling stochastic and complex constraints is difficult [156] - Feasible solution is not guaranteed
Heuristics	- Consistent computational time - Termination criteria can be adapted, depending on the user's needs - Wide choice of well documented heuristic and metaheuristic methods - It is possible to combine multiple approaches, which generally improves quality of results - Far more widely used for RVRPs compared to exact methods - Most approaches guarantee a feasible solution - More robust compared to exact methods	- Optimal solution not guaranteed

There are very few published applications of exact methods to RVRPs and SVRPs. One of the reasons for this is that the state-space of many real world problems is simply too large to guarantee an optimal solution in reasonable computational time [146]. Based on these considerations, it was decided that a heuristic approach should be used to solve the offshore wind farm vessel routing problem. The choice of modelling approach was influenced by the key findings of Section 2.3 (Summary of the Practicalities of Planning Offshore Wind Farm O&M) and conclusions from the literature review discussed in Section 4.3.

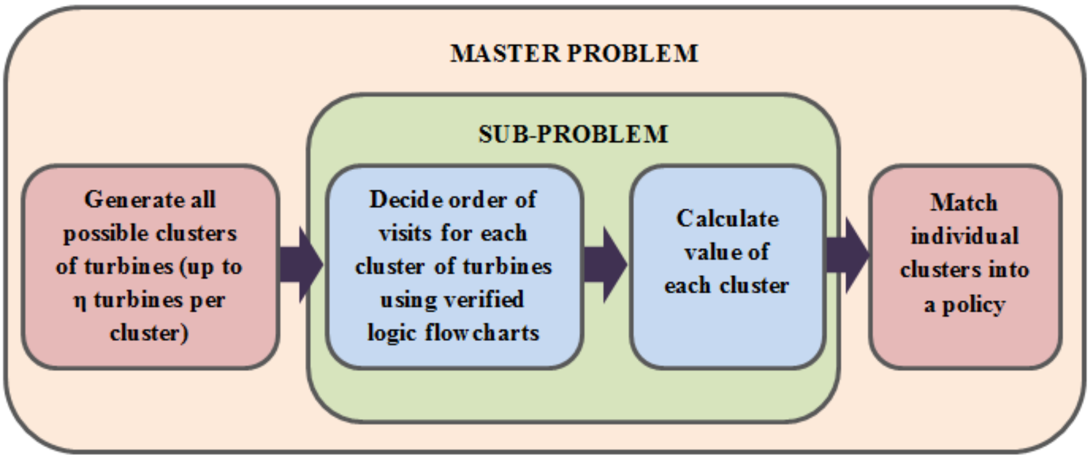

Figure 4.6. Overview of the proposed method.

Decomposing the problem into master and sub-problems was chosen as the basis of the method developed in this thesis, as shown in Figure 4.6. The approach was proven to be effective in Irawan et al. [25], who focused on the deterministic offshore wind farm vessel routing problem. The proposed approach can be considered a variation of the Cluster-first Route-second method, which was shown to be an effective approach for solving VRPs outside of the wind domain (i.e. Dondo & Cerda [140]). Structuring the VRP as a set of independent problems, allows a choice of solution methods:

i. In the master problem part 1 (left hand side of the master problem as shown in Figure 4.6), clusters can be generated using k-means clustering [191] or enumerated
ii. In the sub-problem, routes for individual clusters can be optimised using approximation algorithm or a metaheuristic
iii. In the master problem part 2 (right hand side of the master problem as shown in Figure 4.6), individual clusters of known value can be matched into policies using a heuristic method, or by formulating the problem as an integer linear programming problem and using a commercial solver to produce an exact solution

Having a range of possible approaches makes the overall methodology robust; if during modelling a chosen approach does not fulfil the requirements a-j) or does not meet the user's expectations in terms of computational time or visual output, this particular module can be solved using a different method without impacting the rest of the model. Approaches provided as examples in i-iii can be "mixed and matched" to ensure the best overall configuration, balancing solution quality with computational time.

Taking i. as an example, enumerating all clusters may be time consuming for large problems; it would be of interest if a high quality solution is required. However, if short computational time is crucial, the user could select a subset of high quality clusters or impose restrictions on the maximum number of turbines per cluster. Having the flexibility to adapt individual parts of the solution procedure depending on their performance is one of the key advantages of the approach shown in Figure 4.6. The proposed initial solution methods are shown in Table 4.5.

Table 4.5. An overview of the chosen initial solution approach.

Problem	Proposed solution
1) Cluster generation (master problem part 1)	Enumerate all clusters, imposing a limit on the number of turbines per clusters to reduce the computational time (approach similar to Irawan et al. [25]).
2) Cluster route optimisation (sub-problem)	Approximation algorithm, which mimics the decision making process followed by practitioners. Schedules are automatically created by following a pre-defined logic based on the expected duration of repair and distances between turbines.
3) Matching clusters into policies (master problem part 2)	A novel heuristic method, wherein all clusters are sorted by value and policies are created using combinations of high-utility clusters.

The solution to problem 1) from Table 4.5 was chosen as it has already been proven effective in Irawan et al. [25], which in the author's opinion provides a good balance between quality of solution and computational time.

Proposed solution to problem 2) was selected as a robust and extremely computationally effective method, which can easily be modified by the user depending on their needs (e.g. site specific constraints). Approximation algorithms can facilitate multi-objective optimisation, allowing minimisation of both the number of technicians required and minimisation of policy time. To the author's knowledge, this approach is novel and has not been applied in widely cited publications on VRP solution methodologies. It offers an alternative to the current solution methods, which in the wind domain, are mostly based on constraint programming (exact algorithms) or metaheuristics (i.e. GA). One of the key reasons for not applying a well-established solution method to solve the sub-problem was that those exact methods suffer from disadvantages discussed in Table 4.4. However, since the proposed framework is modular in nature, if the proposed approach fails, it could be replaced by one of the more established methods.

Problem 3) can be solved using a commercial solver as shown in Irawan et al. [25]. However, this exact approach is associated with the disadvantages described in Table 4.4. Instead, a new heuristic method is proposed, as the literature review did not reveal any suitable heuristics for this particular problem. This is partly due to the fact that few researchers encounter this problem, as most approaches in literature do not divide the problem into a master and a sub-problem. The performance of the proposed heuristic is compared to that of a commercial solver to evaluate its effectiveness in Chapter 7.

The following Chapter (Chapter 5) describes the solution procedures for the master and sub-problems. In Chapter 6, the performance of the decision making tool is evaluated using two case studies, which are continuations of the scenarios first described in Chapter 3.

Chapter 5. Solution Procedures for Master and Sub-Problem

The structure of this chapter reflects the order of the solution procedure as outlined in Figure 5.1; first, the clusters of turbines are generated and assigned a vessel in Section 5.1. Second, the sub-problem is solved using an approximation algorithm in Section 5.2, which also contains a step-by-step solution procedure (Section 5.2.4). Description of the heuristic method for creating policies from individual clusters is provided in Section 5.3. Resulting policies are then evaluated using Monte Carlo analysis, as discussed in Section 5.4. Finally, this chapter's conclusions are discussed in Section 5.5.

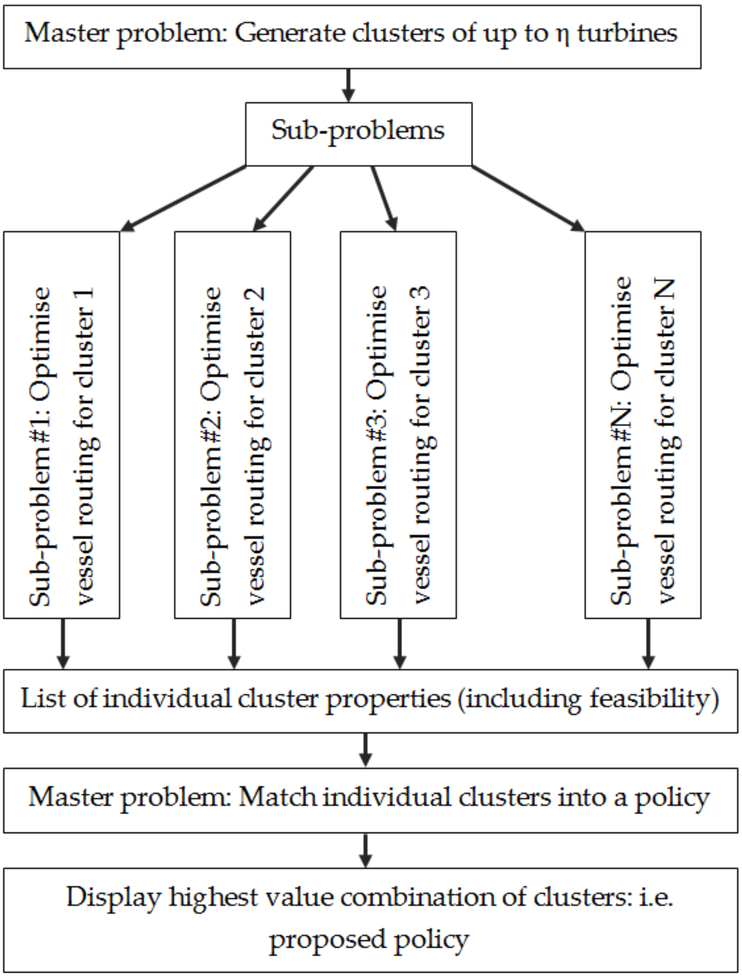

Figure 5.1. Overview of the solution methodology.

5.1 Generation of Wind Turbine Clusters

A cluster consists of a set of wind turbines requiring maintenance and a vessel, which has been assigned to visit those turbines. At the beginning of the optimisation process, there is no way of knowing the combination of clusters which constitutes the optimal solution. Enumerating all combinations of turbine-vessel assignment would ensure clusters which make up the optimal solution are not discarded. However, the computational effort required to enumerate and process all possible clusters in a problem with 20+ turbines would be excessive (using the proposed solution procedure, the computational time would likely exceed 20 hours).

$$Number\ of\ Clusters = \sum_{i=1}^{\eta} \frac{Z!}{i!\,(Z-i)!} \qquad (Equation\ 5.1)$$

Equation 5.1, where η is maximum amount of turbines in a cluster and Z is the total number of turbines, can be used to calculate size of the cluster generation problem. For a case with 20 turbines requiring maintenance (Z = 20), enumerating all possibilities (i.e. η=20) would result in over a million unique clusters. A number this large would require a substantial computational effort in the following steps of the solution procedure. Since it is very unlikely that a single vessel would be capable of visiting 20 turbines in a single day, the amount of turbines in a cluster (η) can be limited to reduce computational time. From Equation 5.1, if η is limited to 4, the total number of permutations is only 6195, reducing the computational time significantly.

Irawan et al. [25] conducted an analysis of the effect η has on the results and computational time of their vessel routing solution algorithm. They have showed that limiting η to 4 can still guarantee close-to-optimal solutions to offshore wind farm vessel routing problems. Depending on the dataset used, the average deviation from the optimal solution, when using η equal to 4, was between 0.33% and 1.9%. On average, the increase in computational time required to guarantee the optimal solution was shown to be between 159% and 304%, depending on the dataset used. The analysis provided by Irawan et al. [25] still holds in the context of the methodology proposed in this thesis, as both approaches employ the same division of the vessel routing problem into a master and sub-problem.

The process of cluster generation is illustrated in Table 5.1; using an example of 5 turbines (WT1-WT5) and η =4, which, from Equation 5.1, yields a total of 30 clusters.

Table 5.1. Enumeration of clusters in a case with 5 turbines requiring maintenance and η =4.

Cluster size	Possible combinations	Total combinations
1-turbine clusters	WT1 ǀ WT2 ǀ WT3 ǀ WT4 ǀ WT5	5
2-turbine clusters	WT1 WT2 ǀ WT1 WT3 ǀ WT1 WT4 ǀ WT1 WT5 ǀ WT2 WT3 ǀ WT2 WT4 ǀ WT2 WT5 ǀ WT3 WT4 ǀ WT3 WT5 ǀ WT4 WT5	10
3-turbine clusters	WT1 WT2 WT3 ǀ WT1 WT2 WT4 ǀ WT1 WT2 WT5 ǀ WT1 WT3 WT4 ǀ WT1 WT3 WT5 ǀ WT1 WT4 WT5 ǀ WT2 WT3 WT4 ǀ WT2 WT3 WT5 ǀ WT2 WT4 WT5 ǀ WT3 WT4 WT5	10
4-turbine clusters	WT1 WT2 WT3 WT4 ǀ WT1 WT2 WT3 WT5 ǀ WT1 WT2 WT4 WT5 ǀ WT1 WT3 WT4 WT5 ǀ WT2 WT3 WT4 WT5	5
TOTAL:		30

Limiting η to 4 can be justified by the practical constraints on vessel capacity and the maximum duration of a work shift. For example, a standard CTV is capable of carrying 12 technicians; many corrective actions require three or more technicians to carry out [39]. Most corrective actions take a full shift (or more) to complete [39], meaning that teams carrying out repairs are usually only able to complete maintenance on one turbine in a day.

Limiting η to 5 was also considered, however, Irawan et al. [25] have shown that this would result in an average improvement of 0.3% in terms of total policy cost compared to η equal to 4. This comes at a price: a fourfold increase in computational time, which, in the author's view, is excessive given the minor improvement in solution quality. While there are some differences in cases analysed in Irawan et al. [25] and the problems solved in this thesis, it is unlikely that increasing η to 5 would be computationally worthwhile. It was therefore decided to carry out case studies using η equal to 4.

In the next step of the solution procedure, each of the clusters is paired with each of the vessels. For example, consider the first cluster of Table 5.1 in which only WT1 is visited. In the proposed procedure, this single-turbine-cluster is matched with each vessel available to the operator on the day. In this example, WT1 visited by Vessel 1 and WT1 visited by vessel 2 become unique clusters, to be analysed separately in the latter stages of the solution algorithm. This effectively multiplies the number of clusters by the number of vessels. If the vessels were homogenous, there would be no need to pair individual vessels with clusters. However, assuming that vessels are capable of travelling at different speeds, certain clusters may only be completed within the user-specified time constrained by the quicker vessels. Similarly, in high wave conditions, only the capable vessels may be able to access certain turbines. The resulting matrix of clusters is then used an input to the sub-problem, where each individual cluster is evaluated, as described in the following section.

5.2 The Sub-Problem: Optimising the Order of Wind Turbine Visits

Once turbines requiring maintenance have been assigned to vessels, the order of turbine visits is determined. The aim of the sub-problem solution procedure is to generate efficient[24] routes between turbines in a given cluster, while taking constraints described in Table 4.1 into consideration. Stochastic inputs, such as maintenance task duration, are incorporated into the model at the sub-problem level, as described in Section 5.2.3. At the end, the relative value of visiting each cluster is calculated. A step-by-step example of calculating a cluster's value using the proposed approach is provided in Section 5.2.4.

5.2.1 Inputs, Outputs & Assumptions

The inputs and outputs of the sub-problem are outlined in Table 5.2. It is assumed that for a maintenance action expected to take two or more days, the estimated task duration is limited to the maximum work-shift achievable given travel and transfer to-and-from turbine (e.g. a 2 day task expected to take 12 hours is defined as a 6 hour task today and 6 hour task the following day).

Task duration is also assumed to include the time required for technicians to climb to the nacelle (if that is where the maintenance action is taking place). If multiple maintenance actions are required on a wind turbine, individual task durations are added together, as is weight of spare parts.

The vessel is assumed to leave the O&M base once a day. If a maintenance task takes longer than expected, recourse action is to cease work and leave the maintenance task unfinished, to prevent exceeding the time window. It is assumed that a single team of technicians can visit either one, or two turbines on the same day.

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[24] Definition of efficiency depends on the user-specified KPI's, as discussed in Section 2.2.6.Optimisation objectives are discussed in more detail in Section 5.2.2.

Table 5.2. Inputs and outputs to/from the sub-problem. For definitions of terms such as time window and transfer time, see Definitions Section.

Inputs	Outputs
- Matrix of wind turbine clusters, for which the routes will be optimised - Wind turbine locations - Vessel properties (speed, capacity, probability of successful crew transfer in a given significant wave height etc.) - Maintenance action properties (estimated duration, spare part and technician requirements) - Transfer time - Time window - Significant wave height at individual wind turbines - Speed correction factor	- Recommended order in which turbine should be visited - The shortest time in which all actions in a cluster can be completed (to evaluate if a given cluster is feasible) - Times of pick up and drop off, to be used when generating a policy Gantt chart - Number of technicians required for each cluster - Distance travelled by each vessel and the total fuel cost - Probability of completing all maintenance tasks within a cluster

5.2.2 Objectives

The solution procedure of the sub-problem aims to satisfy the following objectives:

a) Minimise the time taken to visit all turbines in a cluster. Since clusters which do not meet the user-specified constraints are eliminated; and given the fact that the time limit is one of the key constraints in this problem, it is crucial to ensure the overall time to carry out all maintenance actions is minimised. The actual durations of maintenance tasks can differ significantly from estimates. Minimising the policy time maximises the slack time at the end of the day. Sufficient slack time at the end of the day may ensure all maintenance tasks are finished despite some taking more time than expected.

b) Minimise the cost of fuel. This objective is aligned with a) as generally, less time spent travelling between turbines means reduced fuel costs and more man-hours spent on maintenance tasks.

c) Minimise the number of technicians required to carry out all repairs in a given cluster. This can be achieved by assigning a single team of technicians to maintenance tasks of relatively short duration on multiple turbines. Reducing the amount of technicians required for a given cluster increases the workforce available to carry out maintenance on turbines outwith the cluster.

Note that objectives may sometimes be in conflict; maintaining two turbines using a single team of technicians is more time consuming than carrying out the same actions using two teams. An explanation of how this conundrum is addressed is provided in Section 5.2.4.

5.2.3 Methodology

An approximation algorithm was created to generate the vessel routes for individual clusters of turbines. The proposed approach can be described as case based reasoning method with elements of "longest processing time-first"[25]. A set of rules, which mimic the logic followed by wind farm operators, is used to construct individual vessel routes. The structure of the proposed sub-problem solution procedure is shown in Figure 5.2.

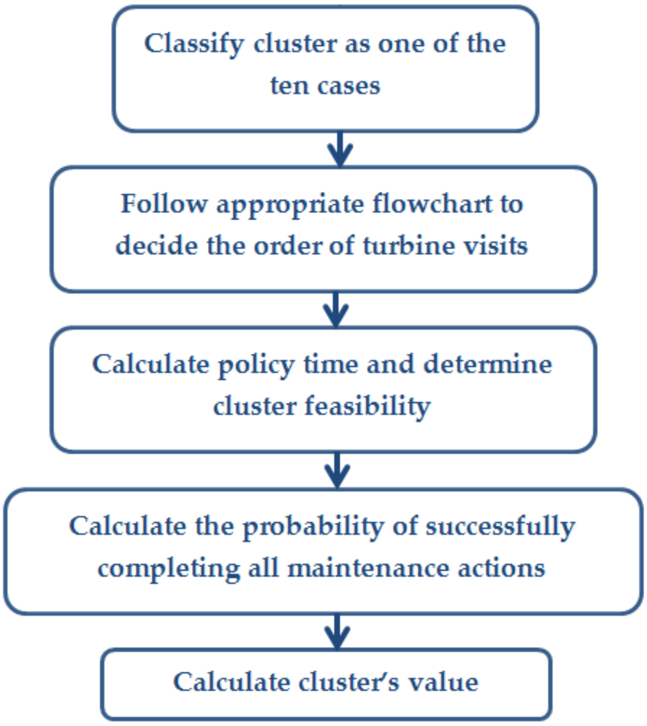

Figure 5.2. Sub-problem solution procedure.

The first step of the algorithm is categorisation of the input cluster. The logic used to optimise the order of wind turbine visits will depend on the number of turbines to be visited and the expected duration of all maintenance tasks. In the proposed approach, if the number of turbines in a cluster is limited to 4, the total number of cases is ten, as shown in Table 5.3. A unique logic algorithm has been developed for each of the

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[25] Generally, attending tasks with the longest processing time first minimises the overall policy time. While a large proportion of the proposed logic adheres to the "longest processing time-first" approach, there are exceptions, which include logic for Case #7 shown in Figure E.6.

10 cases (each assigned a different case identifier), to determine the order of wind turbine visits and produce the outputs as defined in Table 5.2. An example of a logic algorithm is shown in Figure 5.5 (Case #8), all remaining flowcharts can be found in Appendix E. Logic Flowcharts for the Sub-Problem.

Table 5.3. Categorisation of individual clusters.

Turbines per cluster (η)	Individual cases (Case number)
One turbine cluster	One crew visits one turbine (#1)
Two turbines cluster	One crew visits two turbines (#2) **OR** Two crews visit two turbines (#3)
Three turbines cluster	Two crews visit three turbines, crew visiting two turbines is dropped off first (#4) **OR** Two crews visit three turbines, crew visiting one turbine is dropped off first (#5) **OR** Three crews visit three turbines (#6)
Four turbines cluster	Two crews visit four turbines (#7) **OR** Three crews visit four turbines, crew visiting two turbines is dropped off first (#8) **OR** Three crews visit four turbines, crew visiting two turbines is **NOT** dropped off first (#9) **OR** Four crews visit four turbines (#10)

It is necessary to develop different logic flowcharts for different cases, because in the proposed approach, there is no "one size fits all" strategy to ordering turbine visits. Although different cases may share parts of the logic algorithm, it is more computationally efficient to categorise each cluster as a particular case and apply a set of rules to decide the order of visits than to attempt to create a generalisation which would be valid for all cases of clusters. Categorisation of the cluster's case number is achieved by following the logic outlined in Figure 5.4 in Section 5.2.4.

Once a cluster has been categorised as one of the 10 cases, the logic defined in the flowchart corresponding to that case is followed to determine the order of turbine visits. This involves calculation of the expected time of all crew transfers, as well as an estimation of the total policy duration. Since the MATLAB code used to achieve this is over 1700 lines long, it would be impractical present equations describing this process in this section. Instead, a worked example of the procedure of generating a cost efficient vessel route for a cluster and calculating the policy time are described in detail in Section 5.2.4.

Outputs from this procedure, such as the aforementioned policy time and the total number of technicians required are compared to the user-defined constraints, to evaluate whether a particular cluster is feasible. For some input clusters, there may not be a feasible solution in which all maintenance actions are completed. If a cluster breaches any constraints, the proposed algorithm will discard it from the optimisation process.

The reader should bear in mind that removing clusters, which do not meet constraints, from further analysis does not remove the turbines constituting the cluster. Consider the first entry in second row of Table 5.1: a cluster of WT1 and WT2 with Vessel 1 assigned to it. If the time required to complete maintenance tasks on those two turbines (including travel from base to turbines, transfers etc.) exceeds the maximum time limit, the cluster is removed from the solution procedure. However, two 1-turbine clusters in row 1 of Table 5.1 (i.e. WT1 and WT2 as separate clusters), remain in the solution procedure; they are assessed against constraints independently.

As shown in Figure 5.2, the next step is to calculate the probability of completing all maintenance actions in a cluster. This probability is then used to calculate the value of the policy generated for the selected cluster of turbines. The proposed methodology for calculating the probability and cluster's value is described in the following subsection. The solution procedure shown in Figure 5.2 is repeated for all input clusters, resulting in a list of feasible clusters and their values. Outputs of the sub-problem are used as inputs to the heuristic algorithm, described in Section 5.3.

Calculation of the Probability of Completing All Maintenance Tasks and Cluster's Value

As highlighted in Section 2.2.7, it is crucial to consider uncertainties when modelling real-world vessel routing. A brief example of how uncertainty may affect decision making was described in row 7 of Table 4.1. A literature review into approaches for dealing with uncertain variables in optimization problems was conducted in Section 4.2.4.

In this section, a framework for incorporation of uncertain crew transfer, uncertain maintenance action duration and the possible failure to complete a maintenance task is proposed. These three uncertainties were selected as they are highly relevant to the real-world problem and have a significant influence on the choice of optimal policy.

In the proposed approach, the probability of completing all maintenance actions in a cluster is calculated. Consider the following example with two different clusters of turbines:

a) Cluster A, which consists of three turbines, requires 6 technicians and takes 10 hours, 59 minutes to complete
b) Cluster B, which consists of two turbines, requires 4 technicians and takes 9 hours 45 minutes to complete

Let us assume a time window of 11 hours. Bearing in mind that, as recommended by the wind farm operator and Gomez et al. [185], the service time of each individual maintenance action should be modelled as a positive skew probability distribution, what is the likelihood that all repairs in Cluster A will be repaired on time? The answer is: very low (though it can be calculated, as shown in Section 5.2.4). Given multiple maintenance tasks on three different turbines and one minute of slack at the end of the day, the probability that some of the tasks will not be completed within Cluster A is high. The impact of incomplete tasks was previously described in Section 3.3; in short, leaving unfinished tasks on a turbine is inefficient, as when technicians come back to the same turbine at a later date to finish the task, significant amount of time will be lost on transferring crews and tools onto the turbine and up to the nacelle.

Cluster B on the other hand, does not visit as many turbines as B, but the probability of completing all planned maintenance actions is much higher. The user may therefore want to discourage clusters such as A, and encourage clusters such as B to promote efficient work organisation. To achieve this, and to incorporate uncertainties on the crew transfer and task completion into the decision making process, the following four-step approach is proposed:

- **Step 1)** Calculate the headroom; i.e. the slack time for each task within the policy (this requires analysing the order of wind turbine visits to determine which tasks are on the critical path[26] and which are not).
- **Step 2)** Using the output of Step 1 and the user-defined probability distribution on service times on individual tasks, calculate the likelihood of the user-specified time constraint being breached.
- **Step 3)** Using the output of Step 2 and the user-defined crew transfer and task completion probabilities, calculate the overall probability of completing all maintenance actions in a cluster.
- **Step 4)** Using the output of Step 3, the user-specified risk aversion factor and all costs and rewards associated with the cluster at hand, calculate the cluster's value. This value is used in later stages of the process to compare the quality of different clusters depending on the amount of maintenance tasks completed, costs associated with visiting those turbines and the probability of actually completing all planned tasks.

The proposed four-step approach was implemented to facilitate multi-objective optimisation, with the two objectives being high cluster value and high probability of successfully maintaining all turbines in a cluster. Discussion of the trade-offs associated with the choice of "optimal" policy and Pareto front graphs are provided in Section 6.3.2. An example numerical calculation, illustrating the procedure outlined in steps 1-4 is provided in Section 5.2.4.

[26] Defined in the Definitions section.

Step 1 – calculate slack time on each task

The aim of this step is to calculate the maximum time each task in a cluster can take, without breaching the overall time constraint. First, the policy slack time and the individual task slack times are calculated. The policy slack time, G_e is simply defined as the difference between the policy time and the time window. The individual task slack time, G_i is the maximum amount of time by which a task could overrun without delaying the tasks on the critical path. Note that the latter slack time applies only to the tasks which are not on the critical path. To illustrate this, a Gantt chart for making tea was created, as shown in Figure 5.3.

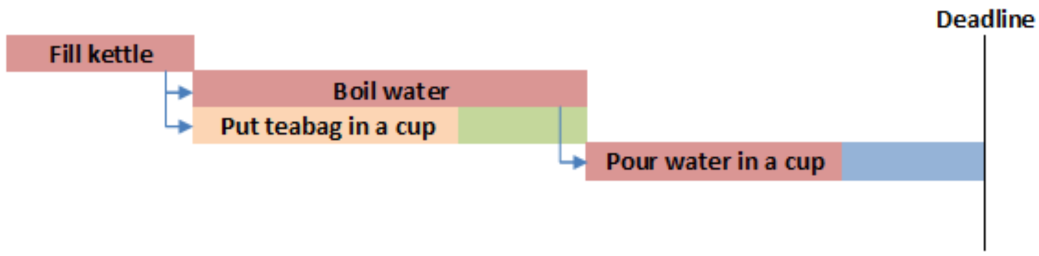

Figure 5.3. Making tea - Gantt chart. Critical path tasks are indicated in red, tasks not on the critical path are in yellow. Policy slack time G_e was marked in blue, individual task slack time G_i in green.

The maximum time a maintenance task on turbine i can take without breaching the time constraint (i.e. the user-specified time limit), X(i), is defined as:

$$X(i) = K(i) + G_e \varphi(\mathrm{i}) + G_i \quad (minutes) \qquad (Equation\ 5.2)$$

where K(i) is the expected task duration and φ(i) is the slack multiplier. This multiplier is introduced to divide the policy slack G_e among all turbines in a cluster. The slack multiplier values for individual cases are shown in Table F.1, Appendix F. Slack Time Distribution. Note that, for all ten cases:

$$\sum_{i=1}^{i=Q} \varphi(\mathrm{i}) = 1 \qquad (Equation\ 5.3)$$

where Q stands for the number of turbines assigned to a cluster (as defined previously). While dividing the slack evenly among all turbines would be possible, it would oversimplify the problem. Multiplier values shown in Table F.1 were tailored to individual cases to ensure fair distribution of policy slack, which maximises the overall probability of completing all tasks in a cluster Pv. Tasks on the critical paths are assigned a higher proportion of policy slack as they do not benefit from individual slack times (G_i). The user can easily change the slack time distributions for individual cases to suit their needs.

Consider the aforementioned cluster B with tasks on two different turbines. The policy slack time of this cluster can be calculated as 1h15min (11h time window minus 9h45min policy time). The individual slack time for the crew picked up last is 0 (as it's on the critical path). The individual slack time (G_i) for the other crew is the amount of time the vessel is idle after picking them up, but before picking up the last crew. It is the time this task could overrun, without delaying arrival at base. Numerical example of the procedure for calculating slack times for a cluster of 4 turbines is shown in Section 5.2.4.

Step 2 – calculate the probability of completing all tasks in a cluster within the time limit

Having calculated X(i), the following question can be asked:

> "Given a probability density function defining the expected task duration, how likely is it that the actual time required to complete the maintenance task will not exceed X(i)?"

In principle, the user can specify any probability distribution to define the expected maintenance task durations. In this thesis, gamma distribution with positive skewness was used for reasons discussed in Section 4.2.4. A gamma distribution can be described by shape (α) and scale (β) parameters. The above question can be answered by solving Equation 5.4, which uses the cumulative distribution function of a gamma distribution to calculate the probability of the value of X(i) not being exceeded (denoted as Pr(i)). Pr(i) is the quantity which answers the question posed at the start of this subsection, i.e the probability that servicing turbine i will take less time than the time available for this maintenance task.

$$\Pr(i) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)}\int_{0}^{X_i} K^{\alpha-1}e^{\frac{-K}{\beta}}dK \qquad (Equation\ 5.4)$$

Where Γ is the gamma function. In practice, Equation 5.4 is resolved using "gamcdf" MATLAB function[27]. Naturally, different maintenance tasks can be characterised by different gamma distributions, however, the mean value of each distribution should equal the expected duration of the particular maintenance task. Note that for tasks on

[27] More information available on: https://uk.mathworks.com/help/stats/gamcdf.html?s_tid=doc_ta Accessed on 11/10/2017.

multiple turbines carried out by the same crew, the distributions of two tasks can be added together, provided the scale parameters of both distributions are the same. This is achieved by simply adding the shape parameters of both distributions. Finally, the overall probability that all maintenance tasks in a cluster will be completed on time, Pr(c), can be calculated from Equation 5.5:

$$\Pr(c) = \prod_{i=1}^{Q} \Pr(i) \quad (Equation\ 5.5)$$

Step 3 – calculate the probability of completing maintenance on all turbines in a cluster, considering all user-specified uncertainties

So far, the probability of completing all maintenance tasks within the allowable time constraint has been calculated. In this step, uncertainties on crew transfer Pt (between vessel and turbine) and task completion, Pd (i.e. whether technicians will be able to complete the maintenance action) are incorporated into the model.

Before the start of the simulation, the user is asked specify the expected significant wave height at each wind turbine and the vessel's capability to transfer crew onto turbine in a given significant wave height. The latter is defined as a probability; for example there may be an 80% chance that vessel j will be able to transfer crew onto a turbine which is experiencing significant wave heights of 1.4-1.6 meters. This enables modelling uneven wave fields across the wind farm, as each wind turbine can be assigned a different expected significant wave height. Similarly, individual vessel capabilities (to cope with crew transfer in a range of significant wave heights) can also be modelled. The overall probability that all crew transfers attempted by a vessel within a given cluster will be successful, Pt(c), can be calculated using Equation 5.6.

$$\mathrm{Pt}(c) = \prod_{i=1}^{Q} Pt(i,j) \quad (Equation\ 5.6)$$

where Pt(i,j) is the individual probability of successful transfer from vessel j onto turbine i. Note that the user can define Pt(i,j) equal to 0, preventing a particular vessel from visiting a given turbine. This feature may be useful when modelling site-specific practical constraints.

A similar procedure is used to calculate the total probability of all turbines being correctly diagnosed and therefore successfully maintained given the technicians and spare parts used, denoted as Pd(c). At the start of the simulation, the user is asked to define the probability of correct diagnosis for all turbines (as defined in Definitions section), Pd(i). Its value can be set to 1 if the user is confident about the diagnosis; however, if the cause of condition monitoring alarm or the nature of repair required is unclear, the value will be set to <1, depending on the operator's degree of confidence. Pd(c) can then be calculated using Equation 5.7.

$$\mathrm{Pd}(c) = \prod_{i=1}^{Q} Pd(i) \quad (Equation\ 5.7)$$

Finally, the overall probability of successfully maintaining all turbines within a cluster, P, can be calculated by multiplying individual probabilities calculated in this, and previous step.

$$\mathrm{P} = \mathrm{Pr}(c) * Pt(c) * Pd(c) \quad (Equation\ 5.8)$$

Additional uncertainties could easily be incorporated into the proposed approach by multiplying right-hand-side of Equation 5.8. Note that since Pt, Pd and Pr are all probabilities, their values are constrained as follows:

$$0 \leq \mathrm{Pt(i, j)} \leq 1$$

$$0 \leq \mathrm{Pd(i)} \leq 1$$

$$0 \leq \mathrm{Pr(i)} \leq 1$$

It is important to clarify that the primary reason for the calculation of P was to compare different clusters in terms of how likely they are to be successful in completing wind turbine maintenance. The calculation procedure shown in Steps 1-4 is slightly pessimistic due to double counting[28]. However, since this effect is likely to be minor and considering the fact that it affects all clusters equally, in the author's view there is no need to address it at this stage as the performance of the model is in no way affected by it[29].

[28] Double counting would occur in a case where the random numbers generated resulted in, for example, both "no access due to high wave" and "misdiagnosed turbine". This would be logged as two failed maintenance actions, even if they both took place on the same turbine.

[29] For example, assuming 90% of failures are diagnosed correctly, and 80% transfers are successful, the double counting in this case would result in approx. 0.1*0.2=0.02 i.e. 2% reduction in the number of turbines repaired. The outputs of this procedure serve only as comparison of different policies, so the effect of this is negligible.

Step 4 – calculate the value of a cluster

This step describes the procedure for calculating the value of a cluster, which includes the previously calculated P. This can be achieved by calculating the monetary value of servicing a set of turbines, which includes all costs and rewards associated with vessels and maintenance and adding a non-monetary incentive derived from P. However, the P cannot simply be added onto the value, for the following three reasons:

i. It would skew the results, favouring clusters with a single turbine; as for clusters with multiple turbines, the probabilities of successfully servicing individual turbines are multiplied resulting in much lower P values.
ii. Since the value of P, by definition, can only range from 0 to 1, its magnitude is insignificant compared to monetary value of servicing a cluster of turbines
iii. The user would have no control over the degree to which P affects the cluster value calculation

To address i., Px, i.e. weighted probability of completing maintenance on all turbines within a cluster, is calculated in Equation 5.9.

$$Px = P * \frac{Q}{\eta} \qquad (Equation\ 5.9)$$

Issue ii. was addressed by multiplying Px by the mean utility for visiting a wind turbine(U_{mean}) within a given cluster. Methodology for calculating U is described in Chapter 3. U_{mean} is simply a mean of utility values of all maintenance actions to be carried out on a given day. This step increases the value of Px to approximately the order of magnitude of costs and rewards.

To address iii., risk aversion factor (Y) input was created, enabling user control over the degree to which Px influences the value of a cluster. The formula to calculate a cluster's value (Ω) is shown in Equation 5.10.

$$\Omega = \sum_{i=1}^{Q}[U_i - Cr_i] - \sum_{j=1}^{J}[Cf_j + Ch_j] + (Px * U_{mean} * Y)\ \ (Y \geq 0) \qquad (Equation\ 5.10)$$

where Cr^i is the cost of repairing wind turbine i, Cf_j is the cost of fuel incurred by vessel j, Ch_j is vessel's hire cost and U_{mean} is the average reward across all turbines considered for maintenance on the day. If the user does not wish for the uncertain inputs to have a n impact on the results, Y can be set to 0 to yield cluster value exclusive of the effects of uncertainties ($\Omega_{y=0}$), as shown in Equation 5.11..

$$\Omega_{y=0} = \sum_{i=1}^{Q}[U_i - Cr_i] - \sum_{j=1}^{J}[Cf_j + Ch_j] \qquad (Equation\ 5.11)$$

Specifying a moderate-to-high Y value (i.e. Y>2) favours:

- Policies featuring more capable vessels travelling to turbines with higher expected significant wave height
- Policies with an ample amount of slack time to allow for some repairs taking longer than expected. High Y may also favour assigning faster vessels to clusters with multiple time consuming maintenance actions, to increase the slack time
- Policies featuring visits to turbines with high likelihood of being correctly diagnosed and therefore completed, are prioritised

The effect of varying risk aversion factor is discussed in greater detail in Section 6.2 and Appendix G. Example of Cluster Value Calculation Using Low and High Risk Aversion Factors. The disadvantage of specifying a non-zero risk aversion factor is that it may favour policies with lower actual value ($\Omega_{y=0}$). However, the user may wish to trade-off higher policy cost for the following, potential advantages of specifying a positive risk aversion factor:

- Incorporating the uncertainties into the proposed decision making process is designed to result in fewer unfinished maintenance actions, leading to improved organisation of work
- Taking into account the vessel's capability to transfer crews onto turbines in a given significant wave height can lead to higher proportion of successful crew transfers, increased technician safety and reduced time required to transfer crews and spare parts onto the turbine
- Specifying a non-zero Y may favour policies which aim to visit fewer turbines (compared to Y=0). However, planning to visit fewer turbines does not mean that fewer maintenance actions will be completed (due to uncertainties); in fact, the opposite may be true

Generally, it is recommended that a single scenario is solved using a number of risk aversion factors, to provide the user with a choice of low-to-high risk policies. This process is demonstrated in Sections 6.2 & 6.3, which also contain further discussion on the choice of risk aversion factor. The next section provides a comprehensive example of application of the sub-problem solving procedure.

