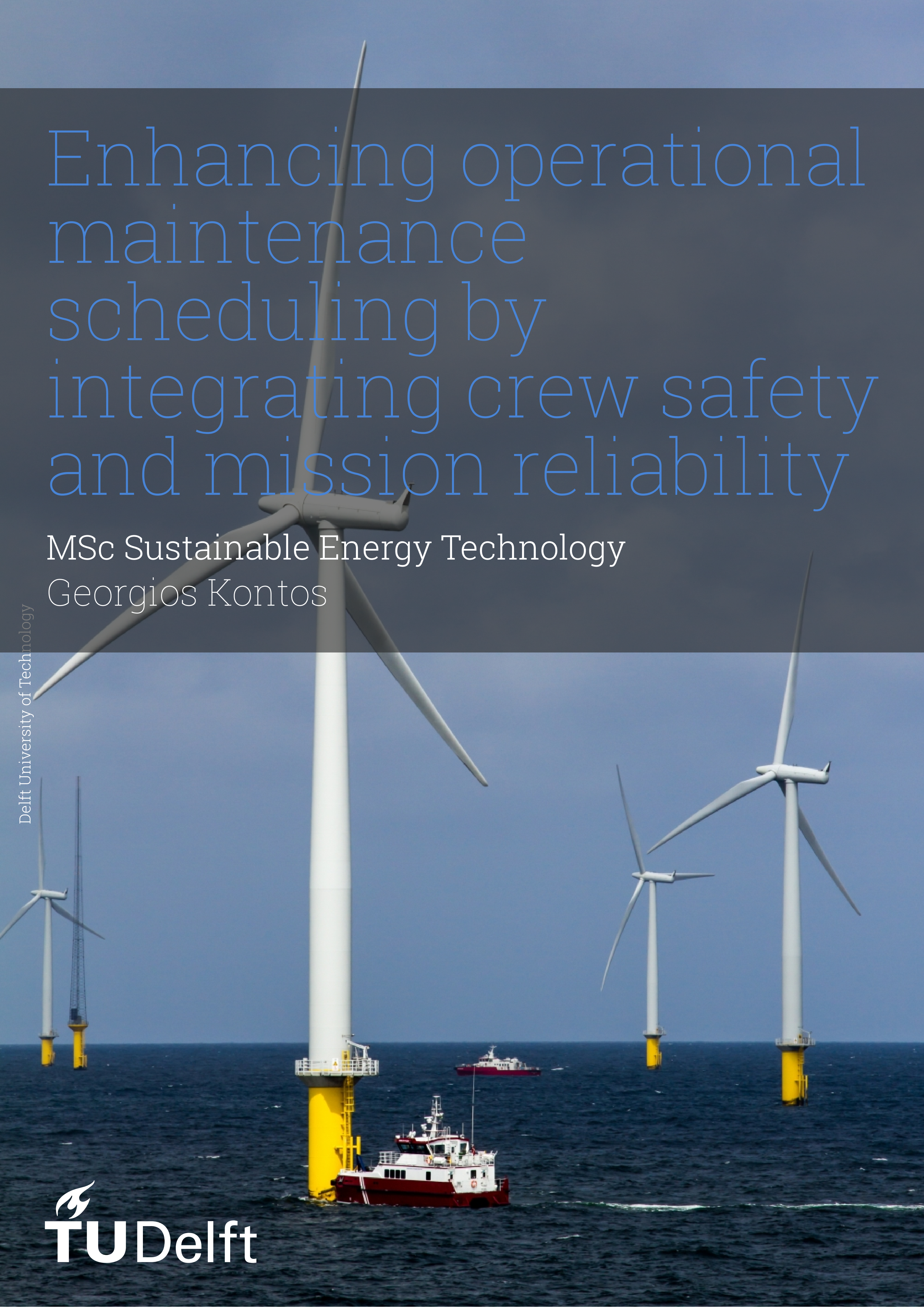

Enhancing operational maintenance scheduling by integrating crew safety and mission reliability

MSc Sustainable Energy Technology

Georgios Kontos

Delft University of Technology

Enhancing operational maintenance scheduling by integrating crew safety and mission reliability

by

Georgios Kontos

to obtain the degree of Master of Science in Sustainable Energy Technology
at Delft University of Technology,
to be defended publicly on Tuesday July 22, 2025 at 2:00 PM.

Thesis committee	
Chair:	Prof.dr. S.J. (Simon) Watson
Daily supervisor:	Dr. D. (Donatella) Zappalá
Committee member:	Dr. M.J. (Marta) Ribeiro
Daily co-supervisor:	M. (Marco) Borsotti
Project Duration:	December, 2024 – July, 2025
Faculty:	Wind Energy Group, Faculty of Aerospace Engineering, Delft University of Technology, Faculty of Electrical Engineering, Mathematics and Computer Science, Delft University of Technology

Cover: https://www.larousse.fr/encyclopedie/divers/Ãľnergie_renouvelable/87381
Style: TU Delft Report Style

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TU Delft

Preface

This work marks the completion of my Master's studies at TU Delft. My interest in offshore wind, vessels, and economics led me to explore the logistics of offshore wind maintenance, a topic that sits at the intersection of engineering and real-world decision making. The journey of this thesis came with its share of challenges, learning moments, and it would not have been possible without the support and encouragement of the people around me.

My deepest gratitude goes to my supervisors, Dr. Donatella Zappalá and Marco Borsotti, for their continuous support and constructive feedback throughout this project. Their availability and regular guidance were invaluable to keep me on track and their encouragement during the most stressful and challenging moments helped me stay calm, focused, and motivated.

Finally, I want to thank my family and friends for their constant support, especially during the more difficult and busy times. Their encouragement meant a lot to me during this journey.

Georgios Kontos
Delft, July 2025

Summary

Offshore wind farms face significant operational and financial challenges due to weather-related uncertainties that disrupt short-term maintenance planning. Operational decisions are critical to maintaining turbine performance and ensuring technician safety. When such decisions fail to effectively account for short-term risks like adverse weather and human limitations, they can result in failed maintenance attempts, prolonged downtime, increased CO_2 emissions, and substantial financial losses.

This thesis develops a probabilistic decision-support model designed to improve the reliability, cost-efficiency, safety, and sustainability of offshore wind maintenance operations by incorporating short-term weather forecasts, vessel operability constraints, and crew safety—specifically, the risks of seasickness during transit to the offshore wind farm (OWF) and unsafe technician transfer from vessel to turbine platform.

The model was evaluated through a 10-year case study simulating 19,090 minor repair tasks executed by a Crew Transfer Vessel (CTV), drawn from 75 maintenance schedules across 10 turbines, for a potential OWF site located approximately 40 km offshore from Cabo Silleiro, Spain, in the Atlantic Ocean. Hindcast weather data (2001–2010) for the offshore location were used to compare two maintenance scheduling strategies: a standard industry approach using deterministic vessel operability thresholds and fixed crew size (**Case 1**), and the proposed probabilistic model integrating transit and transfer uncertainties, a cost-loss decision framework and dynamic crew size optimization (**Case 2**).

Mission feasibility was determined using the combined probability of mission success, calculated as the product of (i) transfer success probability, based on wave height, wind speed, and wave period, and (ii) transit success probability, modeled using a Binomial distribution, to estimate the likelihood that enough technicians remain healthy (not seasick) upon arrival at the turbine. This probability was derived using Motion Sickness Incidence (MSI) empirical values and sea state conditions. A mission was attempted only if this combined probability exceeded the cost–loss ratio, which compares the cost of a mission attempt with the expected loss from failure. The two strategies were evaluated based on key performance metrics, such as combined probability of mission success, expected operational costs, and environmental impact (CO_2 emissions). A sensitivity analysis further confirmed the model's robustness across different weather conditions by testing three scenarios: Scenario 1 (20% harsher than hindcast weather), Baseline scenario (hindcast weather), and Scenario 2 (20% more favorable weather).

Results showed that Case 2 improved the average combined probability of mission success to 68.7%, compared to 43.3% in Case 1 (a 58% increase), and reduced expected financial losses by approximately $540,000 over the planning horizon. It also reduced CO_2 emissions from re-attempted trips by up to 45.8%. Although Case 2 introduced an average delay of 35 days in baseline conditions by avoiding risky missions, it consistently maintained a success rate above 67% even in the worst-case scenario, demonstrating reliable and robust performance across diverse weather conditions.

The study acknowledges several limitations. Due to confidentiality constraints, real-world maintenance records were not available for validation. Seasickness was estimated using empirical MSI values under simplified assumptions. The model also assumes a fixed start time for daily shift, a single task per day using one CTV, and does not currently account for task prioritization. Despite these constraints, the framework is adaptable and suitable for real-world implementation.

Future research could focus on validating the model using industry maintenance data, developing a new metric for seasickness estimation, and extending the scheduling logic to support multiple vessels and dynamic shift planning. Broader applications could include SOV-based operations, major repairs, and prioritization of critical tasks.

In conclusion, this thesis presents a practical, flexible, and sustainability-oriented framework for offshore wind maintenance planning. By enabling smarter, risk-informed decisions, the model supports reduced unnecessary vessel trips, lower emissions, and more efficient use of resources.

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Nomenclature

Abbreviations

Abbreviation	Definition
ABM	Agent-Based Model
aWRMS	Weighted Root Mean Square Acceleration
CBM	Condition-Based Maintenance
CO_2	Carbon Dioxide
CTV	Crew Transfer Vessel
DC	Daughter Craft
DP	Dynamic Positioning
EMD	Empirical Mode Decomposition
GPR	Gaussian Process Regression
GW	Gigawatt
HLV	Heavy Lift Vessel
IEA	International Energy Agency
KPI	Key Performance Indicator
LCOE	Levelized Cost of Energy
LR	Logistic Regression
LSTM	Long Short-Term Memory
MILP	Mixed-Integer Linear Programming
MPC	Model Predictive Control
MSI	Motion Sickness Incidence
O&M	Operation and Maintenance
OAV	Offshore Access Vessel
OEM	Original Equipment Manufacturer
OWF	Offshore Wind Farm
PSD	Power Spectral Density
RAO	Response Amplitude Operator
RUL	Remaining Useful Life
SATV	Semi-Autonomous Transfer Vessel
SES	Surface Effect Ship
SET	Sustainable Energy Technology
SOV	Service Operation Vessel
SWATH	Small Waterplane Area Twin Hull
VMMS	Vessel Motion Monitoring System
W2W	Walk-To-Work

Symbols

Symbol	Definition	Unit
$\sum C_i$	Cost of attempting maintenance	[$]
$C_{technicians}$	Technician wages	[$]
$C_{vessel\ rent}$	Vessel charter fees	[$]
$C_{vessel\ fuel}$	Fuel costs for transit	[$]
$C_{spare\ parts}$	Cost of spare parts required for the task	[$]
CF	Carbon factor	[t CO_2/kg]

Symbol	Definition	Unit
E_{trip}	CO_2 emissions per single vessel trip	[t CO_2]
E_{total}	Total CO_2 emissions from re-attempted maintenance trips	[t CO_2]
FC	Fuel consumption rate of the vessel	[l/h]
H_s	Significant wave height	[m]
L	Economic loss from an unsuccessful mission	[$]
L_{energy}	Lost revenue from turbine downtime between a failed and a successful attempt	[$]
L_{retry}	Additional cost of re-attempting the maintenance	[$]
$N_{T,required}$	Minimum number of technicians required	[-]
$N_{T,deployed}$	Number of technicians deployed for maintenance	[-]
n	Total number of technicians deployed (in binomial model)	[-]
p	Probability a technician becomes seasick (from MSI)	[-]
$P_{s,combined}$	Combined probability of mission success	[-]
$P_{s,transfer}$	Transfer success probability	[-]
$P_{s,transit}$	Transit success probability	[-]
R_{lost}	Revenue lost per hour due to turbine outage	[$/h]
$t_{downtime}$	Downtime durationbetween a failed and a successful attempt	[h]
t_{shift}	Total technician shift duration	[h]
$t_{transit}$	Round-trip transit time	[h]
V_{wind}	Wind speed	[m/s]
X	Number of seasick technicians (random variable)	[-]
$\mathbb{E}[C]$	Expected operational cost	[$]
ρ_{fuel}	Fuel density	[kg/l]

1 Introduction

This thesis presents the final project for the MSc in Sustainable Energy Technology (SET) at TU Delft. It addresses a critical challenge in offshore wind operations: how to improve maintenance planning under uncertain and often harsh weather conditions. As offshore wind capacity continues to expand globally, ensuring efficient and reliable maintenance becomes increasingly essential to the performance, sustainability, and cost-effectiveness of these systems. The research focuses on developing a probabilistic, same-day decision-support model that integrates environmental forecasts, technician health risks, and cost-based criteria to support smarter maintenance scheduling. The goal is to reduce unnecessary vessel trips, improve operational reliability, and ensure that maintenance activities are both feasible and economically justified.

This Chapter introduces the background and context of the study in Section 1.1, followed by the problem statement in Section 1.2. The research objectives and questions are presented in Sections 1.3 and 1.4, respectively. Section 1.5 discusses the study's relevance to the SET program, and Section 1.6 reflects on its contribution to system integration and socio-economic factors. Finally, Section 1.7 provides a roadmap for the rest of the thesis.

1.1. Background

The global offshore wind market is expected to experience substantial growth in the coming two decades, with global offshore wind capacity projected to reach approximately 560 GW by 2040 [1]. However, at present, offshore wind power is not fully harnessed due to its higher costs compared to other renewable energy technologies [2]. Operation and Maintenance (O&M) accounts for up to 30% of the total lifecycle costs of offshore wind farms (OWFs), significantly impacting their economic feasibility [3]. Optimizing O&M strategies is critical to ensuring the long-term economic viability of OWFs.

One of the key challenges in offshore O&M is the uncertainty in maintenance execution, driven by harsh weather conditions, technician workability, and vessel accessibility [4]. Many existing O&M models assess weather-dependent vessel constraints using deterministic thresholds but do not explicitly consider technician welfare, particularly the impact of motion sickness on workforce availability [5], [6]. Given that motion sickness can significantly reduce the number of available technicians upon arrival at the turbine, neglecting this factor may lead to inefficient or unsafe decision-making.

Additionally, most existing decision-support tools focus on whether the vessel can reach the wind turbine but do not evaluate the combined probability of mission success, which should integrate both technician transfer feasibility from the vessel to the wind turbine, and technician workability. As a result, current models may overestimate the likelihood of successful O&M execution, leading to unnecessary mobilizations, increased costs, and wasted fuel consumption.

Beyond feasibility assessments, economic considerations play a critical role in O&M decision-making. Failed maintenance attempts incur direct costs, including fuel and personnel expenses, and may also result in extended downtime losses if a corrective maintenance task is delayed. However, current models on seasickness lack an integrated cost-based decision framework, meaning that operators do not weigh the financial implications of mission success and failure when making scheduling decisions. In addition, workforce deployment is typically based on fixed assumptions regarding the number of technicians per task, with no consideration of how this number might be optimized under varying environmental conditions.

This study addresses these gaps by developing a probabilistic decision-support framework that estimates the probability of mission success under short-term weather forecasts, incorporates economic feasibility using a cost-loss decision model, and introduces an optimization mechanism to identify the minimum number of technicians required to achieve an economically viable maintenance operation.

1.2. Problem statement

A major challenge in offshore wind O&M is the uncertainty in mission execution, which arises from both environmental and human factors. A maintenance task may be planned based on forecasted conditions, but upon arrival at the offshore wind farm, technicians may find that transfer to the turbine is unsafe, or that some crew members are unfit to work due to motion sickness due to the transit [7], [6].

Existing O&M decision-support models mainly rely on deterministic thresholds for vessel operations, to determine whether the vessel can reach the turbine safely. However, they fail to account for uncertainties in technician workability and technician transfer to the wind turbine, even though motion sickness can significantly affect workforce availability, and difficult metocean conditions can hinder technician transfers. Furthermore, most models assess technician transfer feasibility and technician availability separately, rather than integrating them into a single probabilistic metric to determine overall mission feasibility. As a result, O&M operators may make suboptimal decisions, leading to unnecessary mobilizations, increased costs, and inefficient resource allocation.

In addition to technical feasibility, cost considerations are often overlooked. Maintenance scheduling decisions are typically made based on vessel accessibility rather than an detailed cost-benefit analysis. If a mission fails, the costs include fuel consumption, technician wages, lost energy revenue due to potential extended downtime, and re-attempt costs. However, existing models do not provide a structured method for weighing the probability of success against these economic consequences.

Lastly, technician deployment is usually treated as a fixed input, mostly determined by operators' experience, despite the fact that the optimal number of technicians is uncertain. This static approach misses an opportunity to improve cost-efficiency and the probability of success through dynamic crew sizing. These limitations showcase a need for a decision-support framework that integrates environmental risk, technician health and safety, cost-based decision rules, and crew size optimization into a single probabilistic model.

1.3. Research objective

The primary objective of this thesis is to develop a same-day probabilistic decision-support model that enhances offshore wind operational maintenance planning under uncertain conditions. The model will:

- Calculate the combined probability of success by integrating technician transfer feasibility from the vessel to the wind turbine based on metocean conditions, and seasickness likelihood affecting technician availability.
- Introduce a cost-based decision framework, where the combined probability of success is weighed against the financial impact of mission cancellation to determine when maintenance should be attempted.
- Optimize the number of technicians deployed by identifying the minimum crew size required to meet a predefined cost-efficiency threshold, ensuring economic and operational viability.

By combining probabilistic modelling and economic optimization, this framework aims to improve O&M planning, minimize unnecessary sailing, reduce operational costs, and enhance decision-making for OWF maintenance.

1.4. Research questions

The main research question guiding this study is:

How can offshore wind maintenance operations be scheduled more effectively by incorporating seasickness risk, transfer safety, and cost-efficiency into decision-making?

To address this, the following sub-questions are explored.

1. What environmental, operational and human factors influence the probability of successful offshore maintenance execution?
2. How can short-term weather forecasts be integrated with vessel and technician constraints to assess the probability of mission success?
3. How can it be determined when maintenance is economically justified, based on the probability of success and associated costs?
4. How can technician deployment be optimized to minimize costs while maintaining an acceptable probability of success?

1.5. Relevance to SET

This thesis aligns with the objectives of the MSc in Sustainable Energy Technology (SET), particularly in the field of offshore wind energy optimization. Offshore wind represents one of the fastest growing industries that plays a crucial role in the global transition to renewable energy. However, its continued development requires significant improvements in reliability, cost-efficiency, and sustainability.

This project contributes to these goals by developing a probabilistic decision-support model that enhances offshore maintenance planning. It brings together engineering insights, risk analysis, and economic evaluation to improve how offshore wind assets are maintained under uncertain weather conditions. In doing so, it also addresses human factors such as technician health and safety and contributes to sustainability by reducing unnecessary vessel trips and emissions. By combining technical, economic, and human-centered considerations, the project reflects the multidisciplinary focus of the SET program and offers a practical tool for real-world application in the offshore wind sector.

1.6. System integration and socio-economic implications

As offshore wind becomes an increasingly important part of the renewable energy mix and the number of offshore wind turbines grows, maintaining these assets efficiently is essential for the performance and integration of the wider energy system. This thesis supports system integration by improving the logistics and resource use in offshore wind operations. By increasing the probability of successful maintenance execution through the consideration of seasickness risk and transfer limitations, the model helps avoid failed maintenance attempts and unnecessary vessel trips.

This leads to better use of fuel, technician time, and vessel availability, all of which are valuable resources in offshore operations. In this way, the model contributes to a more efficient and integrated energy system. It also considers socio-economic dimensions by including financial risk in the decision-making process, addressing workforce safety and comfort, and reducing environmental impact. These elements are crucial to ensuring that the offshore wind industry grows in a safe, sustainable, and socially responsible manner.

1.7. Thesis outline

This thesis is structured into seven Chapters, each addressing a specific component of the research. In specific, Chapter 1 outlines the background, problem statement, research objectives, and research questions. It frames the challenges of offshore wind O&M under uncertainty and highlights the need for a probabilistic, cost-aware, and technician-optimized decision-support model.

Chapter 2 provides a comprehensive literature review on the state of the art in offshore wind O&M, investigating vessel capabilities, technician health and safety considerations, weather uncertainty modelling, and existing decision-support tools. It also discusses relevant key performance indicators (KPIs) and examines how technician deployment is typically handled in practice.

Chapter 3 presents the methodology developed in this study. It introduces a probabilistic framework that combines technician transfer success and technician availability due to motion sickness. It also incorporates a cost-loss decision model and proposes an optimization approach for determining the minimum number of technicians required to achieve an economically viable maintenance mission.

Chapter 4 applies the developed model to a realistic offshore wind scenario using ten years of historical weather data. It defines and compares three decision strategies, showing how each approach affects scheduling, technician deployment, and operational feasibility.

Chapter 5 presents and the outputs of the case study, including success probabilities, expected costs, optimized schedules, and the impact of varying technician numbers. A sensitivity analysis explores how changes in weather conditions influence model outcomes.

Chapter 6 summarizes the main findings of the research. It discusses the results of the study and reflects on the limitations of the proposed model.

Chapter 7 serves as the conclusion of this study. It addresses the research questions introduced in Chapter 1 and provides recommendations for future work.

2
Operations and Maintenance in Offshore Wind

This Chapter provides a comprehensive review of current practices and emerging developments in offshore wind O&M, with a focus on the environmental, operational, and human factors that shape maintenance strategies. Section 2.1 outlines the present state and projected expansion of the offshore wind sector. Section 2.2 categorizes prevailing maintenance strategies and examines recent advancements. Section 2.3 reviews the capabilities of O&M fleet and ongoing efforts to reduce its environmental impact. Section 2.4 explores modelling approaches used to optimize logistics and support decision-making under uncertainty. Section 2.5 addresses technician health and safety, including the effects of seasickness and transfer risk. Section 2.6 discusses common maintenance task types and technician assignment processes. The Chapter concludes in Section 2.7 by identifying key gaps in the literature and outlining opportunities for advancement.

2.1. Offshore Wind Outlook

Offshore wind is among the most rapidly expanding sectors within the renewable energy industry and is expected to play a crucial role in global electricity generation, driven by its untapped potential and the urgent need to decarbonize energy systems [8], [1]. According to the International Energy Agency (IEA), the most favorable offshore wind locations have the potential to generate more electricity than the world currently consumes, even when utilizing only those sites located near to shores [1]. By 2040, offshore wind capacity is projected to increase 15 times globally, amounting approximately to 560 GW, supported by cumulative investments exceeding $1 trillion [1].

The continuous upscaling of offshore wind turbines, as illustrated in Figure 2.1, plays a critical role in meeting industry projections for increased renewable capacity. Leading manufacturers such as Vestas and Siemens Gamesa have already achieved commercially deployed turbines with rated powers of up to 15 MW [9], [10]. More recently, Siemens Gamesa has begun testing a 21.5 MW prototype in Denmark, marking a significant milestone in turbine development [11].

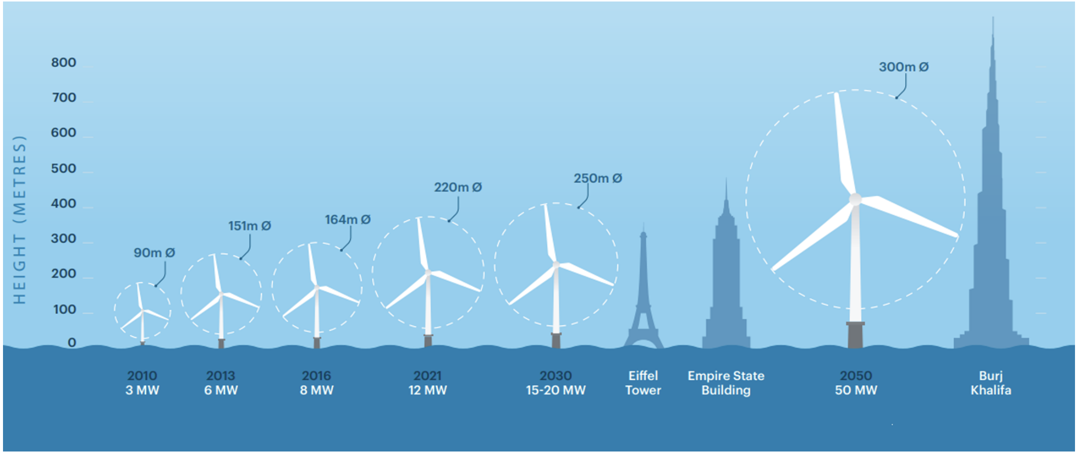

Figure 2.1: The evolution of wind turbine size and power output [12]

However, as turbine size increases, so do the operational risks. The impact of component failure becomes more severe, with each maintenance delay potentially resulting in greater energy losses. Simultaneously, the upscaling trend is placing growing strain on offshore infrastructure. Current port capacities and the availability of suitable vessels are not scaling in line with the increasing size and weight of turbine components, creating logistical bottlenecks that not only affect installation but also have significant implications for operations and maintenance (O&M)[1]. These logistical and operational constraints underscore the importance of adopting risk-informed maintenance scheduling strategies. In particular, approaches that minimize unsuccessful maintenance attempts and make more effective use of limited weather windows and offshore logistics are becoming increasingly essential.

Efficient O&M strategies are vital to addressing these challenges by minimizing downtime, preventing energy production losses, and improving the overall performance of the wind farm. O&M expenditure, which includes maintenance, service costs, and other variable expenses, represents up to 30% of the total levelized cost of electricity (LCOE), making it a critical area for improvement [13], [14]. Moreover, O&M indirectly affects wind farm availability, operational lifespan, and energy production, all of which influence the LCOE. Consequently, enhancing O&M efficiency is essential to achieving the ambitious cost-reduction targets for offshore wind energy and remains a key focus for developers, operators, and researchers [15], [16].

2.2. O&M Strategies

This Section provides a brief overview of the key maintenance strategies' categories and subcategories in offshore wind. As depicted in Figure 2.2 the two main maintenance strategies are reactive or corrective, and proactive maintenance. In reactive maintenance, repairs are carried out only after a component fails, without prior intervention to prevent breakdowns. Although this strategy requires low upfront costs and allows components to be used to their maximum lifespan, it results in significant unplanned downtime and may cause additional failures to surrounding components [17]. In contrast, proactive maintenance refers to carrying out maintenance tasks ahead of potential failures and is divided into periodic maintenance, condition-based maintenance, predictive maintenance, and prescriptive maintenance. Periodic maintenance follows schedules suggested by the original equipment manufacturer (OEM) and can be time-based, where wind turbines are serviced at fixed intervals, age-based, where maintenance depends on the component's lifespan, or use-based, where servicing is determined by the amount of electricity generated. As condition monitoring technology has advanced over the past few years, sensor data provides the potential for a maintenance strategy that bases decisions on component condition [18].

While condition-based maintenance, predictive maintenance, and prescriptive maintenance all utilize component condition for decision-making, they differ in their approaches. Condition-based maintenance is triggered when sensors detect a change in a component's condition, signaling a potential issue before the wind turbine fails. Predictive maintenance, on the other hand, involves analyzing operational data

[1] From discussions with industry experts during the WindEurope Annual Event 2024 in Bilbao.

to forecast when a failure is likely to happen, allowing for maintenance to be scheduled proactively. Prescriptive maintenance builds upon predictive maintenance by not only anticipating failures but also providing specific O&M recommendations to minimize operational risks [18]. Finally, opportunistic maintenance utilizes favorable situations to perform maintenance tasks in OWF. In contrast to proactive maintenance, which follows a predetermined schedule, this strategy seizes unexpected opportunities to execute necessary maintenance to also address additional,not highly significant, tasks [17]. Its primary goal is to enhance maintenance efficiency by consolidating tasks, optimizing resource utilization, minimizing downtime, and improving the overall reliability and performance of offshore wind turbines by making the most of advantageous circumstances [16].

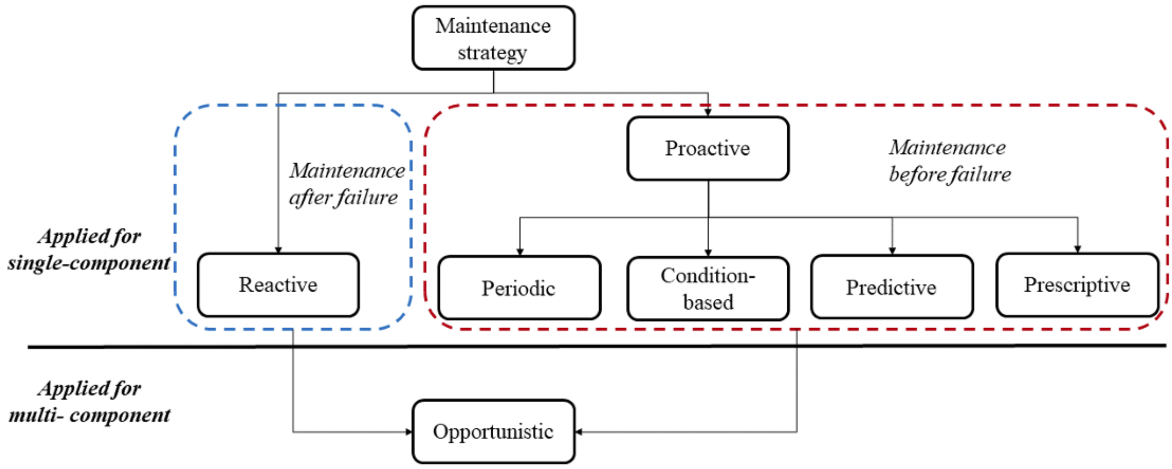

Figure 2.2: Categories and sub-categories of maintenance strategies [18]

2.3. O&M Fleet

Offshore wind farms present unique challenges for O&M due to increasing distances from shore and harsh marine environments. Ensuring accessibility, safety, and efficiency in O&M activities requires a diverse and evolving fleet of specialized vessels and alternative access methods, as well as a growing focus on sustainability. This Section provides an overview of the key vessel types used in O&M, discusses the role of helicopters as a rapid access resource, and highlights recent initiatives aimed at decarbonizing offshore O&M fleet. An overview of vessel characteristics and capabilities is provided in Table 2.1.

Table 2.1: Overview of maintenance vessel characteristics and capabilities [18], [19], [20], [21], [17]

Vessel	HLV	SOV	CTV	SATV
Travel speed (knots)	10	7.5-14	15-39	16-25
Technicians on-board	24	25-50	12	10
Limit wave height H_s (m)	2.5	up to 4	up to 2.2	2
Limit wind speed at sea (m/s)	36.1	25	25	25
Limit wind speed at hub (m/s)	15.3	–	–	–

2.3.1. Heavy Lift Vessels (HLVs)

HLVs play a critical role in offshore wind operations, particularly for tasks requiring the replacement of large turbine components. These vessels are equipped with specialized cranes capable of lifting thousands of tonnes, making them essential for handling massive offshore wind turbine parts such as blades, nacelles, or tower sections. These vessels can lift their hulls above the waterline, providing a stable platform for maintenance activities. HLVs operate continuously for up to 24 hours a day and can remain on-site for multiple days, completing one maintenance task at a time, and with their operations being restricted by environmental factors. Specifically, jacking up and down is constrained by wave height and wind speed at sea level, while the actual maintenance tasks are further constrained by wind speed at the turbine hub level [18]. An example of a HLV can be seen in Figure 2.3.

Figure 2.3: Van Oord Aeolus HLV [22]

2.3.2. Crew Transfer Vessels (CTVs)

CTVs are specialized vessels designed for fast and efficient transfer of technicians and small cargo to offshore wind turbines. They access the turbines by jumping from the vessel's bow to the boat landing, as the former creates frictional contact with the latter [20]. The CTV collects all technicians once the work is finished and returns to port. A standard shift lasts 12 hours, and upon completion the CTV either remains in port overnight or departs again for the OWF with different crew and technicians [21]. Based on the shape of their hull, CTVs can be further divided into five sub-categories [20], [21]:

- **Monohulls:** Monohulls were the earliest CTVs utilized in offshroe wind operations, which were already used as pilot tender boats.
- **Catamarans:** Catamarans dominate the current market due to their high transit speeds and superior seakeeping performance in moderate sea conditions.
- **Trimaran:** Trimarans offer further improvements in stability and operabilty.
- **Small Waterplane Area Twin Hull (SWATH):** SWATH vessels offer exceptional stability by minimizing the hull's cross-section at the waterline, making them ideal for transferring large numbers of technicians during wind farm installation and commissioning. However, their higher cost and lower speeds compared to catamarans limit their broader application.
- **Surface Effect Ships (SES):** SES technology integrates air cushions to enhance stability and fuel efficiency while maintaining high transit speeds. However, their design complexity and their high construction costs have restricted widespread adoption.

While operability limits usually vary depending on the vessel type and specific design characteristics, CTVs are generally considered safe to operate in sea states with significant wave heights (H_s) up to 2.2 meters [21]. This threshold serves as a commonly accepted upper limit in industry practice when assessing vessel accessibility for offshore maintenance activities. An example of a CTV (catamaran) can be seen in Figure 2.4.

Figure 2.4: Catamaran CTV during maintenance execution [23]

2.3.3. Service Operation Vessels (SOVs)

Service Operation Vessels (SOVs) serve as primary maintenance hubs for large offshore wind farms, particularly those far from shore, where the transit times of CTVs become impractical. Designed to accomodate 25 to 50 technicians for two to four weeks, SOVs feature workshops and accommodations, allowing for efficient, long-term operations. These vessels return to port every two weeks for resupply and crew rotation, usually traveling overnight to avoid disrupting technicians' work schedules. SOVs are significantly costlier than CTVs, with day rates 8–10 times higher, but their superior seakeeping capabilities enable operations anytime throughout the year except extreme weather conditions.

Equipped with dynamic positioning (DP) systems, SOVs safely maneuver within turbine safety zones and use Walk-To-Work (W2W) systems for technician transfers. These systems enhance accessibility, supporting transfers in waves up to 2.8 meters in practice and allowing spare parts or tools to be wheeled across gangways. Some W2W systems also function as motion-compensated cranes, increasing operational flexibility. SOVs often operate at slower speeds (7.5–14 knots) to minimize technician fatigue and nausea during transit. To address limitations such as slow transit speeds, SOVs may deploy daughter crafts (DCs), which are small vessels used for urgent tasks. DCs can transport 8–10 technicians and up to one ton of cargo at high speeds (25–45 knots), though their smaller size limits their operability in rough seas (H_s = 1–1.2 meters). Despite these challenges, SOVs remain quite significant for preventive and some corrective maintenance, particularly in large or remote wind farms, where their advanced features and operational efficiency outweigh their higher costs [21], [20]. An example of a SOV can be seen in Figure 2.5.

Figure 2.5: Siemens Windea La Cour SOV during maintenance execution [24]

2.3.4. Service Accommodation Transfer Vessels (SATVs)

SATVs are designed to remain offshore for extended periods, typically making weekly transfers to and from wind farms. This concept aims to reduce the LCOE especially for turbines located farther from shore. With accommodations for overnight stays, SATVs can house more technicians than CTVs. Moreover, they generally offer greater seakeeping capabilities than CTVs while still employing the same push-on method for transferring technicians at turbine boat landings [20]. In specific, SATVs perform safely in sea state conditions of up to 2m H_s [21]. Additionally, SATVs are more maneuverable than SOVs when navigating between turbines. However, although a quite promising alternative to CTVs and SOVs, SATVs are a developing concept with only one vessel being in operation [20], [19]. An example of a SATV can be seen in Figure 2.6.

Figure 2.6: The first SATV in operation "Ventus Formosa" [25]

2.3.5. Helicopters

Helicopters play a critical role in offshore wind farm maintenance, particularly for corrective tasks where vessel access is too slow or impractical. Their primary advantage is speed, allowing technicians and parts to be delivered directly to nacelles without additional lifting operations, significantly reducing downtime [20], [21]. Helicopters can operate in challenging conditions, including wind speeds up to 20 m/s and wave heights of 6 meters, though they are restricted by freezing, thunder, and visibility requirements [19], [21]. Operating from onshore heliports, helicopters usually transport around 3–6 technicians and some lightweight spare parts. However, their high operating costs and the need for multiple round trips make them a high-cost solution that is mostly selected only in the case of urgent offshore wind maintenance tasks [19], [21]. An example of a helicopter can be seen in Figure 2.7.

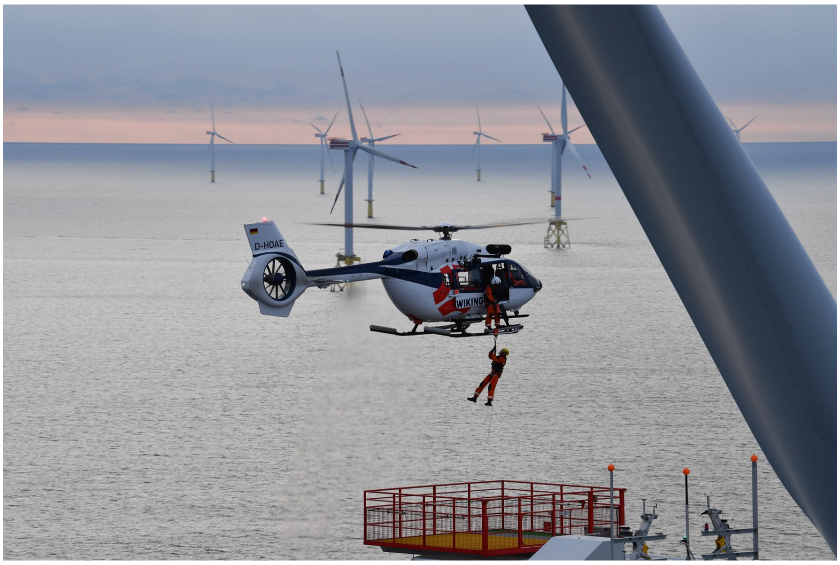

Figure 2.7: Maintenance task execution using helicopter [26]

2.3.6. Decarbonizing offshore O&M vessels

Offshore wind is projected to play a significant role in the sustainable energy transition worldwide, as numerous nations work towards achieving net zero emissions. Although compared to other electricity production methods, offshore wind has a substantially lower carbon footprint, every stage of an offshore wind farm's lifecycle contributes to greenhouse gas (GHG) emissions.

Within the O&M phase, vessels are the dominant source of emissions. A Danish industry analysis estimates that vessel operations can contribute up to 20% of the total life-cycle GHG emissions of an OWF [27]. More specifically, Arvesen et al. (2013) found that vessels used for maintenance are responsible for approximately 83–85% of all O&M-related CO_2 emissions [28]. Minimizing this impact is essential to accelerate progress towards meeting net-zero targets. As achieving sustainability goals becomes more and more important, KPIs, such as environmental impact, are beginning to have a crucial role in assessing the performance of OWFs [29].