5.2.4 Step-by-step Solution Procedure: An Example

Model inputs

The inputs to the sub-problem were identified in Table 5.2. Numerical values of all inputs used in this example are shown in Tables 5.4-5.7. Vast majority of the inputs used in this example are similar to inputs to case studies presented in Chapter 6. Values were provided by the wind farm operator the author had worked with. However, the user can easily change all inputs to suit their needs.

Table 5.4. General model inputs.

Input	Symbol	Value
Vessel assigned to this cluster	j (vessel identifier)	CTV 1
Time window (hours)	W	10
Transfer time (between vessel and wind turbine, in hours)	B	1/3
Speed correction factor	E	1.5
"Half-day" action maximum duration	N/A	<=2.5 hours
Maximum number of turbines in a cluster	η	4
Risk aversion factor	Y	1

Speed correction factor determines the increase in travel time between turbines in a wind farm compared to vessel's cruise speed (discussed in more detail in Table 4.1 factor 4). For example, a speed correction factor of 2 means that if a vessel is able to travel 1km in two minute when cruising, travelling 1km between turbines at a wind farm will take four minutes. This is to account for vessel acceleration/deceleration and navigation while at the wind farm.

"Half-day action maximum duration" is a site specific constraint; 2.5 hour limit means that a single crew of technicians will be able to complete maintenance tasks on two different turbines, provided the combined time to complete both actions does not exceed 5 hours. It was assumed that on this site, for a 10 hour time window, this would not be achievable for tasks of longer duration. This threshold is used for classification of a cluster into one of the ten cases defined in Table 5.3.

Table 5.5 defines the vessel properties used in this example; data was provided by an offshore wind farm operator; it aligns closely with CTV properties defined in [39].

Table 5.5. Model inputs: vessel properties (CTV 1).

Input	Symbol	Value
Vessel speed (km/h)	Vv	40
Vessel capacity (technicians)	Vct	12
Vessel capacity (spare parts – in kg)	Vcs	1200
Fuel consumption (£ per km travelled)	Vf	6
Probability of successful crew transfer in a given significant wave height at turbine i using vessel j	Pt (i,j)	1 @ H(i) <=1.4m 0.8 @ H(i) > 1.4m 0.5 @ H(i) > 1.6m 0 @ H(i) > 2m

Table 5.6 defines the properties of the maintenance actions required. Discussion of the inputs used here and in other case studies presented in this thesis is provided in Section 2.2.2. Note that the utility value for carrying out maintenance actions was previously calculated in Section 3.4.2 (SMDP summer day case study).

Table 5.6. Model inputs: maintenance action properties. Note: utility values come from the SMDP model (see Table 3.8).

	Symbol	WT 1	WT 2	WT 3	WT 4
Significant wave height at turbine i (m)	H(i)	1.5	1.3	1.3	1.3
Maintenance action required	N/A	Manual Reset	Retrofit	Grease Top-Up	Manual reset
Task duration (hours)	K	2	4	3	2
Probability of correct diagnosis	Pd	1	1	1	1
Technicians required	M	2	2	2	2
Weight of spare parts (kg)	L	0	200	20	0
Cost of repair	Cr	£0	£1,000	£1,000	£0
Utility value	U	£98,700	£4,700	£10,700	£98,700

In order to calculate the time it takes for a vessel to travel between turbines, the distance between turbines (and O&M base) needs to be calculated. The user can either specify the geographical coordinates of individual wind turbines, or define the distance matrix (as shown in Table 5.7). If the former option is chosen, the distance matrix can be calculated from the Haversine formula[30], which outputs the distance

[30] https://en.wikipedia.org/wiki/Haversine_formula

between two points on a sphere, in km. The distance matrix for this example, which also includes the distance between base and each of the turbines, is shown in Table 5.7.

Table 5.7. Distance matrix (in km).

	WT 1	WT 2	WT 3	WT 4
WT 1	0	1.1	1.1	1.6
WT 2	1.1	0	1.6	1.1
WT 3	1.1	1.6	0	1.1
WT 4	1.6	1.1	1.1	0
O&M Base	81.1	80.3	81.7	81

Cluster categorisation

As discussed in Section 5.2.3, the first step of the solution process is to categorise the cluster as one of the ten cases. The logic used for cluster categorisation is shown in Figure 5.4.

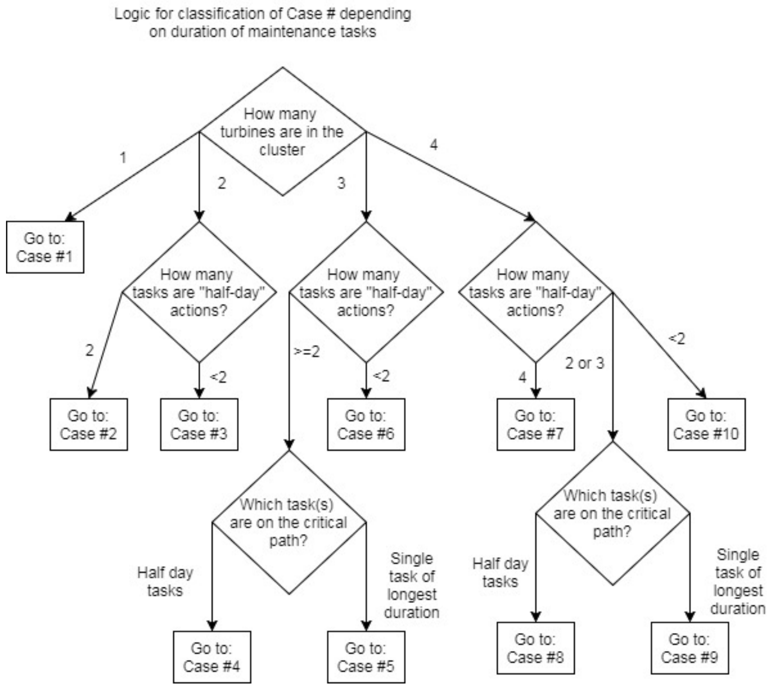

Figure 5.4. Flowchart of case categorisation logic.

From Table 5.6, the cluster consists of four turbines, three of those are considered “half-day” maintenance actions. This means that 2 out of 3 “half-day” tasks can be carried out by one team of technicians. The remaining two tasks will be assigned a crew each. In this case, maintenance on all turbines could not be completed with fewer than three crews.

Following the logic shown in Figure 5.4, with four turbines in the cluster and three "half-day" actions, we arrive at decision node requiring us to determine the critical path. This decision node requires us to answer the following question: what will take more time: carrying out the longest maintenance action or carrying out two "half-day" tasks? The task(s) on the critical path determine the first turbine to be visited and the case number (i.e. logic to be used). Having defined task durations, transfer time, vessel speed and distances between turbines allows calculation of the process critical path.

To determine whether it takes more time to carry out a single, "longer" maintenance action, or the two, "shorter" tasks, duration of the former - K(i) is compared to the value calculated in Equation 5.12, which yields the equivalent time of completing repairs on two turbines by a single team of technicians.

$$\begin{aligned} &Equivalent\ task\ duration \\ &\quad = K(WT1) + B + \frac{E * F(WT1 \rightarrow WT2)}{Vv} + B \\ &\quad + K(WT2) \quad (Equation\ 5.12) \end{aligned}$$

where K(WT1) and K(WT2) are the expected maintenance task durations for the two shortest "half-day" tasks, B is the transfer time, E is the speed correction factor (as defined in Table 5.4), F(WT1→WT2) is the distance between the two turbines and Vv is vessel speed. From the data provided in Table 5.4:

$$Equivalent\ task\ duration = 2 + \frac{1}{3} + \frac{1.5 * 1.6}{40} + \frac{1}{3} + 2 = 4.727\ hours$$

Comparing the task duration of the single longest action (4 hours) and the equivalent time required to complete the two shortest "half-day" tasks (4 hours and 44 minutes), it is clear that the latter should be attempted first in order to minimise the total policy time. From Figure 5.4, this cluster is classified as Case #8.

Figure 5.5 shows the flowchart for Case #8, defining the logic to be followed if the input cluster comprises of four wind turbines, with at least two "half-day" maintenance actions (total of three crews required) which are on the critical path.

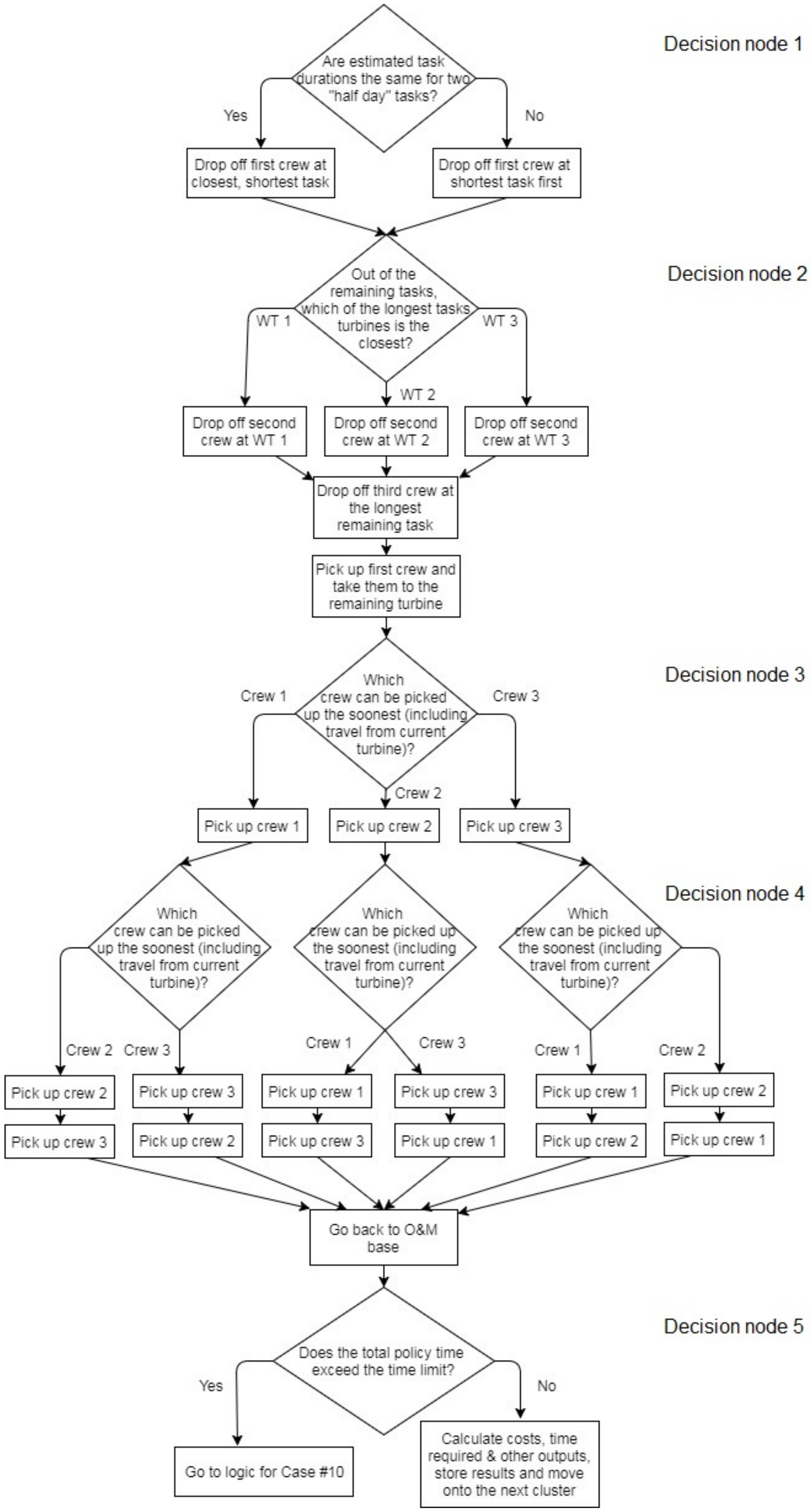

Figure 5.5. Flowchart for Case #8.

The proposed logic was discussed with the wind farm operators, who confirmed they use a similar approach when deciding the order of wind turbine visits. Logic flowcharts for all other cases are provided in Appendix E. Logic Flowcharts for the Sub-Problem.

Following the flowchart logic to determine order visit and calculate policy time

Starting from the first decision node in Figure 5.5, a comparison needs to be made as to which of the shortest maintenance action in the given cluster is the closest to base. Manual resets are required on turbines 1 & 4; from Table 5.7, WT4 is the turbine closer to the O&M base. Hence, the first turbine to be visited on the day is WT4.

In decision node 2, the closest out of the longest remaining tasks is selected to be visited next. Since the durations of remaining tasks are 2, 4 and 3 hours for wind turbines 1, 2 and 3 respectively, the next turbine to be visited is WT2. The proposed approach ensures minimisation of the total policy time; by dropping off technicians at turbines requiring maintenance tasks which are expected to take the longest first, reducing the overall critical path duration.

Since the two tasks which are completed by a single team of technicians should also be the actions with the shortest durations: i.e. the two manual resets on WT1 & WT4, this leaves WT3 as the only remaining turbine where the third team of technicians can be dropped off. The updated order of turbine visits is now WT4, WT2, WT3.

The vessel has now dropped off all the technicians at turbines. Depending on the transfer time and distances between the turbines, the vessel may be idle for some time, waiting for the first team of technicians on WT4 to finish the manual reset maintenance action. Once the action is finished and the crew is transferred back on the vessel, they are transported to the final turbine: WT1, where Crew 1 is dropped off.

In the next step of the process, decision node 3 needs to be resolved, which requires calculation of the expected task completion time at each of the turbines. The automated process of calculating the policy duration in MATLAB is illustrated in Table 5.8. Since the vessel movements up to this point are known, the drop off times can be calculated. The duration of each vessel movement is calculated in the same way as shown in Equation 5.12: by multiplying the distance between turbines (or the O&M base) by speed correction factor (where applicable) and dividing the result by the vessel's cruise speed. In Table 5.8, the results have been rounded up to the nearest minute for clarity. The resulting time stamps are used to automatically generate Gantt charts of the recommended policy in Excel.

Table 5.8. Estimated vessel movement times.

Vessel Movement/Transfer	Duration (minutes)	Start Time	End Time
Travel from O&M base to WT4	81*60/40 = **122**	7:00	9:02
Transfer Crew 1 onto WT4	20	9:02	**9:22**
Travel from WT4 to WT2	1.5*1.1*60/40 = **3**	9:22	9:25
Transfer Crew 2 onto WT2	20	9:25	**9:45**
Travel from WT2 to WT3	1.5*1.6*60/40 = **4**	9:45	9:49
Transfer Crew 3 onto WT3	20	9:49	**10:09**
Travel from WT3 to WT4	1.5*1.1*60/40 = **3**	10:09	10:12
Wait until Crew 1 finishes	**70** (9:22+120=11:22)	10:12	11:22
Transfer Crew 1 onto vessel	20	11:22	11:42
Travel from WT4 to WT1	1.5*1.6*60/40 = **4**	11:42	11:46
Transfer Crew 1 onto WT1	20	11:46	**12:06**

In the fourth column of Table 5.8, drop off times at each turbine, which define the beginning of each maintenance task, have been marked in bold. These values are used in Table 5.9 to estimate the maintenance action finishing time at each turbine.

Table 5.9. Estimated task completion times.

Turbine ID	Task Duration (h)	Start Time	End Time
WT1	2	12:06	14:06
WT2	4	9:45	13:45
WT3	3	10:09	13:09
WT4	2	9:22	11:22

Once the expected task completion time for each of the turbines has been calculated, decision node 3 from Figure 5.5 can be resolved. From Table 5.9, the next turbine to be visited should be WT3, as maintenance there will be completed before other turbines. The order of visits now becomes: WT4, WT2, WT3, WT4, WT1, WT3.

A similar procedure is used to resolve decision node 4: there are two crews remaining to be picked up. Technicians working on WT2 are expected to finish 21 minutes earlier than WT1. This finalises the order of visits:

O&M base, WT4, WT2, WT3, WT4, WT1, WT3, WT2, WT1, O&M base

The calculation of the estimated vessel movement times shown in Table 5.8 can now be extended for the remaining movements until the end of the work shift, as shown in Table 5.10.

Table 5.10. Estimated vessel movement times: continued.

Vessel Movement/Transfer	Duration (minutes)	Start Time	End Time
Travel from WT1 to WT3	1.5*1.1*60/40 = **3**	12:06	12:09
Wait until Crew 3 finishes	60	12:09	13:09
Transfer Crew 3 onto vessel	20	13:09	13:29
Travel from WT3 to WT2	1.5*1.6*60/40 = **4**	13:29	13:33
Wait until Crew 2 finishes	12	13:33	13:45
Transfer Crew 2 onto vessel	20	13:45	14:05
Travel from WT2 to WT1	1.5*1.1*60/40 = **3**	14:05	14:08
Transfer Crew 1 onto vessel	20	14:08	14:28
Travel from WT1 to O&M base	81.1*60/40 = **122**	14:28	16:30
Total policy time:	**570**	**7:00**	**16:30**

Calculating all vessel movements also yields the total policy time, as shown in the last row of Table 5.10. This enables resolution of decision node 5 from Figure 5.5. As the total policy time of 9.5 hours is shorter than the 10 hour time window, this policy will not be discarded. However, if the policy time exceeded the time window, a different flowchart would be followed (Case #10, shown in Figure E.8), in an attempt to shorten the policy time by utilising two more technicians. This explains how the conundrum of conflicting objectives, mentioned in Section 5.2.2, is resolved: first, an attempt is made to minimise the number of technicians by attempting to use three crews of technicians to service four turbines. However, if this is unsuccessful and time constraint is breached, the objective focus shifts to minimisation of the policy time of a scenario in which four turbines are serviced by four teams of technicians.

The approximate locations of the O&M base and turbines requiring maintenance, along with the order of vessel movements are shown in Figure 5.6. Figure 5.7 provides another visualisation of the order of visits, in the form of a Gantt chart. It helps to identify the periods when the vessel as idle and the order of vessel movements. While Figure 5.7 was created manually, example of an automatically generated Gantt chart is shown in Figure 6.14.

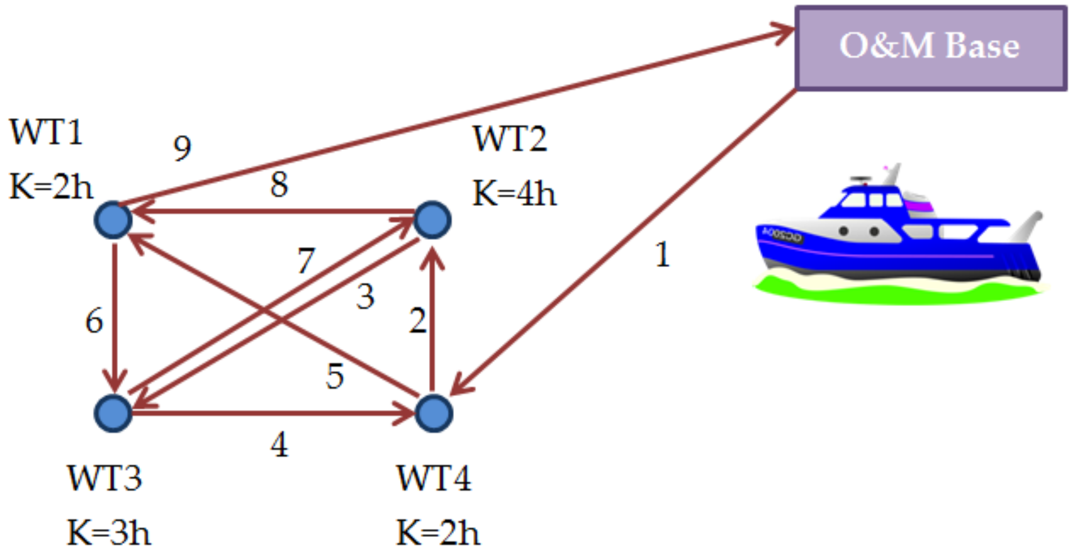

Figure 5.6. Recommended turbine visit order.

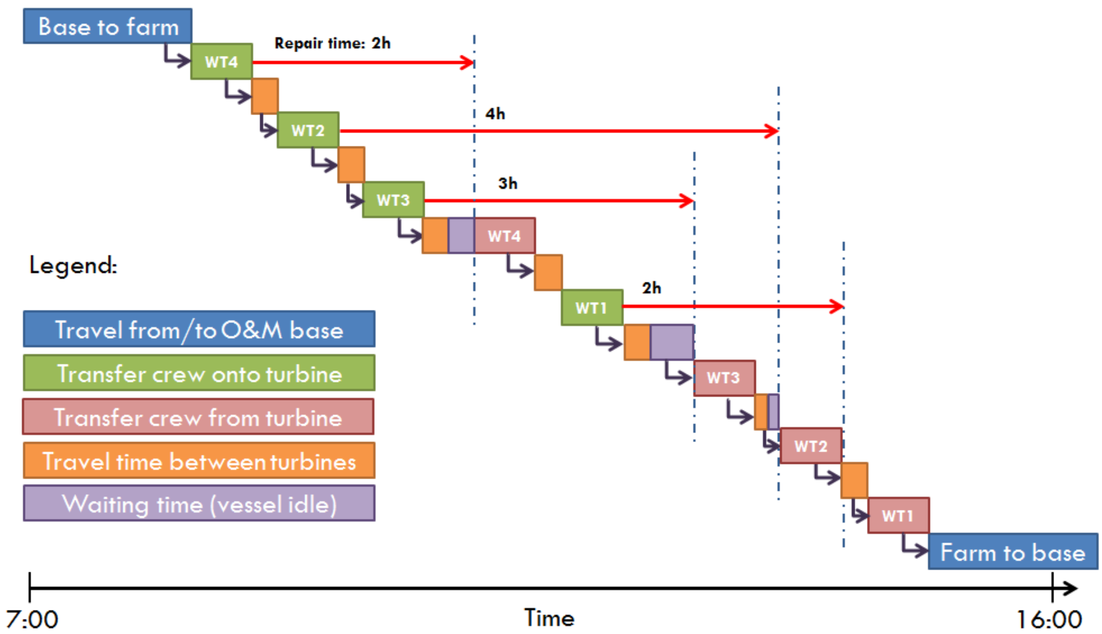

Figure 5.7. Gantt chart/visualisation of the order of wind turbine visits (not to scale).

Determining whether the cluster satisfies constraints

The policy must also satisfy the constraint on the vessel's carrying capacity. The constraints on the carrying capacity of technicians and vessels were previously defined in Table 5.5. Equations 5.13 and 5.14 show that in this example, both constraints are satisfied as the user-specified limits are not exceeded, i.e. the cluster is feasible and should be included in further analysis. Note: Lc and Mc stand for the total load and maximum number of technicians carried on the vessel when servicing a given cluster, Vcs and Vct are vessel's load and technician carrying capacities respectively.

$$Vcs = 1200\ kg$$

$$Lc = \sum_{i=1}^{i=\eta} L(i) = 0 + 200 + 20 + 0 = 220 \quad (Equation\ 5.13)$$

$$Vcs \geq Lc\ is\ TRUE$$

$$Vct = 12$$

$$Mc = \sum_{i=1}^{i=\eta} M(i) = 2 + 2 + 2 + 2 = 8 \quad (Equation\ 5.14)$$

$$Vct \geq Mc\ is\ TRUE$$

Calculation of the probability of completing all tasks and the cluster's value

Once it has been determined that the cluster satisfies user-specified constraints, its value and probability of completing all tasks can be calculated, by following the process outlined in Section 5.2.3. Before the start of the simulation, the user is asked to specify the probability distributions of expected task durations. The mean value of the probability density function (pdf) should correspond to the expected task duration. As discussed in Section 4.2.4, positive skew gamma distribution is used. A graph of the gamma distributions used in this example is shown in Figure 5.8.

Step 1

In Step 1, the time available for each maintenance action is calculated. Table 5.11 shows the slack time for each maintenance task; these were extracted from Table 5.10. For the purposes of this example, let subscript cp denote the critical path tasks, g refers to grease top up task and r the retrofit.

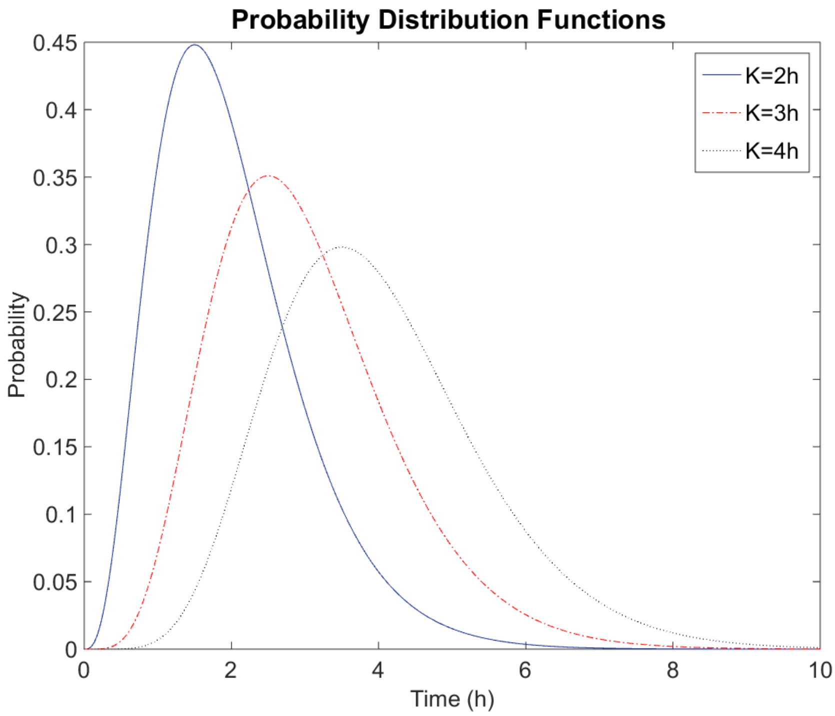

Figure 5.8. Probability distribution functions used for different maintenance tasks (Manual reset - K=2h, Grease top up - K=3h, Retrofit - K=4h).

Table 5.11. Summary of the slack time on each maintenance task.

Quantity	Label	Source	Value (minutes)
Slack at the end of the day	G_e	Time window – policy time	30
Slack on two critical path actions (manual resets)	G_{cp}	No slack as both tasks on critical path	0
Slack on grease top up task	G_g	Table 5.10 row 5	12
Slack on retrofit task	G_r	No slack as no wait at WT1 (Table 5.10)	0

Note that since both tasks on the critical path are the same type of maintenance action, they are characterised by the same gamma distribution function. Their distributions can be added; the sum of two gamma functions with the same scale parameter can be obtained by simply adding their shape parameter. Since both tasks are carried out by the same crew, the two manual reset actions are effectively treated as a single maintenance action for the purposes of Pr(c) calculation. The maximum time for each maintenance action, X(i), is calculated from Equation 5.2 as shown in Table 5.12.

Table 5.12. Calculation of X(i) for each maintenance task.

Task(s)	Label	Proportion of Ge assigned	Calculation (service time + task slack + proportion of total slack – Equation 5,2)	Value (minutes)
Critical path tasks	X_{cp}	0.4	2*120+0+0.4*30	252
Grease top up action	X_g	0.3	180+12+0.3*30	201
Retrofit action	X_r	0.3	240+0+0.3*30	249

Step 2

In the next step, Equation 5.4 is used to calculate the probability of each of the tasks being completed within the allowed time limit. For example, inputting X(i)=201 minutes, α=6, β=0.5 and K=180 into Equation 5.4 gives a probability of 66.6%, i.e. there is over 66% chance that a 3 hour task will be completed within 201 minutes. Repeating this procedure for the remaining maintenance actions allows calculating the overall probability of finishing all tasks in this cluster within the allowable limit:

$$\Pr(c) = \Pr_{cp} * \Pr_g * \Pr_r = 0.605 * 0.666 * 0.591 = 0.238$$

Note that there is approx. 10% difference between the highest and lowest individual Pr values; keeping this difference small through the use of slack multipliers ensures maximisation of the total probability of finishing on time[31].

Step 3

In Step 3, the overall probability of successfully servicing all turbines in a cluster is calculated by considering the other two probabilities on correct task diagnosis and crew transfer. The former and the latter are calculated from Equations 5.15 and 5.16 respectively. The individual values of Pd and Pt are user inputs, as defined in Table 5.5 and Table 5.6. Note that when considering probabilities on crew transfer and correct diagnosis, both critical path tasks can no longer be considered as a single

[31] Since product of similar numbers is higher than the product of dissimilar numbers, even if sums in both cases are the same: for example 0.3+0.3+0.3=0.7+0.1+0.1 but 0.3*0.3*0.3=0.027 while 0.7*0.1*0.1=0.007.

maintenance action; subscript cp1 and cp2 was assigned to the first (WT4) and second (WT1) manual reset tasks respectively.

$$\mathrm{Pd(c)} = \mathrm{Pd}_{cp1} * \mathrm{Pd}_{cp2} * \mathrm{Pd}_{g} * \mathrm{Pd}_{r} = 1 * 1 * 1 * 1 = 1 \quad (Equation\ 5.15)$$

$$\mathrm{Pt(c)} = \mathrm{Pt}_{cp1} * \mathrm{Pt}_{cp2} * \mathrm{Pt}_{g} * \mathrm{Pt}_{r} = 1 * 0.8 * 1 * 1 = 0.8 \quad (Equation\ 5.16)$$

Note that the probability of successful transfer onto WT1 is lower compared to other turbines, as it is experiencing a higher significant wave height (defined in Table 5.6). The overall probability of completing all maintenance tasks in a cluster can therefore be calculated from Equation 5.5, as shown below.

$$\mathrm{P(c)} = Pr(\mathrm{c}) * Pd(\mathrm{c}) * Pt(\mathrm{c}) = 0.238 * 1 * 0.8 = 0.19$$

Step 4: calculate cluster's value

Equation 5.9 is then used to calculate the weighted probability Px, however, since the number of turbines in this cluster Q is equal to the limit η, the value of Px is the same as P:

$$\mathrm{Px} = P * \frac{4}{4} = 0.19$$

The cost of fuel can be calculated by multiplying the total distance travelled by the vessel by the fuel consumption (defined in Table 5.5). Distance travelled was obtained from the distance matrix (Table 5.7) and the order of wind turbine visits shown in Figure 5.6. This allows calculating fuel cost (Cf), as shown below.

$$Distance\ travelled\ by\ vessel = 81 + 1.1 + 1.6 + 1.1 + 1.6 + 1.1 + 1.6 + 1.1 + 81.1 = 171.3km$$

$$Cf = 171.3 * 0.006 = £1027.80$$

Normally, U_{mean} is calculated from all turbines requiring maintenance on the day. However, since this example only considers four maintenance tasks, the only values to calculate U_{mean} are those specified in Table 5.6.

$$U_{mean} = \frac{98{,}700 + 108{,}700 + 4{,}700 + 98{,}700}{4} = \frac{310{,}800}{4} = £77{,}700$$

Finally, the cluster's value can be calculated from Equation 5.10:

$$\Omega = (310{,}800 - 2 * 1{,}000) - (1{,}027.8 + 5{,}000) + (0.19 * 77{,}700 * 1) = £317{,}535$$

Note that setting Y to 0 (i.e. eliminating the probability calculation) would yield:

$$\Omega_{y=0} = (310{,}800 - 2 * 1{,}000) - (1{,}027.8 + 5{,}000) = £302{,}772$$

The outputs of the sub-problem solution procedure are summarised in Table 5.13. These are used as inputs to part 2 of the master problem, as discussed in Section 5.3.1.

Table 5.13. Key properties of the four turbine cluster analysed in this example.

Property	Value
Flowchart logic case	#8
Technicians required	6
Time required	9.5 hours
Cluster value	Ω=£317,535 $\Omega_{Y=0}$=£302,772
Probability of completing all maintenance tasks within the time limit	19%
Order of wind turbine visits	O&M base, WT4, WT2, WT3, WT4, WT1, WT3, WT2, WT1, O&M base

5.3 Heuristic Method for Cluster Matching (Master Problem Part 2)

The outputs of the sub-problem have been summarised in Table 5.2 and Table 5.13. Given a large set of clusters with different properties, the second part of the master problem aims to select a combination of those clusters which yields the highest overall value, while satisfying the user-defined constraints.

Although it has been demonstrated that this combinatorial problem can be solved exactly, using a commercial optimiser software as shown in [25], here a heuristic approach is proposed[32]. The word "heuristic" is derived from a Greek word that means "to discover". Although finding the optimal solution is not guaranteed, a heuristic approach has a number of advantages over the exact methods, as discussed in Table 4.4.

This following section describes the Cluster Matching Algorithm (CMA), developed specifically for the problem at hand. In the proposed method, high-value clusters are used to produce offspring, selected from the pool of remaining, high-value viable clusters. Iteratively repeating this process results in an efficient search of the state-space, as combinations of high-quality clusters are matched into tens of thousands policies within seconds.

[32] Performance of the proposed heuristic algorithm is evaluated against commercial optimiser software in Section 7.4.

5.3.1 Methodology

The proposed CMA approach is based on matching high value clusters, processed in the sub-problem, with other, compatible high value clusters, creating multiple policies. At the end, the highest value policy is selected as the recommended vessel routing plan. An overview of the proposed method is shown in Figure 5.9.

First, all clusters generated in Master problem part 1 are sorted according to their value (in descending order). The highest value cluster is then selected and an attempt is made to match it with additional clusters. To add a second cluster, all incompatible clusters have to be eliminated from the list of possible candidates. There are three cluster removal criteria:

a) A cluster is assigned the same vessel
b) A cluster visits the same turbine(s)
c) Selecting given cluster would create a policy which exceeds the number of technicians available on the day

Clusters which do not breach any of the criteria specified in a-c) are then sorted according to their value. The highest value cluster is selected to be matched with the original cluster. The process of is then repeated; clusters incompatible with both clusters, are eliminated and the highest remaining cluster is added to the policy. This procedure continues until either of i-iii. becomes true:

i. All turbines are assigned a vessel
ii. All vessels are exhausted
iii. All technicians are exhausted

In other words, if three vessels are available, the first policy created would composed of the highest value cluster (let us call it A), highest value cluster compatible with A (let us call it B) and the highest value cluster compatible with both A & B (let us call it C)[33].

However, there is no need to constrain the process by selecting only the highest value cluster at each stage. Since the proposed method does not require a significant amount of computational time, it can be repeated iteratively to generate a wide range of policies by allowing a wider range of highest value clusters to become parents at each stage. The user can select the total number of iterations to be computed by specifying the number of children each tier of clusters creates. For example, if a, b and

[33] Note: This assumes sufficient number of technicians and turbines to be visited, otherwise the policy may only be composed of one or two clusters

c denote number of children at first, second and third tier respectively, the total number of policies created will be a product of a, b and c.

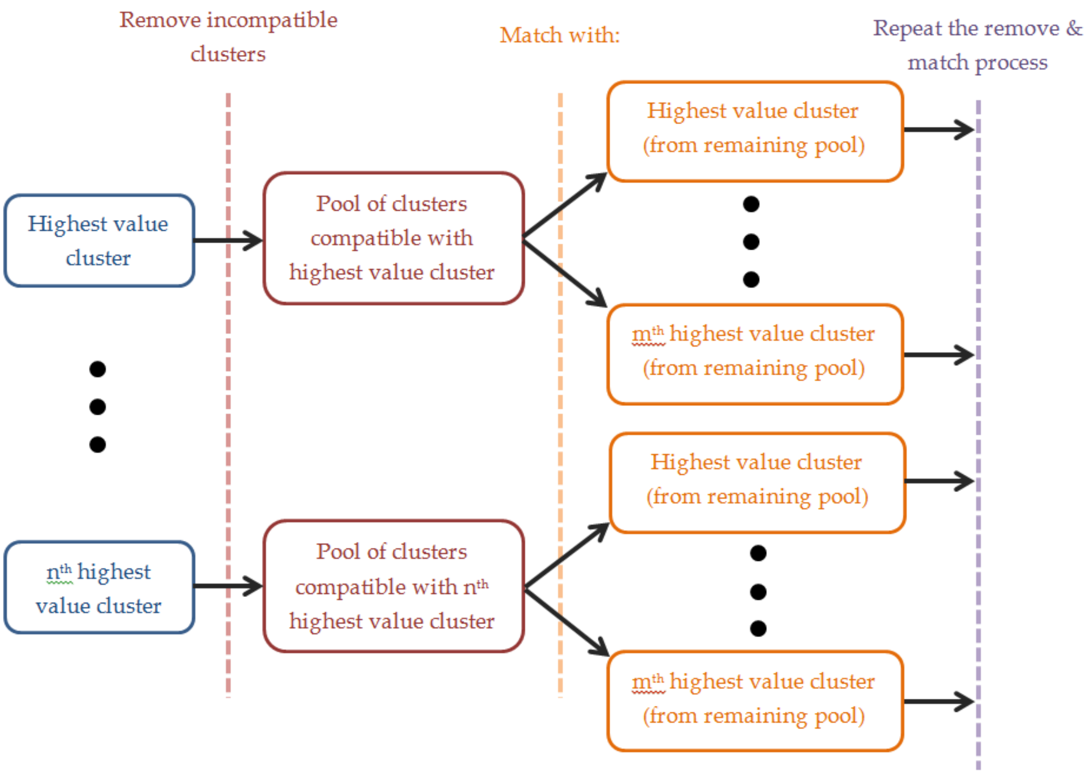

Figure 5.9. Visualisation of the CMA procedure.

Note that in a scenario with 3 tiers (i.e. 3 vessels) the children of clusters in tier 1 are parents of clusters in tier 3. For example, if a is set to 100, a hundred highest value clusters will create children. Setting b equal to 10 means that each of the 100 children from tier 1 will be matched with 10 highest value compatible clusters in tier 2. In a case with 3 vessels, c should be set to 1, as at the final tier the maximum policy value can only be achieved by using the highest value cluster. Clusters available for selection in tiers below the top one vary depending on the clusters chosen in the tiers above it.

The total value of the policy can then be calculated as simply the sum of values of individual clusters:

$$Policy\ value = \Omega(Cluster\ A) + \Omega(Cluster\ B) + \Omega(Cluster\ C) \quad (Equation\ 5.16)$$

A step-by-step solution procedure (a simplified representation of the CMA MATLAB code) is shown in Figure 5.10. At the end of the simulation, once the value of all policies has been calculated, the policy with maximum value is selected and displayed to the user.

```
Sort all clusters according to value, in descending order
Define tier limits a and b (in this example, c=1 as 3 vessels available)
i=1
For n=1:a
  Select nth best value cluster
  If all turbines have been assigned a vessel
    Store the policy properties based on cluster n
    PolicyValue(i)=Value(Cluster n)
    i=i+1
   Else
    Remove clusters using the same vessel or visiting the same turbines as cluster
    n
    For m=1:b
      Select mth best value cluster-vessel pairing
      If all turbines have been assigned a vessel
        Store policy properties based on clusters n and m
        PolicyValue(i)=Value(Cluster n)+Value(Cluster m)
        i=i+1
      Else
        Remove clusters which are incompatible with cluster m
        For p=1
          If Cluster(p) exists
            Select the highest value cluster-vessel pairing
            Store the policy properties based on clusters n, m and p
            PolicyValue(i)=Value(Cluster n) +
            Value(Cluster m)+Value(Cluster p)
            i=i+1
          Else
            Store the policy properties based on clusters n and m
            PolicyValue(i)=Value(Cluster n) +
            Value(Cluster m)
            i=i+1
          End (If)
        End (p)
      End (If)
    End (m)
  End (If)
End (n)
Select the highest PolicyValue
```

Figure 5.10. CMA solution procedure: an example based on scenario with 3 vessels.