To decarbonize the sector, the use of sustainable fuels is necessary. RWE in collaboration with Acta Marine is currently building two environmentally friendly SOVs designed to run on both methanol and battery power, with operations estimated to start between 2025 and 2026 [30]. In addition, Vestas alongside Windcat Workboats initiated a pilot program to assess the potential of the first hydrogen-powered CTV globally. This vessel operates on a dual-fuel system, enabling it to run on a mix of hydrogen and marine gas oil, and is expected to reduce CO_2 emissions by 158 tonnes, which translates into a 37% decrease compared to a conventional CTV [31]. Similarly, Blåvinge through their pilot program test wether offshore wind vessels could run on green ammonia. Success in this project would substantially contribute to emissions' reduction [32].

Moreover, Damen has introduced a SOV that is entirely electric. The ship comes with two diesel generators to ensure reliability even if battery power is exhausted. Furthermore, dedicated offshore charging stations will be deployed on offshore wind turbines and substations to support sustainable energy use [33], as can be seen in Figure 2.8a. Also, as depicted in Figure 2.8b these SOVs could be used as charging points for electric CTVs [34]. It should be mentioned that the offshore wind sector has the advantage of generating renewable electricity on-site, with the potential to produce green hydrogen in the coming years. This capability could be utilized to power offshore refueling stations for vessels, supporting the transition to sustainable maritime operations [29].

(a) Damen electric SOV charging concept

(b) Damen electric CTV getting charged from electric SOV

Figure 2.8: Electric vessel charging concepts by Damen [34]

2.4. O&M Modelling in Offshore Wind

The utilization of models in managing O&M and logistical operations for offshore wind farms can be categorized into two key applications according to [15]:

- **Analytical tools:** These models are used to enhance comprehension of the systems they simulate. For instance, they allow researchers to explore the factors influencing O&M costs or assess the impact of wind farms being installed at greater distances from the shore on maintenance logistics.
- **Decision support tools:** These models are designed to support stakeholders in addressing specific challenges. Typical users include wind farm developers, owners, operators, maintenance vessel providers, shipping companies, or innovators developing new O&M concepts.

Although both areas are of quite importance for the O&M improvement, this master thesis focuses on reviewing and improving the latter. Offshore wind O&M planning is a complex task in which various decisions must be made throughout different phases of the lifecycle of wind farms. These decisions can be categorized into three areas based on their time horizon [35], [15], [16]:

- **Strategic decisions:** Covering a time horizon ranging from 5 to 20 years, these decisions focus on long-term planning and significantly influence the entire lifecycle of offshore wind farms. They involve selecting the most beneficial sites for designing wind farms to maximize reliability, determining the optimal location and capacity of maintenance facilities, choosing maintenance strategies, and evaluating whether to outsource repair services. Strategic decisions play a crucial role in the farm's overall operational efficiency and cost-effectiveness.
- **Tactical decisions:** Covering a time horizon ranging from several months to up to 5 years, these decisions focus on medium-term planning, and they typically include managing spare parts inventory, organizing maintenance support systems, selecting the vessel fleet, and deciding on whether to purchase or lease maintenance vessels. These decisions ensure that the necessary resources are available and ready to support maintenance activities efficiently.
- **Operational decisions:** Covering a time horizon ranging from one day to several weeks, these decisions focus on short-term planning, and mainly the immediate execution of maintenance tasks. This includes scheduling maintenance activities, routing vessels, and monitoring performance. These decisions are essential to ensure the safety, efficiency and reliability of ongoing maintenance operations.

This classification framework ensures a comprehensive approach to managing offshore wind maintenance logistics, optimizing performance across all levels. Figure 2.9 depicts examples of different decisions that are to be taken by different key stakeholders in the three different time horizons.

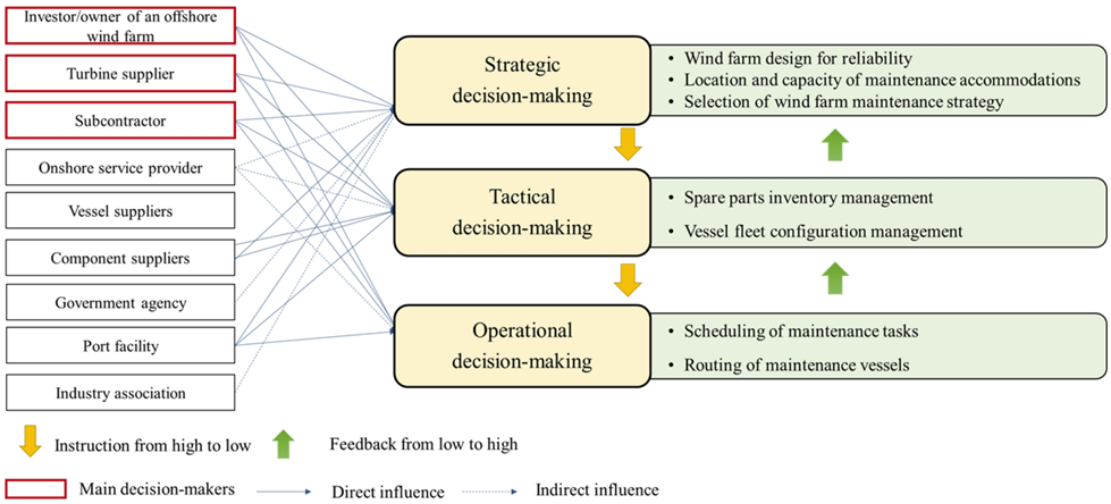

Figure 2.9: Decision-making levels in maintenance logistics for offshore wind energy systems and related stakeholders [18]

As can be seen in Figure 2.9, the maintenance logistics for wind farms engage multiple stakeholders, including wind farm owners, turbine suppliers, and service providers. Turbine suppliers usually offer maintenance contracts for two to five years, covering system failures and offering technical support. After the contract ends, wind farm owners manage maintenance costs and may hire independent service providers. These contracts typically include performance targets and payment structures, such as a fixed amount of money or charges per task. Additionally, other sectors like vessel and component suppliers, along with indirect contributors such as government agencies, port facilities and industry associations, also play a role in organizing maintenance logistics [18].

2.4.1. State of the art in offshore wind O&M

Effective O&M strategies are essential for maximizing the performance, reliability, and cost-efficiency of OWF. Given the complexities of remote locations, challenging weather conditions, and logistical constraints, researchers have developed various simulation models and optimization techniques to enhance maintenance planning, vessel operations, and accessibility. This Section explores key studies on O&M modelling in offshore wind. These studies address critical factors such as vessel selection, accessibility constraints, cost minimization, and the integration of predictive maintenance strategies. The findings contribute to improving turbine availability, reducing operational costs, and enhancing decision-making for offshore wind farm maintenance. An overview of the examined studies can be seen in Table 2.2.

Van Bussel and Bierbooms (2003) [36] analyzed transportation methods for crew and small parts at the DOWEC reference offshore wind farm, consisting of 80 turbines located 43 km off the Dutch coast. They looked into the wave height and wind speed operational constraints to assess various access systems, including five vessel types, and categorized maintenance activities into four types. Using Monte Carlo simulations, they concluded that achieving high wind farm availability, even at remote locations, depends on optimizing access systems and maintenance strategies.

Scheu et al. (2012) [37] developed a simulation tool to evaluate maintenance strategies for large offshore wind farms, focusing on turbine availability and economic performance. The model uses a Markov Chain-based approach to generate realistic weather conditions, incorporating significant wave height and wind-wave correlations to simulate wind speeds. The study analyzed the effects of varying maintenance fleets, wave height constraints, and weather forecast accuracy on turbine availability and production losses. Results demonstrated that higher wave height limits for access systems can enhance availability and reduce downtime costs. They concluded that accurate weather forecasts improve operational efficiency by reducing canceled operations and enabling better scheduling of vessel deployments. Crane vessels reach optimal performance with 48-hour forecasts, while maintenance vessels such as CTVs can perform efficiently with just 24-hour forecasts.

Hofmann and Sperstad (2013) [38] developed NOWIcob aiming to optimize O&M strategies for offshore wind farms and reduce overall costs. Using a Monte Carlo-based, time-sequential simulation, the model evaluates maintenance activities and costs by considering weather uncertainty, vessel logistics, and resource constraints. It models different vessel concepts, maintenance strategies (time-based, corrective, and condition-based), and logistics configurations and provides outputs such as availability, lifecycle profit, and O&M costs. A case study demonstrated the model's ability to compare logistical strategies, such as using a mothership versus an offshore platform, revealing its potential to identify cost-effective solutions.

Sperstad et al. (2014) [39] analyzed access restrictions for vessel routing in offshore wind farm maintenance using both single- and multi-parameter wave criteria. Multi-parameter criteria included significant wave height as a function of peak wave period and wave heading, and they concluded that a single-value limit for significant wave height can provide similar outcomes to a multi-parameter wave approach for availability, costs, and fleet optimization, as long as it is carefully estimated to reflect vessel and site-specific wave conditions.

Wu (2014) [40] analyzed docking operations between service vessels and offshore wind turbines, focusing on the impact of vessel design and access systems on operational efficiency and downtime reduction. The study developed numerical methodologies to evaluate docking performance with motion-compensated systems and fenders. Applied to a medium-sized supply vessel and a small personnel transfer vessel, the analysis identified operational constraints under various wave conditions. These methodologies enable the evaluation of docking operability, supporting safer and more efficient transportation of maintenance personnel, equipment, and spare parts.

Dalgic et al. (2015) [41] proposed a comprehensive approach for optimizing&M strategies for offshore wind farms, focusing on minimizing costs, reducing revenue loss, and maximizing power production. Using Monte Carlo simulations, the study evaluates climate parameters (wind speed, wave height, wave period), failure modes, and transportation systems, including CTVs, helicopters, offshore access vessels (OAVs), and jack-up vessels. They identified jack-up vessel operations as the most significant cost driver, requiring careful charter planning. Helicopters provide valuable accessibility, especially in challenging conditions, but their cost-effectiveness is expected to improve as the sector advances. The study underscores the importance of remote condition monitoring and calls for innovative O&M vessels and ship-based strategies to ensure reliable turbine access in increasingly remote offshore locations.

Endrerud et al. (2015) [42] developed a simulation model combining agent-based and discrete-event methods to optimize marine logistics for offshore wind park maintenance. The model uses inputs such as weather data (wind speed, wave height), turbine characteristics, vessel specifications, and cost parameters to evaluate decision alternatives. Key performance metrics include availability, lost production, logistics costs, and vessel use. A case study comparing two CTVs to one SOV for maintaining a 67-turbine wind park, found that CTVs offered higher availability and lower costs, showcasing the model's value in optimizing O&M strategies for offshore wind parks.

Browell et al. (2016) [43] examined short-term maintenance scheduling for offshore wind farms under uncertain weather conditions. They proposed a probabilistic decision-making approach using a cost-loss model to balance the economic value of maintenance missions against the risks of failure due to adverse weather. The method uses logistic regression with day-ahead meteorological forecasts to predict access windows, improving the utilization of potential workdays. A Monte Carlo-based OPEX model demonstrated that the probabilistic approach increased turbine availability and reduced operational costs compared to deterministic methods. Case studies highlighted significant revenue improvements and fewer missed maintenance opportunities, underscoring the value of advanced forecasting in offshore wind operations.

Irawan et al. (2017) [44] proposed an optimization framework for scheduling and routing maintenance at offshore wind farms, aiming to reduce costs while adhering to logistical and environmental limitations. The model considers various vessels, O&M bases, technicians, wind farms, and time periods. By employing a Dantzig–Wolfe decomposition-based algorithm, it identifies practical maintenance schedules and vessel routes while accounting for factors such as weather conditions, resource availability, and operational constraints. Using integer linear programming, the model then minimizes the costs associated with transfers, technicians, and maintenance delays. Although the model incorporates weather constraints, it does not account for uncertainty due to the high expected accuracy in short-term forecasts, highlighting an area for potential future enhancement [45].

Borsotti et al. (2024) [16] proposed an innovative approach aimed at optimizing O&M for OWF by utilizing prognostic-driven scheduling and advanced optimization methods. Unlike conventional strategies that focus on components' age thresholds, this model incorporates Model Predictive Control (MPC) and Condition-Based Maintenance (CBM) principles to deliver a more adaptive and cost-efficient approach. The model is centered on leveraging Remaining Useful Life (RUL) predictions of wind turbine components to guide maintenance scheduling. These predictions are embedded into a Mixed-Integer Linear Programming (MILP) framework, which optimizes maintenance timing to minimize costs while maximizing reliability and equipment utilization. Using a rolling horizon approach, the model dynamically adjusts maintenance schedules as new data and forecasts become available. This adaptability ensures that maintenance activities are aligned with real-time conditions, reducing the risk of unexpected failures and minimizing downtime. However, this model does not currently consider weather constraints in the decision-making process and thus assumes that vessels are capable of accessing the OWF without assessing the existence of weather windows or technicians' welfare.

Table 2.2: Comparison of parameter coverage in O&M papers, including performance metrics.

Study	Weather Parameters					Operational Parameters	Modelling	Performance							
	Wind Speed	Wave Height	Wave Period	Wave Heading	Weather Uncertainty	Vessel Limits	Method	Probabilistic	Costs (O&M, LCOE)	Availability/Downtime	Accessibility	Revenue Loss	Power Yield	Environmental Impact	Health and Safety
Van Bussel and Bierbooms (2003) [36]	✓	✓	–	–	✓	✓	Monte Carlo Simulation	✓	–	✓	✓	–	–	–	–
Scheu et al. (2012) [37]	✓	✓	–	–	✓	✓	Markov Chain	✓	✓	✓	–	–	–	–	–
Hofmann and Sperstad (2013) [38]	✓	✓	–	–	✓	✓	Monte Carlo Simulation	✓	✓	✓	✓	–	✓	–	–
Sperstad et al. (2014) [39]	✓	✓	✓	✓	✓	✓	Discrete Event Simulation	–	✓	✓	✓	–	–	–	–
Wu (2014) [40]	–	✓	✓	✓	–	✓	Frequency-domain Simulation	–	–	✓	✓	–	–	–	–
Dalgic et al. (2015) [41]	✓	✓	✓	–	–	✓	Time-domain Monte Carlo Simulation	✓	✓	✓	✓	✓	✓	–	–
Endrerud et al. (2015) [42]	✓	✓	–	–	–	✓	Agent-Based / Discrete Event Simulation	✓	✓	✓	–	–	–	–	–
Browell et al. (2016) [43]	✓	✓	–	–	✓	✓	Monte Carlo Simulation	✓	✓	✓	✓	✓	–	–	–
Irawan et al. (2017) [44]	✓	✓	–	–	–	✓	MILP	–	✓	–	–	–	–	–	–
Borsotti et al. (2024) [16]	✓	✓	–	–	–	–	MILP	✓	✓	✓	–	–	–	–	–

2.4.2. Weather Uncertainty

The O&M of OWF is significantly influenced by natural uncertainties such as weather, particularly wind speed and wave height, which vary seasonally and regionally. These environmental conditions define accessibility to offshore turbines, since maintenance vessels are subject to operational limits, as discussed in Section 2.3. In extreme cases, wave heights may exceed operational thresholds for an entire month, preventing access to turbines and delaying necessary repairs [46]. This results in increased downtime and O&M costs, highlighting the need for accurate weather forecasting models to optimize maintenance scheduling and reduce financial losses. Various methods that have been used to account for weather uncertainty are discussed in this Section, and are depicted in Table 2.3.

Browell et al. [43] address weather uncertainty in OWF maintenance by using probabilistic forecasting and a cost-loss decision model. Instead of relying on deterministic weather predictions, they employ logistic regression to estimate the probability of access windows based on day-ahead wind and wave forecasts. To manage uncertainty, they incorporate two sequential weather forecasts: the first, issued one day before the scheduled maintenance, assesses whether vessel operational limits (wave height and wind speed) are exceeded. If unsafe conditions are predicted, the mission is canceled. Otherwise, a second forecast on the morning of the operation reassesses accessibility. The study highlights that even a one-day forecast difference significantly impacts decision-making, as updated forecasts improve accuracy, reducing unnecessary cancellations or failed missions. Accurate weather prediction is crucial for determining available workdays, as approximately 4% of potential maintenance opportunities are lost, significantly affecting long-term wind farm availability. It is important to note that this percentage accounts only for missed opportunities to perform maintenance when the weather would have permitted it. Additionally, there are instances where forecasts indicate safe operational conditions, but on the actual day of execution, the weather proves otherwise [7].

Si et al. [47] predict day-ahead wind and wave conditions and accounts for uncertainty by using Empirical Mode Decomposition (EMD) and Long Short-Term Memory (LSTM) neural networks. The EMD-LSTM model proved highly accurate for forecasting wind speed (R^2 up to 0.801) and wave height (R^2 up to 0.898), making it a reliable choice for daily OWF maintenance scheduling. Moreover, Scheu et al. [37] account for weather uncertainty using a discrete time Markov chain approach to produce wave height time series and wind-wave correlation to produce wind speed time series. Markov chain modelling is also used by Hofmann and Sperstad [38], ensuring that future weather conditions are influenced only by the present state, and not by past weather conditions. The same approach is followed by Sperstad et al. [39]. Van Bussel and Bierbooms [36] consider weather uncertainty using Monte Carlo simulations and historical weather data to estimate the availability of weather windows. Additionally, Pandit et al. [48] compared LSTM and Markov chain in long-term weather forecasting, showing that for wave height, LSTM provided better forecasts than the Markov model, whereas for wind speed, the Markov chain model offered better predictions than LSTM.

Table 2.3: Comparison of approaches to account for weather uncertainty in OWF maintenance.

Study	Logistic Regression	Markov Chain	Monte Carlo	EMD-LSTM	LSTM
Van Bussel & Bierbooms (2003) [36]	–	–	✓	–	–
Scheu et al. (2012) [37]	–	✓	–	–	–
Hofmann and Sperstad (2013) [38]	–	✓	–	–	–
Sperstad et al. (2014) [39]	–	✓	–	–	–
Browell et al. (2016) [43]	✓	–	–	–	–
Pandit et al. (2020) [48]	–	✓	–	–	✓
Si et al. (2025) [47]	–	–	–	✓	–

While the previously discussed models emphasize weather uncertainty due to their longer planning horizons, studies focused on short-term operational decision-making, and particularly for CTV-based maintenance, typically assume that same-day weather forecasts are sufficiently accurate for planning purposes. Hence, long-range forecasts provide limited additional value. In [37] it is explained that while HLVs require accurate forecasts of two days or more to optimize scheduling, this is not the case for CTV-based operations. Due to the shorter transit and repair durations associated with CTVs, improving the accuracy or extending the length of the forecast beyond a day does not lead to significantly better decision-making or scheduling performance.

In line with this, [44] developed a short-term scheduling model for CTV deployment under the assumption that the weather conditions within the planning horizon can be predicted with sufficient accuracy. This approach aligns with current industry practice, as demonstrated in [49], where operational decisions for CTV missions are made on the day of the scheduled task, based on the latest available weather data. As a result, most CTV-focused models assume high reliability of short-term forecasts and do not explicitly account for longer-term weather uncertainty.

2.4.3. Key Performance Indicators

Key Performance Indicators (KPIs) in offshore wind O&M are essential for optimizing OWF performance and ensuring effective asset management [50]. As shown in Table 2.2, among the most commonly observed KPIs for O&M are costs, which could be further translated, for instance, into maintenance costs or LCOE, availability, accessibility and downtime of OWF, as well as revenue losses and power production.

What can also be observed is that environmental impact and health and safety of personnel is frequently overlooked. However, as discussed in Subsection 2.3.6, given the ambitious goals for carbon neutrality, sustainability metrics are expected to become increasingly important in the coming years. Therefore, attention should be given to incorporating sustainability aspects into O&M KPIs.