One of the advantages of the proposed CMA is that the user can determine the approximate computational time by setting the tier limits according to their needs.

The algorithm is capable of providing a feasible solution in a fraction of a second. If, however, the user can afford to spend more time computing the vessel routing plan, setting high tier limits will likely result in improved solution quality.

This method has been developed for problems with 10+ turbines and 3+ vessels. Smaller problems can be solved by enumerating all possible combinations of turbine-vessel assignment, which can be achieved in reasonable computational time.

The proposed policy then undergoes evaluation and post-processing; visualisations and Gantt charts are created, key policy information is displayed to the user in MATLAB. The automatically generated outputs of the model are discussed in detail in Sections 6.2 and 6.3. One of the post-processing steps is the evaluation of the policy generated by the CMA, as discussed in the following section.

5.4 Policy Evaluation Using Monte Carlo Analysis

The developed tool gives the user a degree of freedom when selecting certain quantities, such as the risk aversion factor Y. This section is focused on the development of an algorithm, which determines how effective a given policy is at servicing wind turbines under uncertainty. This section aims to answer the following question:

"Given the user-specified uncertainties, if a candidate policy were carried out 10,000 times[34], how many maintenance tasks, on average, would be completed in carrying out the given policy? "

Note: candidate policies are policies generated under different assumptions: for example using different risk aversion factors. To answer this question, a Monte Carlo simulation is run for each candidate policy. In each iteration of the Monte Carlo simulation, three random numbers (for each turbine) are generated: λm will be used to determine the estimated maintenance task duration, λt will determine whether crew transfer will be possible and λd will be used to decide whether diagnosis was correct (i.e. three random numbers correspond to three uncertainties considered).

The number of turbines not serviced due to unsuccessful transfer, or misdiagnosis can then be calculated:

$$if\ \lambda\mathrm{t} > \mathrm{Pt}(\mathrm{i},\mathrm{j}), maintenance\ failed$$

[34] This number is sufficiently large to eliminate any statistical deviation and the results can be computed in reasonable computational time.

$$if\ \lambda\mathrm{d} > \mathrm{Pd(i)}, maintenance\ failed$$

Actual duration of a maintenance action is generated from the user-specified probability distribution and random number λm, using the inverse gamma cumulative distribution function (as discussed in Section 5.2.3). In practice, the calculation is performed using “gaminv” MATLAB function[35]. The resulting actual maintenance durations of all actions are then input into the corresponding logic algorithm, which was used to create the policy in the first place (i.e. for the cluster analysed in Section 5.2.4, updated crew pick-up order would be created using logic shown in Figure 5.5). The new pick up order is optimised for the actual maintenance task durations. Note that the order of technician drop offs is assumed to be the same; the operator has no way of knowing how long a task will take before it is started, but the pick-up order and times may differ from the original plan.

If some tasks take longer than expected, the constraint on the maximum policy time may be breached. In this case, the number of tasks which can be completed, within the time constraint, needs to be determined. This is achieved by following the logic outlined in Figure 5.11. In simple terms, this logic determines the first maintenance task not cut short by the need to go back to the O&M base to satisfy the time constraint. All tasks completed prior to that task (inclusive of it) are considered complete.

In the last step, the total number of tasks completed in this iteration, for a given policy is calculated using the following formula:

$$\begin{aligned} Tasks\ completed \\ &= Tasks\ planned \\ &- Tasks\ incomplete\ due\ to\ exceeding\ the\ time\ constraint \\ &- Tasks\ incomplete\ due\ to\ unsuccessful\ transfer \\ &- Tasks\ incomplete\ due\ to\ misdiagnosis \end{aligned}$$

This procedure is repeated 10,000 times per policy, logging the number of completed tasks at each iteration. At the end of the Monte Carlo analysis, the average number of completed tasks is calculated and used to compare against policies created using different assumptions (e.g. risk aversion factor).

[35] More information on: https://uk.mathworks.com/help/stats/gaminv.html Accessed on 11/10/2017.

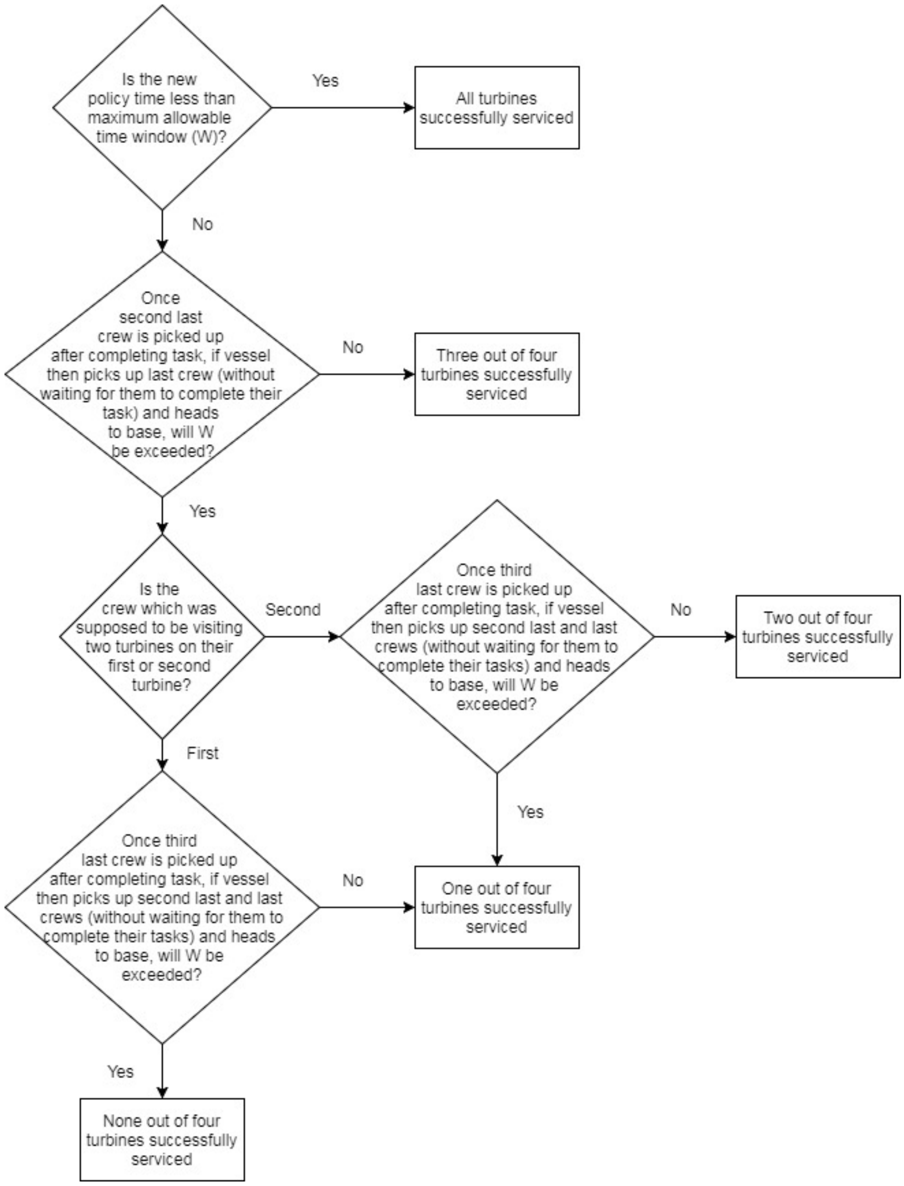

Figure 5.11. Flowchart describing the logic which determines the number of turbines serviced in Case #8.

Note that this procedure does not consider recourse actions (other than giving up on a task and heading back to base at the latest possible time to meet the time constraint). For example, in the real world, if no access was possible onto one turbine, an attempt would likely be made to access a different turbine, which may be experiencing a lower significant wave height. However, these decisions are usually made on a case-by-case basis and generalisation of this decision making process (it would need to be generalised, since the procedure is repeated 10,000 times) would be a very difficult problem in itself. For this reason, recourse actions other than giving up on a task have not been considered. The Monte Carlo analysis was carried out for both Summer and Winter Case Studies presented in Sections 6.2 and 6.3.

5.5 Conclusions

This chapter provided a detailed description of the proposed solution procedure for the offshore wind farm vessel routing problem. The entire procedure is summarised in Figure 5.12, where the division of the entire problem into Master and Sub-problems is visualised. Key research contributions arising from this section include:

Development of the sub-problem solution algorithm:

The proposed method mimics the decision making process of wind farm operators. It is characterised by high computational efficiency; optimising the order of visits for 30,000 clusters takes less than a second. This approach is an alternative to well-established solution methods such as constraint programming, which, to date; have not been successfully applied in the offshore wind domain.

Development of a methodology for incorporating uncertainties into the decision making process:

In real life decision making, the uncertainties have a significant impact on the choice of policy; yet researchers solving the vessel routing problem in the offshore wind domain have so far neglected this. In the proposed methodology, the user can define the effect uncertainties have on the final policy. The model can be run with different risk aversion inputs, producing a range of candidate policies. At the end, the user is presented with low, medium and high risk policies along with an indication of their expected effectiveness in terms of the number of turbines serviced. These outputs can facilitate real world decision making by reducing the time required to create a vessel routing plan and potentially improving organisation of work.

Development of the new heuristic method (CMA):

The proposed heuristic creates policies from individual high value clusters. A feasible solution is guaranteed almost instantaneously and hundreds of thousands of unique policies can be computed in under a minute. Benefits of the proposed CMA heuristic are discussed in more detail in Section 7.4, where its performance is compared to a commercial solver.

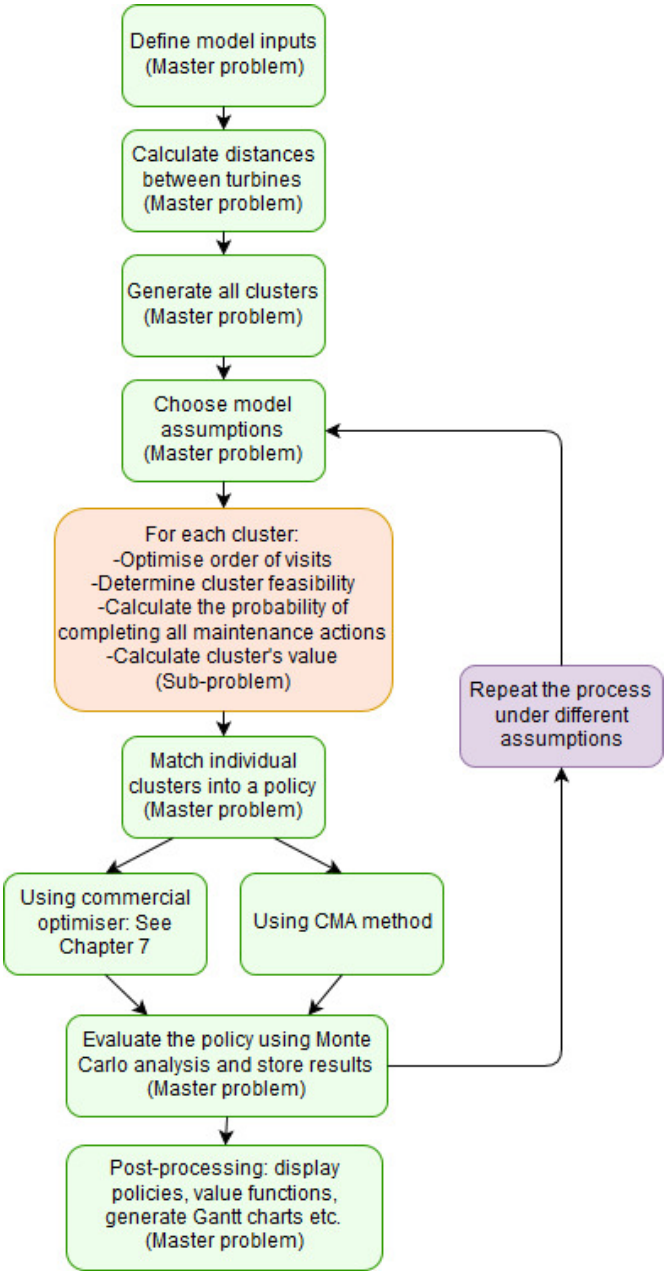

Figure 5.12. Detailed overview of the proposed approach.

The proposed decision support tool as a whole is very versatile. Additional user-specified uncertainties can easily be incorporated into the model. The logic determining the order of visits can be adapted to suit user needs or to consider practical, site specific constraints. While the model has been created with vessels in mind, helicopters could also be modelled by modifying the properties of the mode of transport (e.g. specifying a much faster speed, lower carrying capacity and higher fuel cost).

The framework shown in Figure 5.12 provides the user with a choice of the heuristic approach; both the CMA developed by the author or a commercial solver are compatible with the rest of the solution procedure. Discussion on how CPLEX software can be applied to the cluster matching problem is provided in Section 7.4. If the CMA is used, the user can also set the computational time required to generate the proposed routing policy.

Examples of how the model's application to real life and synthetic case studies are described in the following chapter. Model validation is discussed in detail in Chapter 7.

Chapter 6. Case Studies

The aim of this chapter is to illustrate how the methodologies described in Chapters 3 and 5 can be applied to aid real-world decision making. Chapter 3 provided an overview of the methodology for quantifying the utility of carrying out maintenance on turbines, depending on the type of action required, turbine's performance and the weather. The utility was used as an input to the model described in Chapter 5, which aims to optimise the movement of vessels and technicians to maximise the rewards for completing the maintenance actions while minimising costs and policy time. In this chapter, the proposed logistics optimisation model is applied to two different scenarios to illustrate the process a decision maker would go through using the model, from inputting data to interpreting the suggested policies.

Both Case Studies presented in this chapter are continuations of the winter and summer Case Studies from Chapter 3. Case Study 1 was focused on a winter scenario, with numerous wind turbine failures and high waves. Case Study 2, a summer day scenario, featured a higher overall number of maintenance actions required. The latter case study, consisting of many non-critical maintenance tasks, was heavily constrained by the number of technicians available to demonstrate how the model copes with resource shortages. In addition to the two Case Studies discussed in this chapter, the model has also been applied to a real-world problem, as discussed in Section 7.5).

This chapter is structured as follows: model inputs and the user interface are discussed in Section 6.1, Case Studies 1 and 2 are described in Sections 6.2 and 6.3 respectively. Case Study results are summarised in Section 6.4.

6.1 Model Inputs

6.1.1 User Interface

MS Excel was used as the main method of data input, as it is a widely used engineering software. Data saved in Excel can be easily imported into Matlab, where the optimisation code runs.

It is recommended that the model user begins data input by defining the properties of maintenance actions to be carried out in near future and vessels available. Figure H.1 in Appendix H. Decision Support Tool User Interface shows the Excel table used to assign turbines to tasks, while Figure H.2 shows the table used for defining task and vessel properties. The latter spreadsheet allows the user to specify each turbine's expected significant wave height, which will affect crew transfer.

The remaining user inputs, such as the number of technicians available, length of the weather window and the time required to transfer crew between a vessel and a turbine are defined in Matlab, as shown in Figure H.3.

6.1.2 Inputs Common to Both Case Studies

Both Case Studies 1 and 2 were based on the same wind farm, consisting of 100 turbines arranged on a square, ten-by-ten grid. It was assumed that the wind farm is serviced by a single O&M base, located 80km from the centre of the wind farm, in the North-Eastern direction. Table I.1 in Appendix I. Logistics Model Inputs to Case Studies 1 and 2 contains the coordinates of turbine and O&M base locations, allowing the research community to replicate the case studies described here.

In their paper, Dinwoodie et al. [39] outlined properties of four maintenance actions which can be carried out by CTVs: manual reset, minor repair, medium repair and annual service. In this thesis, additional three actions have been added: grease top-up, retrofit and high priority repair. Maintenance action cost and the number of technicians required for each task were adapted from Dinwoodie et al. [39], as shown in Table 6.1.

Table 6.1. Action cost and the number of technicians required. *From discussions with wind farm operators, it was recommended that 3 technicians (instead of 2) should perform minor repair actions.

Maintenance action	Corresponding action in Dinwoodie et al. [39]	Cost of consumables	Technicians required
Manual reset	Manual reset	£0	2
Grease top up	Minor repair	£1,000	2
Retrofit	Minor repair	£1,000	2
Minor repair	Minor repair	£1,000	3*
Medium repair	Medium repair	£18,500	3
High priority repair	Medium repair	£18,500	3
Annual service	Annual service	£18,500	3

Interviews with wind farm operators provided the remaining required maintenance task properties, including task duration, probability of correctly diagnosing the fault (as defined in Definitions Section) and the weight of spare parts and equipment. An outline of task properties is shown in Table 6.2.

The time window (as defined in Definitions Section) was assumed to be 11 hours in both case studies. Time required to transfer technicians and spare parts from vessel onto turbine and vice versa was set at 20 minutes.

Table 6.2. Maintenance task properties.

Maintenance action	Task duration (h)	Probability of correct diagnosis	Spare part and equipment weight (kg)
Manual reset	2	1	50
Grease top up	3	1	70
Retrofit	4	1	100
Minor repair	5	0.8	150
Medium repair	6	0.9	450
High priority repair	5	0.95	550
Annual service	6	1	450

So far, only the inputs common to both case studies have been discussed; the following section outlines the differences between inputs to Case Studies 1 and 2.

6.1.3 Unique Inputs

One of the key differences between the two case studies is the number and the nature of maintenance actions required. Case Study 1, which takes place in the winter, features maintenance actions on 14 randomly selected turbines. Most actions in Case Study 1 are corrective. Case Study 2 comprises of tasks on 24 turbines, with a larger proportion of preventative actions. For continuity, the rewards for completing maintenance tasks used in winter and summer case studies are imported from Chapter 3. The rewards generated using the SMDP approach are shown in Table 3.7 and Table 3.8 respectively[36]. A summary of maintenance task properties for the winter and summer Case Studies are shown in Table I.2 and Table I.3 respectively.

Two dissimilar case studies were devised to demonstrate the tool's versatility. Winter day case study features large uncertainties on the maintenance task durations. Variable wave field is also modelled in Case Study 1, with some turbines experiencing significant wave heights of up to 1.7m, hindering transfer of technicians and spare parts. The aim of this Case Study is to demonstrate how the tool copes with uncertain

[36] Note: Table 3.8 only contains 20 unique maintenance actions. To increase the complexity of the problem, maintenance tasks on turbines 72, 76, 37, and 96 were duplicated, to be carried out on turbines 9, 28, 43 and 63 respectively. The full list of all maintenance actions in the Summer Case Study, including rewards is shown in Table I.3 in Appendix I. Logistics Model Inputs to Case Studies 1 and 2.

inputs and how the user can influence the degree to which uncertainties drive the policies recommended by the tool. Case Study 2, on the other hand, features lower significant wave heights and lower uncertainty on task duration, however, it is heavily constrained by the number of technicians available, making it impossible to complete all maintenance actions on day 1. This demonstrates how the logistics model works in conjunction with the SMDP model described in Chapter 3 to decide which turbines are maintained on the day and which tasks are delayed to be completed in the future. A summary of the differences in inputs is shown in Table 6.3.

Table 6.3. Comparison of case study inputs.

Input	Case 1 - Winter	Case 2 - Summer
Number of turbines requiring maintenance	14	24
Vessels available to operator	5	6
Technicians available	35	45
Wave field	Variable (Figure 6.1)	Uniform
Gamma distributions	High uncertainty (Table I.4)	Low uncertainty (Table I.4)
Number of policies generated by the CMA	4.8 million	4.8 million

In the Summer Day Case Study, the wave field is uniform: expected significant wave height is equal to 1.2m for all turbines. Under those conditions, safe transfer can be achieved using both Class 1 and Class 2 (as defined in Definitions Section) vessels with 100% certainty. The wave field used in the winter day case study is shown in Figure 6.1, with high waves affecting turbines exposed to sea from the North and East directions.

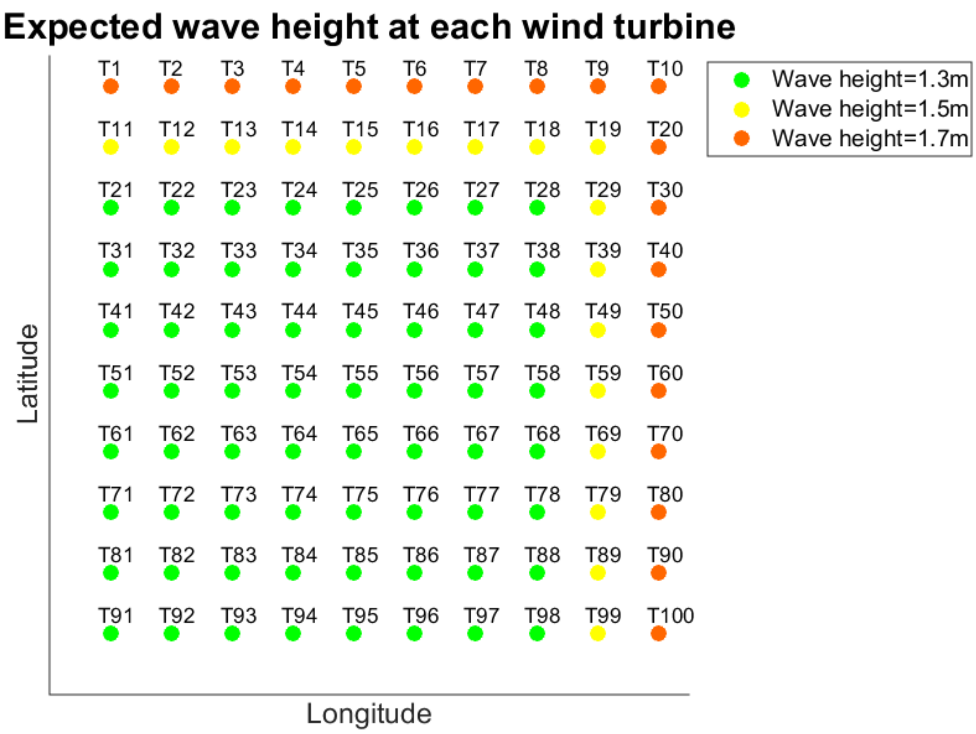

Figure 6.1. Variable wave field used in Case Study 1 (winter day).

In Case Study 1, the operators have five vessels available to them; the vessel properties, including speed and capacity are shown in Table 6.4. Each vessel's probability of successful transfer of technicians onto a turbine in a given significant wave height is provided in Table 6.5.

Table 6.4. Vessel properties used in Case Study 1.

Vessel ID	Crew capacity	Speed (km/h)	Fuel consumption (£'000/km)	Charter cost (£'000/day)	Load capacity (kg)
1	12	48	0.01	0	20,000
2	12	48	0.01	20	20,000
3	12	37	0.006	0	15,000
4	12	37	0.006	0	15,000
5	12	37	0.006	10	15,000

Note that two types of vessels are available to operators; fast and capable vessels 1 and 2 are referred to as "Class 1" vessels and standard CTVs (vessels 3-5), referred to as "Class 2" vessels (as discussed in Section 2.2.3). It is assumed that three of the vessels were owned (or chartered on a long-term basis), meaning that no charter cost will be incurred if those vessels are used on the day. While Dalgic et al. [46] and Dinwoodie et al. [39] reported CTV charter rates of £1,750-£3,000 per day for a standard CTV, prices on the spot market (e.g. if decision of whether to use a vessel or not is made hours before the vessel is dispatched) will inevitably be higher. It is assumed that vessels 2 and 5 can be hired out at a charge of £20,000 and £10,000 for an additional Class 1 or 2 vessel respectively.

Carrying capacity and speed of Class 2 vessel are based on the standard CTV widely used in the offshore wind industry, as described by Dinwoodie et al. [39]. Properties of the Class 1 vessels are based on the Seacat Intrepid 26m vessel[37]. Fuel consumption and probabilities of successful transfer inputs were provided by a major UK offshore wind farm operator.

In Case Study 2, wind farm operators have an additional Class 1 vessel available to them. Unlike Case Study 1, cost of all vessels are set to zero to investigate the effect free vessel hire has on the policy recommended by the tool. All other vessel properties, including fuel consumption are unchanged from Case Study 1.

Table 6.5. Probability of successful technician transfer in a given significant wave height, for a given vessel.

Vessel	Hs<1.4m	1.4 ≤ Hs < 1.6m	1.6 ≤ Hs < 1.8m	1.8 ≤ Hs < 2m	Hs > 2m
1	1	1	0.75	0.5	0
2	1	1	0.75	0.5	0
3	1	0.8	0.5	0	0
4	1	0.8	0.5	0	0
5	1	0.8	0.5	0	0

Table 6.5 shows each vessel's probability of transfer in a given significant wave height. These values were provided by a UK wind farm operator during a site visit (discussed in Section 7.5). In the winter Case Study, transfer using Class 2 vessels is hindered at 36 out of 100 turbines (forecasted significant wave height is shown in Figure 6.1). Access using more capable Class 1 vessels is only affected at 19 turbines experiencing significant wave heights of 1.7m.

The user is able to define any desired normal or gamma distributions, which reflect the probability distributions of maintenance task durations. To illustrate the effect of using different gamma distributions as inputs, different shape and scale parameters are used in Case Studies 1 and 2. A summary of parameters used in both case studies, for all types of maintenance action, are shown in Table I.4 in Appendix I. Logistics Model Inputs to Case Studies 1 and 2. Gamma distributions with positive skewness

[37] Details available on: http://www.seacatservices.co.uk/library/vessels/26m_spec_sheet.pdf. Accessed on 20/11/2017.

are used in both Case Studies, as discussed in Section 4.2.4. The spread on possible maintenance task durations in Case 1 is much larger than Case 2, as shown in Figure 6.2, hindering the process of planning vessel routing.

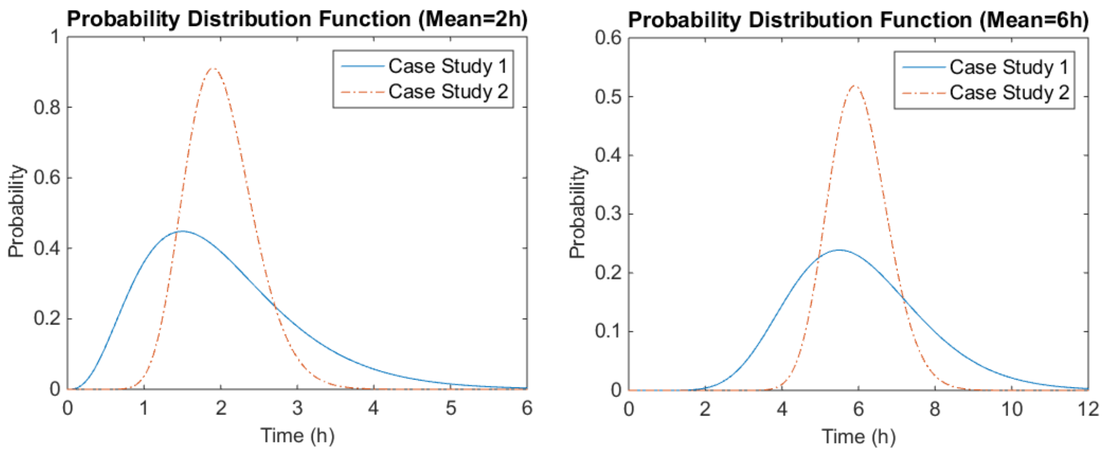

Figure 6.2. Comparison of the PDFs representing the expected maintenance task duration of manual service (left) and medium repair (right) in Case Studies 1 and 2.

The maximum simulation time for both Case Studies is capped at 5 minutes, which is short enough to be practical for real world application (considering the problem may need to be solved multiple times with different risk aversion factors). In this time, the number of policies generated can reach 5-6 million. However, to ensure that time limit is not breached, 4.8 million is chosen as the number of policies generated in both cases. The tier limits (their use is demonstrated in Figure 5.10) used to generate 4.8 million policies in each of the case studies are shown in Table 6.6. Taking winter Case Study as an example, each of the 500 highest value policies are matched with each of the 80 highest remaining policies and each of those is matched with 30… etc. There is no Tier 6 limit in Case Study 1 as there are only 5 vessels available to the user on the day.

Table 6.6. Tier limits used in both case studies.

Case\Limit	Tier 1	Tier 2	Tier 3	Tier 4	Tier 5	Tier 6
Case 1 - Winter	500	80	30	4	1	N/A
Case 2 - Summer	100	40	25	12	4	1

Note that to date, the only criteria for choosing individual tier limits was that they decrease with increasing tier number (for best algorithm performance) and that their product equals to 4.8 million. Performing an optimisation exercise to develop universal guidelines for choosing optimal the ratios between tiers may lead to enhanced CMA performance, as discussed in more detail in Section 8.3.2.

6.2 Results for Case Study 1: Winter Day

This case study is solved six times, using six different risk aversion factors, ranging from 0 to 10 (in intervals of 2). By choosing such a wide range of values, the effects of varying risk aversion factor on the policies produced by the model are illustrated. Setting a risk aversion factor as high as 10 would, in most cases, be excessive and result in policies which do not fully utilise the resources available. This is demonstrated both in Section 6.2.1, where model outputs are discussed and in Appendix G. Example of Cluster Value Calculation Using Low and High Risk Aversion Factors, where a numerical example is provided illustrating the effect high risk aversion factor has on cluster's value.

Once the user specifies all inputs, the solution procedure can be initiated. Here, a different simulation was run for each risk aversion factor, however the model can be set up to run multiple back-to-front simulations in one go. The tool was run on a 3.4GHz i7-3770 CPU with 8GB of RAM and 64-bit Windows 7 operating system. The average computational time across all cases was 260.1 seconds; a breakdown of computational times is provided in Table 7.7.

The first output presented to the user is a map of the wind farm showing turbines requiring maintenance, with colour-coded expected task durations, as shown in Figure 6.3. Upon each simulation's completion, the user is presented with a range of outputs, which include a list of turbines to be visited by each vessel (as shown in Figure 6.8), a map of the vessel routing plan (Figure 6.6) and additional visualisations such as value functions (discussed in more detail in Section 6.2.3) and Gantt charts for each vessel (Figure 6.14).

For clarity, this section is focused on cases A, C and E, computed for risk aversion factors of 0, 4 and 8 respectively. Outputs from those cases are summarised in Table 6.7. Full results for all cases (i.e. A-F) are presented in Table J.1 in Appendix J. Logistics Model Outputs: Winter Case Study. Cases B and D were not discussed here as the policies generated in those runs are very similar to case C. The policy generated for Case F is briefly discussed in the following section, but due to its low value it would be an unlikely contender to be selected by the user as their preferred policy.

The maximum number of turbines to be visited in all cases is 13, despite there being 14 turbines requiring maintenance. This is caused by the negative reward of retrofit action on WT21, calculated in Chapter 3 as -£2,100. The model was discouraged from selecting this turbine, as maintaining it in the future, rather than today, would be more beneficial in the long term (due to high wind speed today and the preventative nature of the task).

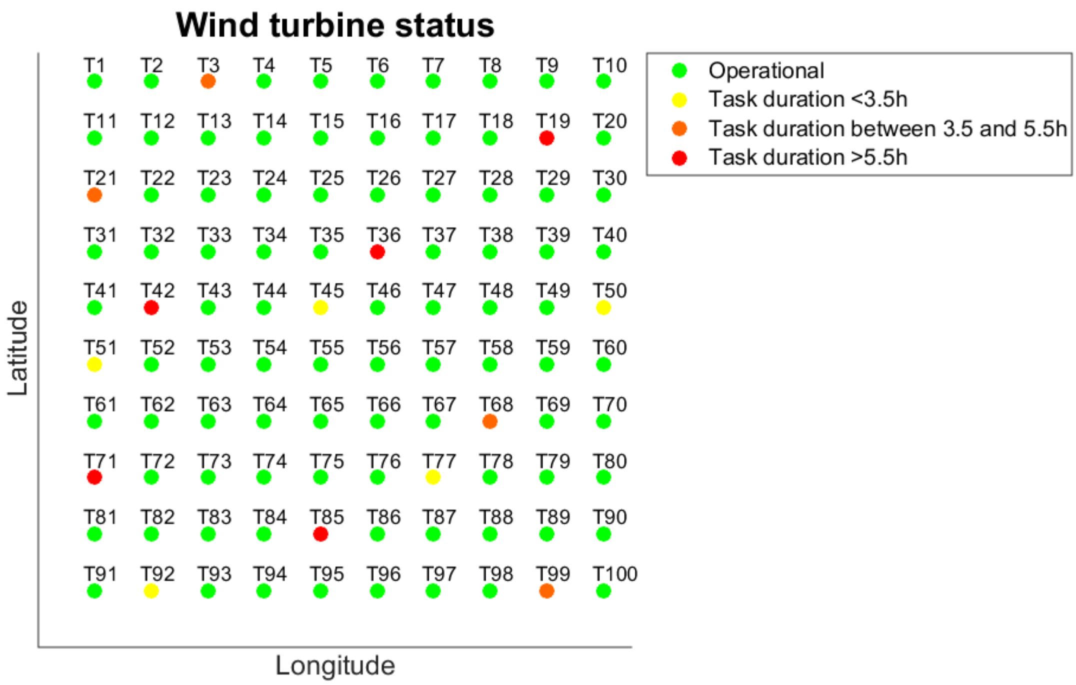

Figure 6.3. Wind turbine status (in terms of the expected maintenance duration) in Case Study 1.

As the risk aversion factor (Y) increases, the planned number of turbines to be visited decreases. Cases A and C aimed to visit 13 turbines, this number stood at 11 for Case E. With increasing risk aversion factor, the tool selects policies with higher probability of visiting all turbines scheduled to be maintained. This is achieved by reduction in the number of turbines to be visited, or by choosing to visit turbines which take a shorter time to maintain. As a result, the expected policy value decreases with increasing Y.

The number of vessels used in Case A is four; the minimum number which enables visiting all 13 turbines. In Cases C and E, five vessels are used, despite the charter rate of £10,000 per day and the additional fuel costs associated with use of the fifth vessel. Visiting all the turbines with five, rather than four vessels, spreads the workload and increases the average slack time at the end of the day, lowering the probability of unsuccessful maintenance actions due to tasks taking longer than expected.

Table 6.7. Summary of winter Case Study results.

	Case A	Case C	Case E
Risk aversion factor (Y)	0	4	8
Planned number of turbines to be repaired (/14)	13	13	11
Number of vessels used	4	5	5
Computational time (s)	250.1	255.8	243.2
Expected policy value (not including value added due to a non-zero Y) (£ '000)	1301.1	1289.9	1126.1
Number of technicians required to carry out all maintenance actions	31	33	27
Mean policy time (h)	10.69	10.17	9.78
From Monte Carlo simulation (as described in Section 5.4):			
Average number of turbines actually maintained (/14)	7.1	8.1	7.4
Maintenance actions not completed due to repairs taking longer than expected	4	3.4	2.1
Turbines not repaired due to incorrect diagnosis	0.8	0.8	0.6
Turbines not repaired due to unsuccessful transfer	1.1	0.7	0.9

The last 4 rows of Table 6.7 contain the results of Monte Carlo analysis, which estimates the average number of turbines successfully maintained once the user-specified uncertainties are realised. This methodology used to obtain this number is described in Section 5.4. If the policy generated in Case A was implemented, maintenance would be completed on an average of 7.1 out of 13 turbines. This is the lowest value out of the three cases. The breakdown provided in the three last rows of Table 6.7 reveals that the main reason for unsuccessful maintenance across all cases is tasks taking longer than expected. This is expected, considering the high uncertainty associated with task durations (as shown in Figure 6.2).

In the next subsection, results of the Monte Carlo analysis are discussed in more detail. This is followed by an in-depth analysis of policies A and C, demonstrating the advantages of using a non-zero risk aversion factors.

6.2.1 Discussion of the Monte Carlo Analysis Results

A histogram summarising the results of the Monte Carlo analysis is shown in Figure 6.4. On the x-axis is the number of turbines maintained in a given policy, y-axis displays the total number of occurrences (out of 10,000 Monte Carlo iterations) of each x-axis quantity. Policy A has the highest number of occurrences in which between one and five turbines were maintained. This is a disappointing result, as in approximately 20% of the Monte Carlo iterations, only 5 or less (out of 14) turbines are maintained. On the other end of the graph, Case C ensures the highest probability of maintaining 10 or more turbines. As expected, the policy created in Case E is never capable of maintaining more than 11 turbines, as the plan was to only visit 11 turbines.

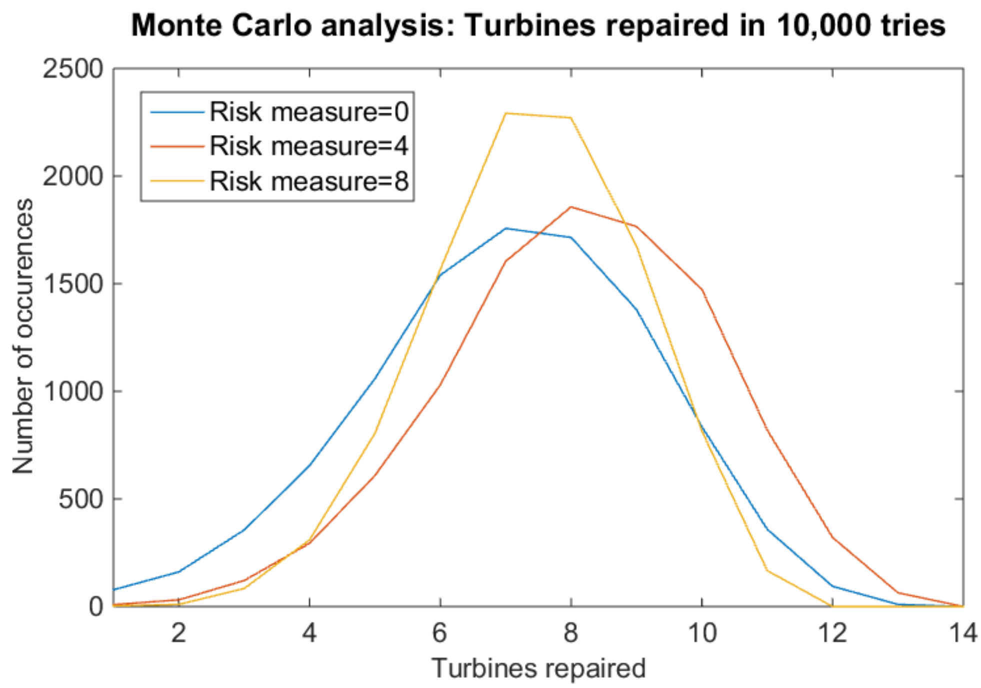

Figure 6.4. Breakdown of the total number of occurrences of each quantity of turbines repaired for policies with varying risk aversion factor.

Comparing the average number of turbines maintained in Case A and E, the latter is more successful despite aiming to visit fewer turbines to begin with. The first reason for this is the use of an additional vessel. Spreading the workload across five, rather than four vessels creates additional slack time at the end of the day, reducing the impact of tasks taking longer than expected. Second reason for Case E being more successful is that the two turbines dropped are medium repairs. This results in significant reduction in crew-hours[38] worked, as shown in Figure 6.5. Planning to complete 12 crew-hours fewer yields an improved success rate. However, this may not be the ideal long term strategy; continually putting off difficult maintenance actions can lead to accumulation of medium repairs, potentially reducing the revenue generated by the wind farm.

[38] Crew-hours, as defined in Definitions Section, are calculated by summing the expected duration of tasks completed in a given policy.

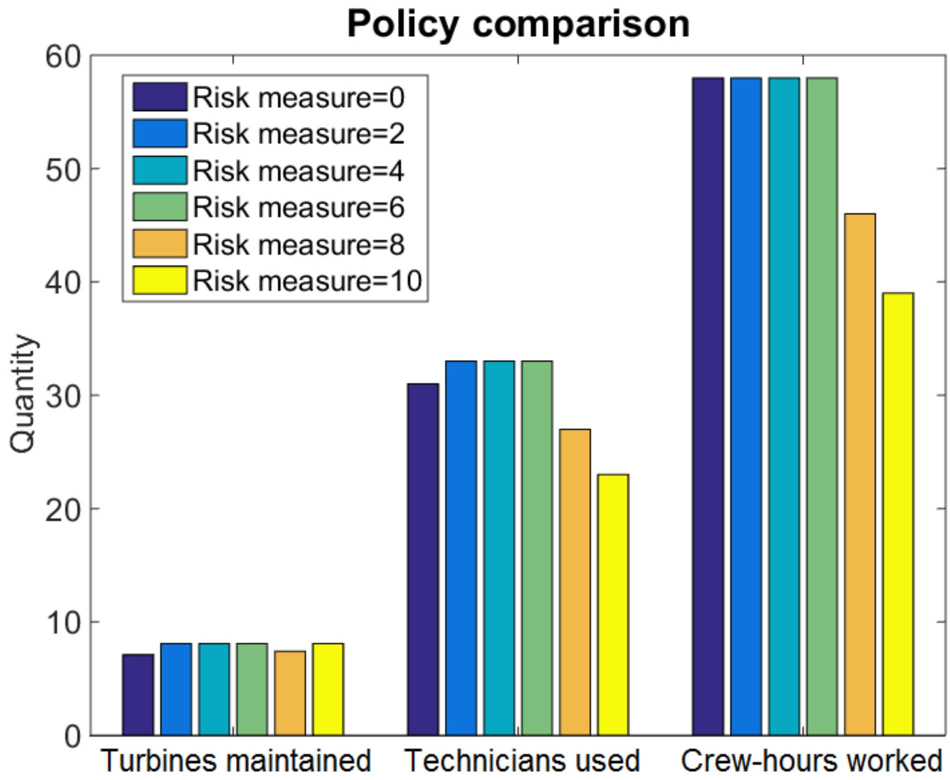

Figure 6.5. Comparison of policies generated in Cases A-F. Note: Crew-hours worked represent the planned value, not actual.

The reduced number of crew-hours of work planned in Case E leads to reduced demand for technicians: only 27 were required compared to 33 in Case C. In the long term, minimising the number of technicians required to complete maintenance actions is certainly an advantage, as overheads are reduced. However, reduction in Case E was achieved by delaying medium repairs until a later date, which does not necessarily mean long term savings could be achieved. Furthermore, as discussed in Section 2.2.1, planning offshore maintenance often takes place hours before the policy begins. In this example, it was assumed that 35 technicians would be available. Last minute change to reduce the number of technicians by 8, if policy from Case E was selected, would result in significant changes to their shift pattern.

The Monte Carlo analysis also revealed that the number of maintenance actions failed due to unsuccessful transfer is highest in Case A. This is expected as using a risk aversion factor equal to 0 provided no incentive for using more capable vessels to visit turbines affected by higher waves. This is discussed in more detail in Section 6.2.2.

The results shown in Table 6.7, Figure 6.5 and the above discussion would suggest that policy created in Case C would likely be the best choice out of the six cases.

Although it would cost £11,300 more than Case A (£10,000 additional vessel charter plus £1,300 in fuel costs), it would most likely result in an additional turbine being successfully maintained. Policies generated using risk aversion factor of 8 or greater significantly under-utilise the technicians and yield policies which avoid visits to turbines time consuming tasks.

6.2.2 Discussion of Case A and C Policies

Figure 6.6 shows the vessel dispatch plan for Case A. Class 1 vessels, i.e. vessels 1 and 2, are both assigned to visit 3 turbines each. Given that 4 vessels in total are used, the average number of turbines assigned to a vessel across all vessel types in Case A is 3.25. The reason for lower utilisation rate of more capable vessels compared to Class 2 vessels (3 vs. 3.25), is their increased fuel cost. Utilisation rate of Class 1 vessels in Case C is significantly higher at 3.5 turbines per Class 1 vessel, especially when compared to the average number of turbines per vessel which amounts to 2.6.

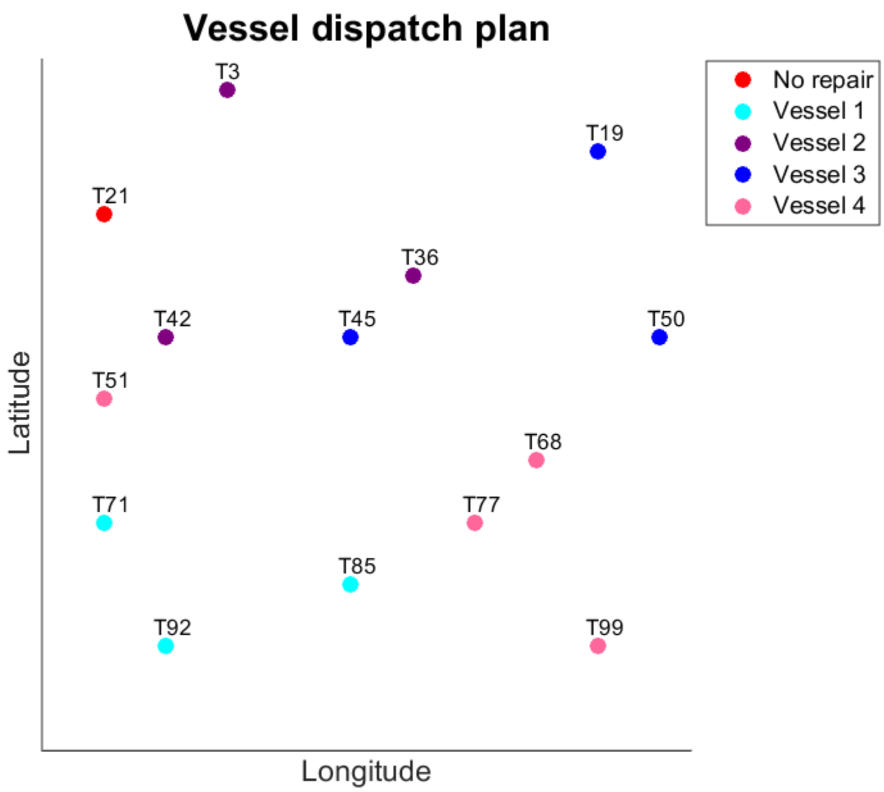

Figure 6.6. Vessel dispatch plan for Case A.

In Case A, only one out of four turbines affected by high waves[39] is visited by Class 1 vessel (T3, as shown in Figure 6.6). In Case C, this number stands at three, which resulted in a significant decrease in the number of unsuccessful transfers (from 1.1 to 0.7), as shown in the last row of Table 6.7. In Case C, the increased fuel cost is insignificant[40] compared to the benefits resulting from higher utilisation of Class 1 vessels, such as the improved transfer capability at turbines affected by higher significant wave height.

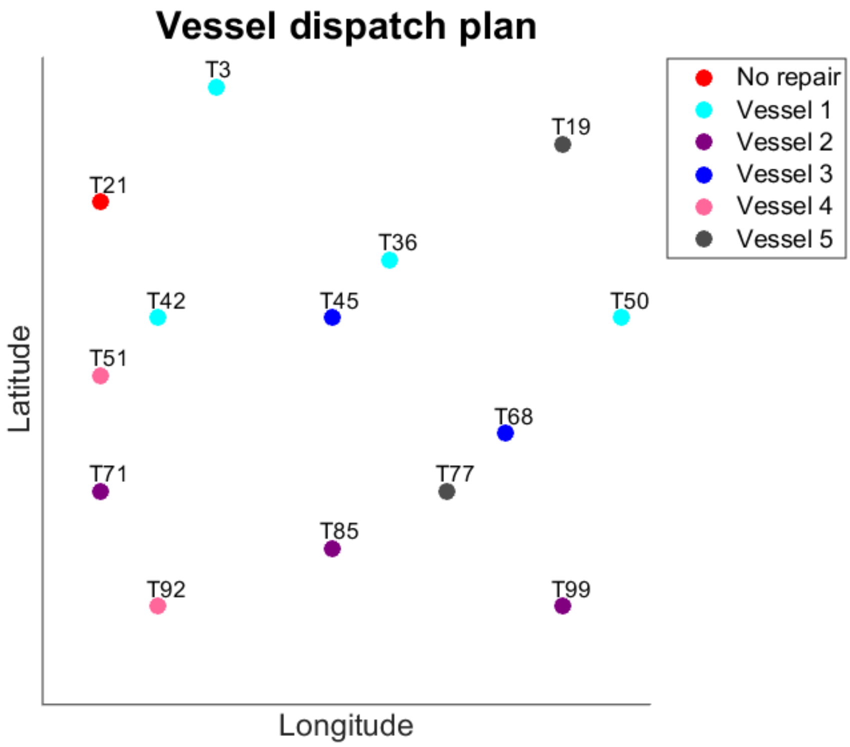

Figure 6.7. Vessel dispatch plan for Case C.

The number of maintenance tasks which were unsuccessful due to repairs taking longer than expected is higher for Case A compared to Case C (4 for the former and 3.4 for the latter). There are two reasons for this difference. First, two additional technicians are used in Case C, reducing the policy time of one of the vessels. Second, the addition of the 5th vessel results in significant policy time decreases on the remaining 4 boats. This can be seen in row 7 of Table 6.7 – the average policy time in Case C is over half an hour shorter compared to Case A. Having additional slack time

[39] A map of expected significant wave height for all turbines is shown in Figure 6.1.
[40] Fuel cost in Case A: £5,760; Case C: £7,190 (difference: £1,430).

at the end of the day means that maintenance tasks are more likely to be completed even if some actions take longer than expected.

Comparing the two policies shown in Figure 6.6 and Figure 6.7, the former features clusters of turbines located close to each other being serviced by the same vessel (particularly for vessels 1 and 2, which have higher fuel costs). The latter graph showing Case C policy features vessels visiting turbines scattered across wind farm. Geographical locations of turbines are no longer a key optimisation objectives, as the fuel cost penalty for increased distance covered by vessels is negligible compared to incentives arising from non-zero risk aversion factor (Equation 5.10).

The tool suggests an order of turbine visits, which is displayed to the user along with additional information, such as policy time for each vessel and the probability of successfully maintaining all turbines in a cluster (Figure 6.8).

The number of technician crews each vessel is carrying can be deduced from the turbine visit order, as shown in Figure 6.8. Consider the recommended visit order for Vessel 4. The first stop is always a drop off (T92) and since the second stop is at a different turbine (T51), it is also a drop off. From this, it can be concluded that vessel 4 is carrying two crews of technicians. The following order of visits: T92-T92-T51-T51 would indicate that the second stop is a pick-up, meaning that the vessel is carrying only one team of technicians.

Table 6.8. Order of technician drop offs for vessel 1 in Case C.

Turbine	Task	Duration (h)	Order of visit
T36	Manual reset and minor repair	6.5	1
T42	Medium repair	6	2
T3	Minor repair	5	3
T50	Grease top-up (3)	3	4

Consider the order of turbine visits for Vessel 1 in Case C. For clarity, the order of drop offs is provided in Table 6.8 alongside with the expected durations of each maintenance task. The technicians are dropped off in an order from the longest expected duration to the shortest, minimising the overall policy time. A more in-depth analysis of the order of wind turbine visits recommended by the tool, including the pick-up order, is provided in Section 6.3.1.

```
Dispatch vessel 1 to:
Wind turbine T3    (Minor repair)
Wind turbine T36    (Manual reset and minor repair)
Wind turbine T42    (Medium repair (3))
Wind turbine T50    (GTU (3))
Gantt Chart is located in Sheet 10.
Policy time is 10.93 hours.
Probability of successfully carrying out all tasks in this policy is 4.8654%
Vessel 1 order:
    'T36'    'T42'    'T3'    'T50'    'T50'    'T3'    'T42'    'T36'

Dispatch vessel 2 to:
Wind turbine T71    (Medium repair (3) (no time to fix minor repair))
Wind turbine T85    (Medium repair (4) (High performance))
Wind turbine T99    (GTU (4) and manual reset)
Gantt Chart is located in Sheet 6.
Policy time is 10.74 hours.
Probability of successfully carrying out all tasks in this policy is 10.9074%
Vessel 2 order:
    'T85'    'T71'    'T99'    'T99'    'T85'    'T71'

Dispatch vessel 3 to:
Wind turbine T45    (Manual reset (High performance))
Wind turbine T68    (High priority repair)
Gantt Chart is located in Sheet 3.
Policy time is 10 hours.
Probability of successfully carrying out all tasks in this policy is 64.7218%
Vessel 3 order:
    'T68'    'T45'    'T45'    'T68'

Dispatch vessel 4 to:
Wind turbine T51    (Manual reset)
Wind turbine T92    (GTU (2) (High performance))
Gantt Chart is located in Sheet 3.
Policy time is 8.36 hours.
Probability of successfully carrying out all tasks in this policy is 74.2906%
Vessel 4 order:
    'T92'    'T51'    'T51'    'T92'

Dispatch vessel 5 to:
Wind turbine T19    (Medium repair (2))
Wind turbine T77    (GTU (2))
Gantt Chart is located in Sheet 3.
Policy time is 10.78 hours.
Probability of successfully carrying out all tasks in this policy is 37.8661%
Vessel 5 order:
    'T19'    'T77'    'T77'    'T19'
```

Figure 6.8. Matlab-generated manifest including the recommended order of wind turbine pick-ups and drop-offs (Case C).

6.2.3 Plotting Value Functions

One of the by-products of the proposed heuristic approach is a high volume of policies (4.8 million generated in this Case Study; however, not all of those are unique[41]). Information contained in the sub-optimal policies may be useful to gain better understanding of how the heuristic arrives at the final solution.

Policy value can be plotted against iteration number, as shown in Figure 6.9 (a) and (b). There are two differences between the two plots. First, the length of x-axis in (a) only covers the first 50 data points, while (b) zooms out to provide a view of 24,000 policies. Second, point markers are used instead of lines in (b). The latter graph only contains the first 24,000 policies (out of 4.8 million); this is both for clarity and due to very high computational effort required to plot millions of data points on a graph. A different approach was chosen in (c), where policy value was plotted against the number of technicians used and policy time (number of points in this graph was also restricted to 24,000).

It is unlikely that either plot presented in Figure 6.9 would be useful to a wind farm operator. There seems to be no connection between adjacent iterations; the value variation between iterations seems random, despite the fact that most adjacent policies share multiple clusters[42].

As discussed in Section 4.2.5, Pareto graphs are an effective tool for visualising trade-offs of solutions to problems with multiple objectives. The two key objectives in the problem solved in this Case Study are maximisation of policy value and maximisation of the probability of maintaining all turbines in a policy. In the graph shown in Figure 6.10, the two objectives are plotted on x and y-axis respectively. The following procedure is used to create the Pareto graph:

1) Take 10,000 highest value (including added term due to probability) policies from Cases A, C, E and F.
2) Select every 50th policy in each of the cases, yielding 200 data points per case. This step reduces the number of points on the graph for clarity.
3) Plot selected data points, using the actual value (excluding added term due to probability) on the x-axis and probability of maintaining all turbines in a policy, as defined in Equation 5.9, on the y-axis.

---

[41] Consider the policy generated in Case A; another policy may exist with turbines to be visited by Vessels 1 and 2 swapped between them. Since both vessels are the same, the two policies would not differ on value, turbine assignment or time taken.

[42] The iteration generation procedure is described in Section 5.3.1.

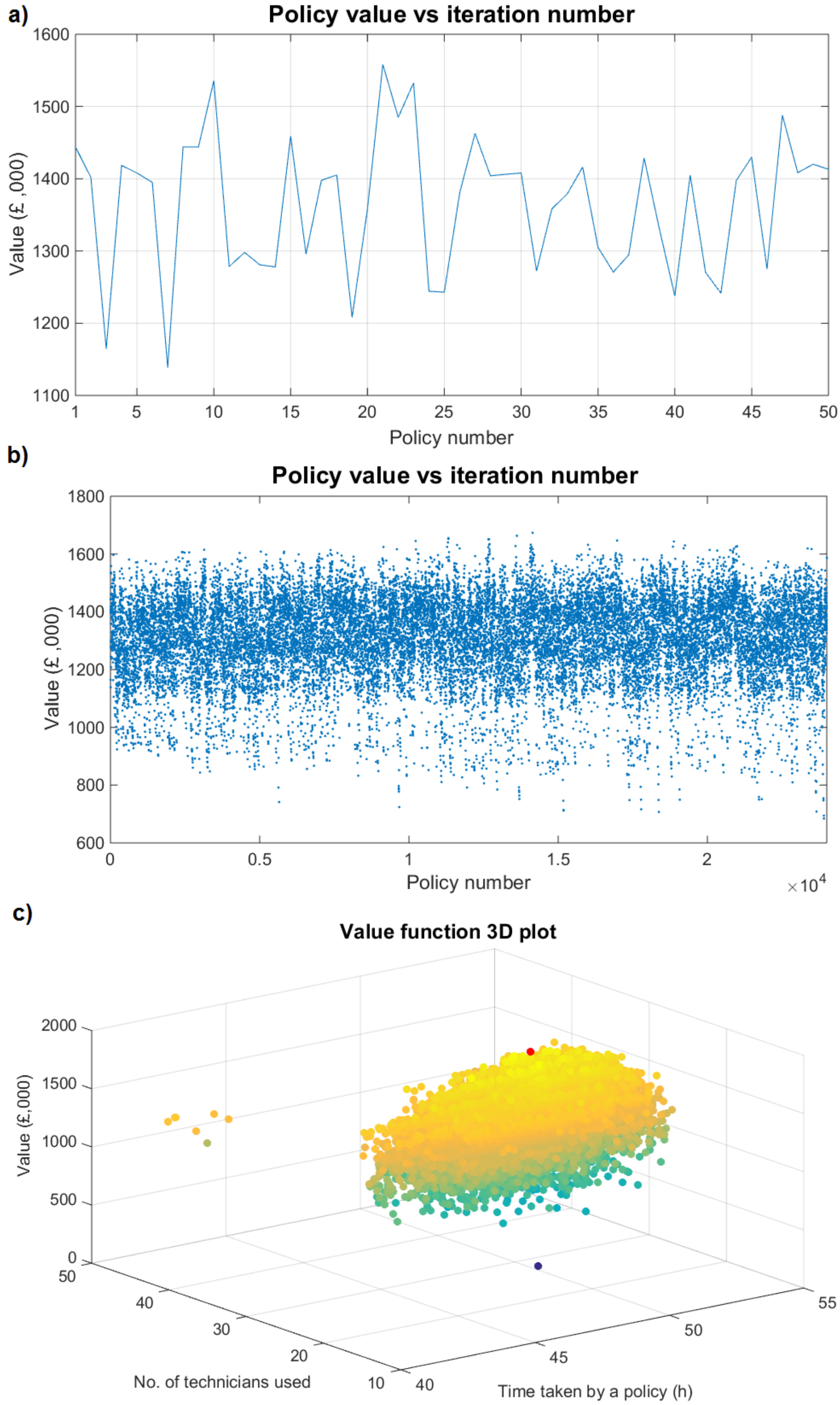

Figure 6.9. Value of policies plotted against iteration number (a-b) and against the number of technicians used and time taken by policy (c). In c), highest value policy is shown in red.

Since only every 50th point was selected to be displayed in Figure 6.10, it is unlikely that optimal policies for each case are present in the graph. Instead, Figure 6.10 shows the breadth of policies created in each Case. A similar analysis was performed for the Summer Case Study (Section 6.3.2); except instead of taking every 50th point, 200 policies with highest values for each Case were shown[43].

Actual policy value was used in the plot, rather than value which includes added term due to probability, as the former allows fair comparison of policies. The latter approach would skew the results, favouring policies created in Cases B-D due to the added probability value term, which is not present in Case A. The y-axis probability was calculated using the following formula:

$$Probability\ of\ maintaining\ all\ turbines = \prod_{c=1}^{c=\varepsilon} Px(c) \qquad (Equation\ 6.1)$$

where c is the cluster identifier, ε is the number of vessels (clusters) in a policy. Px, the probability of completing maintenance on all turbines in a cluster was previously defined in Equation 5.9. Ideally, the number of turbines actually maintained, obtained in the Monte Carlo analysis, would be used as the y-axis of Figure 6.10. It is a better indicator of policy's quality compared to the probability defined in Equation 5.9. However, conducting a separate Monte Carlo Analysis for each solution (i.e. each point on the graph) would be very computationally intensive. Alternatively, a sum, instead of product, of individual cluster probabilities can be plotted on the Pareto graph's y-axis; this is shown in Figure 6.16 in the Summer Case study.

[43] Meaning that the optimal solutions for each of the cases are present in Figure 6.15 but not Figure 6.10.

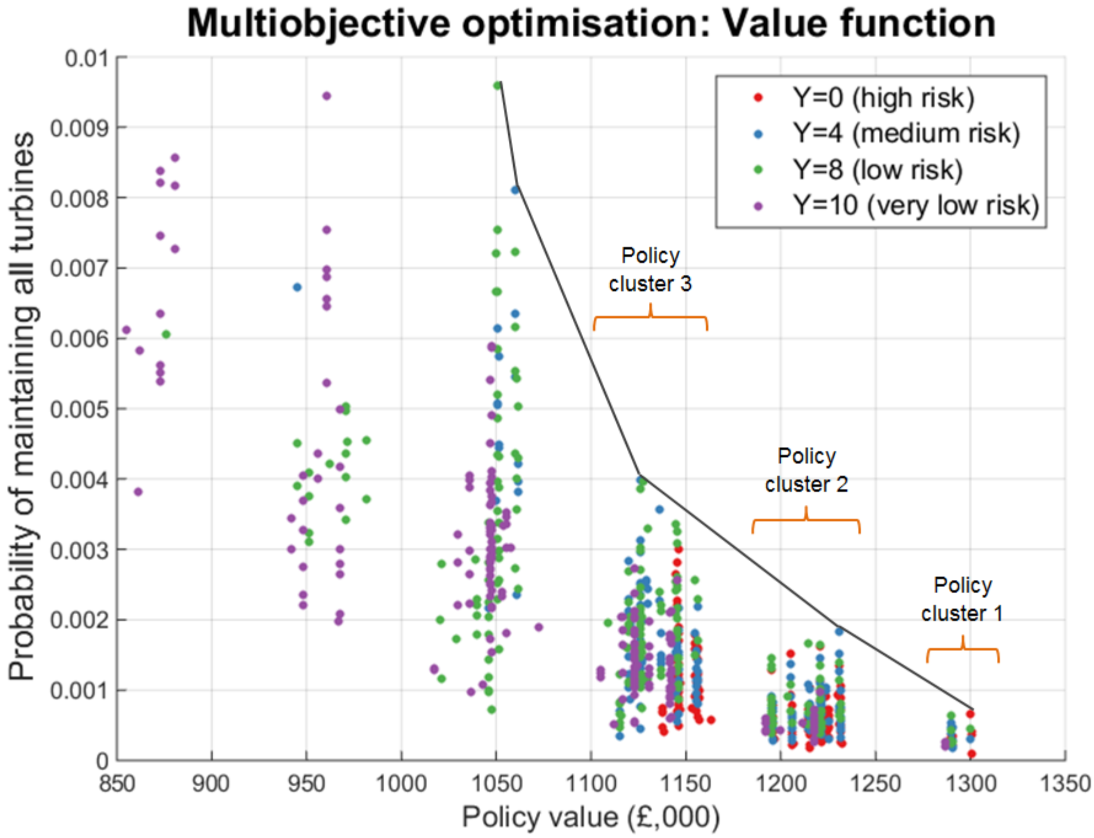

Figure 6.10. Policy value vs probability of maintaining all turbines in a policy.

The graph shown in Figure 6.10 features a number of distinct clusters; three of those are labelled Clusters 1-3. Policies in Cluster 1 all have similar value as all of them aim to visit all of the high value turbines (turbines associated with a reward greater than £80,000). Cluster 2 comprises of policies which only aim to visit 10 out of 11 high reward turbines.

X-axis span of Cluster 2 is significantly wider than Cluster 1 due to a more diverse population of possible turbine reward combinations. For example, Cluster 2 may contain two policies, one does not include a visit to Turbine 51, with a reward of £87,800 while the other does not include a visit to Turbine 85, with a reward of £113,300 (Note: these values originate from Table 3.7). Going from right to left, as the number of high value turbines not visited increases, the possible differences in value also increase, resulting in wider cluster spans.

All of the red markers, i.e. high risk policies generated using a zero risk aversion factor, are located in Clusters 1-3. This is expected, as setting Y to zero encourages high value, low probability of success policies. The space to the left of cluster 3 is mostly populated by green and purple markers, i.e. low risk policies, which were created by incentivising policies with high probability of success. Interestingly, cluster 1 contains all marker colours, demonstrating that medium-to-very low risk aversion factors result in solutions which probe the entire solution state space.

Figure 6.10 features a Pareto front drawn in black, made up of five data points. These five non-dominated solutions (as defined in Section 4.2.5) are Pareto optimal (for the data points shown in the graph). However, the policies constituting the Pareto front cannot be easily analysed; data such as number of technicians used or vessel movement maps would have to be generated manually for each point. From the operator's point of view, the histogram display shown in Figure 6.5 is certainly more useful as it provides a better overview of individual policy details. One of the advantages of the Pareto graph is that can be used to display the value and probability of hundreds of policies; histograms such as Figure 6.5 can only visualise a handful of policies.

Further discussion of the Pareto graph is provided in the Section 6.3.2, which includes plots for data generated in the Summer Case Study.

6.3 Results for Case Study 2: Summer Day

Winter Case Study shows that risk aversion factors greater than 6 produce policies which are unlikely to be favoured by the wind farm operator. In this case study, simulations were run using Y values of 0, 2, 4 and 6. The key difference between the winter and summer Case Studies is that the latter features more turbines needing maintenance (24 vs 14). There is also a severe shortage of technicians in the summer Case Study, making it impossible to service all turbines on day 1.

The number of policies generated by the heuristic is kept at 4.8 million, despite the substantial increase in problem complexity. This causes a drop in result quality; however, the heuristic results were within 3.3% of optimum for all cases, as shown in Table 7.8. Computational time required to produce results remained under 5 minutes for all cases, as shown in Table 6.9.

There are multiple similarities in winter and summer Case Study results. First, setting a risk aversion factor of 0 resulted in a policy which does not utilise all available vessels. Unlike Winter Case study, there is no additional charge for using the 6th vessel here. Despite this, the tool recommends only using 5 vessels in Case A in an attempt to reduce fuel costs.

Table 6.9. Summary of the summer Case Study results.

	Case A	Case B	Case C	Case D
Risk aversion factor (Y)	0	2	4	6
Planned number of turbines to be maintained (/24)	20	19	19	17
Vessels used	5	6	6	6
Expected policy value (£ '000)	2054.2	2043.6	1893.7	1708.9
Policy value including value added due to non-zero Y (£ '000)	N/A	2368.1	2758.2	3255.5
Technicians required to carry out all maintenance actions	45	45	43	37
Crew-hours worked (h)	86.5	83.5	78.5	66.5
Mean policy time (h)	10.9	10.5	10.2	9.9
Simulation time (s)	280.7	264.9	240.8	235.3
From Monte Carlo simulation (as described in Section 5.4):				
Average number of turbines actually maintained (/24)	13.9	15.4	16.2	15.4
Maintenance actions not completed due to tasks taking longer than expected	5.3	2.8	2.1	1
Turbines not maintained due to incorrect diagnosis	0.8	0.8	0.7	0.6
Turbines not maintained due to unsuccessful transfer	0	0	0	0

Further similarities between case studies are the decreasing number of crew-hours worked and decreasing mean policy time with increasing risk aversion factor. These results are expected, as setting higher Y encourages policies with additional slack time at the end of the day, which in turn incentivises carrying out fewer maintenance tasks.

Let us compare the number of actions not completed due to tasks taking longer than expected in Case C policies from both the winter and summer Case Studies. The former stood at 3.4, while the latter was 2.1, despite the fact that the latter policy aimed to visit 6 additional turbines. This significant difference is caused by the definition of task duration PDF (Table I.4), which has a significant impact on the Monte Carlo analysis results.

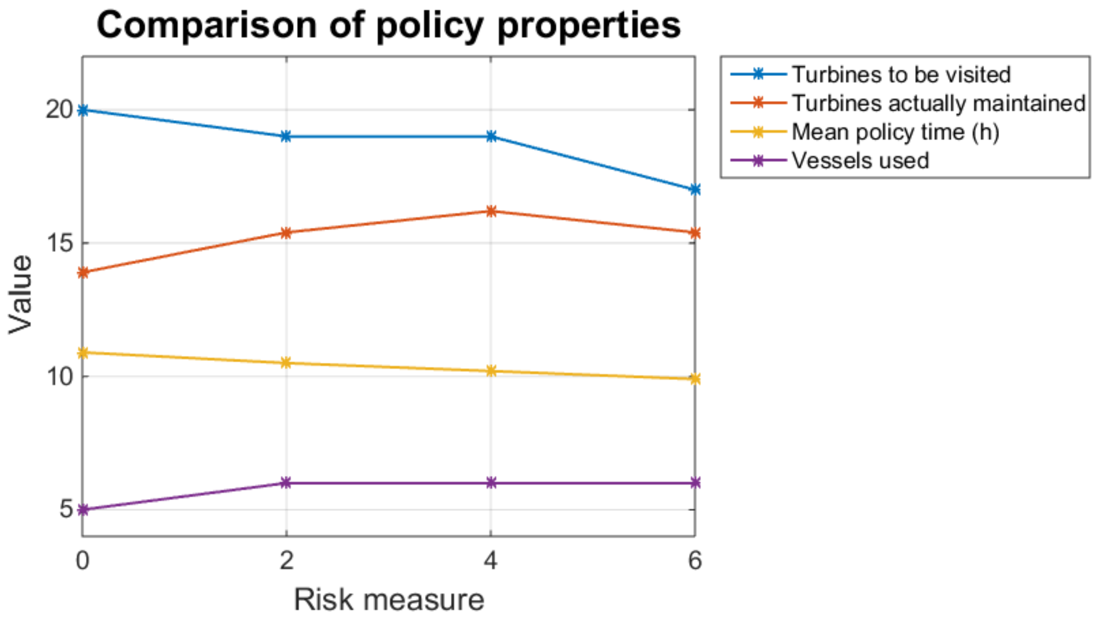

Figure 6.11. Comparison of policies generated in Cased A-D.

A visualisation of some of the summer Case Study results is shown in Figure 6.11. The mean policy time in Case A stands at 10.9, meaning that the average slack time at the end of the day is just 6 minutes. As a result, the number of turbines actually maintained is lowest in Case A; this is also the case in the Winter Case Study. Monte Carlo analysis also shows that no maintenance actions fail due to unsuccessful transfer. This is expected as the significant wave height across the wind farm is set to 1.2m, well within crew transfer capabilities of Class 1 and 2 vessels.

Figure 6.11 clearly shows the decreasing gap between turbines to be visited (in blue) and turbines actually maintained (in red). As expected, policies created using higher risk aversion factors are more effective at completing the planned number of maintenance tasks.

Interestingly, the nature of the problem changes with the risk aversion factor used. In Case A, the problem is severely constrained by the number of technicians available (with a surplus vessel). In Case D, there is a surplus of technicians; the problem is constrained by the number of vessels instead. Permitting use of another vessel would likely see some of the 8 surplus technicians utilised to visit a higher number of turbines.

A map of the wind farm showing locations of maintenance tasks and the policies recommended by the tool in each of the test cases are shown in Figure 6.12.

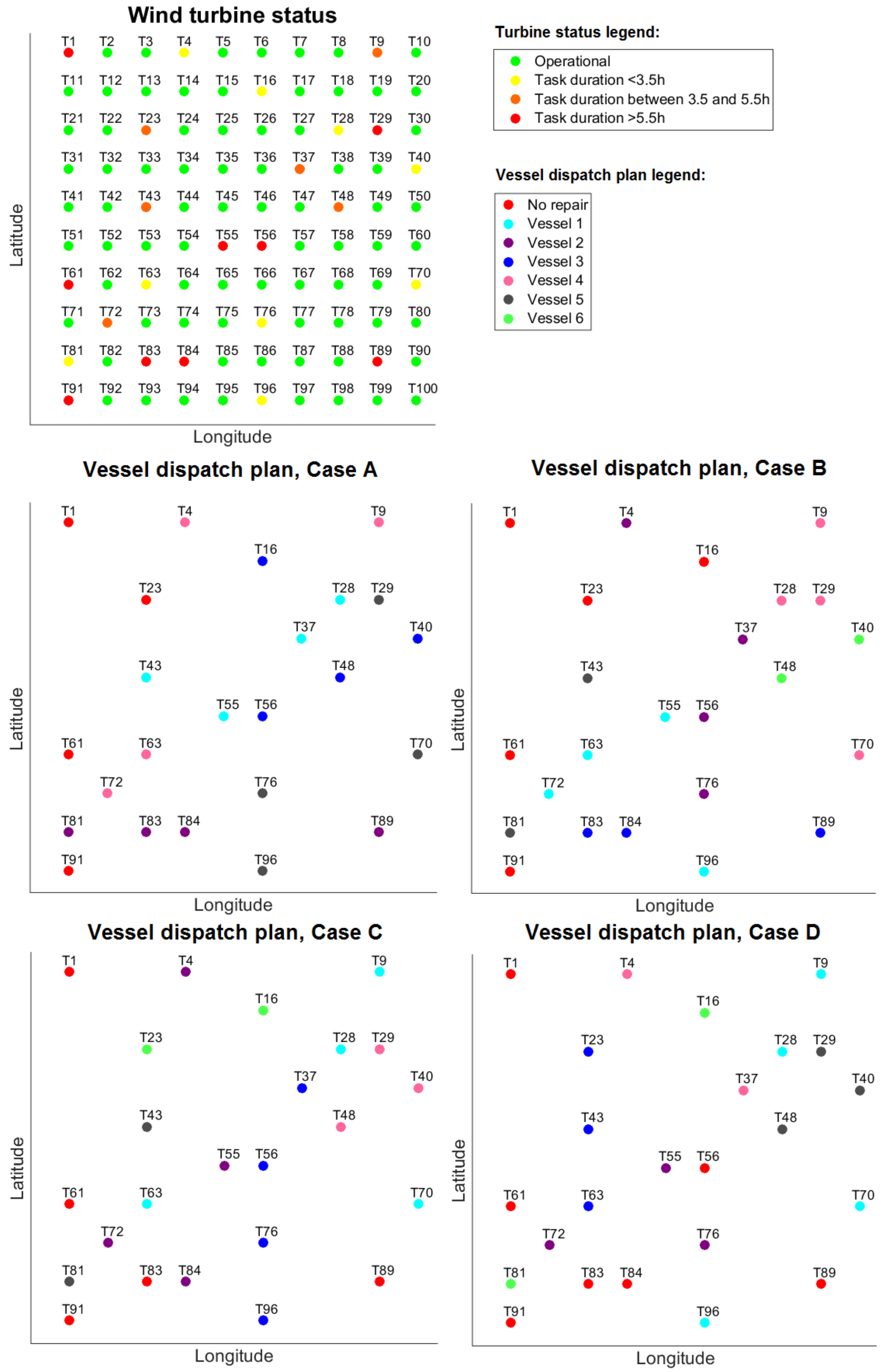

Figure 6.12. Summary of Case A-D vessel dispatch plans.

Details of turbines which were not serviced in one or more cases are shown in Table 6.10. Neither policy recommends visiting turbines 1, 61 and 91. The former two of those three are annual services, without an immediate deadline[44]. Turbine 91 requires a grease top-up, which can be delayed until tomorrow and a retrofit. Those two tasks combined are expected to take 6.5 hours, which is the joint longest duration out of all turbines.

There are two main reasons why these 3 turbines were not visited in either of four cases. First, they are associated with a reward equal to or lower than £15,400; significantly less than the average reward across all turbines (£94,421). Second, tasks on those three turbines are expected to take 6 hours (for annual service tasks) and 6.5 hours for turbine 91. This is significantly higher than the average task duration of 4.5 hours. The tool recognised that dispatching technicians to maintain those three turbines is poor use of technicians' time, given the associated rewards.

Table 6.10. Summary of dropped turbines sorted in order of ascending reward.

Turbine ID	Dropped in	Reward	Description
23	Cases A & B	£4,700	Retrofit
1	**All Cases**	£10,200	Annual service (3 days' work required in the next 10 days)
61	**All Cases**	£10,200	Annual service (3 days' work required in the next 10 days)
16	Case B	£10,700	Grease top-up (no immediate deadline)
91	**All Cases**	£15,400	Grease top-up (no immediate deadline) & retrofit
83	Cases C & D	£98,700	Medium repair (2 days' work required in the next 10 days)
56	Case D	£101,600	Annual service (6 days' work required in the next 10 days)
89	Case D	£101,600	Annual service (6 days' work required in the next 10 days)
84	Case D	£120,200	Medium repair (4 days' work required in the next 10 days)

There is another factor driving the choice of policies recommended by the tool: the turbine's location with respect to O&M base. Among the dropped turbines shown in Table 6.10, there are seven turbines requiring a maintenance task of duration equal to

[44] Details of those maintenance actions and associated rewards are provided in Table I.3 in Appendix I. Logistics Model Inputs to Case Studies 1 and 2.

six or more hours. Six of those turbines also happen to be located furthest away from the O&M base[45]. Furthermore, out of five turbines with expected task duration of 5.5 hours or more closest to O&M base, four are visited in all cases. It is clear that when the tool selects the turbines not to be visited due to resource shortages, the decision is driven not only by task duration and reward, but also the travel time required to reach the asset.