2.5. Technician welfare during offshore wind maintenance

Maintenance activities in offshore wind farms are subject to environmental constraints not only due to vessel operability, but also because of human-related limitations. Two primary risks impacting technician welfare and task feasibility are (i) seasickness during transit and (ii) unsafe transfer to the turbine platform [6], [4]. These factors can severely affect a technician's ability to safely reach and effectively perform maintenance tasks. This section reviews literature addressing both of these challenges, and summarizes key modelling approaches used to capture them in decision-support frameworks. A brief overview of the existing work can be seen in Table 2.4.

2.5.1. Seasickness during offshore wind transits

Although weather conditions and vessel seakeeping capabilities often allow maintenance activities to proceed, technicians frequently experience seasickness during transit to offshore wind farms [6], [7], [49]. This condition can significantly affect their ability to perform tasks upon arrival. This Section provides an overview of motion sickness, examines its impact on offshore operations, and reviews existing models used to predict and understand its occurrence.

Motion sickness

Motion sickness is a feeling of discomfort because of motion and can be triggered by various modes of transportation, including land, sea, air, and space transportation [45]. The neural mismatch theory, introduced by Reason in 1978 [30], is the most widely accepted explanation for motion sickness. This theory suggests that motion sickness arises when there is a conflict or mismatch between the signals received by different sensory systems, namely the vestibular system (responsible for balance and spatial orientation), the ocular system (responsible for vision), and the brain's prior expectations or cognitive models of motion based on past experiences [51]. The most frequently observed symptoms can be classified into four categories: cognitive (such as dizziness or light-headedness), temperature-related (such as clamminess or sweating), sopite-related (such as fatigue and irritability), and gastrointestinal (such as nausea and vomiting) [51]. This discomfort can become especially disturbing on long journeys, where individuals may feel trapped in a situation that worsens their symptoms. Among the different types of motion sickness, seasickness is the most commonly encountered one [45].

However, it is also worth mentioning that the neural mismatch theory emphasizes that motion sickness is not simply a dysfunction but a process that triggers sensory-motor learning [52]. When faced with unfamiliar motion, the body attempts to recalibrate its sensory and motor systems to adapt to the new environment, and thus this adaptation, over time, can result in the situation where people are less susceptible to motion sickness.

Research on seasickness has explored the specific characteristics of ship motion that contribute to nausea and discomfort among sailors. While various types of motion, including roll, pitch, and heave, have been investigated, studies indicate that vertical (heave) motion is the primary cause of motion sickness, with little to no significant effects from pitch and roll [53]. O'Hanlon and McCauley [54] conducted extensive experiments in a vessel motion simulator, exposing over 300 subjects to vertical sinusoidal motion at different frequencies and acceleration magnitudes for up to two hours. Their findings introduced the Motion Sickness Incidence (MSI) metric, quantifying the ratio of individuals experiencing vomiting under varying motion conditions. As illustrated in Figure 2.10, the results revealed that motion sickness susceptibility peaked at a vertical motion frequency of 0.167 Hz, making it the most nausea-inducing frequency. Moreover, it can be seen that MSI increases as acceleration increases, but not linearly. The MSI is estimated as:

$$\mathrm{MSI} = K_m \cdot \left\{ \int_0^T [a_w(t)]^2 \, dt \right\}^{\frac{1}{2}} \tag{2.1}$$

where K_m is equal to 1/3 for a mixed-gender population, and $a_w(t)$ is the instantaneous frequency-weighted acceleration in the vertical (z-axis) direction [6].

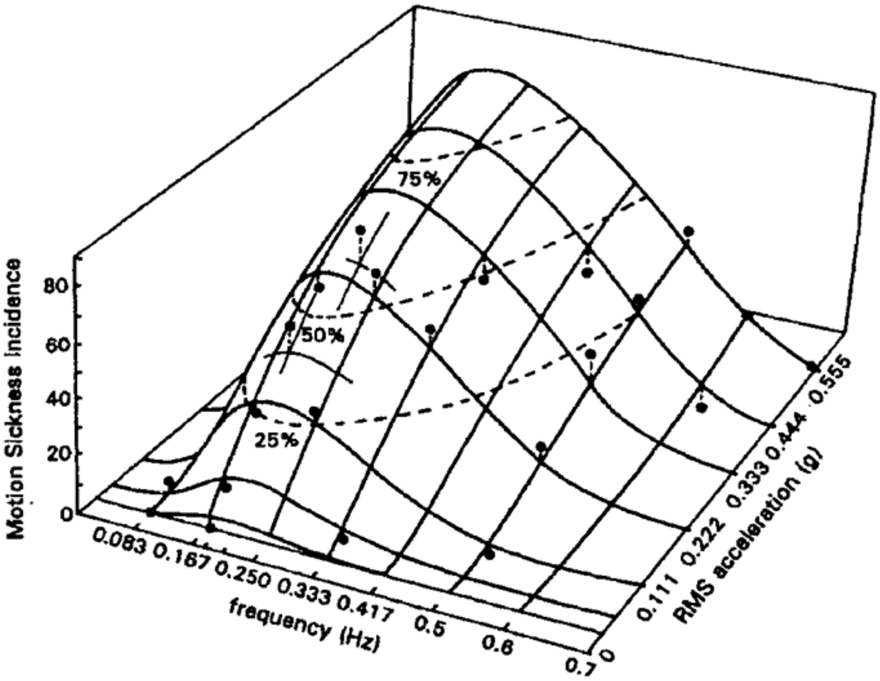

Figure 2.10: Empirically derived relationship of MSI to wave frequency and average acceleration for vertical sinusoidal motion by O'Hanlon and McCauley [54], [53]

Wertheim et al. [55] challenged the traditional assumption that heave is the main cause of sea sickness, while pitch and roll have negligible effects. Their experiments using a ship motion simulator revealed that pitch and roll, when combined with considerably small heave motions (too small to independently provoke seasickness), significantly increased MSI, with almost 50% of the participants experiencing intense symptoms. Additional experiments isolating pitch and roll showed that these motions alone have limited potential to induce seasickness, but their combination with heave creates a nonlinear interaction that significantly increases MSI. In addition, Khalid et al. highlighted that accounting for both vertical and horizontal motions slightly improves the MSI estimation compared to considering only vertical motions [56].

Existing models considering seasickness

In the context of offshore wind, seasickness is a common phenomenon that can occur during technicians' transits to OWF. The weather conditions at sea result in vessel motions, which create an unfamiliar environment that sometimes lead a number of maintenance crew to get seasick during the journey to the turbine. However, this uncertainty is usually not taken into account in the O&M decision making process, which relies mostly on vessel operational constraints to predict the existence of weather windows to safely access the OWF and perform maintenance tasks [7]. Limited literature exists in the field of considering technician welfare in O&M planning, with the following models being the most complete works.

Nachimuthu (2020) [46] considered seasickness as a key factor affecting the availability of maintenance technicians for offshore wind turbine repairs. To model this uncertainty, the study represents the proportion of technicians affected by seasickness during CTVs' transit as a beta-distributed random variable, capturing the likelihood that technicians will be unable to work. The probability of success of the trip, defined as having enough technicians available for maintenance, is determined by comparing the number of technicians deployed to the turbine with the expected proportion affected by seasickness. The study incorporates empirical seasickness rates from prior literature, finding that 20% of technicians experience seasickness in low-motion conditions , while 46.2% experience seasickness in high-motion conditions. Using these values, a mathematical model is then applied to optimize the number of technicians deployed per trip, balancing costs associated with additional personnel, vessel usage, and downtime due to failed trips. However, this study uses only two discrete motion categories, for $H_s \in [0.5, 1] \cup [1.5, 2]$ based on an experiment conducted by [57] that did not specifically target offshore CTVs.

Tomaselli et al. (2021) [7] introduced a decision-making tool for OWF O&M planning using CTVs that replaces traditional reliance on metocean thresholds with direct measures of workability, including MSI to estimate seasickness. The tool operates through an Agent-Based Model (ABM) framework, leveraging pre-computed vessel-specific Response Amplitude Operators (RAOs) to simulate vessel motions during transits, task execution, and return trips. By identifying weather windows for safe operations, the tool was shown to outperform traditional approaches in a case study at the Horns Rev 3 OWF, reducing false-positive and false-negative weather predictions by up to 12% in a 5-day forecast and 6-month hindcast analysis. This tool provides a fast and effective method for integrating safety and technician welfare into both short- and long-term O&M planning.

Earle et al. (2022) [49], [51], under the SPOWTT project, developed a seasickness prediction model for CTVs that integrates hydrodynamic simulations, real-time vessel motion monitoring, spectral analysis, and regression modelling to assess the likelihood of motion-induced discomfort during offshore wind farm transits. The nonlinear hydrodynamic simulation code PANSHIP, developed by the Maritime Research Institute Netherlands (MARIN), is used to simulate vessel responses in six degrees of freedom under various sea states, generating RAOs that predict vessel behavior based on wave conditions. These precomputed vessel responses are validated using real-world motion data from VMMS, which records high-frequency accelerations and rotations in real time. The motion data is analyzed using spectral methods (FFT) to extract Power Spectral Densities (PSD) at critical motion sickness-sensitive frequencies, such as 0.16 Hz and 0.4 Hz. A Logistic Regression (LR) model is then applied, linking these motion characteristics to technician-reported seasickness symptoms collected via a mobile survey. The model outputs the likelihood of seasickness (SS) under current transit conditions, with vertical acceleration at 0.16 Hz showing the strongest influence.

Uzuegbunam et al. (2023) [6] developed a machine learning model to predict technician welfare during CTVs' transit to offshore wind farms, focusing on two key proxies: composite weighted root mean square acceleration (aWRMS) to assess vibration-related discomfort, and MSI to estimate the possibility of seasickness. The model utilized data from Vessel Motion Monitoring Systems (VMMS), which recorded acceleration data in six degrees of freedom, as well as vessel speed, heading, and GPS location with time stamps. Additionally, meteorological data, including significant wave height, wave direction, wave period, sea surface height, current speed, current direction, wind speed, and wind direction, were integrated into the analysis. The dataset, corresponding to 850 transit days, was divided into a training set (75%) to teach the model the relationships between input variables and outputs and a testing set (25%) to evaluate its predictive accuracy. A Gaussian Process Regression (GPR) model was identified as the best performer, achieving an R^2 of 0.67 for aWRMS, indicating moderate accuracy in predicting discomfort, while the R^2 for MSI was lower at 0.49, highlighting the model's limitations in capturing the complexity of seasickness. To inform operational decisions, the aWRMS values were compared against the ISO 2631-1 comfort thresholds [58], a widely recognized standard that relates magnitudes of root mean square (RMS) accelerations to levels of passenger discomfort. For instance, RMS accelerations below 0.315 m/s^2 are considered "not uncomfortable", while values exceeding 2 m/s^2 are considered "extremely uncomfortable". Based on these thresholds, "sail" or "not-sail" recommendations were generated, presenting a novel framework for integrating technician welfare considerations into operations and maintenance planning for OWFs.

2.5.2. Safe transfer to offshore wind turbines

Offshore wind O&M activities are subject to various risks, due to their susceptibility on weather conditions. In addition to transit's uncertainty and potential seasickness of the technicians, there is also a significant risk associated with the actual transfer of technicians from the vessel to the turbine once on site.

In current industry practice, the decision to attempt a transfer is typically made only after the vessel has arrived at the turbine location, and is based on the judgment of the vessel Master and the technicians. This judgment is influenced by their experience during transit and by the real-time sea conditions encountered upon arrival [49]. However, this reactive approach means that a vessel may reach the site only to find that safe transfer is not possible, resulting in a return to port and a failed mission.

As mentioned in Section 2.3, in tasks operated by CTVs, technicians access the turbine jumping from the vessel's bow to the turbine's boat landing. However, it can be understood that harsh metocean conditions make this access sometimes difficult and unsafe, and these transfers are usually needed to be performed multiple times throughout task's duration [7]. This uncertainty is modelled in [7] by estimating the significant bow displacement of the CTV bow using vessel motions and RAOs to determine whether the vertical displacement of the bow is within a safe range for crew transfers.

An alternative approach was proposed by Hadjoudj and Pandit (2023) [4], who identified wind speed, significant wave height, and peak wave period as the most critical environmental factors influencing safety in technician transfers. This study adopts a probabilistic approach, deriving the probability of a safe transfer based on each factor's value, informed by industry discussions and recommendations.

Table 2.4: Comparison of weather parameters, operational parameters, technician welfare metrics, and modelling approaches.

Study	Weather Parameters				Operational Parameters			Technician Welfare Metrics						Modelling				
	Wind Speed	*Wave Height*	*Wave Period*	*Wave Heading*	*Vessel Limits*	*Seasickness*	*Safe Transfer*	*MSI*	*aWRMS*	*SS*	*Significant Bow Displacement*	*Empirical Rates*	*Successful Transfer Probability*	*Hydrodynamic Modelling*	*ABM*	*GPR*	*LR*	*Probabilistic*
Nachimuthu (2020) [46]	✓	✓	–	–	✓	✓	–	–	–	–	–	✓	–	–	–	–	–	✓
Tomaselli et al. (2021) [7]	✓	✓	✓	✓	✓	✓	✓	✓	–	–	✓	–	–	✓	✓	–	–	–
Earle et al. (2022) [49]	✓	✓	✓	✓	✓	✓	–	–	–	✓	–	–	–	✓	–	–	✓	–
Uzuegbunam et al. (2023) [6]	✓	✓	✓	✓	✓	✓	–	✓	✓	–	–	–	–	–	–	✓	–	–
Hadjoudj and Pandit (2023) [4]	✓	✓	✓	–	✓	–	✓	–	–	–	–	–	✓	–	–	–	–	✓

2.6. Maintenance repair types and technician selection

Wind turbines are subject to failures that require maintenance interventions. These failures are commonly classified into minor and major failures based on the time required for repair. Minor failures, which are those that can typically be fixed within a day, make up 75% of all failure events but contribute around 5% to overall downtime. On the other hand, major failures, which take more than a day to repair, account for 25% of failures but cause 95% of total downtime [59].

The repair type not only determines the time and vessel type required but also directly influences the size and composition of the technician crew. Offshore wind maintenance operations are typically grouped into three categories including minor repairs, major repairs, and major component replacements [60].

Detailed analysis from [61], based on extensive data collected from over 300 offshore wind turbines across ten European wind farms, provide deeper insights into this categorization. Figure 2.11 presents the average repair durations for each turbine sub-assembly or component, clearly demonstrating the substantial differences across repair types and specific components. Notably, major replacements of components such as hubs, blades, and gearboxes require repair times exceeding 200 hours, highlighting their criticality and complexity. In contrast, minor repairs consistently show shorter durations, usually only a few hours, underscoring their routine and less complex nature.

In addition, Figure 2.12 supports these information by illustrating the corresponding average number of technicians required for each repair type and component. The data highlight significant variation. For example, blade and gearbox replacements may require teams of up to approximately 20 technicians, whereas minor and major repairs typically require much smaller crews, generally between two to four technicians. These figures emphasize the necessity of flexible, task-specific crew assignments rather than relying solely on fixed crew sizes.

Traditionally, maintenance crew sizes are standardized based on operator experience and predefined classifications, with minor repairs generally assigned two or three technicians, and major repairs requiring between three to six, depending on the task complexity [14], [61]. Such practices are prevalent in O&M modelling studies, where technician counts are typically treated as fixed parameters [62, 16]. However, the analytical insights provided by Figure 2.11 and Figure 2.12 suggest that fixed crew assignments may oversimplify operational realities.

Furthermore, research by [44] proposes incorporating technician skill sets (electrical, mechanical, electromechanical) into scheduling models to better align technician expertise with specific maintenance tasks. While this approach enhances precision in technician-task matching, it still commonly relies on predetermined, fixed crew sizes. The component-specific details captured in Figure 2.11 and Figure 2.12 indicate potential opportunities to optimize crew sizing dynamically based on real operational data, ultimately improving efficiency and resource utilization in offshore wind turbine maintenance planning.

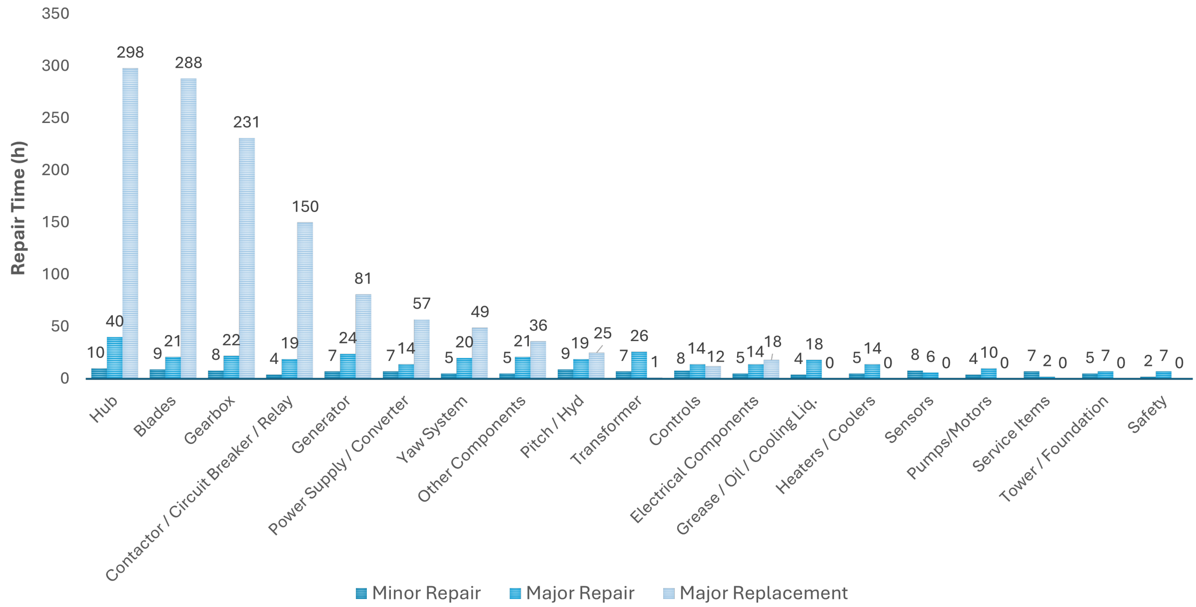

Figure 2.11: Average repair time (hours) for each wind turbine sub-assembly/component across minor repairs, major repairs, and major replacements (adapted from [61])

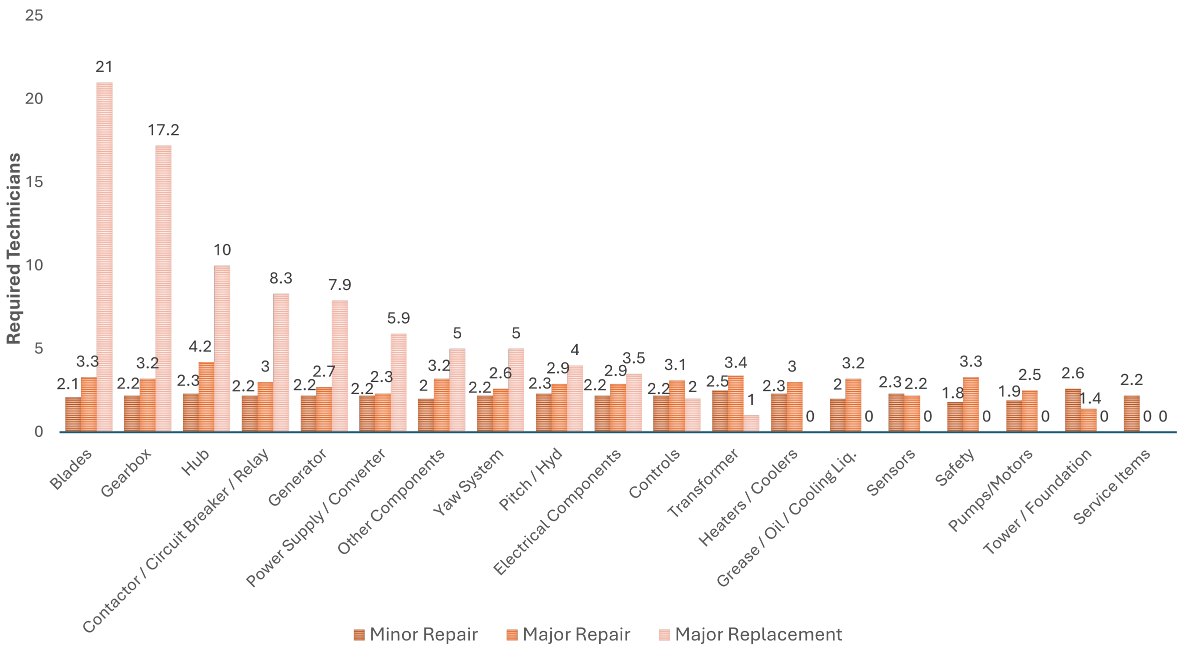

Figure 2.12: Average number of required technicians per wind turbine sub-assembly/component across different repair types (adapted from [61])

2.7. Identified gaps in literature

This Chapter has reviewed the state of the art in offshore wind O&M, focusing on vessel capabilities, maintenance strategies, and the need to recognize the importance of technician health and safety, particularly in relation to seasickness and vessel-to-turbine transfers. A wide range of decision-support models have been examined, especially those addressing environmental constraints and scheduling under weather uncertainty. Among weather parameters, wind speed, wave height, and wave period are the most commonly considered.