In Case D, the tool recommends dropping seven wind turbines, including four with an above average reward. From Table I.3 in Appendix I. Logistics Model Inputs to Case Studies 1 and 2, these seven turbines are the seven lowest-reward turbines with expected maintenance task duration of 6 hours or more. In this Case, the results were driven by the following logic:

"Do not visit turbines with the longest task duration and lowest value when risk aversion factor is medium-to-high"

However, this logic was never explicitly defined in the tool. It is a result of the way rewards and the value function, which favours policies which are likely to be successful, are defined. Policies involving multiple tasks with an expected duration of 6 hours or more do not allow sufficient slack time[46]. Once the user-specified uncertainties are realised, insufficient policy slack leads to incomplete maintenance actions, as some tasks take longer than expected.

The tool does not always decide to drop low value turbines. Turbine 40, for example, was selected in all cases, despite its low value (£10,700). There are three main reasons for this:

- T40 is located close to the O&M base (3rd closest out of 24)
- Its task duration is below average (3 vs 4.5 hours)
- Only 2 technicians are required to carry out maintenance

The Monte Carlo analysis demonstrates that the most effective policy in terms of turbines actually maintained once the uncertainties are realised is Case C, where the 5 turbines dropped were all tasks with a duration of 6 hours or more. Comparing Case A and C policies, the latter manages to reduce the number of turbines not repaired due to tasks taking longer than expected by three. This is achieved despite only reducing the total number of turbines to be visited by one!

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[45] O&M base was located to the North-East of the wind farm.
[46] Slack time covers both spare time at the end of the day (i.e. policy slack time Ge) and individual task slack time Gi.

One of the main reasons for Case C topping the number of maintenance task completed in the Monte Carlo analysis is effective organisation of work, which maximises slack time. This is partly achieved by higher utilisation rates of the more capable Class 1 vessels, which stands at 4 turbines per vessel compared to 2.33 turbines per Class 2 vessel. Class 1 vessels are assigned to 4 out of 6 longest (5.5 hours or more) tasks. The tool recognises that faster vessels should be assigned to visit more turbines, which resulted in a reduction in mean policy time as shown in Figure 6.11, contributing to the higher number of completed maintenance actions.

In summary, two important conclusions can be derived from this Case Study:

1. When faced with a resource shortage, the tool sensibly selects the maintenance tasks to be dropped. High priority repair, which has to be completed by the end of tomorrow[47], is never dropped. Generally, turbines dropped were characterised by low rewards and high resource requirements. Increasing risk aversion factor encourages dropping turbines with above average rewards, trading off value and crew-hours worked for increased maintenance success rate, which is what it has been designed for.
2. The above shows that rewards generated by the SMDP model, discussed in Chapter 3, are compatible with the logistics model. It is important that the rewards do not dominate the vessel routing decision – while they do influence the results significantly, the priority ranking produced by the SMDP model does not set in stone the turbines to be visited. Vessel dispatch plan is influenced by a multitude of factors, including turbine's location (with respect to O&M base and proximity to other turbines) and duration of the maintenance task; neither of which was considered in the utility value calculation proposed in Chapter 3.

6.3.1 Detailed Analysis of a Single Vessel Route

This section provides a step-by-step analysis of a vessel movement plan produced by the tool. The route analysed was created in Case A, assigned to Vessel 5. It features a fairly complex order of wind turbine visits, with little slack time; a key characteristic defining all Case A policies. Table 6.11 contains a summary of tasks visited by Vessel 5, while Figure 6.13 shows a visualisation of individual vessel stops, including the pick-up and drop-off times. Matlab-generated output summarising Case A policy properties is shown in Figure K.1 in Appendix K. Logistics Model Outputs: Summer Case Study.

[47] As discussed in Section 3.4.1.

Since Case A in the Summer Case Study is severely constrained by the number of technicians, Vessel 5 is only carrying 3 crews of technicians. One of the teams is assigned to complete two tasks with the shortest maintenance duration – T70 and T96. A description of the individual vessel movements shown in Figure 6.13 is provided below.

Table 6.11. Order of wind turbine visits: Case A.

Turbine	Visit order	Task duration	Technicians required	Assigned Crew
T29	1	6	3	Crew 1
T70	2	2	2	Crew 2
T76	3	3	2	Crew 3
T96	4	2	2	Crew 2

Movement 1: The first turbine visited is T29, which also happens to be closest to the O&M base. Expected duration of the medium repair on T29 is 6 hours, the longest of all four turbines. In this case, T29 had to be visited first; it is the first and last stop of the entire route and the policy slack time at the end of the day is only 5 minutes. Had T29 been visited second, or later, technicians would not have sufficient time to complete the medium repair.

Movement 2: The second turbine visited is T70. The closer of the two 2-hour tasks is selected to ensure maintenance begins as early as possible. T76 is not selected as the second stop, despite being the longer task, as both T76 and T96 are to be maintained by the same crew. The combined duration of two 2-hour tasks is significantly longer than the 3 hours required for a grease top-up on T76.

Movement 3: Vessel 5 arrives at T76 at 10:07. Since the crew and equipment transfer from vessel onto the turbine is assumed to take 20 minutes, they will be on the turbine at 10:27, over an hour later than first crew, who were dropped off at T29.

Movement 4: It is 10:27 and Vessel 5 is expected to pick up technicians from T70 at 11:56, when they finish the manual reset. Excluding travel time between T76 and T70, the vessel has an idle time of 1 hour and 18 minutes. Interviews with wind farm operators (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators) revealed that this time may be spent on auxiliary tasks such as cleaning wind turbine transition pieces.

Movement 5: Technicians are picked up from T70 and taken to T76 to complete their second manual reset. This procedure takes 54 minutes: two transfers of 20 minutes and 14 minutes travel time between turbines.

Movement 6: Technicians at T76 are due to be picked up at 13:27, meaning that the vessel will be idle for 32 minutes (excluding travel time) before crew transfer can occur.

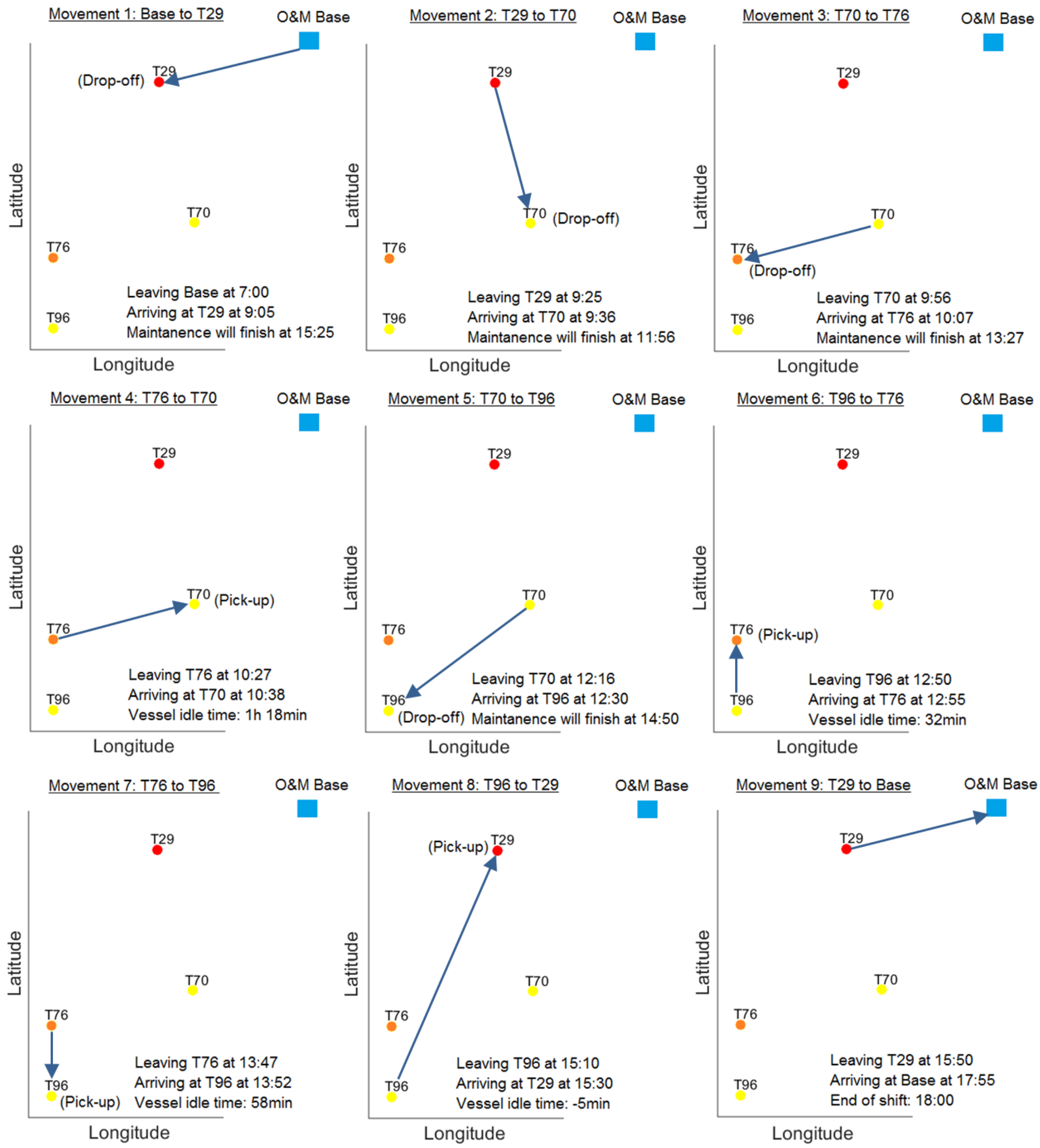

Figure 6.13. Step-by-step vessel movement analysis for vessel 5 in Case A. Legend: turbine in red: 6 hour task, in orange: 3 hour task, in yellow: 2 hour tasks.

Movement 7: Vessel 5 has now picked up technicians from T76. There are two crews of technicians yet to be picked up: Crew 1 at T29, who are set to finish maintenance at 15:25 and Crew 2, who will finish the manual reset at T96 at 14:50. The latter is chosen as the next destination: maintenance at the latter turbine will be finished sooner and it is closer to the vessel's current location. Vessel 5, with one crew on-board arrives at T96 at 13:52, 58 minutes before Crew 2 is set to finish manual reset.

Movement 8: Crew 2 is picked up and Vessel 5 sets off towards T29, where Crew 1 is picked up at 15:30.

Movement 9: Once all crews have been collected, Vessel 5 heads back to O&M port, arriving at 17:55, 5 minutes before the end of the shift.

Figure 6.14 shows the Gantt chart for this policy. Two periods when the vessel is idle can clearly be seen; first just before 12:00 (movement 4) and second just before 15:00 (movement 7). The Gantt chart also helps to visualise the proportion of time spent travelling between the O&M base and wind farm (first and last horizontal bars). An end-of-day Gantt chart could also be created by inputting actual pick up-and drop off times. This would enable comparison of planned and actual policy timings.

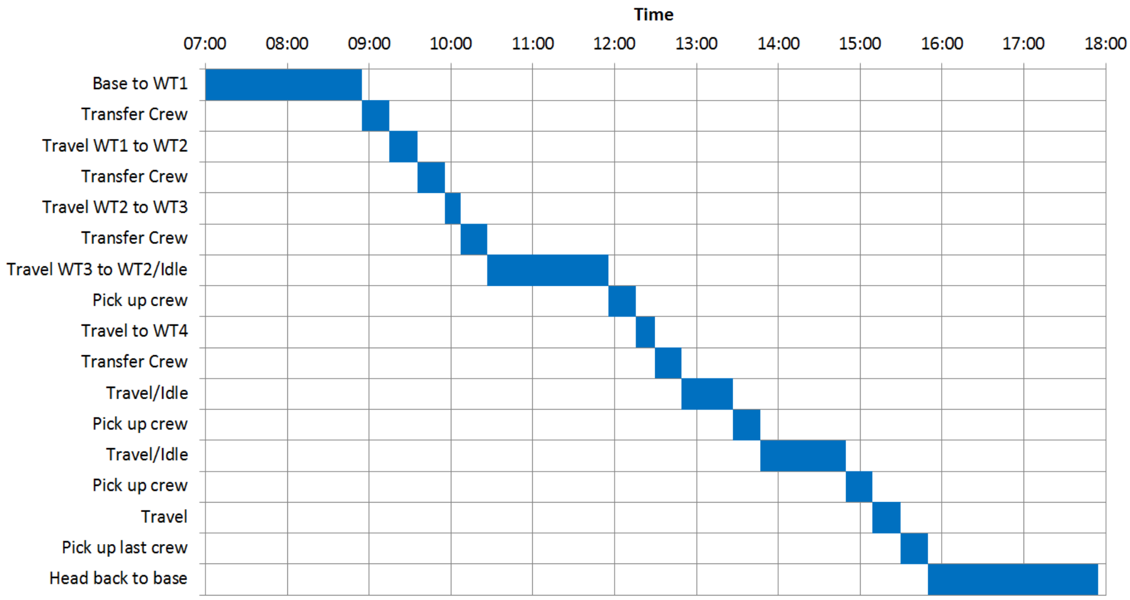

Figure 6.14. Gantt chart visualising the expected pick-up and drop-off times. Note: Gantt chart, unlike Figure 6.13, is one of the tool's automatically generated outputs.

In addition to the automatically generated Gantt chart, the tool's user is displayed with an animation visualising the chosen vessel's step-by-step movement. In future work, the crude animation[48] (screenshots provided in Figure K.2) may be improved to resemble Figure 6.13.

[48] Note: Currently, Matlab is used for animating the policy, however, its capabilities are limited and it is not first-choice software for animation creation.

In total, 13 crew-hours of maintenance are completed on this cluster of 4 turbines. Nearly 1 crew-hour is spent on an idle on vessel. Another 0.1 crew-hour is spent idly at a turbine; as technicians waited to be picked up. The proportion of the idle time to productive time was approximately 8.5% (1.1/13), meaning that crews were carrying out maintenance over 90% of the time (not counting travelling on the vessel and climbing up to the nacelle). Since the operator knows about the idle crew-hours in advance, it can be prevented by assigning additional preventative tasks to idle crews, on the turbines they are assigned to visit.

The sub-problem is a multi-objective optimisation problem, as discussed in Section 5.2.2. The order of wind turbine visits discussed in this section achieved the following objectives:

- Minimised the number of technicians by servicing both manual resets with one crew.
- Minimised policy time by visiting turbines in the order of longest task duration to shortest.
- Minimised fuel cost by minimising distance travelled by the vessel. This was achieved by taking into account wind turbine locations when planning the next stop (as discussed in Movement 2). Note that there were two "repeated" journeys in this policy (journeys between turbines T70 & T76 and T76 & T96 were both covered twice, once each way). Both repeated journeys were also the two shortest possible turbine-to-turbine journeys.

6.3.2 Summer Case Study: Pareto Graphs

In the winter Case Study, a Pareto graph is plotted in Figure 6.10. It was created by taking every 50th policy (out of the top 10,000) created by the CMA to show the breadth of policies generated in each case. In this section, the Pareto graph is created using the same procedure described on page 171, except the top 200 value policies from each case were selected to be plotted. The resulting graph is shown in Figure 6.15.

In Figure 6.15, policies A-D indicated with arrows correspond to the optimal policies selected in each of the cases shown in Table 6.9. It seems that a policy superior to policy D exists, with a similar value but almost double the probability of maintaining all turbines. A comparison of policies D and X is provided in Table 6.12.

Table 6.12 shows that despite the relatively high probability of completing all maintenance actions, the actual number of turbines maintained once the user-specified uncertainties are realised is lower (15 vs 15.4). The policy values including and excluding the probability term are both lower for Policy Z compared to D; clearly the latter policy is superior.

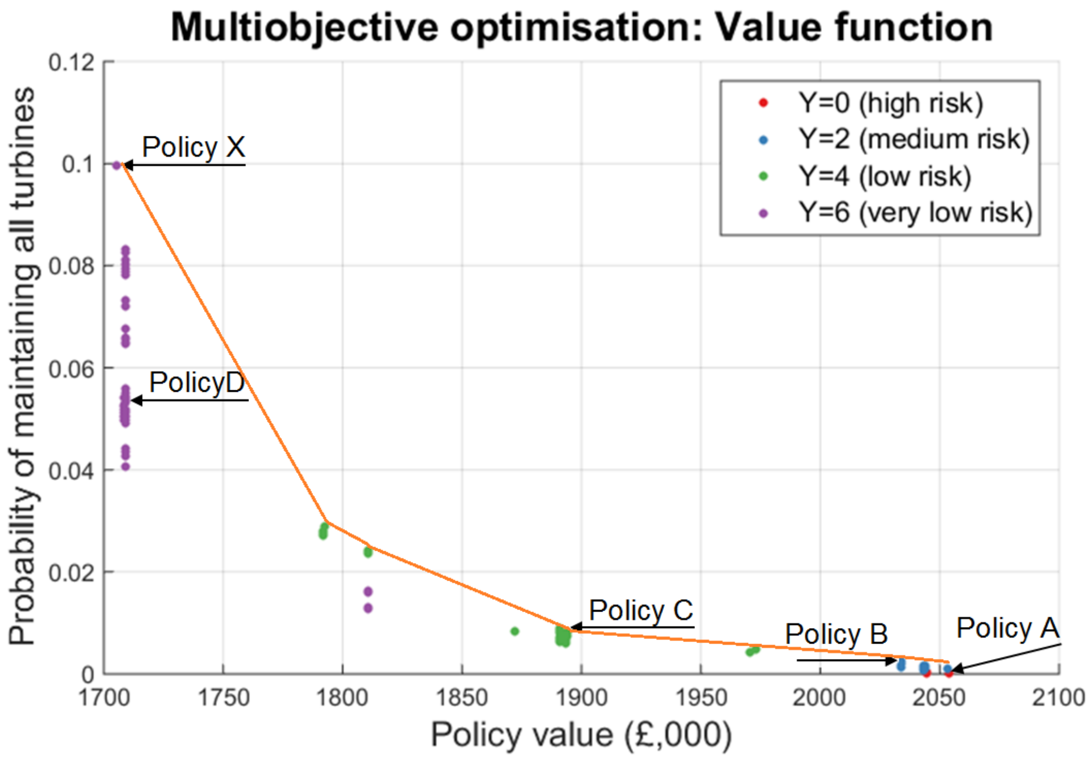

Figure 6.15. Pareto graph, with optimal policies selected in each Case indicated with arrows.

Policy X outperforms D on Pareto graph shown in Figure 6.15 as its range of values of individual cluster probabilities, as shown in Table 6.13, is smaller compared to Policy D. As discussed in footnote 31 on page 143, for two sets of numbers which have the same sum, product of similar numbers is higher than product of dissimilar numbers. This is the case here: overall probability of visiting all turbines is much higher for Policy Z, is much higher, but sums of individual cluster probabilities are similar in both policies.

This example shows that the total probability of completing maintenance on all turbines in the wind farm is not an accurate indicator of policy's real-world robustness to uncertainties. Its value for Policy Z is almost twice as high as Policy D, as shown in the last row of Table 6.13.

Table 6.13 would suggest that a sum of probabilities of maintaining all turbines in individual clusters, rather than a product, may be a better candidate for the y-axis of Pareto graph. However, unlike product, sum of probabilities does not have any meaning. Additionally, policy D's superiority to X was partly caused by the fact that the former planned to complete 17 maintenance tasks compared to 16 for the latter. For an equal value of probability of completing all maintenance tasks, a policy aiming to carry out more tasks is bound to perform better.

Table 6.12. Comparison of Policies D and X.

	Policy D	**Policy X**
Risk aversion factor (Y)	6	6
Planned number of turbines to be repaired (/20)	17	16
Number of vessels used	6	6
Expected policy value (not including value added due to a non-zero Y) (£ '000)	1708.9	1705.4
Policy value (including value added due to a non-zero Y) (£ '000)	3255.5	3223.8
Number of technicians required to carry out all repairs	37	35
Mean policy time (h)	66.5	62.5
Crew-hours worked	9.9	9.9
From Monte Carlo simulation (as described in Section 5.4):		
Average number of turbines actually repaired (/24)	15.4	15
Maintenance actions not completed due to repairs taking longer than expected	1	0.4
Turbines not repaired due to incorrect diagnosis	0.6	0.6
Turbines not repaired due to unsuccessful transfer	0	0

A Pareto graph with a sum of individual cluster probabilities on its y-axis, rather than a product, is shown in Figure 6.16. The red and blue clusters are now isolated, suggesting the 200 highest value policies in Cases A and B were similar. Policy B can be considered superior to A, as a small drop in value results in a large increase in probability.

Similar conclusions were drawn from Table 6.9, which showed that Policy B achieved an average increase of 2.5 turbines maintained by only reducing the number of crew-hours worked by 3.

Table 6.13. Comparison of individual cluster probabilities.

Probability of completing all actions in a cluster	Policy D	Policy X
Vessel 1	0.63	0.72
Vessel 2	0.52	0.52
Vessel 3	0.90	0.51
Vessel 4	0.89	0.89
Vessel 5	0.25	0.68
Vessel 6	0.87	0.87
Sum of probabilities	**4.06**	**4.19**
Product of probabilities	**0.056**	**0.1**

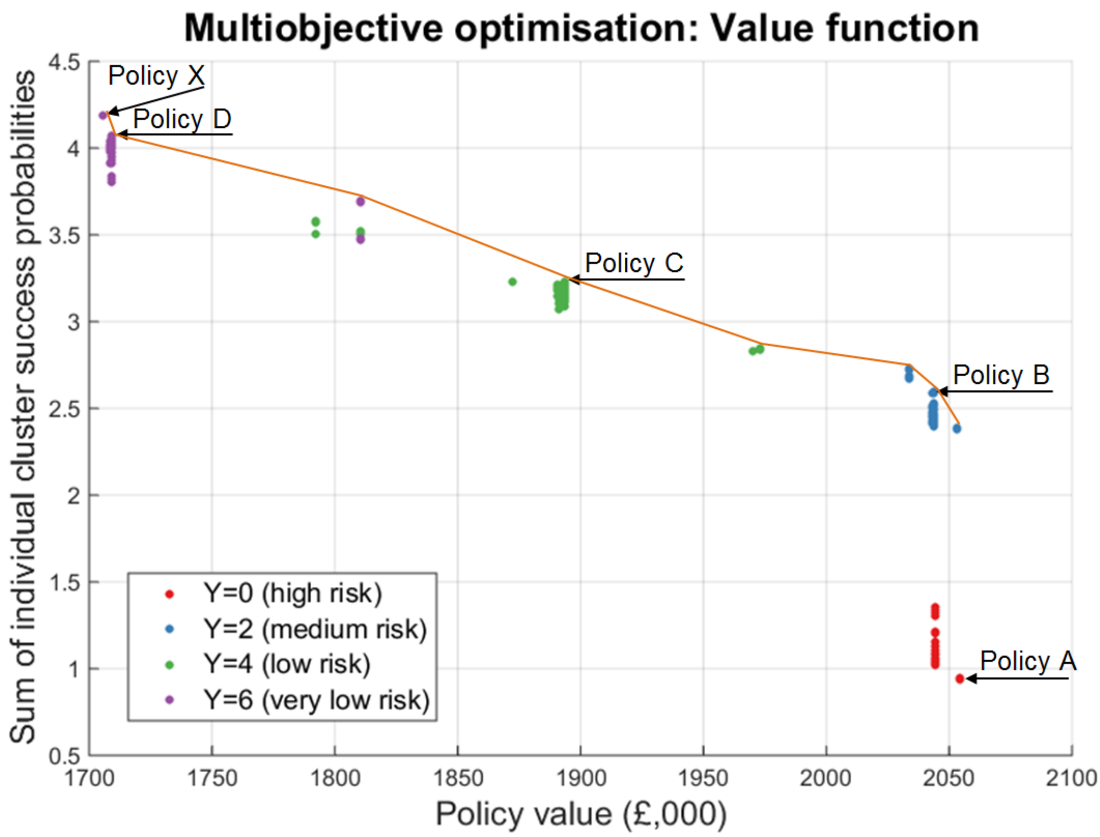

Figure 6.16. Pareto graph with a y-axis consisting of sum of probabilities of maintaining all turbines in all individual clusters in a policy.

In the context of the two Case Studies presented in this chapter, plotting Pareto graphs is an interesting academic exercise providing an insight into the tool's search of the state space. However, in the author's opinion, they do not increase the tool's day-to-day usability, as discussed in 6.2.3.

6.4 Summary

One of the key conclusions emerging from this section is the poor performance of policies created with a risk aversion factor equal to zero. Policies A in both Case Studies were the worst performers in terms of maintenance actions completed once uncertainties have realised, despite aiming to visit the highest number of turbines. Note that this approach of judging a policy purely on costs and rewards is used by all researchers in the offshore wind domain (as discussed in Section 4.2.6). The real-world problems feature multiple uncertainties, which are bound to affect the choice of the vessel routing policy. Not including those factors in the decision making process is an outdated approach, deemed to produce ineffective policies.

Taking the expected significant wave height as an example, Case Study 1 has shown that significant improvements in transfer success (36% reduction in unsuccessful transfers, as discussed in Section 6.2.2) can be achieved through higher utilisation rates of the more costly-to-run Class 1 vessels. Using non-zero risk aversion factor encourages the tool to sacrifice increases in fuel and vessel hire costs for increased chance of maintaining a higher number of turbines. Running the model for a range of risk aversion factors allows the user to choose the policy which matches their risk appetite (in terms of the additional cost they are willing to suffer for a given increase in the expected number of turbines maintained at the end of the day).

Since the real-world problem of offshore wind farm vessel routing is characterised by multiple objectives, it is impossible to select a single "optimal" policy. In the two Case Studies presented, policies generated using a risk aversion factor equal to 4 seem to provide a sensible trade-off between the policy value and probability of maintaining a large number of turbines. However, this may not be the case for scenarios computed under different assumptions and inputs. Generally, in the author's opinion, there is no need to exclude the human decision maker from the policy selection process. Presenting the tool's user with a range of varying policies enables them to select the most suitable one on a given day.

Case Studies presented in this chapter have shown that the methodologies proposed in Chapter 3. and Chapter 5 are compatible. In tandem, the two approaches enable effective task prioritisation while considering a broad range of relevant factors. In cases of resource shortages, tasks to be carried out are selected taking into account the weather, asset performance, completion deadlines, proximity to the O&M base, task duration and resource requirements[49].

Although a constraint on the vessel's capacity to carry spare parts has been modelled, it was never a factor affecting the final policy (in neither of two case studies). The weight of spare parts and tools required for maintenance actions was low compared to the vessel's capacity. This aligns with information gathered from interviews with offshore wind farm operators (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators), who stated that it is unusual for them to consider component weight when planning vessel routing – it is rarely required to do so.

This chapter has shown that the proposed methodology is capable of solving complex, multi-objective VRPs. The following chapter describes the validation procedure for the tool, including application to real world scenarios. In Section 7.4.2 the performance of the proposed CMA heuristic method to a commercial solver (CPLEX), showing that the results produced in Case Studies 1 and 2 are all within 3.3% of optimal. Possible improvements, future work and alternative applications of the tool are discussed in Section 8.3.

[49] The former 3 factors are encapsulated in the output from the SMDP model and the latter 3 factors result from the design of logistics optimisation algorithms.

Chapter 7. Model Validation

This chapter describes the procedure for validation of the methodologies described in this thesis. This chapter is structured as follows; Section 7.1 describes the process of selecting validation approaches. Section 7.2 covers validation of the SMDP model for task prioritisation. Methodologies for solving the sub-problem and master problem are validated in Sections 7.3 and 7.4 respectively. Tool's application to a real world case study is described in Section 7.5, followed by discussion of the expert interview provided in Section 7.6. Sections 7.7 and 7.8 compare the tool's capabilities to other published methods and previously specified constraints respectively. Finally, the conclusions from this chapter are summarised in Section 7.9.

7.1 Validation: Definition and Selection of Approaches

Validation is a necessary step in the process of practical tool implementation. Validation was defined by Schlesinger [192] as:

"Substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model"

Note that for the tool developed in this thesis, "intended application of the model" is real-world decision support. Adapting the above definition to the context of decision support tools yields the following definition of validation:

"Substantiation that the proposed tool produces outputs aiding wind farm operators make better decisions"

One of the widely used validation approaches is comparing a model's output to experimental data, or outputs of other models. However, due to differences is solution approaches and the constraints considered, comparison to other models was not carried out. Discussion on this is provided in Section 7.7, along with comparison of the proposed tool to published models in the field.

Alternatively, decision support tools can be validated by real life application. While this has been attempted in Section 7.5, there are limitations associated with this approach, as discussed in Section 7.5.3.

To evaluate the fitness of a candidate policy, effects of uncertainty realisation have to be explored. Input uncertainties need to be propagated through the model to ensure their effect on the final output is captured. According to Roy & Oberkampf [193], the simplest approach for propagating uncertainties through the model is Monte Carlo

Sampling, which was used in this work (as described in Section 5.4). Given the large number of policies generated using the proposed methodology, running a Monte Carlo Analysis for each candidate policy would take an unreasonable amount of computational time.

As shown in Figure 6.9, adjacent points on the value function graph are seemingly unrelated. Widely used optimisation techniques based on the shape of the value function, such as hill climbing algorithms, are unlikely to be successful at finding the global optimum. It is impractical, if not impossible, to find an optimal solution to compare the model's output for benchmarking purposes (for a problem with uncertain inputs and multiple objectives). Due to the complexity of the problem at hand, there is no optimal solution to compare the model's outputs to.

Researchers agree that in many cases, it is impossible to validate a model fully. Quoting Sargent [194]:

"It is often too costly and time consuming to determine that a model is absolutely valid over the complete domain of its intended applicability. Instead, tests and evaluations are conducted until sufficient confidence is obtained that a model can be considered valid for its intended application"

While most engineering models will never be considered fully valid, many can be deemed requisite after sufficient validation. A requisite model was defined by Phillips [195] as:

"A model is requisite if its form and content are sufficient to solve the problem (…). Everything required to solve the problem is represented in the model or can be simulated by it"

To find out whether the tool considers all relevant inputs, an interview with a wind farm operator should be conducted. Additionally, the interview should be used to identify any potential barriers to tool's practical implementation. This is discussed in more depth in Section 7.6.

The tool developed in this thesis comprises of several models. For example, the SMDP model can be seen as a standalone entity; its outputs may be used for purposes other than inputs to the logistics optimisation model. It was decided that in addition to validating the tool's final output, i.e. the vessel routing policy, validation of the SMDP model, the CMA heuristic method and the proposed sub-problem solution approach would also discussed. A summary of the validation approaches chosen for each part of the tool is presented in Table 7.1.

Table 7.1. Validation techniques selected for the individual parts of the tool.

Model to be validated	Validation technique	Definition	Section
SMDP (Chapter 3)	Face validity	"Test which is to be used in a practical situation should, in addition to having pragmatic or statistical validity, appear practical, pertinent and related to the purpose of the test as well" [196].	7.2
Sub-problem solution approach (Section 5.2)	Comparison to another model	The results of the proposed algorithm were compared to the optimal solutions obtained by brute force analysis.	7.3
CMA Heuristic (Section 5.3)	Comparison to another model	Determination of the optimality gap of the heuristic method for different case studies. Achieved by comparing to a model capable of producing the optimum solution.	7.4
Entire logistics optimisation tool (Chapter 5)	Historical data validation/ Decision maker behaviour reproduction test	"If historical data exist (or data collected on a system specifically for building and testing a model), part of the data is used to build the model and the remaining data are used to determine (test) whether the model behaves as the system does" [194].	7.5
	Expert interviews	"Soft" validation technique involving questioning the experts (maintenance planners) once the tool has been applied to a real-world scenario. Used to determine whether the model considers all relevant inputs and to identify barriers for practical application.	7.6
	Validation against requirements	"A simulation model should only be developed for a set of well-defined objectives." [194].	7.8

The proposed validation process comprises of a number of diverse approaches, as shown in Table 7.1. As recommended by Phillips [195], requisite models should be validated by a mixture of "soft" (e.g. interviews) and "hard" (e.g. comparison to other models) techniques. Individual steps of the validation process are discussed in more detail in Sections 7.2-7.8.

As suggested by Christel & Kang [197], verification of whether the tool meets the previously specified criteria[50] should be done by using case studies, such as the ones described in Chapter 6. This analysis is conducted in Section 7.8. The authors of [197] also point out that evaluation of a model should include comparison to the alternative methods of solving similar problems (including existing systems), to determine whether employing the new methodologies leads to process improvements. The tool's performance compared to existing wind farm decision making process is discussed in Section 7.5.3. The proposed tool's capabilities are compared to other models developed for offshore wind farm vessel routing in Section 7.7.

[50] Previously specified criteria come from conclusions of Chapters 2 and 4.

7.2 SMDP Model Validation Discussion

The SMDP model was designed to quantify the incentive of maintaining a turbine on a particular day, relative to other turbines requiring maintenance. As discussed in Section 3.2.5, literature review found no models suitable for prioritisation of wind turbine maintenance. Comparing the SMDP results to other models is therefore impossible.

Alternatively, the SMDP results could be compared to priorities assigned to turbines by wind farm operators. According to informal interviews with maintenance planners (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators), they do not currently have a methodology for quantifying the incentive of performing different maintenance actions. Although no formal procedure is for task prioritisation was implemented on the wind farm the author has visited, the planners generally made vessel routing decisions using the following logic[51]:

1. Identify the high priority turbines. These include broken down assets, turbines which may fail in near future or turbines with tasks with a near due deadline
2. Plan movements to the high priority turbines
3. Visits to low-priority turbines are planned on an ad-hoc basis; depending on the proximity to high priority turbines, resource availability (for example a team specialising in retrofits is on shift, they may be assigned to a cluster of turbines requiring a retrofit) and other practical considerations.

The two most important considerations influencing the real world turbine visit prioritisation are:

- Contractual deadlines
- Maximisation of power production

These two factors also have the strongest influence on the outputs of the SMDP model, as shown in Table 3.7 and Table 3.8.

There are additional factors which should be taken into account when prioritising wind turbine visits. Taking power production as an example; turbines exposed to higher wind speeds should be assigned a higher priority (for the same corrective maintenance action). Manual checking of every turbine's recent power output is time

[51] Note: in real life, the relative incentives of visiting turbines are not calculated. The process of task prioritisation is integrated with vessel routing planning procedure.

consuming and ultimately, including it in the prioritisation process may not have a significant effect on the final policy. Under pressure, planners do not always have time to consider the turbine's power output when prioritising tasks.

Employing the SMDP methodology can automate this process; relative incentive of visiting a given output can be calculated in less than a second. The advantages of using the SMDP, over the current approach are as follows:

- Reduced time required to prioritise tasks (provided automated data input)
- The SMDP model ensures unbiased, consistent results, while the current process may be influenced the planner's subjective preference
- Assuming automated data input, the SMDP model can consider factors which the planners do not have the time to consider (e.g. turbine's power production)
- Process automation should result in fewer mistakes (e.g. missing a deadline due to misreading a due date)
- Outputs of the SMDP (incentives to visit turbines) can be logged and used to create improved asset management strategies once sufficient amount of data is collected[52]. In the current system, there is no process for logging task prioritisation decisions. The SMDP results could be stored to provide a justification of past decisions

There are numerous factors to consider when prioritising maintenance tasks. The degree to which each factor affects the result is subjective and therefore difficult to model. Additionally, there is no obvious way of using a real monetary value when quantifying task priorities, capable of considering all relevant factors (Table 3.1). Therefore, it is unlikely that a single optimal priority ranking exists for each scenario.

Testing the SMDP model in different scenarios has shown that it meets the criteria for a requisite model (as defined in Section 7.1). All key factors affecting task prioritisation were considered. Discussion provided in Sections 3.4 and 6.3 demonstrated that the SMDP results were coherent, sensible and aligned with the logic applied by wind farm operators. Returning to the definition of face validity, shown in Table 7.1, the following question needs to be asked:

[52] For example, turbines with highest cumulative sum of incentives points are likely to be to high performance turbines which fail often or turbines consistently close to missing contractual deadlines. Identifying those turbines may prompt root cause analysis leading to conclusions which improve maintenance practices.

Does the model's output have pragmatic or statistical validity; does it appear practical, pertinent and related to the purpose of the test?

Based on the evidence and discussions presented here and in Sections 3.4 and 6.3, it can be concluded that the SMDP model meets Mosier's ([196]) criteria of a valid model.

7.3 Validation of the Proposed Sub-Problem Solution Approach

The sub-problem solution procedure is described in detail in Section 5.2. The main aim of the proposed algorithm is to produce an order of visits to a set of input turbines, which **minimises the policy time while minimising the number of technicians required to carry out all maintenance actions.**

The proposed approach is compared to results of a brute force search, which considers all possible combinations of turbine visits (within a given 4-turbine cluster). In total, ten 4-turbine clusters were analysed. Clusters were selected at random from the pool of 4-turbine clusters which constituted Case Study 1, discussed in Section 6.2.

Each 4-turbine cluster requires eight visits – a pick-up and a drop-off at each of the turbines. Assuming the simplest case, wherein all drop-offs are completed before pick-ups commence, the number of possible combinations is $(N!)^2$, where N is the number of turbines visited by a vessel. This yields 576 combinations for every 4-turbine cluster.

By analysing all possible combinations, the brute force algorithm always produces the optimal solution. The optimisation objective for the brute force algorithm was minimisation of total policy time. This objective aligns with minimisation of fuel cost; the longer a vessel spends at sea, the more fuel it will consume.

Table 7.2 compares the results of the brute force algorithm to the outputs of the proposed sub-problem solution approach. The latter model found the optimal solution in 8 out of 10 cases. In the two remaining instances, the difference between the two approaches was never greater than 1% (or 7 minutes). Note that in this test, the number of technicians required to carry out all policies was the same for both solution approaches.

The downside of the brute force approach is lengthy computational time required to analyse all possible combinations. Computing the solution for a single 4-turbine cluster took 0.07 seconds (on a computer with a 3.4GHz i7-3770 CPU, 8GB of RAM and 64-bit Windows 7 operating system). The approximate computational time for

Case Study 1 (14 turbines, 7350 clusters) would be 8.6 minutes for the sub-problem alone[53], compared to 2.2 seconds for the proposed approach. This figure rises to an estimated 76 min solution time for Case Study 2 (24 turbines). Potentially increasing the number of turbines per cluster from 4 (576 possible combinations per cluster) to 5 (14,400 combinations) would mean that the sub-problem alone would take days to solve using brute force.