Despite significant progress, there are several limitations in current approaches. Most models still rely on deterministic thresholds for vessel operability and rarely consider human-related factors, such as seasickness or safe technician transfer. Moreover, the number of technicians required per maintenance task is typically assumed to be fixed, based on industry standards or past experience, rather than evaluated as a variable that could be optimized.

In terms of performance assessment, KPIs such as cost, availability, and downtime are widely used, while environmental and technician welfare metrics remain underexplored. This is quite significant considering the focus on achieving sustainability targets and the increasing emphasis on decarbonization and occupational health and safety in offshore operations.

Another insight relates to the treatment of weather uncertainty across different planning horizons. Long-term and tactical models often incorporate probabilistic weather forecasting, whereas short-term operational models, especially those focused on CTV-based maintenance, commonly assume that same-day forecasts are sufficiently accurate. Furthermore, while seasickness is inherently complex and subjective, MSI remains the most widely used metric, despite its limitations in capturing the full spectrum of technician discomfort.

These identified gaps form the foundation for the modelling approach proposed in this thesis. This study introduces a same-day, probabilistic decision-support framework that integrates human and environmental risk factors. It combines the probability of safe technician transfer and technician availability due to seasickness with a cost-based decision model, and introduces an optimization mechanism to identify the minimum number of technicians required for an economically feasible mission. In doing so, it aims to improve the safety, reliability, cost-efficiency, and sustainability of OWF operational maintenance planning.

3
Methodology

This Chapter details the methodology developed to assess the feasibility and cost-effectiveness of offshore wind turbine maintenance operations under uncertain environmental and operational conditions. The approach integrates a probabilistic framework for evaluating technician transfer risk, the impact of seasickness on workforce availability, and the overall probability of successful maintenance execution.

Section 3.1 defines the overall scope of the model. Section 3.2 then describes the process used to quantify uncertainty in technician transfer and technician availability. The cost-based decision model for maintenance planning is presented in Section 3.3, followed by an explanation of the crew size optimization procedure in Section 3.4. Section 3.5 outlines the approach for estimating the environmental impact of failed maintenance attempts. Finally, Section 3.6 summarizes the KPIs used to evaluate the proposed framework.

3.1. Scope of the model

As identified in Chapter 2, existing offshore wind O&M models largely rely on fixed environmental thresholds, such as wave height and wind speed to assess whether maintenance operations should proceed. While these thresholds reflect vessel operability, traditional models typically overlook critical human factors such as technician fitness post-transit and assume fixed crew sizes, thereby limiting decision realism and flexibility.

To address these gaps, this study develops a probabilistic decision-support model that integrates that integrates environmental, operational, and human-related uncertainties into offshore maintenance planning. The proposed model accounts for two main risks:

- **Technician transfer risk:** The probability that technicians can safely transfer from the vessel to the turbine platform under prevailing sea conditions, denoted as transfer success probability ($P_{s,transfer}$).
- **Technician availability risk:** The probability that a sufficient number of technicians remain fit to work after transit-induced motion sickness, modelled using a binomial distribution and denoted as transit success probability ($P_{s,transit}$).

The product of these two quantities forms the combined probability of mission success ($P_{s,combined}$). The model begins with the input of task-specific parameters, such as component type, maintenance duration, and vessel transit time. It then loads the relevant weather data (wind speed, wave height, and wave period). If the vessel's operability limits are not satisfied, the mission is cancelled.

If limits are met, the model calculates $P_{s,transfer}$ and evaluates $P_{s,transit}$ for each possible number of technicians deployed, $N_{T,deployed}$, ranging from the minimum required, $N_{T,required}$, to a maximum allowable crew size, $N_{T,max}$, depending on the vessel (see Table 2.1). For each deployment scenario, the model calculates $P_{s,combined}$.

A cost-loss framework is then applied: the mission is only considered economically viable if the combined probability of mission success exceeds a threshold given by the cost of attempting maintenance, $\sum C_i$, to the economic loss from an unsuccessful mission, L. If this condition is met, the mission proceeds using the minimum number of technicians that satisfies the threshold. Otherwise, the mission is cancelled.

This approach allows for dynamic crew sizing rather than fixed assumptions, balancing operational feasibility with cost-effectiveness. It provides a safer and more adaptive strategy for offshore maintenance planning, one that responds smartly to daily weather conditions and technician risk. Figure 3.1 illustrates the full process in flowchart form.

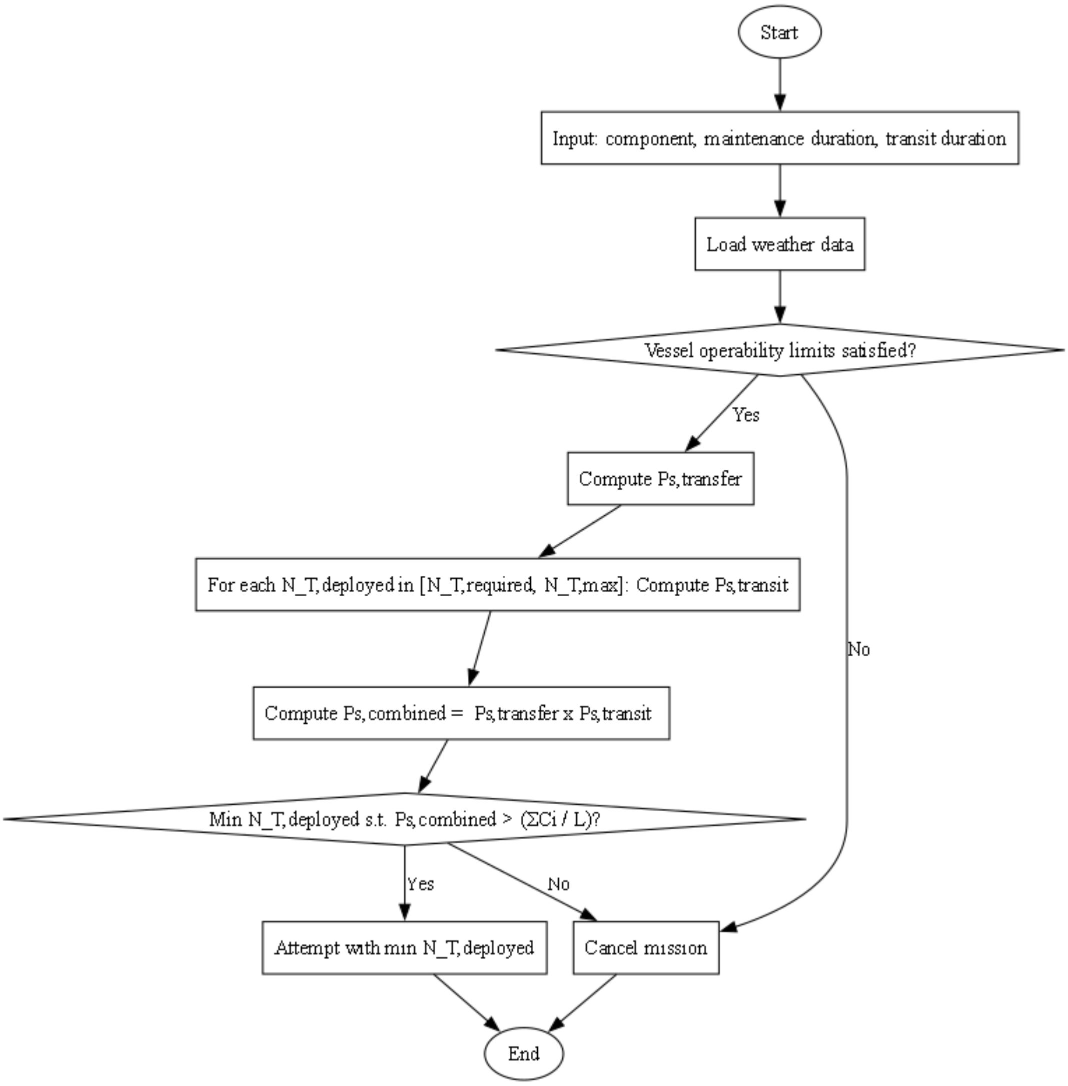

Figure 3.1: A flowchart of the developed model

3.2. Modelling process

To derive a risk-aware combined probability of mission success of a maintenance mission, transfer and transit success probabilities have to be estimated. This Section present the process followed in this model to determine this combined probability of mission success.

3.2.1. Transfer success probability

As seen in Section 2.3, technician transfers are highly influenced by metocean conditions. While for SOV-based operations W2W systems often contribute to improving transfer safety, in CTV-based maintenance technicians must step from the vessel onto the wind turbine ladder to access the wind turbine and perform the required maintenance, as already mentioned in Section 2.5.2. Under harsh metocean conditions, vessel motions can make this transfer highly dangerous, increasing the risk of injuries.

To account for this risk, this project uses as reference the probabilistic approach developed by [4] in collaboration with offshore wind operators. This approach, based on the environmental conditions on-site, including wave height, wave period, and wind speed, determines the transfer success probability of technicians to the wind turbine for offshore operations.

The overall transfer success probability, $P_{s,transfer}$ is computed as:

$$P_{s,transfer} = P_{s,transfer,wh} \cdot P_{s,transfer,wp} \cdot P_{s,transfer,ws} \tag{3.1}$$

where:

- $P_{s,transfer,wh}$ is the transfer success probability given the significant wave height.
- $P_{s,transfer,wp}$ is the transfer success probability given the peak wave period.
- $P_{s,transfer,ws}$ is the transfer success probability given the wind speed.

This formulation assumes that each environmental factor influences transfer feasibility independently. While some interdependencies may exist, for practical modelling purposes, this assumption allows for a computationally efficient probability estimation. As can be noticed, if any of these probabilities is zero, the overall transfer probability is also zero, meaning that the maintenance mission is immediately canceled before deployment.

3.2.2. Transit success probability

Technicians traveling offshore are subject to motion sickness, which can affect their ability to perform maintenance tasks upon arrival at the wind turbine. Seasickness is a complex and subjective phenomenon, influenced by multiple physiological and environmental factors. While extensive research has been conducted to predict the occurrence of motion sickness, and new metrics continue to be developed to improve accuracy, the focus of this study is not to estimate motion sickness itself, but rather to examine its impact on workforce availability for maintenance execution offshore.

Each maintenance task requires a minimum number of of capable technicians to be completed successfully. However, if $N_{T,deployed}$ is the number of technicians deployed to the wind turbine, the number of technicians who remain healthy and ready to work upon arrival is uncertain due to potential seasickness. To account for this uncertainty, this model estimates the probability that at least the required number of technicians will be available and non-seasick to execute the maintenance upon reaching the offshore site.

As discussed in Section 2.5.1, MSI is the most widely adopted seasickness metric. Hu et al. (2018), through case studies for five OWFs, monitored the relationship between MSI and significant wave height. In their study, MSI values were reported for the following discrete significant wave heights: 0.0 m, 0.5 m, 1.0 m, 1.5 m, 2.0 m, 2.5 m, 3.0 m, and 3.5 m. Since MSI has been measured only at discrete wave height values, it is necessary to estimate MSI for intermediate wave heights that are not explicitly reported in [63]. To ensure a continuous representation of MSI as a function of wave height, this study applies linear interpolation to approximate MSI values between known data points. This method was chosen because the MSI–wave height relationship appears to be monotonic (that is, MSI increases with higher wave heights), and linear interpolation provides a reasonable approximation while balancing accuracy and model simplicity.

For a wave height H_s between two known points i and $i+1$ the MSI is calculated using:

$$MSI = MSI_i + \left(\frac{H_s - H_i}{H_{i+1} - H_i} \right) \cdot (MSI_{i+1} - MSI_i) \tag{3.2}$$

This approach allows the model to dynamically compute MSI for any wave height within the observed range, ensuring a more accurate estimation of the likelihood that technicians will experience motion sickness upon arrival at the turbine. The interpolated MSI values are then used as inputs for the probabilistic model that estimates the transit success probability, or in other words the probability of having enough healthy technicians by the end of the transit to the OWF.

Probability distribution
To model the transit success probability, two probability distributions were considered, namely the Beta distribution and the Binomial distribution. The Beta distribution is commonly used to model probabilities and proportions over a continuous interval $[0,1]$ [64].

According to [65], a random variable $x \in [0,1]$ follows a Beta distribution with parameters $a > 0$ and $b > 0$, denoted as $x \sim \text{Beta}(x \mid a, b)$, if its probability density function (PDF) is:

$$p(x) = \begin{cases} \frac{1}{B(a,b)} x^{a-1}(1-x)^{b-1}, & \text{if } 0 \le x \le 1 \\ 0, & \text{otherwise} \end{cases} \tag{3.3}$$

where $B(a,b)$ is the Beta function:

$$B(a,b) = \int_0^1 x^{a-1}(1-x)^{b-1} dx \tag{3.4}$$

The Beta distribution was initially considered due to its previous application in similar offshore maintenance models, such as [46]. However, a key limitation arises when using the Beta distribution to model transit success probability, defined as the likelihood that at least $N_{T,required}$ technicians arrive healthy. However, it is continuous, meaning that the probability of a specific outcome (such as exactly 0 seasick technicians) is technically zero. This presents a problem when modelling technician availability for offshore maintenance.

In particular, if only the minimum number of technicians ($N_{T,required}$) is deployed, the transit success condition requires exactly zero seasick technicians. Since the Beta distribution provides a density, not a probability mass, the probability of exactly $x = 1$ (100% healthy technicians) is zero. This is evident in Figure 3.2, where even under ideal conditions ($H_s = 0.2$ m), the success probability is unrealistically computed as zero for the minimum crew size.

For illustrative purposes, the comparison between probability distributions is based on a minor repair task executed using a CTV. As such, the considered crew size ranges from 2 technicians, the most typical minimum for minor repairs, to 12, which represents the maximum crew capacity of a CTV.

In contrast, the Binomial distribution is a discrete distribution suited to modelling the number of successes in a fixed number of independent trials. According to [66], a random variable X follows a Binomial distribution with parameters n (number of trials) and p (probability of success in each trial), written as $X \sim \text{Bin}(n,p)$, if:

$$P(X = k) = \binom{n}{k} p^k (1-p)^{n-k}, \quad k = 0, 1, \ldots, n \tag{3.5}$$

where:

$$\binom{n}{k} = \frac{n!}{k!(n-k)!} \tag{3.6}$$

In this study, the Binomial distribution is used to model the number of seasick technicians during transit. In the context of this study:

- $n = N_{T,deployed}$ is the number of technicians deployed for a given maintenance task,
- p is the probability of a technician becoming seasick (equal to the MSI value under the given sea state),
- X is the number of technicians who become seasick, such that $X \sim \text{Bin}(n,p)$.

Accordingly, a 'success' in the context of the Binomial distribution corresponds to a technician experiencing seasickness, while a 'failure' corresponds to a technician remaining healthy. The model estimates the probability that at least $N_{T,required}$ technicians arrive healthy and able to perform the maintenance.

The condition for mission feasibility is that the number of healthy technicians after transit is at least equal to the minimum required to perform the task, denoted by $N_{T,required}$. Since X represents the number of seasick technicians, and $N_{T,deployed}$ represents the number of technicians deployed for the maintenance task, this condition can be written as:

$$N_{T,deployed} - X \geq N_{T,required} \tag{3.7}$$

The probability that this condition is satisfied is, namely, the transit success probability $P_{s,transit}$:

$$P_{s,transit} = P(X \leq N_{T,deployed} - N_{T,required}) \tag{3.8}$$

This approach accounts for the discrete nature of technician health outcomes and produces realistic results. As shown in Figure 3.3, even when only two technicians are deployed under favorable conditions, the success probability remains high (approximately 98%).

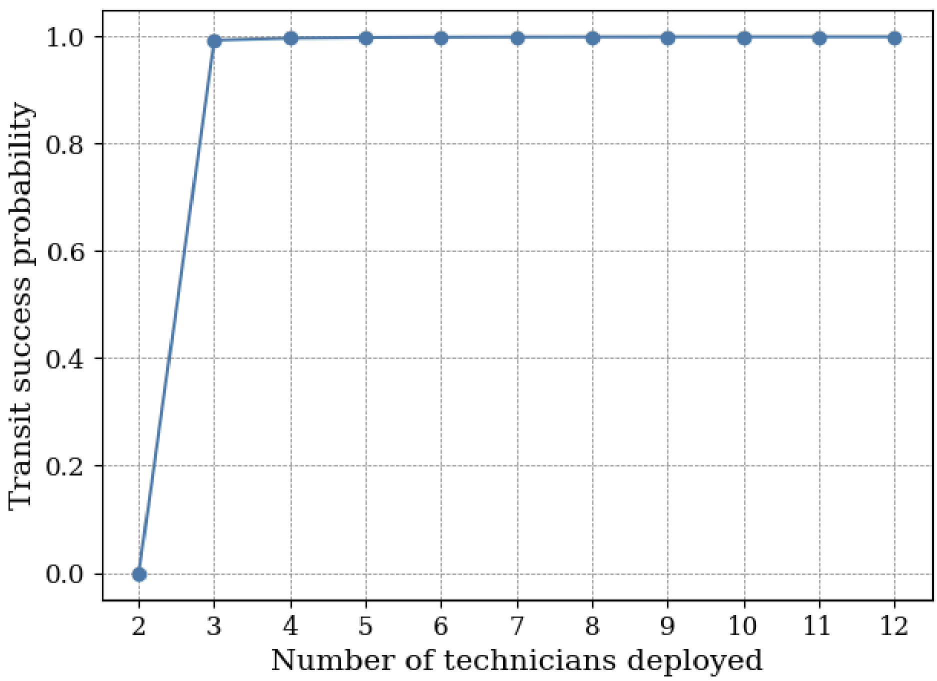

Figure 3.2: Transit success probability as a function of the number of technicians deployed, modelled using Beta distribution at $H_s = 0.20$ m

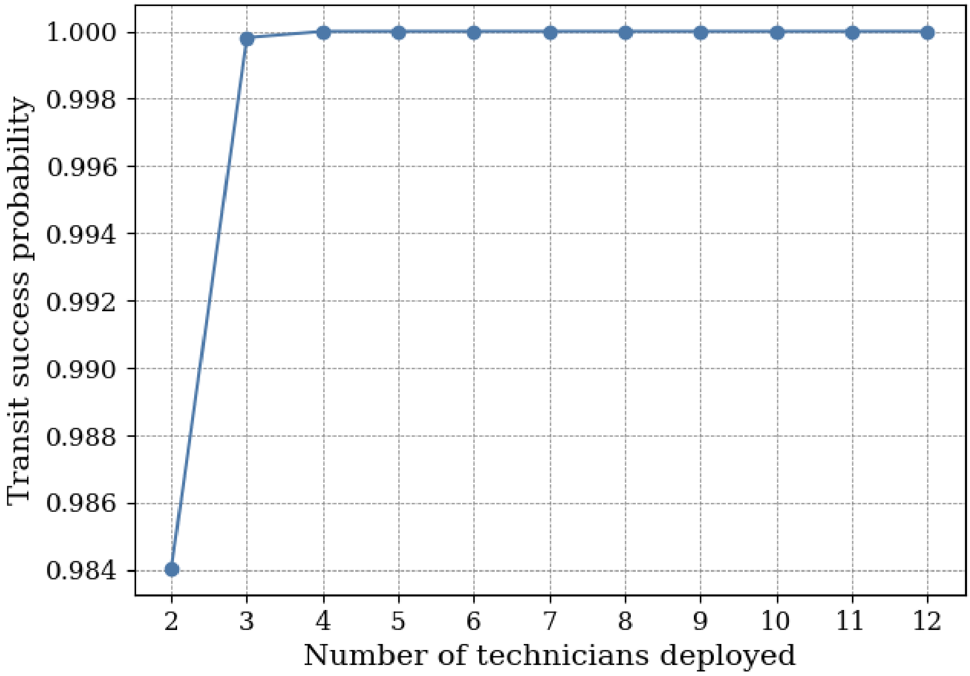

Figure 3.3: Transit success probability as a function of the number of technicians deployed, modelled using Binomial distribution at $H_s = 0.20$ m

In summary, the Binomial distribution offers a more appropriate and operationally relevant model for estimating the likelihood of having enough healthy technicians available for offshore maintenance. It aligns better with the discrete nature of crew health outcomes and provides interpretable, realistic success probabilities under various sea-state conditions.

3.2.3. Combined probability of mission success

The overall probability of mission success depends on two key probabilistic components: the probability of successful transfer to the wind turbine ($P_{s,transfer}$), and the probability of successful transit to the OWF due to the risk of seasickness ($P_{s,transit}$). These components represent independent events in the model, one related to environmental operability and the other to human performance. Therefore, the combined probability of mission success, $P_{s,combined}$, is calculated as the product of these two probabilities:

$$P_{s,combined} = \prod P_i = P_{s,transfer} \cdot P_{s,transit} \tag{3.9}$$

This formulation reflects the requirement that both conditions must be met simultaneously for the mission to be considered successful. First, technicians must be able to reach the OWF, and second, enough of them must remain in suitable condition to carry out the scheduled maintenance task.

3.3. O&M cost-based decision model

In offshore wind farm operations, uncertainty in mission success makes maintenance scheduling a complex and high-risk task. Attempting a mission incurs operational costs, and failed attempts result in further economic losses due to potential turbine downtime and the need to re-attempt maintenance. To determine whether a maintenance attempt is economically feasible, this study adopts a cost-loss decision model, a well-established framework in decision analysis under uncertainty [67]. In its original formulation, the model was used to decide whether to implement protective measures against adverse weather. If the probability of a damaging event exceeded the ratio between the cost of protection and the potential loss if no action was taken, protective measures were justified.

This framework was later adapted for offshore wind maintenance planning by [43]. In their formulation, the cost represented the cost of attempting a maintenance mission, and the loss reflected the economic loss from an unsuccessful mission, primarily the revenue loss from additional turbine downtime between a failed and a successful attempt, as well as the cost of reattempting the task. However, the cost of the failed attempt itself was not included in the loss term.

This study builds upon and extends their approach by incorporating a more comprehensive definition of the loss term. Specifically, the loss incurred from a failed maintenance attempt includes not only the lost energy production revenue and the reattempting costs, but also the operational costs of the failed attempt, such as technician wages, vessel costs, and spare parts. This adjustment reflects real-world cost structures more accurately and enables a more risk-aware and economically grounded decision-making process. This Section presents the cost-loss model in detail, outlines the components of maintenance costs, and demonstrates how the combined probability of mission success informs decision-making.

3.3.1. Cost-Loss model

The cost-loss model evaluates the economic viability of a maintenance mission by comparing the cost of attempting maintenance, $\sum C_i$, with the potential economic loss, L, incurred if the mission fails. Maintenance is economically justified when the combined probability of mission success ($P_{s,combined}$) satisfies the following condition:

$$P_{s,combined} > \frac{\sum C_i}{L} \tag{3.10}$$

where:

- $\sum C_i$ is the cost of attempting maintenance, including vessel deployment, technician wages, and spare parts cost.
- L is the loss incurred if the mission fails, consisting of the cost of the attempt, lost energy revenue from additional turbine downtime between a failed and a successful attempt, and costs of reattempting maintenance.
- $P_{s,combined}$ is the combined probability of mission success, as calculated by Equation 3.9.

3.3.2. O&M mission cost components

The main cost categories associated with offshore wind maintenance missions include vessel charter and mobilization, fuel, technician wages, spare parts, and downtime losses [18], [68]. Each of these costs plays a role in the overall O&M strategy.

Cost of attempting maintenance

The total cost of attempting a maintenance mission, $\sum C_i$, can be calculated using:

$$\sum C_i = C_{technicians} + C_{vessel\ rent} + C_{vessel\ fuel} + C_{spare\ parts} \tag{3.11}$$

where:

- $C_{technicians}$ is the cost of deployed technicians' wages
- $C_{vessel\ rent}$ is the cost of vessel charters
- $C_{vessel\ fuel}$ is the cost of fuel for transit
- $C_{spare\ parts}$ is the cost of spare parts required for the task

Economic loss from an unsuccessful mission

If the attempted maintenance mission fails, the total economic loss, L, is calculated using:

$$L = \sum C_i + L_{energy} + L_{reattempt} \tag{3.12}$$

where:

- L_{energy}: Lost energy revenue from turbine downtime between a failed and a successful attempt.
- $L_{reattempt}$: Additional cost of reattempting the maintenance task on another day.

The lost revenue due to downtime is calculated as:

$$L_{energy} = R_{lost} \cdot t_{downtime} \tag{3.13}$$

where:

- $t_{downtime}$: Duration of downtime (hours) between a failed and a successful attempt.
- R_{lost}: Revenue lost per hour due to turbine being non-operational ($/h).

The cost of reattempting maintenance is estimated as:

$$L_{reattempt} = \sum C_i - C_{spare\ parts} \tag{3.14}$$

This assumes that spare parts do not need to be repurchased for the second attempt, and $L_{reattempt}$ represents the total economic impact of failing to perform maintenance on the first attempt.

Expected operational costs
To evaluate the economic viability of a maintenance mission under uncertainty, the expected operational cost, $\mathbb{E}[C]$, is computed as:

$$\mathbb{E}[C] = P_{s,combined} \cdot \sum C_i + (1 - P_{s,combined}) \cdot L \tag{3.15}$$

Where:

- $P_{s,combined}$ is the combined probability of mission success, incorporating both transit and transfer success probabilities.
- $\sum C_i$ is the cost of attempting maintenance, as defined in Equation 3.11.
- L is the economic loss from an unsuccessful mission, as defined in Equation 3.12.

This formulation allows for a probabilistic cost evaluation that accounts for both the direct costs of deployment and the potential penalties associated with mission failure. It is particularly useful for comparing alternative maintenance scheduling strategies under varying weather and operational conditions.

3.3.3. Decision framework

Using the cost-loss model, two decision outcomes are possible. First, there is the case where mission attempt is proposed. This happens if the combined probability of mission success exceeds the cost-loss ratio, which means that the maintenance attempt is economically justified.

$$P_{s,combined} > \frac{\sum C_i}{L} \tag{3.16}$$

This is typically the case when metocean conditions are favorable for successful technician transfers, and enough technicians are expected to be healthy after transit. Second, there is the case where mission attempt should be cancelled. This happens if the combined probability of mission success is low and does not exceed the cost-loss ratio, making the decision to delay maintenance a better option.

$$P_{s,combined} < \frac{\sum C_i}{L} \tag{3.17}$$

This normally occurs when adverse metocean conditions reduce the transfer success probability for technicians, and lead to high MSI values that increase the risk of having insufficient number of healthy technicians after the transit. This framework allows maintenance planners to incorporate probabilistic forecasting into operational decisions, reducing unnecessary expenditures and turbine downtime while maintaining economic viability.

3.4. Model optimization

While the cost-loss decision model provides a framework for deciding whether a maintenance operation should be attempted, an equally important aspect of offshore maintenance planning is determining the optimal number of technicians to deploy. Sending too few technicians increases the likelihood of mission failure due to motion sickness, whereas deploying more than necessary leads to avoidable personnel costs. To manage this trade-off, an optimization process is introduced to identify the minimum number of technicians required to ensure economic feasibility while at the same time maintaining a satisfactory probability of success.

The objective of this optimization is to determine the smallest number of technicians, $N_{T,opt}$, that satisfies the economic condition derived from the cost-loss model.

$$\min N_{T,deployed} \quad \text{subject to:} \quad P_{s,combined}(N_{T,deployed}) > \frac{\sum C_i}{L} \tag{3.18}$$

Here $P_{\text{s,combined}}(N_{T,deployed})$ is the combined probability of mission success, as defined in Equation 3.9, given the number of technicians deployed $N_{T,deployed}$. The right-hand side of the inequality represents the cost-loss threshold, where $\sum C_i$ is the cost of attempting maintenance and L is the economic loss if the mission fails. The optimization process begins with the minimum required number of technicians, $N_{T,required}$, and incrementally increases the technician count. For each possible value of $N_{T,deployed}$, the model evaluates the combined probability of mission success by incorporating the probability of successful transfer under current metocean conditions, and the probability of successful transit which reflects the probability that a sufficient number of technicians will remain fit for work after transit, due to seasickness risk. This process continues until the inequality in Equation 3.18 is satisfied. The first technician count that meets this condition is selected as the optimal crew size, $N_{T,opt}$. In scenarios where more than the minimum number of technicians is needed, the additional technician cost, $C_{add,technician}$, is included in $\sum C_i$ as:

$$C_{add,technician} = (N_{T,deployed} - N_{T,required}) \cdot C_{technicians} \cdot t_{shift} \tag{3.19}$$

where t_{shift} is the total technician shift duration (hours), including both vessel transit and on-site repair time.

By integrating this optimization step into the decision-making framework, the model supports cost-efficient offshore O&M planning. It ensures that technician number is neither excessive nor insufficient, reducing unnecessary expenditures while maintaining operational feasibility. This approach enhances the economic robustness of offshore maintenance planning by providing a probabilistic, data-driven method for optimizing workforce deployment. Moreover, it extends the cost-loss framework by incorporating probabilistic risk assessments, and economic trade-offs into a single data driven decision-support model.

3.5. Environmental impact estimation

In addition to operational feasibility and cost efficiency, the developed model also estimates the environmental impact of maintenance strategies by quantifying the expected CO_2 emissions caused by failed maintenance attempts. These failed attempts typically result in additional vessel trips offshore, which are a major contributor to emissions in offshore wind operations.

To assess this impact, the model calculates the CO_2 emissions per single vessel trip, E_{trip}, based on [21] approach:

$$E_{trip} = t_{transit} \cdot FC \cdot \rho_{fuel} \cdot CF \tag{3.20}$$

Where:

- $t_{transit}$ is the round-trip transit time (hours),
- FC is the fuel consumption rate of the vessel (liters/hour),
- ρ_{fuel} is the fuel density (kg/l),
- CF is the carbon factor (tons CO_2 per kg of fuel).

Based on this, the total emissions from re-attempted maintenance trips, E_{total}, over the planning horizon are estimated as:

$$E_{total} = N_{reattempts} \cdot E_{trip} \tag{3.21}$$

Where:

- $N_{reattempts} = N_{tasks} \cdot (1 - P_{s,combined})$ is the expected number of failed attempts,
- N_{tasks} is the total number of maintenance tasks scheduled,
- $1 - P_{s,combined}$ is the combined probability of mission failure.

This methodology provides a systematic way to compare environmental performance across different maintenance scheduling strategies.

3.6. Model KPIs

To assess the effectiveness of the proposed decision-support framework, this study defines a set of KPIs that align with the methodology components introduced above and the gaps identified in the literature review. These KPIs support a multi-dimensional evaluation of the model's performance in terms of feasibility, economic efficiency, and sustainability.

- **Combined probability of mission success ($P_{s,combined}$):** This KPI represents the overall likelihood that a maintenance task will be successfully executed, incorporating both the feasibility of technician transfer and the availability of healthy technicians after transit due to seasickness.
- **Optimum number of technicians deployed ($N_{T,opt}$):** This KPI calculates the minimum number of technicians required to ensure that the combined probability of mission success exceeds the cost-loss threshold. This KPI reflects the model's ability to balance operational feasibility with personnel cost efficiency.
- **Expected operational costs ($\mathbb{E}[C]$):** This KPI captures the total expected cost of executing the maintenance mission, including technician wages, vessel costs, spare parts, and losses from failed maintenance attempts. The value is directly influenced by the combined probability of mission success ($P_{s,combined}$), as lower success rates lead to more re-attempts and higher costs. This KPI supports direct economic comparisons between maintenance scheduling strategies under uncertainty.
- **Environmental impact (E_{total}):** This KPI estimates the total CO_2 emissions from re-attempted maintenance missions due to failed attempts. It provides a sustainability-focused metric that reflects the carbon intensity of a maintenance schedule and supports environmentally conscious planning.

4 Case Study

This chapter applies the proposed decision-support methodology to a realistic offshore wind farm scenario to evaluate the performance of alternative maintenance scheduling strategies under real-world offshore conditions. The focus is on minor repair tasks conducted using Crew Transfer Vessels (CTVs). Using predictive maintenance schedules generated by an MPC framework and a 10-year numerical hindcast weather dataset, the study compares a traditional deterministic industry scheduling approach (Case 1) with the probabilistic, risk-informed decision-support model developed in this thesis (Case 2). This setup allows for a robust and consistent comparison across feasibility, reliability, economic, and environmental performance indicators.

Specifically, Section 4.1 provides an overview of the case study, including location, assumptions, and maintenance scheduling strategies. Section 4.2 describes the data used for simulation, including maintenance plans with an illustrative example of a typical maintenance cycle, weather conditions, and cost parameters. Section 4.3 introduces the simulation setup and describes the modelling approach for the combined probability of mission success. Section 4.4 introduces a sensitivity analysis to evaluate how deviations in weather conditions affect the model's recommendations.

4.1. Overview of the case study

The case study focuses on a representative offshore wind farm consisting of 10 turbines, located approximately 40 km off the coast of Cabo Silleiro in northwestern Spain, as seen in Figure 4.1. This location, referred to as "Site No. 3" in the study by Li et al. (2015) [69], is one of several evaluated as potential offshore renewable energy sites and features realistic metocean conditions for CTV-based maintenance.

Figure 4.1: Location of the potential offshore site in Cabo Silleiro, Spain

The analysis combines two main sources of input data:

- A numerical hindcast weather dataset covering the years 2001 to 2010 as used by [69], which provides hourly sea state and wind conditions.
- A set of predictive maintenance schedules generated by the MPC-based framework developed by Borsotti et al. (2024) [16], which uses component degradation estimates to define optimal maintenance time windows.

The case study is used to evaluate and compare two different maintenance scheduling strategies:

- Deterministic industry scheduling, which selects the earliest day that meets basic weather thresholds, with a fixed crew size.
- Probabilistic model scheduling, which applies the decision-support framework to optimize both task timing and technician deployment based on risk and cost considerations.

Both strategies are applied to the same underlying data, enabling a consistent and comparative assessment of their performance in terms of feasibility, reliability, cost, and environmental impact.

4.1.1. Maintenance schedules and data source

The maintenance plans used in this study are derived from the predictive scheduling framework developed by Borsotti et al. (2024) [16], which employs an MPC strategy based on RUL predictions. The original model provides 75 maintenance schedule scenarios over a 20-year period.

To align with the available hindcast weather data, this study considers a 10-year subset of these schedules (2001–2010). Each scenario includes approximately 255 minor repair tasks. These tasks serve as the common input for both evaluation cases introduced below, which apply different decision rules for task execution under uncertain conditions. A detailed breakdown of the number of cycles and minor repair tasks for each of the 75 schedules is provided by Table B.1 in Appendix B.

4.1.2. Evaluation cases

To assess how different decision-making strategies influence maintenance feasibility, success probability, and cost, the study compares two scheduling cases:

Case 1 — Deterministic industry scheduling

In this case, maintenance tasks are attempted on the first available day after their scheduled date that meets typical CTV operational weather thresholds:

- Significant wave height $H_s < 2.2$ m
- Wind speed $V_{wind} < 25$ m/s

This case reflects common industry practice, which relies solely on deterministic weather thresholds [49] and assumes a fixed crew size of two technicians. No consideration is given to seasickness, technician transfer risk, or the likelihood of mission failure.

However, to enable direct comparison with the second case, the full probabilistic model developed in this thesis is also retrospectively applied to the Case 1 schedule. This allows for the estimation of transit and transfer success probabilities, combined probability of mission success, as well as expected operational costs under the deterministic approach.

Case 2 — Probabilistic model scheduling

This case implements the full decision-support model proposed in this thesis. It optimizes both the timing of each maintenance task and the number of technicians assigned, based on weather forecasts, risk factors, and cost-efficiency. The key decision rules are:

- The task is executed on the earliest day that satisfies the cost-loss condition defined in Equation 3.16.
- The number of technicians (between 2 and 12) is selected to satisfy the threshold defined in Equation 3.18.
- If no viable configuration is found within the available operational window (including transit and repair time), the task is cancelled.

Case 2 serves as the reference implementation of the decision-support framework, allowing a comprehensive comparison against common industry practice. Table 4.1 summarizes the key differences between the two evaluation cases defined above.

Table 4.1: Summary of evaluated maintenance strategies, Case 1 and Case 2

Feature	**Case 1: Deterministic industry scheduling**	**Case 2: Probabilistic model scheduling**
Schedule basis	Weather thresholds (CTV operability)	Optimized using probabilistic model
Crew size	Fixed (2)	Optimized (2–12)
Seasickness and transfer risk	–	✓
Cost-loss optimization	–	✓
Evaluation purpose	Reflect industry practice (retrospectively evaluated)	Evaluate full decision-support framework

4.1.3. Execution and assumptions

To ensure manageable complexity and clear interpretation of the results, the following general assumptions were made:

- Both Case 1 and Case 2 use the same set of 75 planned maintenance schedules, with task execution dates adjusted according to the respective decision rules.