Table 7.2. Comparing outputs of the sub-problem solution algorithm (described in Section 5.2) to the optimal solution obtained from a brute force analysis.

Instance	Turbines	Policy time – tool output (min)	Policy time – optimal (min)	Difference
1	T36, T51, T68, T99	629	629	0%
2	T19, T42, T51, T71	665	665	0%
3	T50, T71,T85, T99	644	644	0%
4	T19, T36, T77, T92	654	652	0.3%
5	T42, T68, T92, T99	637	637	0%
6	T3, T21, T42, T45	608	608	0%
7	T42, T50, T71, T77	638	638	0%
8	T3, T36, T71, T92	677	670	1%
9	T19, T42, T85, T99	692	692	0%
10	T21, T51, T68, T71	637	637	0%

[53] From 0.07 * 7350 = 514 seconds.

7.4 Validation of the CMA Heuristic Algorithm

The validation approach selected for the CMA heuristic method was comparison with an existing model, which has already been validated. CPLEX software was identified as the best candidate to compare the CMA to. It is widely used to solve integer programming problems in various domains. CPLEX was also used in one of the publications focused on solving the offshore wind turbine vessel routing problem [25].

The author has already published a paper on validation of the CMA algorithm [198]. Results obtained in those tests are discussed in Section 7.4.1. Additionally, similar tests were run for Chapter 6 Case Studies, with results shown in Section 7.4.2.

7.4.1 Published Results

Tests were run on the same 10-by-10 turbines fictional wind farm, introduced in Section 6.1.2. Three test cases (A-C) were analysed, with 10, 15 and 20 failed turbines respectively. As discussed in Section 5.3.1, the user can choose the number of policies to be analysed by the CMA, which determines the computational time. A summary of the number of policies generated, along with case study properties is shown in Table 7.3.

The only difference distinguishing the ten scenarios in each case are the types of maintenance actions and locations of turbines to be serviced. Some scenarios consist of a higher proportion of tasks with long durations; in those cases it may not be possible to visit all turbines on day 1. These cases are referred to in the latter parts of this section as “severely constrained”. The proportion of severely constrained tasks is the highest in Case B scenarios, as the number of technicians per turbine was the lowest of all cases, as shown in row 3 of Table 7.3.

Table 7.3. Inputs to validation case studies.

	Case A	Case B	Case C
Turbines failed	10	15	20
Technicians available	25	32	45
Technicians per turbine	2.5	2.13	2.25
Vessels Available	3	4	5
Number of policies generated by CMA	15,000	36,000	51,840

Results of Case A analysis are shown in Table 7.4. CMA heuristic found the optimal solution in 9 out of 10 cases. Value of the suboptimal solution found in scenario 2 is only £4 lower compared to optimal. Computational time for both cases is similar for both CPLEX and CMA approaches (less than 5 seconds in all scenarios).

Table 7.4. Case A results.

Instance	CMA value	CPLEX Value (difference)	CMA CPU time (s)	CPLEX CPU time (s)
#1	£88,183	£88,183 (0%)	2	0.6
#2	£86,240	£86,244 (0.004%)	2	0.5
#3	£88,063	£88,063 (0%)	2	4.7
#4	£88,204	£88,204 (0%)	2	0.5
#5	£90,198	£90,198 (0%)	2	0.5
#6	£88,061	£88,061 (0%)	2	0.5
#7	£92,134	£92,134 (0%)	2	0.4
#8	£90,135	£90,135 (0%)	2	0.5
#9	£94,144	£94,144 (0%)	2	0.5
#10	£89,993	£89,993 (0%)	2	0.5

Table 7.5 shows the results for Case B tests. The optimal solution was found by the CMA heuristic in 4 out of 10 cases, however, the difference between the optimal and CMA-generated policy never exceeded £173 or 0.17%. Computational times have increased for both approaches. CMA computational times are very consistent (between 30 and 36 seconds in all cases), while the CPLEX computational times varied between 1.5 to 438.2 seconds. The time required for the CPLEX method to compute instance #1 was longer than the entire CMA simulation time for all ten cases. CMA heuristic outperformed CPLEX in instance 4, as the optimal solution was found in shorter computational time.

Table 7.5. Case B results.

Instance	CMA value	CPLEX Value (difference)	CMA CPU time (s)	CPLEX CPU time (s)
#1	£119,083	£119,104 (0.02%)	32.1	438.2
#2	£116,107	£116,107 (0%)	34.5	5.3
#3	£126,907	£126,951 (0.04%)	33.7	2.2
#4	£116,034	£116,034 (0%)	35.2	53.5
#5	£116,932	£117.133 (0.17%)	32.6	5.1
#6	£114,946	£115,134 (0.16%)	34.1	27.8
#7	£114,093	£114,093 (0%)	30.3	1.5
#8	£124,722	£124, 945 (0.17%)	33.4	1.8
#9	£114,871	£115,036 (0.14%)	35	27.4
#10	£113,862	£113,862 (0%)	30.4	3.3

Results for Case C are shown in Table 7.6. Despite the increase in problem complexity, computational times in all instances, for both solution approaches, remain below one minute. The CPLEX solver significantly outperformed CMA in three instances (#2, #8 and #9), in which following the policy generated by CPLEX allowed visiting an additional turbine.

Table 7.6. Case C results.

Instance	CMA value	CPLEX Value (difference)	CMA CPU time (s)	CPLEX CPU time (s)
#1	£146,952	£147,112 (0.11%)	47	13.6
#2	£143,126	£150,897 (5.43%)	40.4	7.6
#3	£155,034	£155, 269 (0.14%)	48.3	8.5
#4	£150,902	£151,010 (0.07%)	44.2	8.3
#5	£152,883	£153,173 (0.19%)	43.4	7.9
#6	£154,972	£155,192 (0.14%)	48.2	8.7
#7	£145,027	£145, 200 (0.12%)	51.5	8.9
#8	£136,157	£140,995 (3.52%)	38.7	16.3
#9	£139,309	£147,147 (5.63%)	44.1	19.5
#10	£151,163	£151,308 (0.1%)	47.2	8.2

Across all 30 test cases, there were six instances where the CPLEX computational time exceeded 15s. Five of those scenarios were severely constrained. In total, there were 12 (out of 30) severely constrained cases, suggesting that one of the reasons for increased computational time of the CPLEX solver was due to resource shortages in a given scenario. The computational time of the CMA method was not affected by the heavily constrained scenarios.

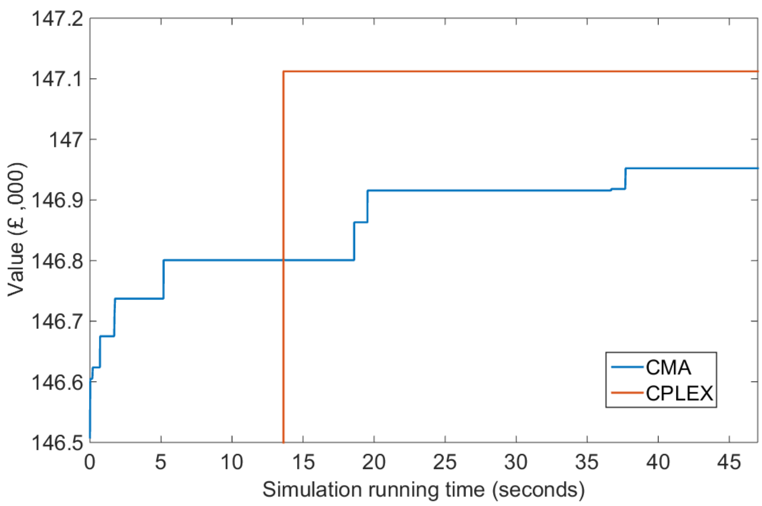

Figure 7.1. Comparison of computational time and performance of CMA and CPLEX.

A graph showing computational time vs. result quality for each solution method is shown in Figure 7.1. The CMA produces a close-to-optimal solution (within 0.34% of optimal) almost instantaneously. The solution improvement rate is high initially; dropping as the computational time increases. Allowing additional computational time (by increasing the number of policies to be computed) would likely result in optimal, or significantly closer to optimal solution being produced by the CMA.

A summary of these results, as well as results from the following section, is provided in Section 7.4.3.

7.4.2 Results for Winter and Summer Case Studies from Chapter 6

The policies described in Chapter 6 were generated using the CMA approach. Here, these problems were solved again using CPLEX. A comparison of winter and summer case study results is shown in Table 7.7 and Table 7.8 respectively.

Table 7.7. Computational time and result quality comparison: Winter Case Study.

Case	CMA computational time (s)	CPLEX computational time (s)	CMA value (£,000)	CPLEX value (£,000)	Difference in value
A	250.1	20.9	1301.1	1301.1	0%
B	245.3	21.3	1488.3	1499.3	0.67%
C	255.8	22.1	1702.6	1702.6	0%
D	253.2	20.8	1909	1909	0%
E	243.2	20.2	2118.9	2143.3	1.1%
F	313	20.5	2452.7	2460.3	0.3%

One of the advantages of the CPLEX solver is that it can assert whether an optimal solution has been found. All CPLEX solutions provided in this, and previous sections, were confirmed to be optimal. In the winter case study, CMA found the optimal solution in three out of six cases. The highest difference between CMA and optimal solutions was 1.1% (Case E). The CMA computational time was over 10 times higher than CPLEX.

The summer case study was significantly more complex (24 turbines requiring maintenance vs. 14 for winter Case Study). This caused an approximately fourfold increase in CPLEX computational time. CMA's computational time was not affected as the number of policies generated was kept constant in both Case Studies. As a result, the CMA did not manage to find the optimal solution in any of the four cases. However, the results remained within 3.3% of optimal in all four cases.

Table 7.8. Computational time and objective value comparison: Summer Case Study.

Case	CMA computational time (s)	CPLEX computational time (s)	CMA value (£,000)	CPLEX value (£,000)	Difference in value
A	280.7	102.7	2054.2	2066.9	0.61%
B	264.9	100.4	2368.1	2441.1	2.99%
C	240.8	102.3	2758.2	2851.5	3.27%
D	235.5	101	3255.5	3337.6	2.46%

7.4.3 Summary of CMA-to-CPLEX comparison

In summary, CPLEX outperformed CMA in most cases, both in terms of computational time and solution quality. However, there are a number of advantages the CMA has over CPLEX:

1) Free-to-use, whereas CPLEX 12-month licence cost[54] is $9,270, with additional charges for multiple workstations (free for academic use)
2) Easy to code and implement in any programming language, depending on the system used (entire solution procedure can be contained on a single page – as shown in Figure 5.10)
3) Consistent computational time (Note: the reason for the significant improvement in consistency of CPLEX computational times from Section 7.4.1 to Section 7.4.2 is unknown)

In addition to the above, one of the problems encountered when running CPLEX from MATLAB (using CPLEX connector for MATLAB), were occasional MATLAB crashes caused by CPLEX. Crashes occurred frequently in severely constrained tests described in Section 7.4.1. Running CPLEX for scenarios presented in Section 7.4.2 only resulted in one crash (in 10 runs). It is possible that the crashes were a result of incompatibility of the MATLAB version used (2014b) and the CPLEX version (12.7.1).

In conclusion, CMA is a heuristic method capable of producing close-to-optimal solutions for most real-world-size problems in reasonable computational time (i.e. under 5 minutes. While it does not guarantee finding an optimal solution, it is a versatile, cost-effective heuristic, which may also be applicable to problems beyond vessel movement optimisation.

[54] From: http://estore.gemini-systems.com/ibm/software-license/industry-solutions/cplex-optimization-studio/ilog-cplex-optimization-studio-de/ Accessed on: 31/01/2018.

7.5 Practical Tool Application

In an attempt to further validate the proposed tool, a visit to a major UK offshore wind farm operations centre[55] has been arranged in February 2017. During the visit, the tool was tested on real-life scenarios. A report summarising the visit is shown in Appendix L. Report Summarising the Offshore Wind Farm Site Visit. The aims of the visit were to:

1) Affirm that the tool solves the real world problem; check if the inputs and assumptions are correct
2) Ensure that all practical considerations have been modelled. Identify features and capabilities to be added to the tool
3) Gather feedback on the user interface, the usefulness of the tool's outputs and potential interface/graphical improvements
4) Validate the model outputs by testing the tool on real-life scenarios and comparing its outputs to the decisions made by planners

Aims 1-3) were achieved through formal and informal interviews with vessel movement planners. A transcript of the formal interview along with a discussion of the operators' comments is provided in Section 7.6. A summary of the real world case study conclusions, categorised by the corresponding aims (1-4) is also provided in Section 7.6. Sections 7.5.1 and 7.5.2 contain the description of the inputs and results of the real world case study.

7.5.1 Inputs & Assumptions

Since the wind farm operators did not wish to have their identity revealed, wind turbine locations were anonymised. The scenario analysed here occurred on a day in February 2017, when 14 maintenance actions were set to be carried out. Turbines to be visited and corresponding tasks were shown in Figure 7.2. Turbines in yellow were half day maintenance actions (approx. duration of 3 hours), orange stood for whole day tasks (approx. duration of 6 hours). High priority maintenance actions (6 hour duration) were marked in red.

A table providing detailed task properties used as inputs in this case study is shown in Table M.1 in Appendix M: Real World Case Study Inputs. Duration of the high

[55] They wish not to be named in this publication. As per their request, all data which could lead to identification of the wind farm was anonymised.

priority tasks was set marginally higher compared to all other tasks (6.1h vs. 6h), to ensure these are visited first.

The operators noted that on that day, factors such as spare parts weight and cost of repair actions would not affect the process of optimal policy selection. Hence, these inputs were equal for all maintenance tasks.

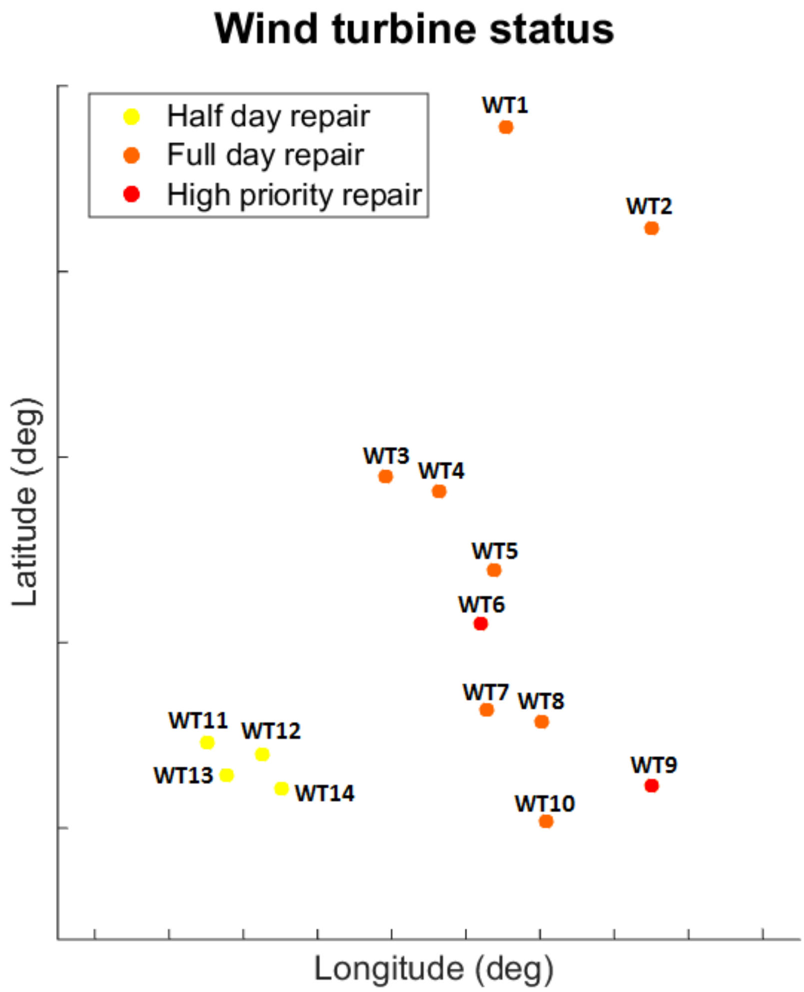

Figure 7.2. Map of wind turbines requiring maintenance.

On that day, the significant wave height across the farm was approximately 1.2m; low enough not to hinder technician transfer. The operators had four vessels available to them. Properties of the vessels available to the operators on the day are shown in Table M.2 in Appendix M: Real World Case Study Inputs.

The number of technicians available on the day was 33. The shift duration was set at 11.5 h. Speed correction factor (as defined in Table 4.1) was set at 1.5. CMA heuristic method was used to match individual clusters into policies to arrive at a final solution.

The tier limits (defined on page 147) used were 100, 40 and 25 respectively, producing a total of 100,000 policies.

The cluster value (i.e. the reward for servicing a set of turbines) was calculated using Equation 5.11. Added terms due to increased probability of servicing all turbines in a cluster were not included in this analysis, as the operators said they did not consider those when creating the plan. This ensures like-for-like comparison of the policy suggested by the tool and the policy created by the wind farm operators.

7.5.2 Results

The computational time required to produce the suggested policy for this scenario was 24.3 seconds (on a computer with a 3.4GHz i7-3770 CPU, 8GB of RAM and 64-bit Windows 7 operating system). Vessel dispatch policy generated by the model is shown in Figure 7.3. The assignment of vessels to turbines suggested by the tool exactly matches the plan created by the wind farm operators.

Since significant wave height and other uncertain inputs were not considered in this case study, maximisation of the number of turbines visited and minimisation of travel cost were the key optimisation objectives. The resulting policy shown in Figure 7.3 features four well defined clusters of turbines located close to each other. The fact that the policy generated by the tool is the same as the decision made by operators demonstrates that the objectives driving the tool's outputs can easily be aligned with the user's needs.

Although the computational time required to produce the policy shown in Figure 7.3 was very short (under 1 minute), inputting the data and setting model parameters at the start of the day took approximately 30 minutes. If the circumstances change during the day – for example an additional maintenance tasks need to be added, policy can be re-created very quickly (under 5 minutes including data input, assuming similar settings).

During the visit, it was observed that the time required to create the initial policy at the start of the day was approximately 45 minutes, with four coordinators/senior technicians involved in the planning process. Changes such as addition of a maintenance task, which required significant re-working of the policy, would take approximately 30 additional minutes, with at least two people involved. However, it is worth noting that planners did assign individual technicians to tasks, meaning the policy created by coordinators and senior technicians was more complex than the one created by the tool. Despite this, significant time savings could be achieved by using the tool for decision support.

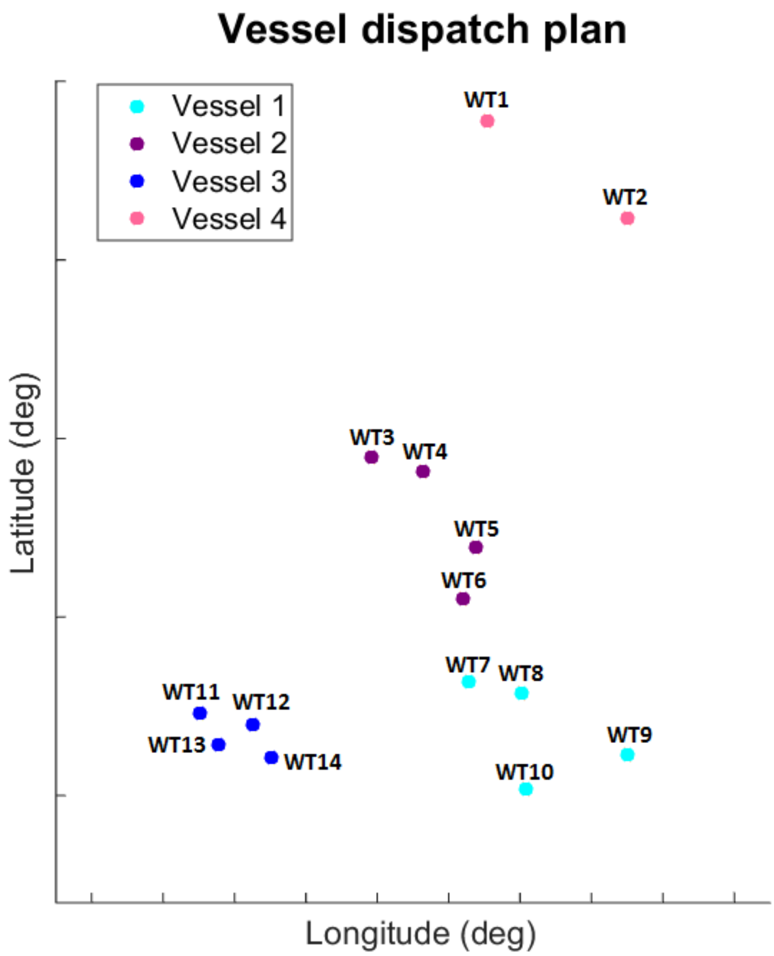

Figure 7.3. Vessel dispatch plan generated by the tool.

In addition to the vessel-to-turbine assignment, the tool also recommends the order of turbine visits. The logic used by the model to choose the drop-off and pick-up order is discussed in Sections 5.2.3 & 5.2.4. The order of drop-offs recommended by the tool is shown in Table 7.9. **The order chosen by the wind farm operators was the same as the tool's output.** The first stop for vessels 1 & 2 were high priority turbines – dropping technicians off at those turbines first maximises the time available to carry out urgent repairs.

Table 7.9. Suggested order of technician drop-offs.

Drop-off order	Vessel 1	Vessel 2	Vessel 3	Vessel 4
1	WT 9 (high priority)	WT 6 (high priority)	WT 14	WT 2
4	WT 10	WT 4	WT 11	WT 1
3	WT 8	WT 3	WT 12	
4	WT 7	WT 5	WT 13	

Table 7.9 does not show the recommended order of pick-ups. In most cases, wind farm operators decide the pick-up order once they receive an updated expected task finish time from technicians.

7.5.3 Summary of the Practical Tool Application Case Study

Results of the blind case study shown in the previous section demonstrated that the tool's outputs align with decisions made by wind farm operators. However, the scenario tested did not test the tool's full capabilities:

a) Scenario did not require the tool to take uncertainties on inputs into account
b) Tool's capability to prioritise visits was not tested, due to limited pool of turbines to be visited on the day

As for point a), an attempt could have been made to conduct a blind case study based on a scenario with large uncertainties. However, if the tool's output and the policy created by the operators differed, it would be very difficult to compare the two and determine which one is superior. If the operator's decision was carried out in real life, the uncertainties associated with movements suggested by the tool wouldn't have realised, making it difficult to quantify the effectiveness of the proposed policy. A single blind case study would not be sufficient to determine whether the tool's outputs are superior or inferior to decisions made the operators – a larger sample size would be required to ensure valid conclusions. In summary, application of the tool to a scenario with no significant uncertainties driving the outcome allowed fair comparison between the two decision making processes.

Regarding point b) from above, selection of the turbines to be visited on the day is a large part of the maintenance optimisation process. During the site visit, the tool user (the author) did not have access to the entire pool of maintenance actions required. Turbines to be visited were pre-selected by planners, who made decisions based on type of task required, maintenance task deadlines, turbine locations and resource availability. All these factors can be captured by the SMDP model described in Chapter 3, however, due to limited visit time and the complexity associated with interfacing MATLAB with wind farm IT systems, it has not been used in the decision making process.

The main barrier to real-world application of the SMDP model is data integration: linking the existing wind farm data structure (task deadlines, alarm codes, weather forecast) to the MATLAB-based model would likely take a considerable amount of time. Data integration is discussed in more detail in Section 8.3.3.

Providing the tool with a greater choice of maintenance actions would not only test the tool's ability to prioritise tasks based on their location, severity, deadlines and weather forecast; it would also make it possible for the tool to create a policy which improves on the wind farm operator's plan. Allowing the tool to select from a larger pool of turbines can enable the tool to create policies which the operators did not consider during their decision making process.

In summary, the optimisation objectives modelled in the tool (i.e. minimise fuel cost/travel time or maximise probability of completing maintenance at the highest possible number of turbines) align with the wind farm operator's objectives. The real world blind case study has shown that the tool is capable of suggesting an order of wind turbine visits similar to the plan created by professional maintenance planners, in shorter time. The wind farm operators' comments on the tool's outputs are discussed in the following section, which provides a transcript of an interview with a member of the offshore wind farm maintenance planning team.

7.6 Expert Interview Discussion

As part of the validation process, an interview has been conducted with a senior technician, who is routinely involved in planning vessel movements at the offshore wind farm where the visit was taking place. A transcript of this interview is shown in Table N.1 in Appendix N.

The four key aims of the site visit are outlined in Section 7.5. Conclusions arising from both the formal interview and informal conversation with wind farm maintenance planners were summarised by the corresponding aim, as shown below.

1) Does the model solve the real world problem? Are assumptions and inputs realistic?

Feedback received: Generally, most assumptions and inputs were correct as the problem has been previously discussed with an engineer who was familiar with the practicalities of planning offshore wind farm vessel routing. During the visit planners provided detailed information on the site specific inputs (e.g. vessel properties). Inputs and assumptions used in the real world Case study are discussed in Section 7.5.1.

2) Ensure that all practical considerations have been modelled. Identify features and capabilities to be added to the tool.

Feedback received: Wind farm operators commented on a number of the tool's features, including some future work recommendations:

- Planning horizon – one day planning horizon is realistic, as the following day's plan largely depends on completion of today's jobs. However, long term needs to be considered when setting turbine visit priorities (Note: this is captured in the tool if the SMDP model described in Chapter 3 is used to define rewards for visiting turbines)
- Variable vessel speed – being able to change the vessel speed multiplier when at the wind farm (as defined in Table 4.1) allows setting a realistic turbine-to-turbine travel times
- Vessel load limit – weight of spares is rarely a factor when planning day's movements; vessels have sufficient carrying capacity to cope with carrying spare parts and tools to multiple turbines. Maintenance planners remarked that it would be useful if the tool facilitated tracking of which spare parts are being carried by each vessel

- Technician grades – modelling technician grades would be a useful feature, enabling assignment of technicians to tasks depending on their qualifications
- Model's limit on the number of turbines visited by a vessel – at the wind farm visited, a vessel may occasionally be dispatched to 5 or more turbines to pre-load tools or spare parts for future maintenance. For annual service campaigns, a vessel may be assigned solely for pre-loading, with up to 10 turbines being visited in a day by the same vessel
- Maintenance actions which require the vessel to remain at a turbine for the duration of the task are very rare; the fact that the tool does not currently allow modelling these task would not affect the day-to-day decision making

In summary, the operators confirmed that most relevant factors have been modelled. As the wind farm in question was located far from its O&M base, dispatching vessels to 5 or more turbines is rare (as the sail time to and from site takes up a considerable portion of the workday). Increasing this limit was previously discussed in Section 5.1. The cost savings resulting from increasing the limit of turbines per vessel would be offset by the significant increase in computational time.

A valid comment was made that modelling technician grades would facilitate decision making on assignment of people to tasks. The real world decision making process is complex, as the operators try to consider multiple factors ranging from qualifications to individual technician skillsets and ability to carry out certain maintenance actions. Documenting this process and integrating it with the decision support tool would take considerable time and effort; it would also add a layer of complexity to the optimisation problem.

3) Gather feedback on the user interface, the usefulness of the tool's outputs and potential interface/graphical improvements

Feedback received: Wind farm operators remarked the tool has potential to make wind farm operator's life easier. They found the model's outputs easy to read and understand. The key output which they found particularly useful was the vessel dispatch plan map (as shown in Figure 6.6). Operators suggested that the map could be improved by having an outer circle on a turbine, identifying the type of maintenance action (i.e. whether it's a corrective action, annual service etc.).

The computational time required to produce the policy discussed in Section 7.5.2 was under one minute, which the operators found quick. They said the model would be particularly useful in cases when a decision has to be made quickly; for example if the routing plan has to be changed early in the morning due to turbine breakdowns during the night.

4) Validate the model outputs by testing the tool on real-life scenarios and comparing its outputs to the decisions made by planners

Procedure: The purpose of Case Studies described in Chapter 6 was to apply the tool to a range of complex problems and examine the results it produces. Testing the tool in a real-world setting, as described in Section 7.5, was aimed at verifying the assumptions and running the tool as the decisions were being made, to find out whether the tool is capable of real-world decision support. The blind case study showed that the tool is capable of producing the same vessel routing plans as maintenance planners, in a shorter computational time.

Unfortunately, during the 3 days spent on site, there were no sail days. However, vessel movement plans were being continuously made and adjusted, under the assumption that the following day would be a sail day. The tool was being run in parallel to the usual decision making process. The tool’s outputs generally aligned with the plans made by wind farm operators.

7.7 Comparison of the Tool's Capabilities Compared to Published Research

One of the possible means of validation of the tool developed in this thesis was direct comparison of its outputs to the outputs of models published by other researchers. Part of the tool has been validated this way; the CMA algorithm was tested against CPLEX software, which was used by a number of models in the offshore wind literature. However, a direct comparison of policies produced by this and other models would be difficult for the following reasons:

1) The tool developed in this thesis calculates the optimal policy for one day horizon. Some published vessel routing models present case studies based solely on planning horizon longer than one day (e.g. Dai et al. [22] and Irawan et al. [25]). An optimal policy calculated on an assumption on a one day planning horizon will, in most cases, be different to one calculated for a two or three day horizon.
2) Models available in literature implemented a constraint on some maintenance actions, which requires the vessel to be present at the turbine for the duration of the maintenance action. Interviews conducted with offshore wind farm operators (summarised in Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators) revealed that such repairs are fairly rare in practice, which is why such constraint has not been modelled here. Since there is not an easy way to implement this constraint, it would be very difficult to compare the tool output to results published by other researchers in the field.

In the end it was deemed that the validation efforts should be focused on application of the tool in a real world scenario (Section 7.5), rather than modifying the tool to be compatible with other published models. All data required to replicate Case Studies shown in Chapter 6 was be made publically available, allowing researchers in the field to apply their models and compare results.

Table 7.10 is an extension of Table 4.3 discussed in Literature Review Chapter (Section 4.2.6), now including the tool developed in this thesis. The proposed tool lacks certain functionalities available in other models (e.g. ability to obtain an exact solution or modelling technician qualifications). On the other hand, there are some features which are only present in the proposed tool, such as a methodology for dealing with probabilistic inputs and variable vessel speed.

Table 7.10. Comparison of published models for offshore wind farm vessel routing optimisation (* - variable cost only).

Heuristic method	✓		✓		✓	✓	✓	✓
Exact method		✓	✓	✓	✓			
Applied to a real world case study						✓		✓
Multi-objective optimisation								✓
Limited no. of technicians				✓		✓		✓
Time horizon > 1 day	✓	✓		✓	✓	✓	✓	
Heterogeneous vessels	✓	✓		✓	✓		✓	✓
Fixed & variable vessel costs	✓	✓	*	*	✓		*	✓
Multiple O&M bases				✓		✓	✓	
Profit collection (rewards for actions)						✓		✓
Penalty costs (e.g. lost revenue)	✓	✓	✓	✓	✓	✓	✓	✓
Uncertainties (e.g. service time)								✓
Variable vessel speed								✓
Vessel stays at turbine (some actions)	✓	✓	✓	✓	✓		✓	
Time window limit	✓	✓	✓	✓	✓	✓	✓	✓
2-d vessel capacity	✓	✓	✓	✓		✓	✓	✓
Transfer time modelled			✓	✓	✓	✓	✓	✓
Technician qualifications				✓			✓	
Maximum no. of vessels	2	2	5	4	2	1	10	6
Maximum no. of turbines	28	8	8	36	25	9	60	24
	Zhang (2014) [23]	Dai (2014) [22]	Stålhane (2015) [24]	Irawan (2017) [25]	Raknes (2017) [26]	Williams (2018) [27]	Schrotenboer (2018)	Dawid (2018) [199]

Table 7.10 is an extension of Table 4.3 discussed in Literature Review Chapter (Section 4.2.6), now including the tool developed in this thesis. The proposed tool lacks certain functionalities available in other models (e.g. ability to obtain an exact solution or modelling technician qualifications). On the other hand, there are some features which are only present in the proposed tool, such as a methodology for dealing with probabilistic inputs and variable vessel speed.

Table 7.10 also contains the largest problem size tackled by each of the models. The proposed tool has shown to produce sensible results (although they have not been proven optimal) when applied to a problem with 24 turbines and 6 vessels (results shown in Section 6.3). The only other models capable of solving problems with similar complexity were the approach proposed by Irawan et al. [25][56] and Schrotenboer et al. [28].

One of the factors distinguishing the proposed tool from other models in the field is the choice to model rewards rather than lost revenue. The advantage of the former approach is that it can consider both lost revenue and other incentives to visit a particular turbine, such as proximity of maintenance deadlines.

In summary, the proposed tool fills a research gap by enabling probabilistic inputs and enabling multi-objective optimisation. The solution methods developed in this thesis differ significantly from the approaches used by other researchers in the field. Wind farm operators' requirements and the key real world considerations were identified early on in the tool's development process (Section 2.2). Solution methods were designed with user friendliness, visual outputs and short computational time in mind. This emphasis on the wind farm operator's perspective was lacking in the models developed by other researchers in the field. Focusing on these aspects increases the chances of the tool's successful practical application.

[56] Note: Irawan et al. [25] tackled a problem with two fewer vessels but 12 additional turbines; they also attempted a problem with 72 turbines but the computational time exceeded 40 hours.

7.8 Comparing the Tool to Previously Specified Requirements

Christel & Kang [197] suggested that results of case studies should be used to verify whether the tool meets previously specified criteria. First set of criteria is presented in Chapter 2. , where an overview of practicalities associated with planning offshore wind farm O&M was provided. Chapter 2. was summarised by a set of recommended factors (Section 2.3) a decision support should take into account in order to be applicable in the real world. The second set of criteria is provided in Section 4.3, which summarised the key conclusions from the literature review of relevant review papers and models for operational decision support.

Based on the case studies presented in Sections 3.4, 6.2, 6.3, and 7.5, the tool was evaluated against the aforementioned criteria, as shown in Table 7.11 and Table 7.12

Table 7.11. Evaluation of the proposed decision support tool against recommendations from Section 2.3.

Tool requirement (Section 2.3)	Remarks	Achieved?
Task priority depends on multiple factors, including type/characteristics of maintenance, deadlines, spare part availability etc. Task priority is a key factor in the process of planning offshore wind farm O&M; it should be quantified and included in the decision making process (Section 2.2.2)	As shown in Section 3.4, the proposed methodology allows the user to input factors such as weather forecast or task deadlines, which influence the reward associated with the task. High reward tasks were prioritised over non-critical tasks with lower rewards in the final policies shown in Sections 6.2 and 6.3.	✓
Wind farms use vessels of varied characteristics, assignment of vessels to tasks may depend on vessel capabilities (Section 2.2.3)	The user can specify any number of vessels with unique characteristics such as speed and transfer probability in a given significant wave height. Vessel capabilities have an effect on the final policies, as shown in Section 6.2.	✓
Unavoidable maintenance costs should not have a significant impact on the next day's routing plan. (Section 2.2.4)	Although in the case studies presented in Sections 6.2 and 6.3, costs of repairs were modelled, they did not have a significant impact on the final policy. The user has the choice of whether to include maintenance task costs in the simulation.	✓
Assignment of technicians to tasks depends on their Health & Safety qualifications (Section 2.2.5)	In the modelling presented in this thesis, the assignment of technicians to tasks was not considered, as it would increase the problem complexity significantly. The possibility of including assignment of technicians to tasks is discussed in Section 8.3.2.	✗
Uncertainties on the weather forecast and duration of maintenance actions should be taken into account when planning offshore wind turbine maintenance (Section 2.2.7)	Section 6.2 demonstrated that taking uncertainty associated with vessel-to-turbine transfer in high waves into account when planning maintenance can result in improved vessel routing policies. Similarly, inclusion of uncertain task duration resulted in higher number of turbines successfully maintained as shown in Table 6.7.	✓

Tool requirement (Section 2.3)	Remarks	Achieved?
In the problem of planning day-to-day offshore wind farm O&M, there can be no single optimisation objective (Section 2.2.6). Key offshore O&M objective to consider include: • Maximisation of the number of completed high priority maintenance actions • Maximisation of operational efficiency (e.g. the average number of hours technicians do useful work) • Minimisation of lost revenue • Maximisation of MTBV • Minimisation of OPEX	The proposed methodology for calculating rewards (Section 3.3) was designed to favour: • Maintenance tasks with upcoming deadlines **(penalty cost reduction – OPEX reduction)** • Non-critical maintenance tasks performed during periods of low wind **(reduced lost revenue)** • Prioritise visits to high performance turbines **(revenue maximisation)** • Favour bundling different tasks on the same turbine, provided task duration does not exceed maximum allowable time **(maximisation of MTBV and increasing operational efficiency)** Additionally, the optimisation function used in the vessel routing optimiser (Equation 5.10) encourages: • Maximisation of the number of wind turbine visits **(minimisation of lost revenue as restored generation is maximised)** • Vessel-to-turbine assignment which maximises the probability of task completion **(increased operational efficiency due to reduction in unsuccessful transfers)** • Minimisation of vessel costs **(OPEX minimisation)**	✓

Table 7.12. Tool's assessment against requirements specified in Section 4.3.

Tool requirement (Section 4.3)	Remarks	Achieved?
Capable of handling stochastic inputs	The tool was shown to be able to handle uncertain inputs, which included uncertain service time, probability of technician transfer in a given significant wave height and probability of correct problem diagnosis.	✓
Focus on next day planning horizon	The tool's primary objective was to facilitate "same day" or "next day" O&M planning, as demonstrated in Sections 6.2, 6.3 and 7.5.	✓
Capable of solving heavily constrained problems with unserved customers	Case Study 2 described in Section 6.3 showed that the tool can sensibly prioritise maintenance tasks in a scenario with severely constrained resources and unserved customers.	✓
Able to handle a wide range of constraints, including problem-specific constraints	The tool was designed to take into consideration multiple constraints, including: • Vessel passenger capacity and spare part carrying capacity • Number of technicians available on the day • A limit on the time window Additionally, problem specific constraints modelled included crew transfer time (and uncertainty associated with vessel-to-turbine crew transfer) and variable vessel speed (to account for navigation/acceleration/deceleration when travelling between turbines).	✓
The approach needs to be flexible	The tool has only been tested at a single offshore wind farm, it is possible that other wind farms have operating constraints not considered in this work. Additions to the model (such as new constraints, modelling SOVs/jack-up vessels or modelling technician qualifications) may require significant effort to implement.	—
Capable of using a measure of risk to produce a range of policies, e.g. moderate, cautious and pessimistic	The tool's ability to produce a range of policies depending on the user's risk appetite is demonstrated in Sections 6.2 and 6.3.	✓

Tool requirement (Section 4.3)	Remarks	Achieved?
Based on real data	The Case Study discussed in Section 7.5 showed that the tool performs well when applied to a real world case study.	✓
Probability distribution of the uncertain service time should reflect the real-world distribution (positive skewness)	Gamma distributions with positive skewness were used to model uncertain service time.	✓
Capable of producing clear visualisations of the recommended policies	At the end of each simulation, the tool automatically generates graphical outputs, which include vessel routing plans and Gantt charts (see Figure 6.6 and Figure 6.14 respectively). The wind farm maintenance planner who evaluated the tool's outputs remarked that the tool's visual outputs would be useful in day-to-day decision making (Table N.1 in Appendix N).	✓
Capable of modelling most factors discussed in Table 4.1	Ten (out of twelve) factors were modelled in the tool (excluding technician qualifications/health and safety certificates and the previous day's assignment of technician teams to vessels).	—
Capable of producing solutions in reasonable computational time (i.e. less one hour for problems with ~20 customers)	The computational times required to generate policies in Winter and Summer Case studies in Sections 6.2 and 6.3 were no longer than 5 minutes per simulation. This is significantly shorter than the time required to make real-world decisions (however, this value does not include the time required to input data).	✓

In summary, the proposed tool met most of the previously specified requirements. With future work, the unmet criteria could be achieved; this is discussed in more detail in Section 8.3.2.