- Numerical hindcast weather data for the Cabo Silleiro site from 2001 to 2010 [69] are used to assess the feasibility of executing each task on its planned day.
- January 1, 2001 is assumed Day 1, while December 31, 2010 is assumed Day 3,652.
- Only one maintenance task can be completed per day.
- All maintenance tasks are executed using CTVs.
- A single CTV is assumed to be available for all maintenance operations.
- All maintenance shifts begin at 08:00.
- The analysis focuses exclusively on minor repair tasks.
- Vessel operability limits are defined as $H_s = 2.2m$, $V_{wind} = 25m/s$.
- All tasks in the same maintenance cycle are equally critical.
- Transit time from port to the OWF is fixed at 1 hour, corresponding to a vessel speed of 22 knots.
- Transit time to any wind turbine within the OWF is considered the same.
- MSI values associated with significant wave heights are sourced from [63].
- Fuel consumption is assumed to be independent of the number of technicians onboard.
- Each failed maintenance attempt results in a full round-trip transit between port and OWF.

4.2. Data description

This case study relies on three key categories of data: maintenance tasks, metocean conditions, and cost parameters. Together, these datasets support the evaluation of the two maintenance scheduling strategies introduced in Section 4.1.2, by enabling the estimation of maintenance feasibility, combined probability of mission success, and expected operational costs.

4.2.1. Maintenance task dataset

As briefly discussed in Section 4.1.1, the maintenance task dataset used in this study originates from the scheduling framework developed by [16], which utilizes an MPC strategy to generate predictive long-term maintenance plans. While the original model includes tasks of varying severity, including minor repairs, major repairs, and replacements, this study focuses solely on minor repair tasks executed via CTVs.

Each task in the MPC schedules is defined by the following attributes:

- Maintenance cycle number (indicating the group of tasks planned for the same maintenance window),
- Ideal start day for maintenance, as suggested by the predictive model,
- Affected component and turbine ID,
- Spare parts cost, as specified in the scheduling output of [16].

Although the task list remains identical across both evaluation cases, the rescheduling logic differs substantially. In Case 1, tasks are executed on the first day meeting weather thresholds. In Case 2, tasks are rescheduled based on probabilistic success metrics and optimized technician deployment. Component-specific repair durations and spare parts costs are assigned to each task using [16], as shown in Table 4.2.

Table 4.2: Minor repair duration and spare parts cost by component [16]

Component	Duration (h)	Spare parts cost ($)
Blades	9	5,050
Bearing	6	1,450
Gearbox	8	5,950
Generator	7	2,350
Pitch system	6	1,000

Illustrative maintenance cycle

To illustrate how the MPC model structures maintenance operations, this Section presents an example maintenance cycle drawn from the framework developed by [16]. In this context, a maintenance cycle refers to a set of repair tasks grouped for maintenance execution within a defined time window, typically selected to maximize the lifetime of the components.

In the example shown in Table 4.3, 11 minor repair tasks, targeting a range of turbines and components, are scheduled to begin on Day 150. This planned day represents the ideal start date for the maintenance cycle, as defined by the predictive model. It does not imply that all tasks will necessarily be executed on that date, but rather that it marks the start of the window in which execution is preferable based on the predicted RUL of the components.

Table 4.3: Ideal task start day for an illustrative maintenance cycle, as planned by the MPC framework proposed by [16]. This schedule serves as input for the rescheduling analysis in Case 1 and Case 2

Task ID	Component	MPC-Planned Day
T1	gearbox_1	150
T2	blades_2	150
T3	gearbox_3	150
T4	generator_3	150
T5	pitch_system_3	150
T6	pitch_system_4	150
T7	pitch_system_5	150
T8	bearing_6	150
T9	pitch_system_6	150
T10	bearing_7	150
T11	blades_8	150

This task list serves as a baseline for evaluating and comparing the rescheduling strategies of Case 1 and Case 2.

4.2.2. Weather data

Weather data for the offshore site were sourced from [69], generated by a numerical hindcast model from National and Kapodistrian University of Athens, and cover the period from 2001 to 2010 with an hourly resolution. The dataset includes metocean parameters such as significant wave height, wind speed, and peak wave period, which are key variables. These variables directly affect both the operational feasibility (vessel operability and transfer success) and the human performance factors (seasickness risk) associated with offshore maintenance operations.

For each scheduled maintenance task, weather data during standard working hours, under the assumption that working shift begins at 08:00, are extracted and used in different ways depending on the case.

- In Case 1, weather data are used to determine whether the conditions meet the basic operability thresholds ($H_s < 2.2m$, $V_{wind} < 25m/s$)
- In Cases 2, the same weather data are used, first to check whether the conditions meet the basic operability thresholds, and second as inputs to the probabilistic model, which evaluates both the transit and transfer success probabilities. These factors together determine the combined probability of mission success of the maintenance task execution.

Using a consistent weather dataset across both cases ensures comparability of results while enabling evaluation of different decision-making strategies under identical environmental conditions.

4.2.3. Cost parameters

The cost parameters used in this study are adapted primarily from the economic modelling framework of [16], with additional assumptions based on literature and standard industry practices. Maintaining consistency in these parameters ensures a valid comparative assessment between the industry standard (Case 1) and the developed model (Case 2) strategies, particularly concerning technician deployment and associated economic impacts.

The key cost categories incorporated into the model include:

- Vessel costs (charter and fuel)
- Technician wages
- Spare parts costs
- Downtime costs

Each of these costs contributes to the total expenditure per task and is treated differently depending on whether the task is completed successfully or must be re-attempted.

Vessel Costs
CTVs are the standard transport option for minor repairs. Their use incurs two primary costs:

- A charter cost of $8,000 per day [16]
- A fuel cost of approximately $5 per km traveled [16]

These costs are incurred for every maintenance attempt, regardless of success or failure, since charter rate and fuel consumption occur even if technicians are ultimately unable to complete the task due to adverse conditions. One-time mobilization costs, which can reach €50,000 [18], are excluded from this analysis under the assumption that once mobilization is completed, this cost does not reoccur for subsequent daily operations.

Technician Wages
Technicians are compensated at a rate of $60 per hour [16], including time spent in transit and at the turbine. Technician costs are calculated based on:

- The number of technicians deployed.
- The total shift duration, including vessel transit and repair execution.

Wages are paid regardless of task success, and are incurred again for re-attempted tasks in case of failure.

Spare Parts
Spare parts are required for all maintenance tasks, with their cost varying significantly based on the type and severity of the fault [61]. However, in contrast to vessels and technicians, spare parts are typically considered a one-time cost. That is, if a maintenance attempt fails, the spare part is not lost or consumed and can be reused for the rescheduled task. Therefore, in the event of a failed mission, spare parts do not need to be repurchased. As such, spare part costs are only included in the cost estimate for the initial task execution and not in the retry component of the model. Spare part costs used in this case study can be seen in Table 4.2.

Downtime Losses
In many offshore maintenance scenarios, delays in executing repairs can result in turbine downtime, leading to lost revenue from ungenerated electricity. The financial impact of such downtime typically depends on the electricity price, turbine capacity, and the duration of unavailability.

However, this case study is executed based on the maintenance task datasets obtained from [16]. In these, minor repairs are assumed to be non-critical and do not require turbine shutdown before maintenance execution. This leads to the following two assumptions.

- Turbines are assumed to remain fully operational prior to maintenance execution, and
- In case of a failed maintenance attempt, turbines are still assumed to remain in operation until the task is successfully re-attempted.

This reflects both the assumptions of the scheduling model [16] and typical offshore O&M practice for minor, non-critical maintenance activities. Consequently, no downtime-related revenue loss is applied in any case, regardless of task success or delay. Table 4.4 summarizes the cost parameters used in this study.

Table 4.4: Cost model parameters [16]

Parameter	Value
Technician wage	\$ 60/h
CTV charter cost	\$ 8000
Fuel cost	\$ 5/km
Spare parts	Task-specific (Table 4.2)
Average CTV speed	22 knots
Transit time	1 h one-way
Downtime	generally variable (zero in this case)

4.3. Simulation setup

This Section describes the simulation process used to evaluate the three cases of maintenance plan strategies defined in Section 4.1, using the datasets and cost models described in Section 4.2. Each case is applied to the same maintenance task list and 10-year weather dataset, but follows a different decision-making logic for scheduling and technician allocation. For each maintenance task, the simulation proceeds as follows.

- The planned start date is taken from the predictive MPC-based schedule [16].
- For Case 1, the first feasible day that satisfies vessel operability limits is selected.
- For Cases 2, the earliest day is selected on or after the planned start date where vessel operability limits are satisfied, and the combined probability of mission success exceeds the economic threshold defined by Equation 3.16.

For both cases, the model assumes that only one maintenance task can be executed per day.

4.3.1. Modelling mission success probability

The probability of successful maintenance execution depends on two primary factors. First, the ability to safely transfer technicians from the vessel to the turbine under given sea-state conditions, and second, the physical condition of technicians upon arrival, influenced by motion sickness during vessel transit. This Section outlines the modelling approach for both components and describes how they are combined to estimate overall mission feasibility.

Transfer success probability

As already mentioned in Subsection 3.2.1, the transfer success probability quantifies the likelihood that technicians can safely step from the CTV onto the turbine platform, based on sea-state and wind conditions. Table 4.5 summarizes the empirical mapping of these conditions to probability levels, as developed by [4] in collaboration with offshore wind operators.

For each hour within a scheduled maintenance window, transfer success is calculated separately for each parameter. The minimum hourly value observed during the task duration is then used as the representative transfer success probability, ensuring a conservative estimate that reflects the most challenging hour of operation.

Table 4.5: Transfer success probabilities based on wave height, wave period, and wind speed for CTV utilization [4]

Wave height (m)	$P_{s,transfer,wh}$	Wave period (s)	$P_{s,transfer,wp}$	Wind speed (m/s)	$P_{s,transfer,ws}$
0–1.6	100%	>6	100%	0–8	100%
1.6–1.8	75%	5–6	75%	8–10	80%
1.8–2.0	50%	4–5	50%	10–12	60%
2.0–2.2	25%	2–4	25%	12–14	25%
>2.2	0%	0–2	0%	>14	0%

Thus, the hourly probability of successful transfer is computed as:

$$P_{\text{s,transfer,hour}} = P_{\text{s,transfer,wh}} \cdot P_{\text{s,transfer,wp}} \cdot P_{\text{s,transfer,ws}}$$

Hence, the overall transfer success probability for the task is defined as the minimum hourly probability over the total number of hours (n) required to complete the maintenance task:

$$P_{\text{s,transfer}} = \min\left(P_{\text{s,transfer,hour}_1}, P_{\text{s,transfer,hour}_2}, \ldots, P_{\text{s,transfer,hour}_n}\right) \tag{4.1}$$

Transit success probability

Even if transfer is feasible, the mission may fail if technicians are physically unable to work due to motion sickness. The MSI metric is used to estimate the probability that each technician remains functional after the transit.

Figure 4.2 illustrates the relationship between H_s and MSI, based on data from five operational offshore wind farms using CTVs, obtained from [63]. Details on how MSI values are interpolated between discrete wave height measurements, can be found in Section 3.2.2 in Chapter 3.

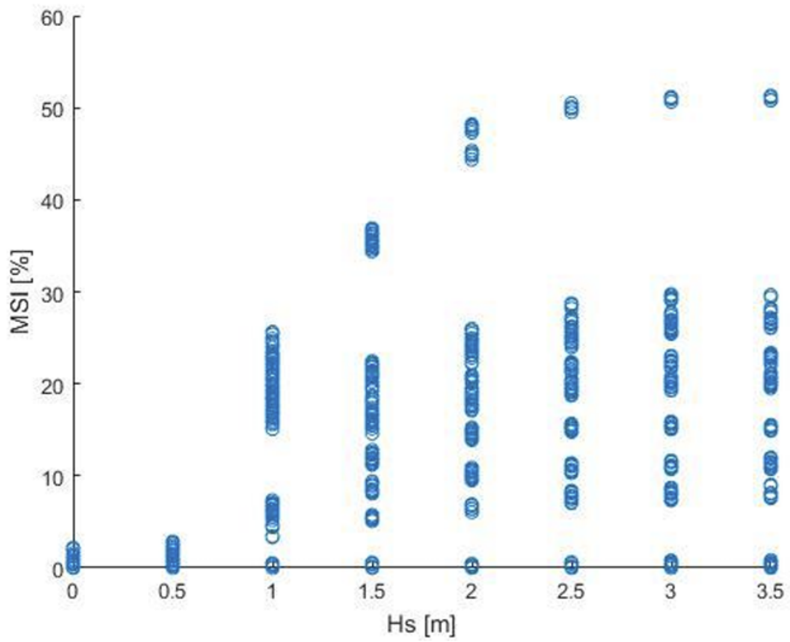

Figure 4.2: Motion sickness incidence versus significant wave height for CTV utilization [63]

Given the MSI value, the probability that a technician becomes seasick is defined as:

$$p = MSI$$

The number of seasick technicians is then modelled as a binomial random variable $X \sim \mathrm{Bin}(n, p)$, where n is the total number of technicians deployed, as described in Section 3.2.2, and the transit success probability is calculated using Equation 3.5. Only the transit to the OWF is evaluated for seasickness, as technician condition upon arrival determines mission success. Any seasickness after maintenance execution does not affect task completion, and thus is not taken into account.

4.3.2. Environmental impact assessment

In line with the model's objective to support sustainable offshore wind operations, this study also considers the environmental impact of maintenance activities. Since vessel trips are a primary source of emissions in offshore maintenance, CO_2 emissions are estimated based on the expected number of failed attempts that require re-attempted transits.

To assess the environmental implications of the maintenance scheduling strategies (Case 1 and Case 2), this study estimates the CO_2 emissions associated with re-attempted offshore missions. The emissions per re-attempted maintenance trip are calculated using the parameters introduced in Section 3.5 and Equation 3.20. The specific values adopted for the case study are listed below:

- Transit duration is 2 hours round-trip as already mentioned.
- Fuel consumption is 290 liters/hour at 22 knots, obtained from [70].
- Fuel density is 0.89 kg/liter, obtained from [21].
- Carbon factor is 0.00321 tons CO_2/kg fuel, obtained from [21].

The resulting CO_2 emissions per re-attempt are approximately 1.66 tons. These will be used to estimate the total environmental impact of each maintenance scheduling strategy in the following Chapter, based on the number of expected failed missions.

4.4. Sensitivity analysis

This Section investigates how deviations from the hindcast weather conditions influence the outcomes of the optimized maintenance strategy. Two hypothetical environmental scenarios are introduced to test the robustness of the model under different wind and sea-state conditions:

- Scenario 1 (Harsh conditions): Significant wave height and wind speed are increased by 20%, and peak wave period is decreased by 20%.
- Scenario 2 (Favorable conditions): Significant wave height and wind speed are reduced by 20%, while peak wave period is increased by 20%.

These two scenarios help assess the sensitivity of the model's recommendations, particularly in terms of technician deployment, success probability, and cost efficiency, to changes in metocean conditions. This analysis provides insight into the model's performance under both optimal and adverse offshore environments. The outcomes of the baseline and sensitivity scenarios, including differences in success probability, technician allocation, and cost metrics, are presented in the following Chapter.

5
Results

his chapter presents the simulation results of evaluating offshore maintenance strategies for a representative 10-turbine wind farm over a 10-year operational horizon. Building on the case study introduced in Chapter 4, the objective is to compare the performance of the proposed probabilistic scheduling model (Case 2) with conventional deterministic industry practice (Case 1). The comparison focuses on operational feasibility, reliability, cost-efficiency, and environmental performance. Reliability is assessed through the combined probability of mission success; economic performance is measured by expected operational costs; and environmental impact is quantified by estimating CO_2 emissions from failed task attempts. In doing so, this chapter demonstrates how risk-aware, adaptive scheduling improves offshore maintenance planning outcomes under realistic environmental conditions.

The chapter is structured as follows. Section 5.1 provides an overview of the evaluated maintenance tasks and introduces the key analytical focus areas. Section 5.2 presents an illustrative comparison of scheduling decisions between the two approaches. Section 5.3 generalizes this comparison across all 75 schedule scenarios. Section 5.4 analyzes success probabilities and expected costs for both strategies. Section 5.5 quantifies the emissions impact resulting from failed attempts under each approach. Finally, Section 5.6 evaluates the robustness of the proposed model under varying weather conditions.

5.1. Evaluated tasks and analysis focus

A total of 75 predictive maintenance schedule scenarios, generated using the framework by Borsotti et al. [16], serve as the foundation for this analysis. Each schedule scenario includes approximately 255 minor repair tasks. These tasks were evaluated under both maintenance execution strategies (Case 1 and Case 2), using numerical hindcast weather data (2001–2010) to simulate realistic offshore conditions.

The evaluation focuses on three key aspects:

- Differences in task execution schedules between cases.
- Variation in the combined probability of mission success, expected operational costs, and CO_2 emissions.
- The impact of optimizing crew size on the combined probability of mission success, expected operational costs, and CO_2 emissions.

Across all scenarios, a total of 19,090 tasks were analyzed. For each task, the model assessed whether the mission could proceed under environmental and economic constraints, whether additional technicians were needed to meet the cost-loss threshold, or whether the task should be cancelled for the given day.

5.2. Rescheduling outcomes of the illustrative maintenance cycle

This Section examines how the proposed probabilistic model (Case 2) modifies the execution schedule of maintenance tasks, introduced in Chapter 4 in Table 4.3, compared to the deterministic industry approach (Case 1). Case 1 schedules tasks solely based on weather thresholds, while Case 2 applies a more comprehensive evaluation that includes technician availability due to seasickness, transfer success, and economic feasibility. This results in different scheduling decisions, including task delays, crew size adjustments, and in some cases, task cancellations.

5.2.1. Maintenance schedule (Case 1 vs. Case 2)

To demonstrate how technician-related constraints influence maintenance planning, this Section compares two scheduling approaches applied to the same maintenance cycle which was introduced in Section 4.2.1. First, Case 1 scheduling tasks only when weather conditions meet basic vessel operability thresholds, and second, Case 2, applying the full probabilistic decision-support model, accounting not only for vessel limits but also for technician-related risks such as seasickness during transit and safe transfer from the CTV bow to the wind turbine platform.

Figure 5.1 presents a combined Gantt chart that shows the resulting schedules under both approaches. Each bar represents a maintenance task, with blue indicating the execution day chosen by Case 1 and green the execution day chosen by Case 2. As can be seen, the Case 1 schedule tends to group tasks tightly. This is because it only checks if sea conditions are good enough for the vessel to operate. But this often overlooks whether technicians are actually able to complete the job safely and effectively. Thus, this schedule has a high risk of uncertainty and it might lead to an increased number of cancellations upon arrival at the OWF, resulting in unnecessary vessel trips, fuel consumption, CO_2 emissions, and technician wages.

Case 2, on the other hand, spreads the tasks out more. It avoids assigning work on days where the risk of seasickness is high or the transfer conditions are poor. As a result, some tasks are delayed but they end up being more likely to succeed when they are rescheduled.

This side-by-side comparison highlights that the Case 1 scheduling approach can lead sometimes to unrealistic expectations regarding task execution. In many cases, it schedules work on days that are operationally infeasible due to technician health and safety risks. In contrast, the optimized strategy achieves more reliable scheduling and provides a plan that better reflects what can be attempted and when.