7.9 Validation Summary

The proposed tool was validated using a wide variety of approaches. Individual model components were validated separately. This was followed by validation of the entire tool through real world scenario application. Softer validation methods employed included expert discussions and comparison of model capabilities to previously specified requirements.

The complexity of the problem tackled in this thesis means that the term "optimal solution" is hardly relevant in the context of the real world vessel routing policy. There are multiple optimisation objectives; the choice of vessel routing plan depends on the weight the user assigns to each objective, which is subjective. Real world decisions may depend on stochastic inputs, making it difficult to quantify the value to a policy. Since defining a true optimal solution in itself is difficult, complete validation would be an even more arduous task.

Brief note on tool's verification

In the context of simulation tools, model verification was defined as follows [200]:

> *"The process of determining that a model implementation accurately represents the developer's conceptual description of the model and the solution to the model."*

The process of verifying the SMDP code was straightforward (as the model can be written in under 40 lines of code); the implementation of equations was cross-checked by thesis supervisors.

The solution method for the master problem was verified by comparing the model's outputs to the already verified CPLEX software (as shown in Section 7.4). The sub-problem of the vessel route optimiser was verified by a manually working out the expected values of parameters and comparing them to the values calculated by the model. An example of this is shown in Table 5.8, where the timings of individual stops were calculated manually and then compared to the timings produced by the model to verify it.

Chapter 8. Conclusions

Optimisation of planning offshore wind farm O&M was the focus of this thesis. A combination of literature review and interviews with wind farm operators allowed the author to gain an in-depth understanding of the real world problem. For large offshore wind farms (100+ wind turbines), planning day-to-day O&M is enormously complex (as discussed in Appendix A. Calculating the Number of Possible Vessel Routing Policies). The problem size and constraints make solving it difficult, both for human decision makers and optimisation algorithm developers. Occasional human error, which is inevitable where no software is present to prevent it, can lead to huge revenue losses. There is a clear demand for decision support tools in this area.

Achievement of the research objective is discussed in Section 8.1. The contributions arising from the work done in this thesis are summarised in Section 8.2. The limitations of the proposed tool and future work are covered in Section 8.3.

8.1 Research Objective

The research objective was defined in Section 1.1 as:

> "The objective of research is to develop methodologies for supporting operational logistical decisions on offshore wind farm, which are suitable for practical application and aim to reduce LCoE through efficient use of resources."

Two methodologies for decision support were developed in this thesis: an SMDP model for task prioritisation and a vessel routing optimisation tool. Either model can be used as a standalone entity, or the two models can be combined into one by taking the outputs of the SMDP model as inputs to the vessel routing optimisation model. Testing the vessel routing optimisation tool at a wind farm using real world data demonstrated that the approach is suitable for practical application.

As demonstrated in Sections 6.2, 6.3 and 7.5 he two models can aid LCoE reductions by:

- Enabling better decision making, maximising restoration of generation, maximising the useful time technicians spend on turbines and minimising lost generation
- Reducing the number of unfinished tasks by discouraging planning work, which is likely to take longer than the time constraint. Higher task completion rates increase the effectiveness, as less time is spent on repeated transfers onto recently visited turbines
- Minimising the vessel use (through optimising the ordering of turbine visits and possible reductions in the number of vessels required to complete maintenance tasks), which in turn leads to minimising fuel cost and wind farm carbon footprint
- Shortening the time required to make operational decisions (time can be reduced form hours to minutes), freeing up planners' time to optimise processes which are not covered by the tool
- Real world decision making can be repetitive and tedious (due to frequent changes of circumstances). This, combined with the complexity of the problem can lead to costly instances of human error. The proposed tool can aid human error reductions as all policies generated by the tool comply with rigid constraints (e.g. maximum number of technicians allowed on a vessel).

8.2 Thesis Contributions

The main contribution of this thesis is the development of a new heuristic methodology, a new task prioritisation approach and application of those novel approaches to a real world problem. As the work done in this thesis was partly driven by the industrial partners (an offshore wind farm operator), invaluable knowledge of the real world processes and constraints was gained. This knowledge was disseminated through the research articles and oral presentations outlined in Section 1.3.

As the work on this topic progressed, the definition of the term "optimal policy" became blurred. The real world problem is characterised by multiple optimisation objectives, such as cost reduction, maximisation of MTBV, maximisation of the number of man-hours spent on turbines and the number of turbines serviced. Furthermore, as demonstrated in Sections 6.2 and 6.3, the cost-optimal policy is not necessarily best in scenarios with uncertain inputs, as low cost policies are often characterised by low probability of completing all planned work. Additionally, it was found that the uncertainty associated with estimated maintenance action time has a significant impact on policy effectiveness. Wind farm operators should keep a log of how long the tasks take to narrow down the uncertainty, enabling better decision making.

This is one of the key findings of the work done in this thesis. By incorporating uncertain inputs into the decision making tool, a research gap was filled. Most researchers working in this field are still attempting to find the single cost-optimal vessel routing policy, which does not exist in most real world scenarios.

In addition to the tool's ability to lower LCoE discussed in the previous section, the developed decision support tool comprising of the proposed two models also has the following advantages:

- Computational time is flexible: urgent decisions can be made in minutes. When planning vessel routing for the following day, the algorithms can be run for hours, increasing the quality of resulting policies.
- Incorporation of the risk aversion factor as a user input enables generating a range of policies with varying likelihood of success. The user can evaluate the proposed policies and use their expert knowledge to choose the one which is likely to be suitable in a given scenario. As demonstrated in Section 6.3.2, Pareto graphs can be used to visualise the trade-offs between optimisation objectives, enabling multi-objective optimisation.
- Ease of use – throughout the development process, the focus has been on the end product usability and practical application. The user is able to define most inputs in Excel. Tool's outputs include visualisations such as vessel routing maps and Gantt charts to facilitate understanding of the suggested policies.
- The tool is modular (the key modules being the SMDP model, master and sub-problem solution algorithms), meaning that a solution method of either of the modules can be changed without affecting the other parts of the tool. An example of this was presented in Section 7.4, where the master problem was solved using CPLEX instead of the proposed heuristic.
- Potential applicability to other fields – there are many industries which could benefit from a tool able to quantify maintenance task priority (SMDP), or use the proposed CMA heuristic to solve an optimisation problem.
- The tool enables a degree of flexibility, allowing the user to tweak the resulting policies to their needs. For example, if a certain task must be done on a given day for contractual reasons, the SMDP priority value can easily be overridden to ensure the task is chosen by the vessel routing optimiser.

- This thesis, along with the journal paper on the vessel routing optimiser (Dawid, McMillan & Revie [199]) are the first publications in the field to offer an in-depth analysis of individual policies generated for complex problems. Demonstration of the generated policies enables the research community (and practitioners interested in applying those models) to evaluate the logic behind the choices and trade-offs made by the algorithms used. Visualising model outputs for individual cases facilitates understanding the assumptions used. It enables assessing the quality of the results produced and the applicability of the proposed solution to a real world scenario.
- In contrast to the literature published in the field, the problem was presented from the perspective of an operator of a large (100+ turbines) offshore wind farm. Insights from an O&M planner were provided in Section 7.6. The large offshore operators need decision support tools capable of solving multi-objective problems with uncertain inputs, 20+ turbines and 5+ vessels, which to date in the offshore wind field, has only been demonstrated by the author of this thesis and Schrotenboer et al. [28].

8.3 Model Limitations and Future Work

8.3.1 Limitations

Currently, the proposed tool does not allow modelling the technicians' qualifications. Usually, teams consist of a team lead, who tends to be more experienced and have additional health and safety qualifications, and a couple of technicians with standard offshore wind training. Team leads are distributed across teams in a process, which is currently done by the planners. Certain maintenance actions can only be carried out by staff with specific health and safety certificates (i.e. high voltage competency training). Modelling the assignment of technicians to tasks would require an understanding of the real world processes used by the planners. Planners create teams with technicians' skillsets and past experience in mind. Future work should include documentation of the logic wind farm operators use in this process.

Modelling health and safety certificates and technician experience could improve the quality of results, for example by letting the user know there is a shortage of technicians with certain qualifications/shortage of team leads. It would also reduce the O&M planner's workload. However, the problem's complexity would increase, which would have an impact on the computational time required to produce a policies.

The sub-problem solution algorithm is currently capable of assigning up to 4 turbines per vessel. In reality, some vessels may be required to visit 5 or more turbines in a day. Removing this constraint could lead to higher quality policies (up to 1.9% [25], as discussed in Section 5.1). This constraint may need to be removed in order to apply the tool at near-shore sites, where time spent travelling between the O&M base and the site is very short (meaning there is more time for one vessel to visit additional turbines).

Scalability can also pose a challenge, if the proposed tool was to be applied to optimise maintenance across multiple wind farms. As the problem complexity increases exponentially with number of turbines visited and number of vessels available, the current methodology may struggle to produce close-to-optimal solutions for problems with 30+ turbines to be visited and 10+ vessels.

According to an O&M planner (interview transcript can be found in Section 7.6) the key barrier to practical application of the proposed tool is integration with the current IT systems. This would include linking the Matlab-based tool to the databases and software currently used by the planners. This is discussed in more detail in Section 8.3.3.

Wind farm operators also suggested that the ability to track spare parts and toolkits would be a useful addition to the model. In some cases, if a team is to change vessel from one day to another, their tools may need to be craned over from one vessel onto the other. As this process can be time consuming, including toolkit locations in modelling may result in more efficient policies.

8.3.2 Future work

The work described in this thesis could be continued to accelerate research on improvements of processes for offshore wind farm O&M planning. Aside from addressing the limitations highlighted in the previous section, future work should focus on:

- Practical application of the SMDP tool for prioritising maintenance tasks. However, due to large volumes of active tasks (10+ per turbine, as reported by an offshore wind farm operator) this would require integration with the wind farm's IT systems.
- The quality of results of the proposed heuristic method may be improved by using a local search or a Large Neighbourhood Search (LNS). Alternatively, a study could be carried out to investigate the effect of tier ratios (ratio of

a/b, a/c and b/c from Figure 5.10) on the quality of results produced by the heuristic method.

- Simplification of the sub-problem solution algorithm could be achieved by asking user to assign task priorities, which would determine the order of wind turbine visits. This would reduce the size of the sub-problem and extend the user's influence on the order of wind turbine visits.

Additionally, a number of studies could be conducted using the proposed decision support tool:

- Feasibility study to investigate possible application to onshore wind O&M planning optimisation
- The tool could be used to estimate future technician and vessel demands. Using past data on average amount of workhours required per day, plus any additional planned work, the staffing requirements could be estimated
- The vessel routing optimiser could also be used to estimate staffing/vessel requirements of wind farms under development

It is tempting to make an attempt at quantifying the benefits of practical implementation of the proposed tools. However, this would be difficult as historical O&M data lacks context. Operators may sometimes be forced to take a sub-optimal decisions, such as not to visit a not-operational turbine due to lack of spare parts/equipment or a temporary access restriction. These constraints are not usually logged anywhere, so the estimated benefits of using a decision support tool would likely be inflated.

8.3.3 Integration with Current Wind Farm Management Systems

Operations at large offshore wind farms are planned using a multitude of software packages. Weather forecasts (wind and wave), which determine future turbine accessibility are stored in large databases, as is wind turbine SCADA data. Wind turbine warnings and alarms are usually processed by turbine's manufacturer software. The warning/alarm code often dictates the type of maintenance work required. Annual services and retrofit campaigns are usually planned in project management software, which can also be used for staffing requirements.

All of the data mentioned in the above paragraph is required as input to the proposed vessel routing tool. Note that the real world case study presented in Section 7.5 lacked input on the tasks required on turbines which were not pre-selected by the planners. The pool of tasks to be carried out at a wind farm with 100+ turbines can easily exceed

1,000; it is simply not feasible to manually enter those into Excel (and then keep them up to date as new issues arise).

Implementation of a short-term O&M decision support tool requires integration with wind farm management systems. This involves linking to multiple software packages and databases. It can also be achieved by creating a "data lake", which would pull information from different data sources together into a single system. Once connections between different systems are established, they need to be monitored and maintained to prevent gaps in the data or corrupted data, which may lead to misinformed decisions.

In summary, the task of integrating all information required for an O&M decision support to truly support decisions and bring significant cost savings is challenging and requires significant IT experience. Note that solving this problem for one wind farm does not mean the end product will be applicable to other operators, who may use different software systems. This, and the problem complexity, are the key reasons for the lack of software solution in the field of short-term O&M decision support for offshore wind farms.

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Appendix A. Calculating the Number of Possible Vessel Routing Policies

Assumptions:

a) There are 20 turbines requiring a maintenance action
b) 5 vessels are used to carry out these maintenance actions, each vising 4 turbines
c) Vessels are unique (have different properties)
d) Vessels drop off all teams of technicians before they start picking them up

There are two factors determining the overall number of permutations:

1) Number of ways 20 turbines can be assigned into 5 sets of 4 and
2) Order in which the turbines within each set of 4 are visited for crew transfer

The formula to calculate 1) is:

$$\frac{20!}{4!\,4!\,4!\,4!\,4!}$$

The formula to calculate 2) is:

$$((4!)^2)^5$$

Assumption d) states that all 4 crews of technicians on each vessel are dropped of first – this can be achieved in 4! permutations. This value is squared as there are as many ways in which all technicians can be picked up from the turbines once the maintenance actions have been finished. Finally, the entire expression is raised to the power of 5, as for each assignment generated in 1), there are 5 unique vessels carrying crews to turbines.

For each assignment of turbines to vessels, each permutation of order of visits is possible; hence to obtain the total number of permutations, the two expressions are multiplied:

$$Total\ number\ of\ permutations = \frac{20!}{4!\,4!\,4!\,4!\,4!} * \ ((4!)^2)^5 = \mathbf{1.9372 * 10^{25}}$$

Considering that the number of stars in the observable universe is estimated to be between $7\text{x}10^{22}$ (according to [57]) and 10^{24} (according to [58]), the number of possible permutations is at least an order of magnitude higher. Note that the proposed

[57] http://www.skyandtelescope.com/astronomy-resources/how-many-stars-are-there/ accessed on 15/08/2017.
[58] https://www.space.com/26078-how-many-stars-are-there.html accessed on 15/08/2017.

calculation of the number of permutations is an underestimation, permutations in which vessels visit fewer than 4 turbines are not considered.

Appendix B. Summary of Informal Interviews with Offshore Wind Farm Operators

Throughout this project, the author kept in touch with engineers and operators of a UK offshore wind farm. The problem description formulated by the practitioners helped structuring the methodology developed in this thesis. Below is a summary of the conclusions arising from informal discussions with wind farm operators:

- Interviewed staff did not hear about decision support tools being used for maintenance planning/vessel routing at UK offshore wind farms.
- In the current decision making process, uncertainties such as the weather and access probability, are not quantified. Operators use their expertise and experience to subjectively incorporate uncertainties into the decision making process.
- According to maintenance planners, the top three uncertain factors to consider when planning vessel routing are: task duration, access probability and probability of correct diagnosis.
- Most real life routing decisions are made with one day planning horizon.
- Frequently, the number of maintenance actions to be carried out exceeds the capabilities of technicians and vessels available. Task prioritisation is required on most sail days.
- Failure to complete all necessary maintenance in the run up to a no access period (i.e. due to significant wave height in the winter) can lead to turbines being inoperative for weeks – meaning hundreds of thousands of pounds in lost revenue.
- It is not uncommon for a large offshore wind farm in the North Sea to experience days with 20+ turbines requiring a high priority maintenance action in the winter (due to a period of reduced access).
- High priority tasks include: actions to restore power generation, actions to prevent failure, actions which nearing deadlines. Note that a missed deadline on a preventative task (i.e. equipment crane inspection) may prevent carrying out corrective actions (a crane which has not been inspected for over a year cannot be used to lift equipment). Low priority tasks include annual services, inspections and retrofits (provided a deadline for those actions is not imminent).
- High priority tasks are usually the first to be started on the day (especially ones with longer expected duration), to maximise the time available for repairs and therefore maximise the probability that the turbine will be operational at the end of the day.

- Maintenance is often delayed if a turbine only requires one, non-critical maintenance action. Holding off maintenance until another action is required aims to increase the MTBV - a key performance indicator for some operators.
- Inevitably, some tasks will take longer to complete than initially expected. To avoid technicians having to work longer-than-12h shifts, tasks taking longer than expected are usually left unfinished at the end of the day (unless there is another task scheduled afterwards which can be delayed or cancelled). If a task takes a shorter time than expected, wind farm operators may make on-the-day modifications to assign an additional task to teams. If technicians have spare time on turbine, it may be used to carry out auxiliary tasks such as cleaning wind turbine transition pieces.
- If a change of circumstances (e.g. turbine failure) occurs towards the end of planner's shift, they may be required to do overtime to create a plan of action for the following day.
- The number of technicians required to carry out a given task is not always fixed – certain maintenance actions are best carried out by 3 technicians, but can also be completed by 2.
- Vessel-to-turbine base and turbine base-to-nacelle transfers take approximately 20 minutes each (for an average of 3 crew members).
- Most "standard" maintenance tasks (minor corrective tasks, inspections and servicing) are carried out by teams of 2-4 technicians.
- It is unusual for maintenance planners to consider component weight when planning vessel routing – it is rarely required to do so.
- While there are maintenance actions which require the vessel to be present at the turbine for the entire task duration, these are very rare

The above is the perspective of one operator; as wind farms vary in size, distance from shore, equipment (including turbine OEM) and location, their operators may see the problem differently.

Appendix C. Wind farm Ownership Structure

Wind farm owner is responsible for financing of the project and assigning the wind farm operator. Examples of owners of UK wind farms include UK Green Investment Bank, Innogy, Orsted (who is also an operator) and Siemens (who is also an OEM).

Wind farm operator is responsible for managing the day-to-day running of the wind farm. UK wind farm operators include SSE, Equinor and Orsted. Wind farm operators report to the wind farm owner.

Turbines are often sold with a 2-5 years' full service warranty provided by the OEM [17]. This entails carrying out all preventive and corrective maintenance as well as providing qualified technicians. Some operators choose to extend this agreement beyond 5 years for an additional fee. Alternatively, an independent maintenance service provider may be hired to carry out wind farm maintenance after the initial 2-5 years.

Appendix D. SMDP Case study Inputs

Table D.1. Grease top up cost matrix for winter day case study. Values expressed in thousands of pounds.

		Day									
Action	State	1	2	3	4	5	6	7	8	9	10
Do nothing	1	0	0	0	0	0	0	0	0	0	0
	2	0	0	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0	0	0
	4	0	0	0	0	0	0	0	0	0	0
Top up grease	1	0	0	0	0	0	0	0	0	0	0
	2	0	0	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0	0	0
	4	-5	-5	-5	-5	-5	-5	-5	-5	-5	-5

Table D.2. Grease top up reward matrix for winter day case study. Values expressed in thousands of pounds.

		Day									
Action	State	1	2	3	4	5	6	7	8	9	10
Do nothing	1	9.6	8	8	8	8	8	8	8	8	8
	2	9.6	8	8	8	8	8	8	8	8	8
	3	9.6	8	8	8	8	8	8	8	8	8
	4	0	0	0	0	0	0	0	0	0	0
Top up grease	1	8	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7
	2	8	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7
	3	8	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7	6.7
	4	3.2	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7	2.7

Table D.3. Grease top up transition matrix on day 1 of winter day case study.

Day 1		Final State			
Action	Original state	1	2	3	4
Do nothing	1	1	0	0	0
	2	0	0	1	0
	3	0	0	0	1
	4	0	0	0	1
Top up grease	1	1	0	0	0
	2	0.8	0	0.2	0
	3	0.8	0	0	0.2
	4	0.8	0	0	0.2

Table D.4. Grease top up transition matrix on day 3 of winter day case study.

Day 3		Final State			
Action	Original state	1	2	3	4
Do nothing	1	1	0	0	0
	2	0	0	1	0
	3	0	0	0	1
	4	0	0	0	1
Top up grease	1	1	0	0	0
	2	0.65	0	0.35	0
	3	0.65	0	0	0.35
	4	0.65	0	0	0.35

Table D.5. Expected durations of different maintenance actions.

Type of maintenance action	Time required (hours)
Manual reset	2
Grease top up	3
Retrofit	4
Minor repair	5
Medium repair	6
High priority repair	5
Annual service	6

Appendix E. Logic Flowcharts for the Sub-Problem

Note that no logic flowchart is necessary for Case #1, as it contains a single turbine; no need to decide the order of visits.

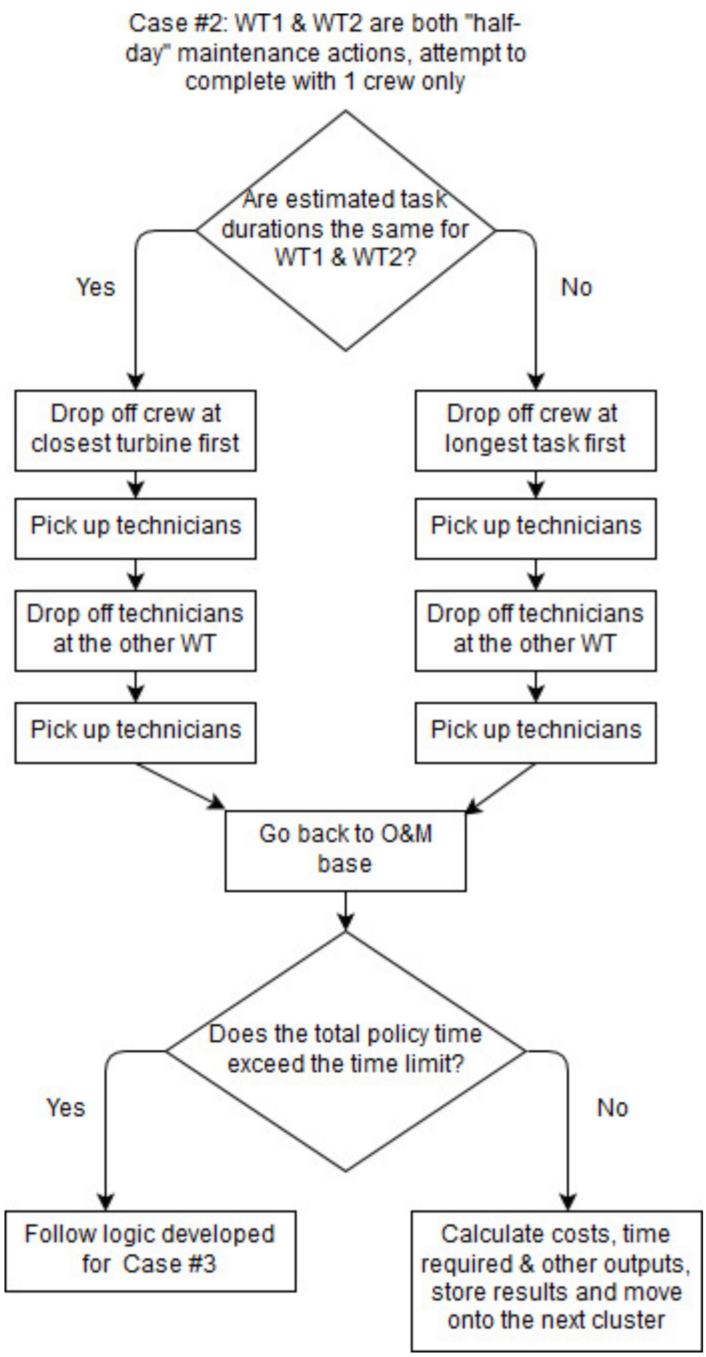

Figure E.1. Logic flowchart for Case #2.

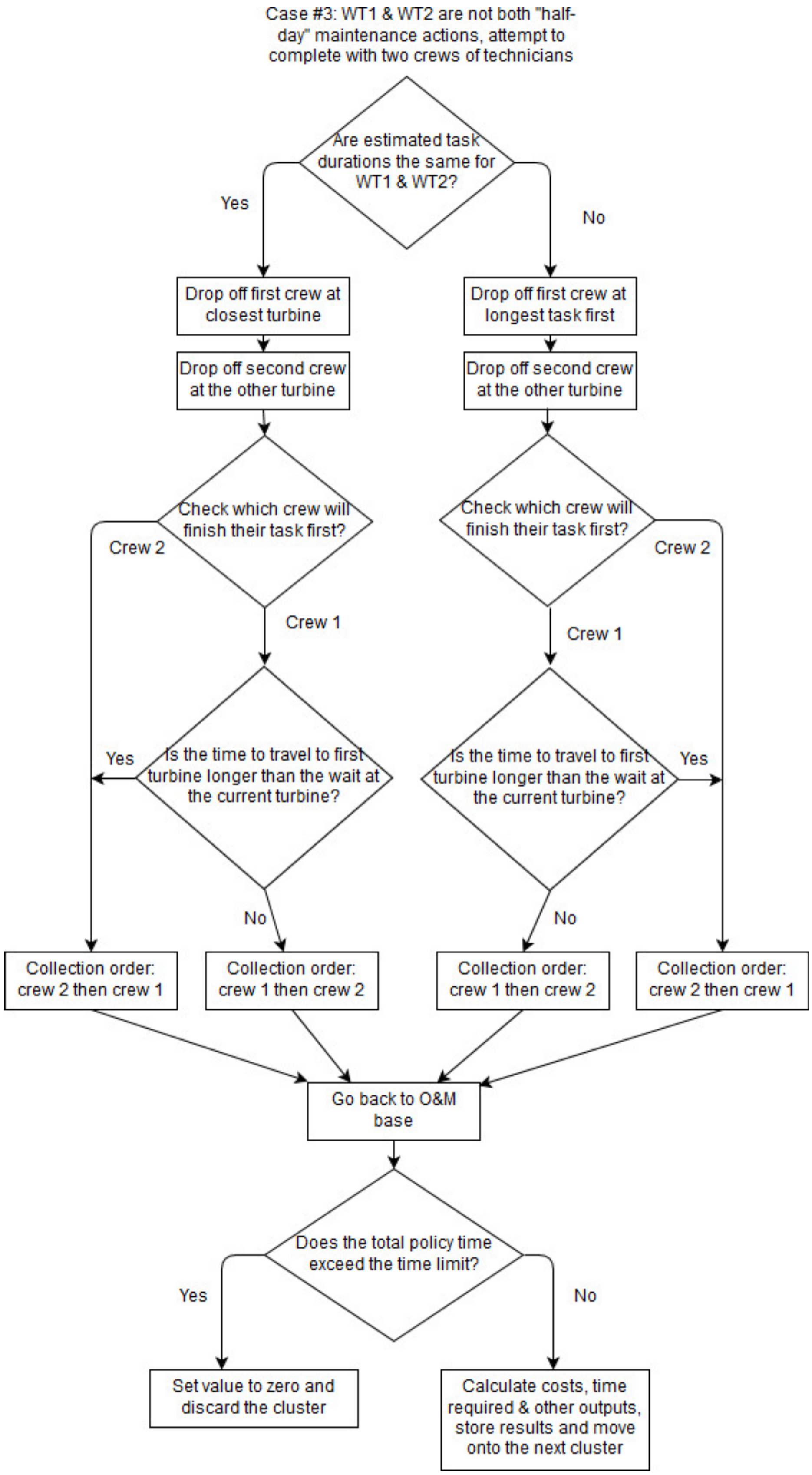

Figure E.2. Logic flowchart for Case #3.

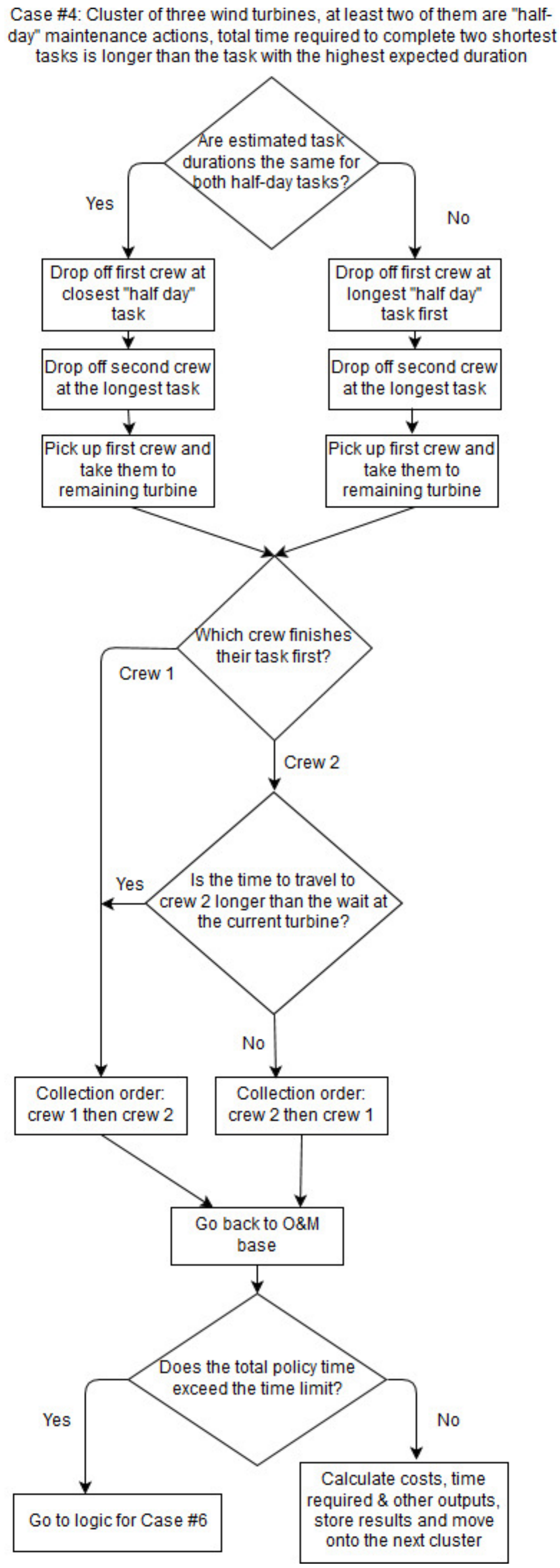

Figure E.3. Logic flowchart for Case #4.

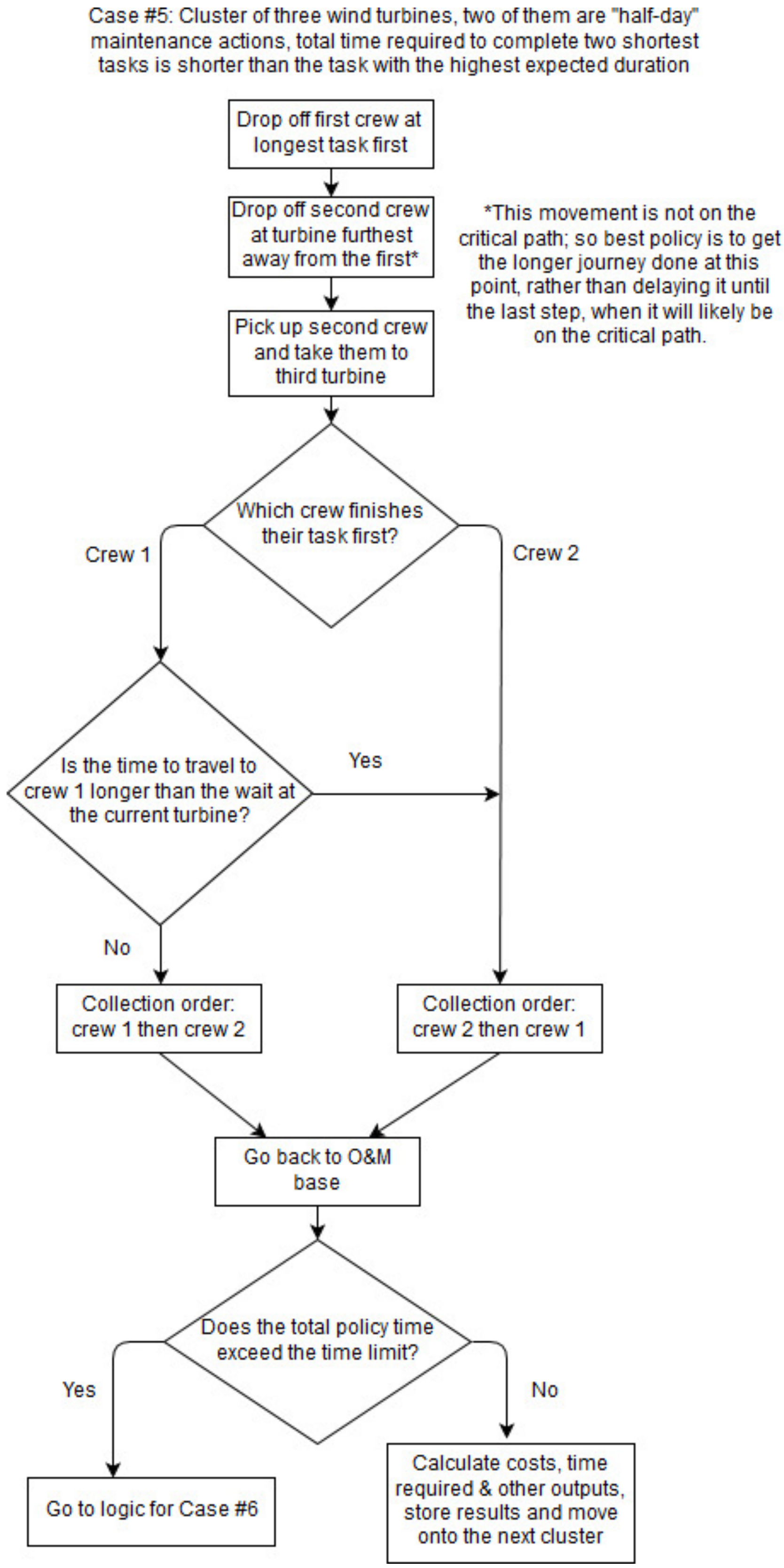

Figure E.4. Logic flowchart for Case #5.

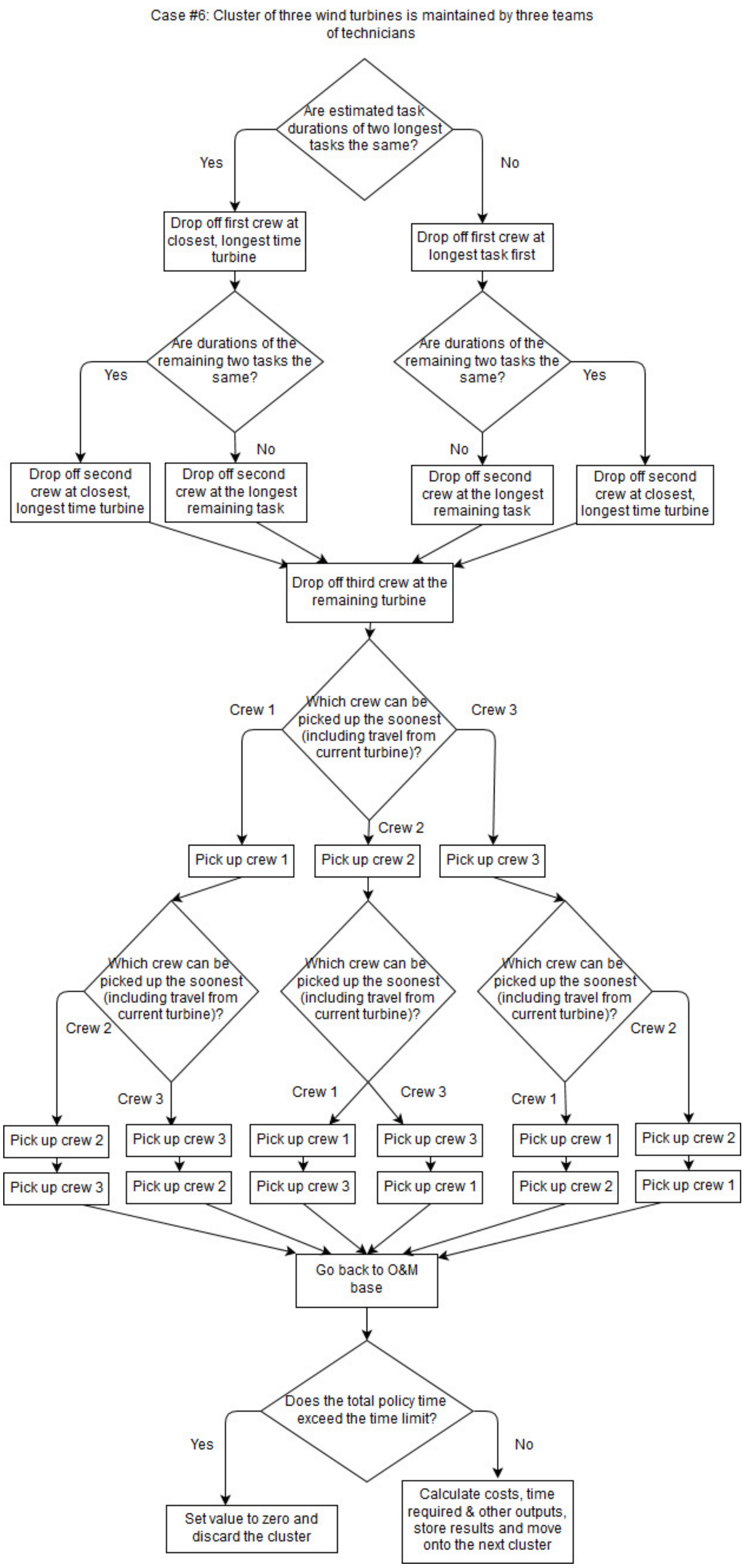

Figure E.5. Logic flowchart for Case #6.

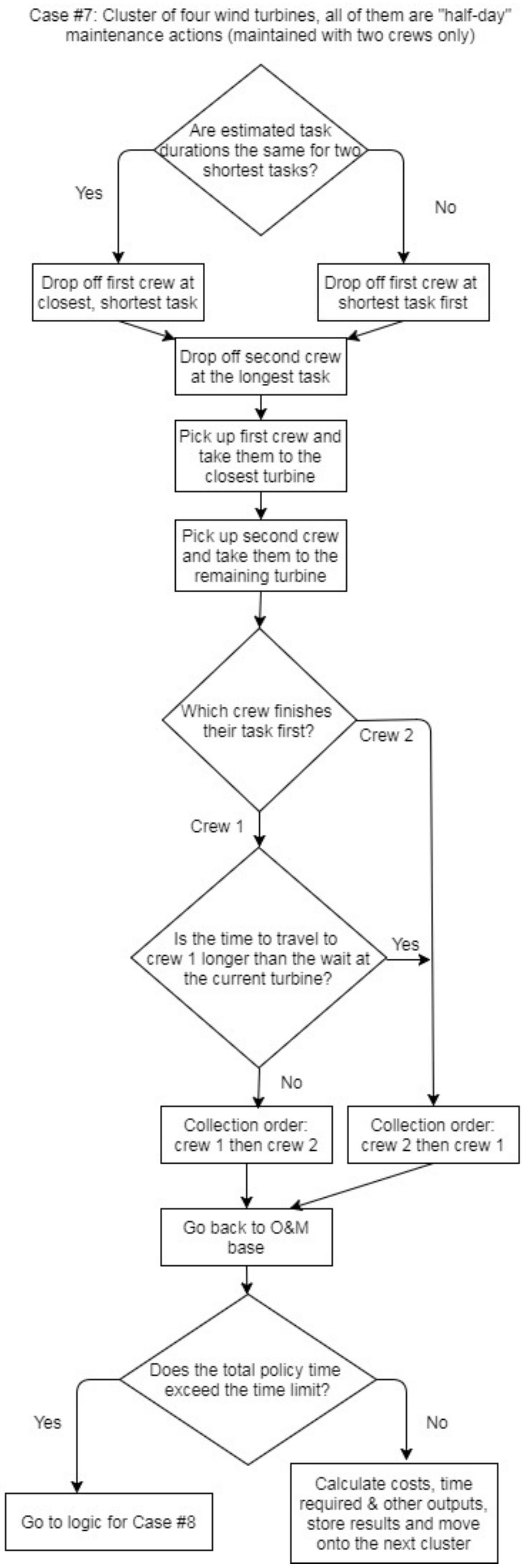

Figure E.6. Logic flowchart for Case #7.

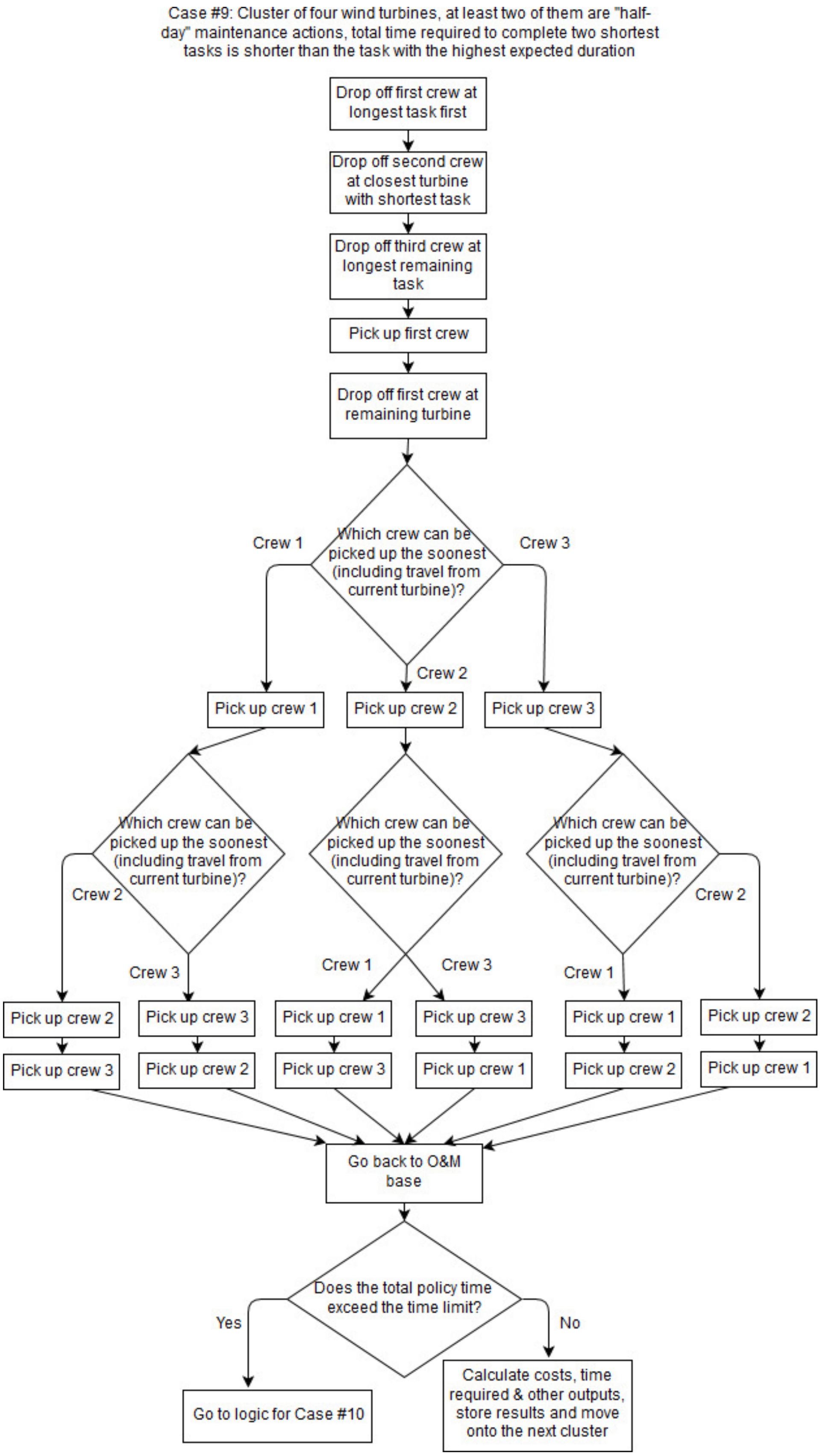

Figure E.7. Logic flowchart for Case #9.

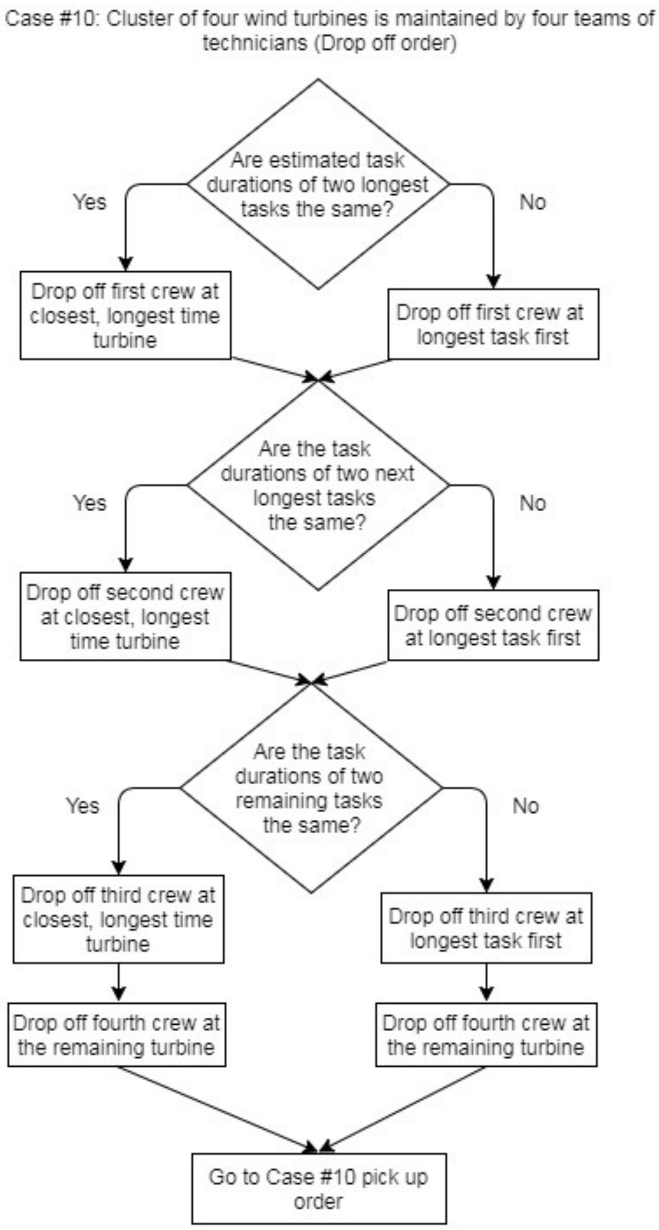

Figure E.8. Logic flowchart for Case #10: Drop off order.

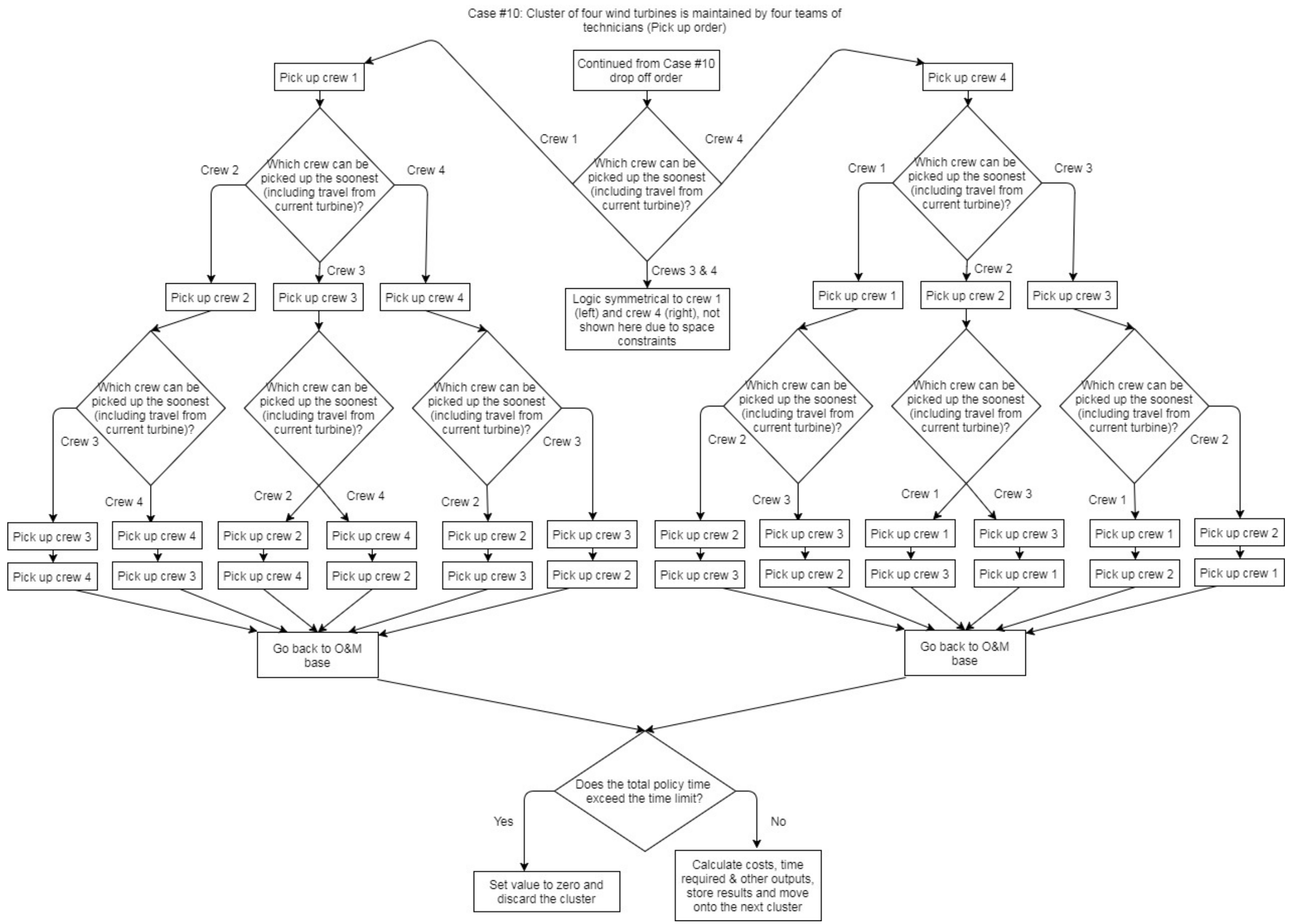

Figure E.9. Logic flowchart for Case #10: Pick up order.

Appendix F. Slack Time Distribution

Table F.1. Slack time distribution for technician teams in different scenarios.

Case	End of day slack (Ge) assignment
#1	All slack assigned to the only maintenance task
#2	All slack assigned to tasks on critical path
#3	70% of slack assigned to the task started first, 30% assigned to the remaining task
#4	70% of slack assigned to critical path actions, 30% to the remaining task
#5	70% of slack assigned to critical path action, 30% to two tasks serviced by the same crew
#6	50% of slack assigned to the task completed last, 30% to task completed second last, 20% to task completed first
#7	40% of slack assigned to two tasks carried out by Crew 1 (first to be dropped off), 60% to tasks carried out by Crew 2
#8	40% of slack assigned to critical path actions, 30% to each remaining action
#9	50% of slack assigned to critical path action, 40% to two tasks serviced by the same crew, 10% to the remaining task
#10	40% assigned to the longest task, 20% to all remaining tasks

Appendix G. Example of Cluster Value Calculation Using Low and High Risk Aversion Factors

The aim of this appendix is to demonstrate the consequences of setting a high risk aversion factor (Y) as model input. Recalling Equation 5.10, used to calculate cluster value:

$$\Omega = \sum_{i=1}^{Q}[U_i - Cr_i] - \sum_{j=1}^{J}[Cf_j + Ch_j] + (Px * U_{mean} * Y) \;\; (Y \geq 0)$$

Consider a cluster with the following properties:

Q – Number of turbines in a cluster = 3

$\sum_{i=1}^{Q}[Ui - Cri]$ – sum of rewards minus repair costs for the 3 turbines in cluster = £210,000

U_{mean} – mean reward for repairing one turbine = £70,000

Px – probability that all turbines in this cluster will be maintained = 0.3

$Cf_j + Ch_j$ – cost of fuel and vessel hire = £11,300

Inputting all of the above, and a low risk aversion factor (Y=1) yields a cluster value of:

$$\Omega = 210{,}000 - 11{,}300 + (0.3 * 70{,}000 * 1) = £219{,}700$$

The artificial monetary value, which is added to favour clusters with higher probability of maintaining all its turbines amounts to **£21,000**. Using a high risk aversion factor (Y=10) yields:

$$\Omega = 210{,}000 - 11{,}300 + (0.3 * 70{,}000 * 10) = £408{,}700$$

The added value due to risk aversion factor in this case is **£210,000**: almost 19 times higher than the real world costs. This not only diminishes the effect costs have on the policy (i.e. fuel cost which has a minimising effect on the amount of vessel travel, leading to reduced policy time), it also discourages visits to turbines with low rewards.

Appendix H. Decision Support Tool User Interface

	B	C	D	G
1				
2	WT ID	State	Total failed WT	Expected Wave Height (m)
3	1	0	14	1.7
4	2	0		1.7
5	3	10		1.7
6	4	0		1.7
7	5	0		1.7
8	6	0		1.7
9	7	0		1.7
10	8	0		1.7
11	9	0		1.7
12	10	0		1.7
13	11	0		1.5
14	12	0		1.5
15	13	0		1.5
16	14	0		1.5
17	15	0		1.5
18	16	0		1.5
19	17	0		1.5
20	18	0		1.5
21	19	8		1.5
22	20	0		1.7
23	21	14		1.3
24	22	0		1.3
25	23	0		1.3

Figure H.1. User can select the turbines requiring maintenance and assign each turbine a maintenance action ID. Properties of maintenance actions are input in a separate table, as shown in Figure H.2.

	C	D	E	F	G	H	I	J	K
1	Speed (km/h)	Fuel consumption (£'000/km)	Hire cost (£'000/day)	Load capacity (kg)	Transfer below 1.4m	Transfer below 1.6m	Transfer below 1.8m	Transfer below 2m	Notes
2	48	0.01	0	20000	1	1	0.75	0.5	Class 1 Vessel
3	48	0.01	20	20000	1	1	0.75	0.5	Class 1 Vessel
4	37	0.006	0	15000	1	0.8	0.5	0	Class 2 Vessel
5	37	0.006	0	15000	1	0.8	0.5	0	Class 2 Vessel
6	37	0.006	10	15000	1	0.8	0.5	0	Class 2 Vessel
7									
8									
9									
10									

	C	D	E	F	G	H	I
11	Time required (h)	Technicians required	Probability of success	Value (£,000)	Cost (£'000)	Load (kg)	Work description
12	5	3	0.95	302.9	18.5	550	High priority repair
13	4.5	2	1	195.4	1	70	GTU (4) and manual reset
14	6.5	3	0.8	175.6	1	150	Manual reset and minor repair
15	6	3	0.9	113.3	18.5	450	Medium repair (4) (High performance)
16	2	2	1	96.6	0	0	Manual reset (High performance)
17	6	3	0.9	94.2	18.5	450	Medium repair (3)
18	3	2	1	92.1	1	70	GTU (3)
19	6	3	0.9	87.8	18.5	450	Medium repair (2)
20	6	3	0.9	87.8	18.5	450	Medium repair (3) (no time to fix minor repair)
21	5	3	0.8	87.8	1	150	Minor repair
22	2	2	1	87.8	0	0	Manual reset
23	3	2	1	2.1	1	70	GTU (2) (High performance)
24	3	2	1	2	1	70	GTU (2)
25	4	2	1	-2.1	1	100	Retrofit

Figure H.2. Vessel and maintenance action properties are defined by the user in Excel.

```
%%%%%%% User inputs   %%%%%%

CSNo=1; %Case study number 1 winter 2 summer
HeurOrCplex=1; %1 for Heuristic method 2 for CPLEX
TechConstrained=0; % 1 if problem is constrained by the number of technicians. If vessels are a constraint use 0.
EncourageLowRisk=1; %1 favours low risk policies. Risk apetite can be changed by varying ProbabilityValue
Monte=1; %1 if Monte Carlo simulation required
PlotValueFunctions=0; % 0 not 1 yes
RiskA=1;  %Higher value encourages low risk policies
Limit=4; % Max number of turbines per vessel
Actions=6; %Do nothing + use each vessel
WeatherWindow=11; % Time available for maintenance activities in hours on a given day
ShortRep=[1.5 2 2.5 2.75 3]; %Repairs of this length can be caried out in series, by one crew
StartTime=7; %hours from midnight when the vessels leave the base
SpeedCorrection=1.5; %Speed correction - vessel speed reduced on turbine-to-turbine journeys
TechAva=35; %Available technicians
TransferTime=1/3; %In hours, both onto and off the turbine

%%%%%%% User inputs end %%%%%%

tic
```

Figure H.3. Inputs such as the number of technicians available and the time limit are defined in MATLAB.

Appendix I. Logistics Model Inputs to Case Studies 1 and 2

Table I.1. Wind turbine coordinates used in Case Studies 1 & 2. (Lat: latitude, Lon: Longitude)

Location	Lat	Lon	Location	Lat	Lon	Location	Lat	Lon	Location	Lat	Lon
Base	1.65	1.65	WT26	0.5	0.7	WT51	0	0.4	WT76	0.5	0.2
WT1	0	0.9	WT27	0.6	0.7	WT52	0.1	0.4	WT77	0.6	0.2
WT2	0.1	0.9	WT28	0.7	0.7	WT53	0.2	0.4	WT78	0.7	0.2
WT3	0.2	0.9	WT29	0.8	0.7	WT54	0.3	0.4	WT79	0.8	0.2
WT4	0.3	0.9	WT30	0.9	0.7	WT55	0.4	0.4	WT80	0.9	0.2
WT5	0.4	0.9	WT31	0	0.6	WT56	0.5	0.4	WT81	0	0.1
WT6	0.5	0.9	WT32	0.1	0.6	WT57	0.6	0.4	WT82	0.1	0.1
WT7	0.6	0.9	WT33	0.2	0.6	WT58	0.7	0.4	WT83	0.2	0.1
WT8	0.7	0.9	WT34	0.3	0.6	WT59	0.8	0.4	WT84	0.3	0.1
WT9	0.8	0.9	WT35	0.4	0.6	WT60	0.9	0.4	WT85	0.4	0.1
WT10	0.9	0.9	WT36	0.5	0.6	WT61	0	0.3	WT86	0.5	0.1
WT11	0	0.8	WT37	0.6	0.6	WT62	0.1	0.3	WT87	0.6	0.1
WT12	0.1	0.8	WT38	0.7	0.6	WT63	0.2	0.3	WT88	0.7	0.1
WT13	0.2	0.8	WT39	0.8	0.6	WT64	0.3	0.3	WT89	0.8	0.1
WT14	0.3	0.8	WT40	0.9	0.6	WT65	0.4	0.3	WT90	0.9	0.1
WT15	0.4	0.8	WT41	0	0.5	WT66	0.5	0.3	WT91	0	0
WT16	0.5	0.8	WT42	0.1	0.5	WT67	0.6	0.3	WT92	0.1	0
WT17	0.6	0.8	WT43	0.2	0.5	WT68	0.7	0.3	WT93	0.2	0
WT18	0.7	0.8	WT44	0.3	0.5	WT69	0.8	0.3	WT94	0.3	0
WT19	0.8	0.8	WT45	0.4	0.5	WT70	0.9	0.3	WT95	0.4	0
WT20	0.9	0.8	WT46	0.5	0.5	WT71	0	0.2	WT96	0.5	0
WT21	0	0.7	WT47	0.6	0.5	WT72	0.1	0.2	WT97	0.6	0
WT22	0.1	0.7	WT48	0.7	0.5	WT73	0.2	0.2	WT98	0.7	0
WT23	0.2	0.7	WT49	0.8	0.5	WT74	0.3	0.2	WT99	0.8	0
WT24	0.3	0.7	WT50	0.9	0.5	WT75	0.4	0.2	WT100	0.9	0
WT25	0.4	0.7									

Table I.2. Properties of maintenance tasks to be carried out in the Winter Day Case Study.

Turbine number	Time required (h)	Technicians required	Probability of success	Value	Cost (£'000)	Load (kg)
68	5	3	0.95	302.9	18.5	550
99	4.5	2	1	195.4	1	70
36	6.5	3	0.8	175.6	1	150
85	6	3	0.9	113.3	18.5	450
45	2	2	1	96.6	0	0
42	6	3	0.9	94.2	18.5	450
50	3	2	1	92.1	1	70
19	6	3	0.9	87.8	18.5	450
71	6	3	0.9	87.8	18.5	450
3	5	3	0.8	87.8	1	150
51	2	2	1	87.8	0	0
92	3	2	1	2.1	1	70
77	3	2	1	2	1	70
21	4	2	1	-2.1	1	100

Table I.3. Properties of maintenance tasks to be carried out in the Summer Day Case Study.

Turbine number	Time required (h)	Technicians required	Probability of success	Value	Cost (£'000)	Load (kg)
72	5	3	0.95	241.9	18.5	550
9	5	3	0.95	241.9	18.5	550
55	6.5	3	0.8	197.4	1	200
29	6	3	0.9	127.6	18.5	450
84	6	3	0.9	120.2	18.5	450
76	3	2	1	108.7	1	70
28	3	2	1	108.7	1	70
96	2	2	1	108.6	0	50
63	2	2	1	108.6	0	50
37	5.5	2	1	103.4	1	150
43	5.5	2	1	103.4	1	150
56	6	3	1	101.6	18.5	450
89	6	3	1	101.6	18.5	450
4	3	2	1	98.7	1	70
83	6	3	0.9	98.7	18.5	450
48	5	3	0.8	98.7	1	150
70	2	2	1	98.7	0	50
91	6.5	2	1	15.4	2	170
81	3	2	1	11.8	1	70
16	3	2	1	10.7	1	70
40	3	2	1	10.7	1	70
1	6	3	1	10.2	1	450
61	6	3	1	10.2	1	450
23	4	2	1	4.7	1	100

Table I.4. Shape and scale parameters of gamma distributions for maintenance task duration used in Case Studies 1 and 2.

		Expected maintenance task duration (h)				
		2	3	4	5	6
Gamma distribution for Case Study 1	Mean (h)	2	3	4	5	6
	Shape parameter	4	6	8	10	12
	Scale Parameter	0.5	0.5	0.5	0.5	0.5
Gamma distribution for Case Study 2	Mean (h)	2	3	4	5	6
	Shape parameter	20	30	40	50	60
	Scale Parameter	0.1	0.1	0.1	0.1	0.1

Appendix J. Logistics Model Outputs: Winter Case Study

Table J.1. Full results for Case Study 1.

	Case A	Case B	Case C	Case D	Case E	Case F
Risk aversion factor (Y)	0	2	4	6	8	10
Planned number of turbines to be repaired (/14)	13	13	13	13	11	10
Number of vessels used	4	5	5	5	5	5
Computational time (s)	250.1	245.3	255.8	253.2	243.2	313
Expected policy value (not including value added due to a non-zero Y) (£ '000)	1301.1	1289.8	1289.9	1289.9	1126.1	986
Number of technicians required to carry out all repairs	31	33	33	33	27	23
From Monte Carlo simulation:						
Average number of turbines actually repaired (/14)	7.1	8.1	8.1	8.1	7.4	8.1
Turbines not fixed due to repairs taking longer than expected	4	3.4	3.4	3.4	2.1	1.2
Turbines not repaired due to incorrect diagnosis	0.8	0.8	0.8	0.8	0.6	0.4
Turbines not repaired due to unsuccessful transfer	1.1	0.7	0.7	0.7	0.9	0.3

Appendix K. Logistics Model Outputs: Summer Case Study

```
SUGESTED POLICY:
Dispatch vessel 1 to:
Wind turbine T28     (GTU (3))
Wind turbine T37     (Manual reset & Retrofit )
Wind turbine T43     (Manual reset & Retrofit )
Wind turbine T55     (Manual reset and minor repair)
Gantt Chart is located in Sheet 10.
Policy time is 10.88 hours.
Probability of successfully carrying out all tasks in this policy is 36.0574%
Vessel 1 order:
    'T55'    'T43'    'T37'    'T28'    'T28'    'T43'    'T37'    'T55'

Dispatch vessel 2 to:
Wind turbine T81     (GTU (2) )
Wind turbine T83     (Medium repair (2))
Wind turbine T84     (Medium repair (4))
Wind turbine T89     (Annual service (6))
Gantt Chart is located in Sheet 10.
Policy time is 11 hours.
Probability of successfully carrying out all tasks in this policy is 10.8921%
Vessel 2 order:
    'T89'    'T84'    'T83'    'T81'    'T81'    'T89'    'T84'    'T83'

Dispatch vessel 3 to:
Wind turbine T16     (GTU (2) )
Wind turbine T40     (GTU (2) )
Wind turbine T48     (Minor repair)
Wind turbine T56     (Annual service (6))
Gantt Chart is located in Sheet 8.
Policy time is 10.86 hours.
Probability of successfully carrying out all tasks in this policy is 15.0304%
Vessel 3 order:
    'T40'    'T56'    'T48'    'T40'    'T16'    'T48'    'T56'    'T16'

Dispatch vessel 4 to:
Wind turbine T4     (GTU (4))
Wind turbine T9     (High priority repair)
Wind turbine T63     (Manual reset)
Wind turbine T72     (High priority repair)
Gantt Chart is located in Sheet 10.
Policy time is 11 hours.
Probability of successfully carrying out all tasks in this policy is 6.7837%
Vessel 4 order:
    'T9'    'T72'    'T4'    'T63'    'T63'    'T4'    'T9'    'T72'

Dispatch vessel 5 to:
Wind turbine T29     (Medium repair (3))
Wind turbine T70     (Manual reset)
Wind turbine T76     (GTU (3))
Wind turbine T96     (Manual reset)
Gantt Chart is located in Sheet 9.
Policy time is 10.91 hours.
Probability of successfully carrying out all tasks in this policy is 25.1584%
Vessel 5 order:
    'T29'    'T70'    'T76'    'T70'    'T96'    'T76'    'T96'    'T29'
```

Figure K.1. Matlab-generated policy outline for Case A of summer day Case Study

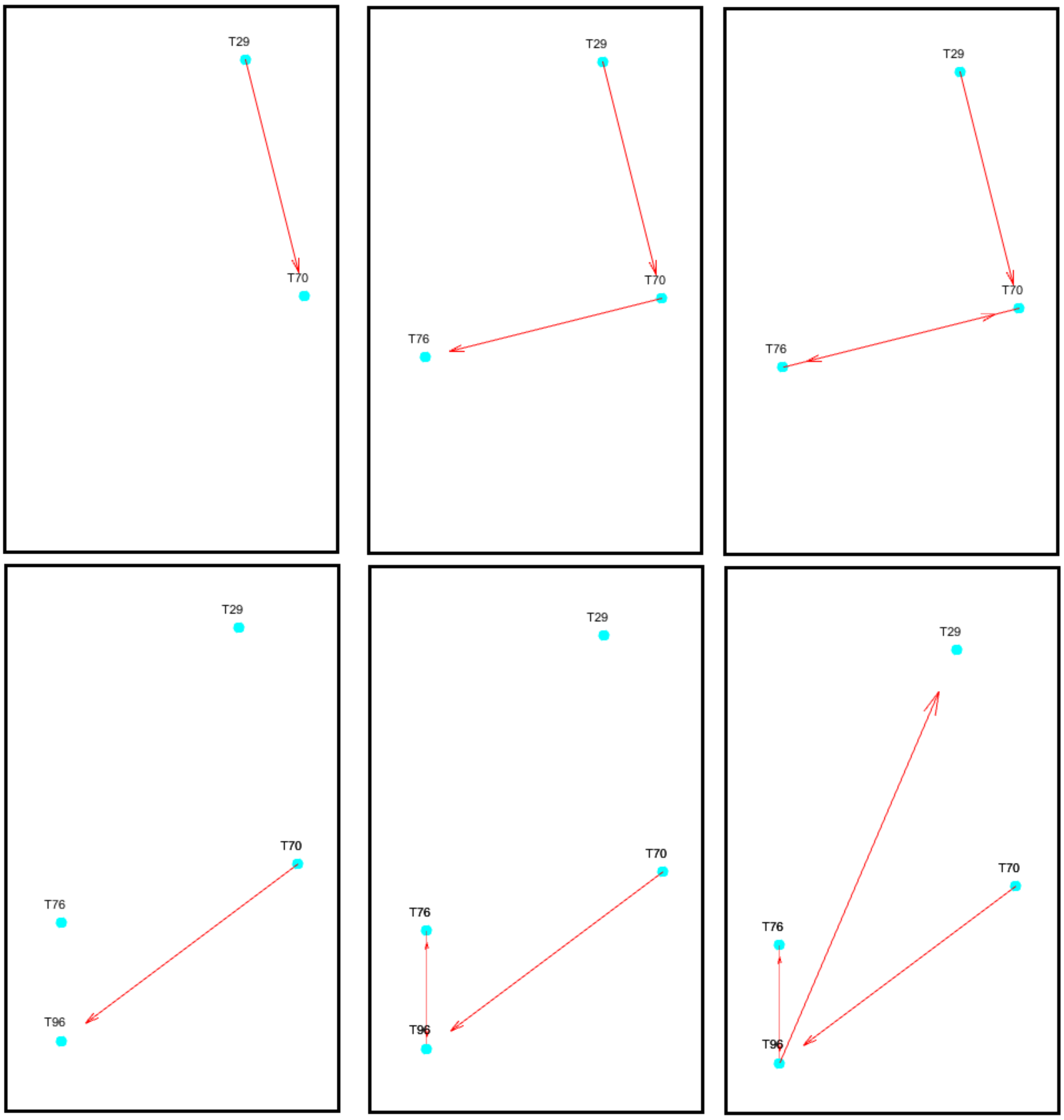

Figure K.2. Screenshots of the Matlab-generated animation visualising the proposed vessel routing policy.

Appendix L. Report Summarising the Offshore Wind Farm Site Visit

Note: Confidential information have been removed from this version of report. This report has been signed off by the offshore wind farm manager.

Background information:

The aim of the visit was to apply the vessel routing model I have developed in the course of my PhD to real life scenarios and to assess its suitability for day-to-day practical use on planning site. I also hoped to gain an understanding of how decisions on vessel routing are made in real life and use that knowledge to improve my model.

8th February 2017

Introductions to the team, explanation of the decision making process, specification of the inputs (types of failure, properties of vessels available etc.). It was a no sail day, the first case study was carried out based on the planned work for the following day. Model's output differed from the decision made by operators due to the model's limitation on the number of turbines a vessel can visit.

The model was also run for the case of 6th February 2017 and the results produced matched the decision made by operators (in terms of assignment of vessels to turbines and the order in which the turbines are visited).

However, preloading tasks and technicians assigned to those tasks were not included in this simulation, or in the simulations that took place on the following days. These can be easily added manually to the policy generated by the model.

9th February 2017

It was another no sail day; an updated plan for the following day was generated by the model based on issues which arose overnight. New routing plan was presented to a senior technician. They were impressed by the model's capability to recommend logical order of visits, automatically produce Gantt charts and take into account significant wave height variations across the wind farm.

The policy generated by the model was feasible, except for ***CONFIDENTIAL***. Senior technicians commented that the tool has the potential to aid decision making in real life situations, particularly on days when 6 vessels are available.

A constraint was added to the model to ensure vessels do not visit turbines in both ***CONFIDENTIAL*** on the same day. Model was run again and produced improved results.

Possibility of integrating the existing alarm handling system with my model was discussed. Data from alarm handling system would most likely need to be input manually, with the user assigning a priority rating for each job.

A meeting with marine operators was arranged. They have explained how significant wave height and direction affect planning and carrying out maintenance actions and highlighted the importance of being able to adapt the routing plan in real time, even once the vessels have left.

My model allows the user to specify their risk appetite, which was discussed with a senior technician. The feedback was that it seems like a useful feature, provided the model also suggests possible technician swaps (currently the model does not have such capability).

10th February 2017

Another day with no maintenance jobs carried out. An interview was conducted with a senior technician to gain feedback on the applicability of my model.

There are certain aspects which planners consider and the model does not. These include:

- Composition of technicians for each action/vessel
- Planning and routing of the preloading tasks
- Taking into account the fact that if technicians are assigned to a vessel different from the one on the previous day, their equipment has to be craned over, wasting valuable time in the morning

Modelling these aspects, although not absolutely necessary, would make the model more applicable to real life cases.

Conclusions

In general, the model's outputs were feasible, but inferior to the policies created by the planners. For the policies generated by the model to match, or improve upon, those of planners, capability to dispatch a vessel to more than 4 turbines would have to be built into the model. Integration with current systems would also require a procedure for assigning a priority to a pool of turbines which are candidates to be visited on a particular date. This value would have to be defined by the planners depending on the actions required on the turbine and whether it is operational or not.

However, if the above could be achieved, senior technicians agree that the tool could add value to the current process of planning the vessel routing.

I am very thankful to ***CONFIDENTIAL*** for organising this visit; it allowed me to partly validate my model and gain deeper understanding of the real life decision making process. I am also thankful to the planners on site who answered all my questions and were very helpful.

Appendix M: Real World Case Study Inputs

Table M.1. Maintenance task properties used in the real world case study.

	High priority repair	All day repair type 1	All day repair type 2	All day repair type 3	Half day repair
Turbines	WT 6 & WT 9	WT 1 - 4, WT 8 & WT 10	WT 5	WT 7	WT 11 - WT 14
Time required (h)	6.1	6	5.5	5	2
Technicians required	3	3	3	2	2
Probability of success	1	1	1	1	1
Value (£'000)	100	100	100	100	60
Cost (£'000)	1	1	1	1	1
Load (kg)	100	100	100	100	100

Table M.2. Vessel properties used in the real world case study.

Vessel ID	Crew capacity	Speed (km/h)	Fuel consumption (£'000/km)	Charter cost (£'000/day)	Load capacity (kg)
1	12	36	0.006	0	12,000
2	12	36	0.006	0	12,000
3	12	36	0.006	0	12,000
4	12	36	0.006	0	12,000

Appendix N. Transcript of the Senior Technician Interview

Table N.1. A transcript of the senior technician interview.

Rafael Dawid (RD): Are all the relevant inputs considered by the model? If not, what additional inputs should be considered?

Senior Technician (ST): It seems that you considered all relevant inputs.

RD: Are all relevant constraints considered?

ST: When making decisions, we split up the troubleshoot teams across vessels not to put all eggs in one basket, it would be good if your model considered it too. Considering which vessels have spares on them would also be useful.

RD: Maximising the number of turbines brought back online on the day is the objective of my model's optimisation algorithm. Was it the right choice? Are there alternative objectives that should be considered?

ST: Mean time between visits is another important metric for us, we try to make sure teams get as much work done as they can on the same asset on the day.

RD: Are outputs presented easy to read and understand?

ST: Yes, especially the nicely colour coded map.

RD: Are there any other outputs the model should produce?

ST: On the vessel dispatch map, it would be nice to see which turbines are stopped or whether it's a service, end of warranty task or retrofit. Maybe if you could have an outer circle in the colour of the type of work required on the turbine and inside the circle the vessel number?

RD: Are policies produced by the model feasible?

ST: The policy you showed us yesterday looked similar to the plan we made, the groupings looked good.

RD: The simulations I ran yesterday took under one minute. Is the computational time acceptable?

ST: Yes, that's quite quick.

RD: Is the ability to specify the risk aversion factor a useful feature?

ST: Yes, definitely. However, the format of it would have to be changed to account for swapping technicians between vessels depending on their qualification and capability.

RD: Any overall comments about what would make this model better?

ST: The ability to select teams would be quite useful. In addition to that, certain jobs on a wind farm have to be done in order (contractors have an ordered plan of visits) which gives you an idea what jobs will likely need doing tomorrow and the day after, it may be useful if your model captured that as well. It would be good if the model considered cases where one turbine is visited by 2 different vessels to carry out different jobs.

RD: Does this model have the potential to make offshore wind farm operator's life easier?

ST: Yes, the visual outputs seem like they would be quite useful. The policy generated by the model could act as a sanity check. The model could also help with on the spot decisions; a turbine came back online, which of the remaining turbines should we divert the vessel to – with this model the coordinator does not have to worry about trying to find the best one to divert the crew to.

RD: Are there any barriers to practical application of this model?

ST: This depends on how difficult it would be to input the failure codes into the model, as transferring them directly from ***CONFIDENTIAL*** is impossible. On busy days, we are very constrained by time.