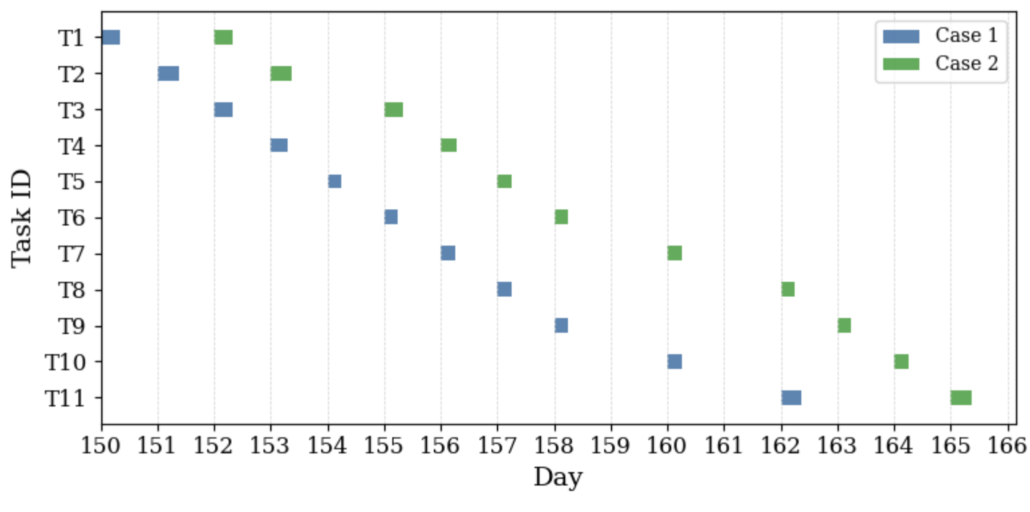

Figure 5.1: Maintenance task distribution for the illustrative maintenance cycle for Case 1 and Case 2

5.2.2. Example task evaluations

To further illustrate how the developed decision-support model (Case 2) reschedules maintenance tasks compared to the industry's standard approach (Case 1), this Section analyzes three representative tasks from the illustrative maintenance cycle introduced in Section 4.2.1 and Table 4.3. These tasks are selected to highlight the range of decisions the developed model can make, including suggesting the use of two technicians, increase it due to risk, or canceling the task for that day. Detailed results showing how Case

2 scheduled all the 11 tasks of Table 4.3 can be seen in Appendix A.

Task T1 execution on day 150 - Cancellation

Task T1, originally scheduled for Day 150 based on Case 1 approach, is a representative case where Case 2 recommends cancellation due to low feasibility and high economic risk. Despite satisfying basic vessel operability conditions, the task fails to meet the cost-effectiveness threshold even with the maximum crew size considered.

The hourly wave and wind values on Day 150 are listed in Table 5.1. These sea-state values are used for the calculation of both the transit success and the transfer success probabilities. These values lead to the following outcomes:

- The minimum transfer success probability is calculated to be 30%, based on the weather conditions during the work window and Table 4.5.
- The MSI is derived from a significant wave height of $H_s = 1.61$ m. Since this falls between 1.5 m and 2.0 m (where MSI ranges from 20% to 25%), the interpolated MSI is estimated at 21.1% during the outbound transit (08:00–09:00), using Equation 3.2. This corresponds to a seasickness probability of $p = 0.211$.

Table 5.1: Wave and wind hourly conditions for day 150, extracted from [69]

Hour	Significant wave height (m)	Wind speed (m/s)	Peak wave period (s)
08:00	1.61	9.14	9.35
09:00	1.61	9.14	9.35
10:00	1.60	9.14	9.35
11:00	1.62	9.63	9.26
12:00	1.67	9.63	5.81
13:00	1.71	9.63	5.88
14:00	1.78	10.69	5.97
15:00	1.88	10.69	6.00
16:00	1.96	10.69	6.21
17:00	2.02	11.09	6.33

Figure 5.2 illustrates how the combined probability of mission success evolves with increasing crew size. The blue curve represents the transit success probability $P_{s,transit}$, or in other words the likelihood that at least two technicians remain non-seasick after transit, while the red dashed line marks the minimum transfer success probability $P_{s,transfer}$. The green curve shows the combined probability of mission success $P_{s,combined}$, whereas the yellow line shows the cost-loss ratio.

As the figure shows, the combined probability of mission success increases with larger crew sizes, but plateaus at 30%, well below the required economic threshold. This limitation arises because $P_{s,transfer}$, which is constant across crew sizes, acts as an upper bound on the combined probability of mission success.

This is justified because $P_{s,transfer}$ is modelled as the minimum transfer success probability across the maintenance duration, derived solely from environmental conditions as seen in Equation 3.1 and Equation 4.1. Thus, even if $P_{s,transit}$ increases, the overall success remains capped by the fixed transfer feasibility.

Since there is no $N_{T,deployed} \in [2, 12]$ for which the combined probability of mission success is higher than the cost-loss ratio, the task is highlighted for cancellation, with this decision serving as a preventive measure to avoid incurring full costs for a likely failed attempt. This decision would not be made under traditional scheduling approaches like Case 1.

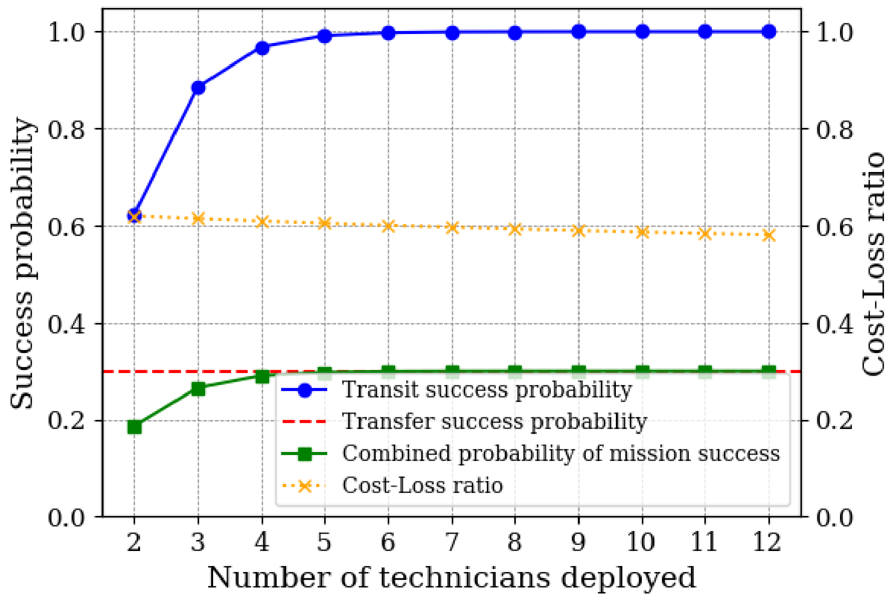

Figure 5.2: Transit, transfer, and combined success probabilities for task T1 on day 150, shown across different crew sizes. The cost-loss ratio indicates the economic feasibility threshold

Task T1 execution on day 152 - Deploy more than two technicians

Task T1 is reconsidered for execution on Day 151 but is cancelled again due to high transit and transfer risks (see Appendix A). However, on Day 152, a few days after the original schedule (Day 150), the weather remains within vessel operability limits and offers a more favorable window for technician transit, transfer, and successful task completion. However, while feasible, the probabilistic model (Case 2) identifies that the standard two-technician crew is insufficient to meet the required cost-loss threshold and recommends sending a larger team.

Table 5.2 provides the hourly environmental conditions used to calculate both transit and transfer success probabilities. The key outcomes derived from these conditions are:

- The minimum transfer success probability is 80%, based on the weather conditions during the work window and Table 4.5.
- The MSI is derived from a significant wave height of $H_s = 1.66$ m. Since this falls between 1.5 m and 2.0 m (where MSI ranges from 20% to 25%), the interpolated MSI is estimated at 21.6% during the outbound transit (08:00–09:00), using Equation 3.2. This corresponds to a seasickness probability of $p = 0.216$.

Table 5.2: Wave and wind hourly conditions for day 152, extracted from [69]

Hour	Significant wave height (m)	Wind speed (m/s)	Peak wave period (s)
08:00	1.66	8.00	9.62
09:00	1.56	8.00	9.62
10:00	1.48	8.00	9.71
11:00	1.39	6.63	9.71
12:00	1.30	6.63	9.71
13:00	1.24	6.63	9.71
14:00	1.19	6.22	9.71
15:00	1.17	6.22	9.71
16:00	1.18	6.22	9.71
17:00	1.19	5.96	9.71

In this case, as seen in Figure 5.3 sending only two technicians results in a combined probability of mission success slightly less than 50% which falls below the cost-loss threshold which is approximately 0.62. As seen in the plot, increasing the size of the crew improves the likelihood of having at least two healthy technicians after transit, which means higher $P_{s,transit}$, and thus increases the combined probability of mission success $P_{s,combined}$. As can be observed $P_{s,combined}$ stabilizes at approximately 80% which is achieved by sending $N_{T,deployed} = 5$. Sending more than five technicians has negligible impact on the combined probability of mission success.

The model indicates that the deployment of three technicians raises $P_{s,combined}$ to approximately 70%, crossing the cost-loss threshold. This marks the smallest viable crew size that satisfies both technical feasibility and economic justification, aligning with the decision rule outlined in Equation 3.18.

This example highlights the importance of an adaptive crew size strategy. While traditional scheduling strategies like Case 1, assume that two technicians are always sufficient, this approach may fall short under marginal environmental conditions. The probabilistic model (Case 2) identifies that a minimal increase in crew size (from two to three) substantially boosts the probability of successful task completion, ensuring the operation meets the required economic threshold without incurring unnecessary risk or cost. This shows the value of flexible, data-informed decision-making in offshore maintenance planning.

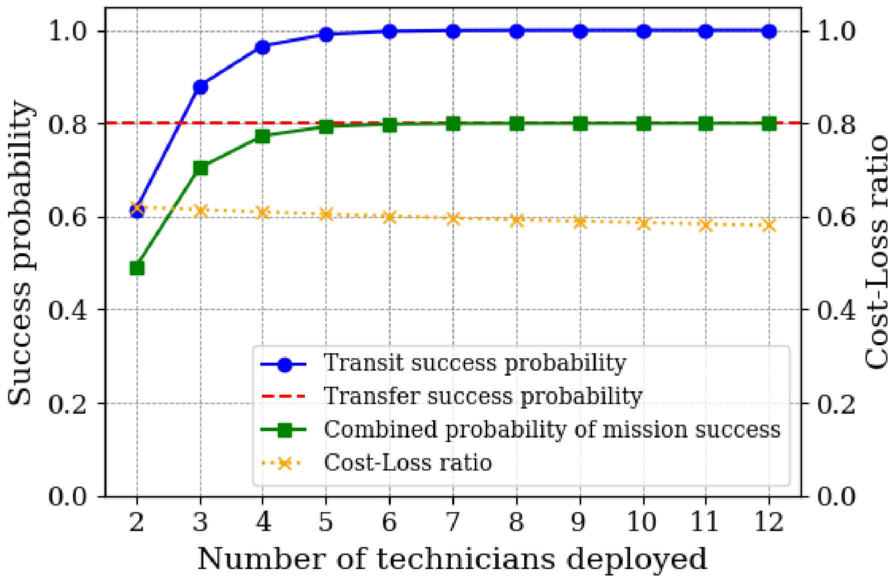

Figure 5.3: Transit, transfer, and combined success probabilities for task T1 on day 152, shown across different crew sizes. The cost-loss ratio indicates the economic feasibility threshold

Task T4 execution on day 156 - Use two technicians

Task T4 was originally scheduled for Day 153 under the Case 1 approach as seen in Figure 5.1. However, due to earlier delays and cancellations in the maintenance task sequence, the task is eventually evaluated for execution on Day 156 under the Case 2 strategy.

Table 5.3 presents the wave and wind conditions for Day 156. As can be observed, the sea state is highly favorable, with consistently low wave heights and wind speeds and high wave periods. These conditions enable high feasibility for safe transfers and low possibility of experiencing seasickness during the transit to the OWF. The following outcomes are derived based on these conditions:

- Transfer success probability is 100%, based on the weather conditions during the work window and Table 4.5.
- The MSI is derived from a significant wave height of $H_s = 0.93$ m. Since this falls between 0.5 m and 1.0 m (where MSI ranges from 2% to 14%), the interpolated MSI is estimated at 12.32%

during the outbound transit (08:00–09:00), using Equation 3.2. This corresponds to a seasickness probability of $p = 0.1232$.

Table 5.3: Wave and wind hourly conditions for day 156, extracted from [69]

Hour	Significant wave height (m)	Wind speed (m/s)	Peak wave period (s)
08:00	0.93	1.16	8.55
09:00	0.94	1.16	8.48
10:00	0.94	1.16	10.21
11:00	0.94	2.30	10.21
12:00	0.94	2.30	10.21
13:00	0.94	2.30	10.21
14:00	0.94	4.02	10.10
15:00	0.94	4.02	10.10
16:00	0.94	4.02	10.00

Figure 5.4 shows the evolution of success probabilities and the cost-loss threshold as a function of crew size. The red dashed line indicates perfect transfer conditions, which leads $P_{s,transit}$ to align fully with $P_{s,combined}$. Under these favorable conditions, even with a crew size of two, the combined success probability is over 75%. In addition, it can be observed that $P_{s,combined}$ reaches almost 100% by sending $N_{T,deployed} = 4$, and further increasing the number of technicians has negligible impact on the combined probability of mission success. However, $P_{s,combined}$ in the case of $N_{T,deployed} = 2$ is already significantly higher than the cost-loss ratio, which stands at approximately 0.5. Hence, the optimized model recommends sending the minimum crew size of two technicians.

This outcome demonstrates that Case 2 does not always recommend larger crews, but it adapts to the situation. When environmental conditions are favorable, it aligns with more standard practices like Case 1, and avoids unnecessary operational costs while ensuring high reliability.

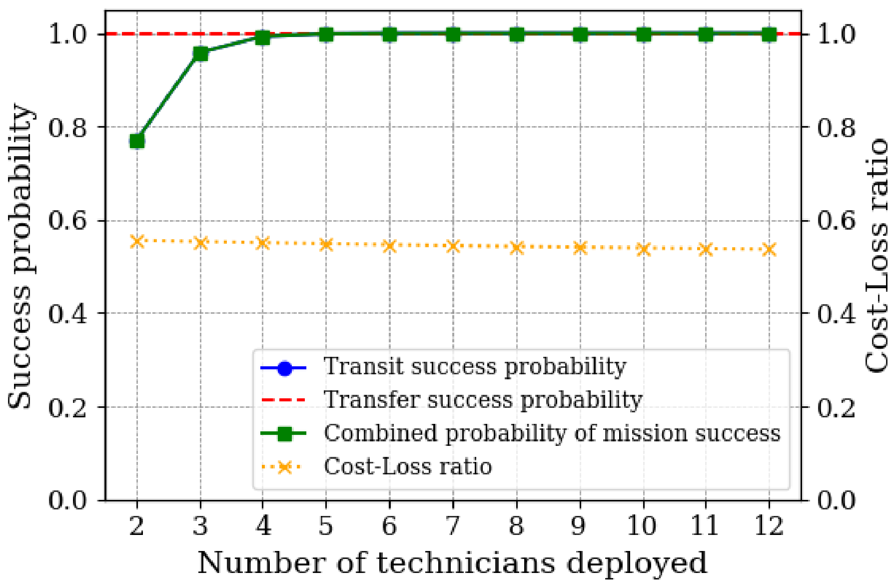

Figure 5.4: Transit, transfer, and combined success probabilities for task T4 on day 156, shown across different crew sizes. The cost-loss ratio indicates the economic feasibility threshold

5.3. Evaluation across all maintenance schedule scenarios

While previous Sections focused on selected tasks to illustrate specific decision outcomes, this Section provides a broader evaluation of how the probabilistic scheduling approach (Case 2) performs compared to the deterministic one (Case 1) across all 19,090 minor repair tasks considered in the study. The analysis focuses on three key aspects, including task rescheduling delays, cancellations due to infeasibility, and technician deployment decisions. Table 5.4 summarizes key outcomes of Case 2 across all evaluated tasks.

Table 5.4: Summary of decision outcomes across all tasks for Case 2

Decision Outcome	Number of Tasks	Percentage
Rescheduled (Case 1 day cancellation)	8,475	44.5%
Use more than 2 technicians	5,932	31.1%
Use 2 technicians	13,158	68.9%

These results indicate that a substantial portion (over 44%) of tasks could not be executed on the scheduled day assigned by Case 1 and had to be rescheduled due to operational constraints, such as seasickness and unsafe transfer risks. Moreover, approximately one-third of the tasks required an increased crew size to achieve a satisfactory probability of mission success.

5.3.1. Task execution delay - Case 2 vs. Case 1

To understand how Case 2 adjusts the schedule compared to Case 1, Figure 5.5 presents the distribution of task execution delays. These delays represent the number of days each task is postponed under Case 2 compared to the day it would have been executed using the Case 1 strategy.

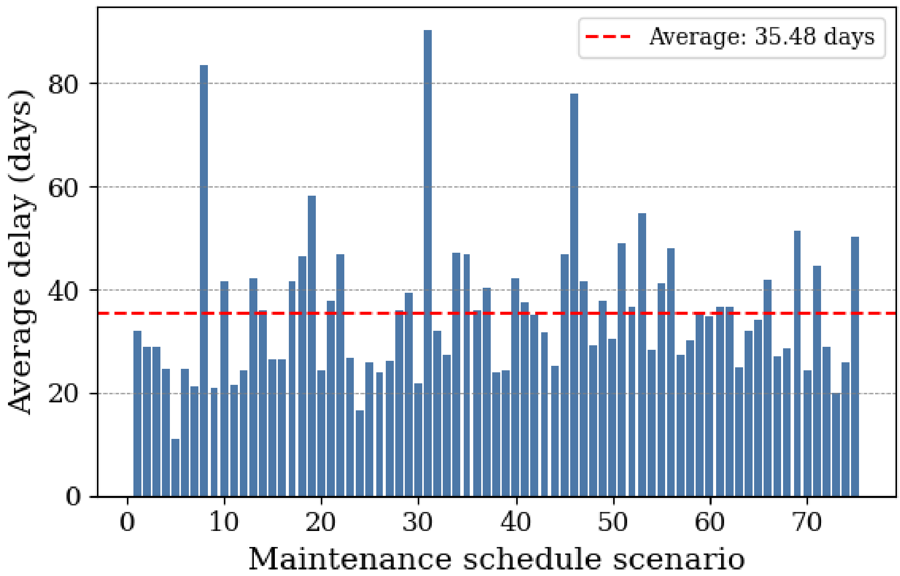

Figure 5.5: Average task delay introduced by Case 2 compared to Case 1 across the 75 maintenance schedules.

As shown in the figure, a significant number of tasks are shifted by a few days, with the average delay being around 35 days. These delays are primarily driven by harsher weather conditions, particularly periods of high wave heights and wind speeds, which reduce the feasibility of technician transfer and increase the likelihood of seasickness during transit. As a result, the model postpones maintenance tasks to later dates with more favorable conditions, aiming to avoid low-probability or high-cost maintenance attempts. However, it should be noted that postponing minor repairs carries the risk that unresolved issues might turn into more severe faults, that could potentially require more complex and expensive maintenance later. This highlights the importance of proactive and risk-aware planning in offshore maintenance.

Some maintenance schedule scenarios exhibit significantly higher average delays, reaching nearly 90 days. For example, Scenario 8 includes tasks from Cycle 8 and Cycle 9 that spanned between March 2002 and July 2002, a period marked by prolonged harsh weather conditions, with frequent high waves and strong winds. Additional delays in this scenario occurred for tasks executed between mid-October 2002 and early March 2003, which also coincided with unfavorable sea states. Scenario 3 displays a similar trend, with many tasks concentrated between January and July 2002. Because each maintenance cycle must be completed before the next one begins, delays continued to increase throughout the schedule. Scenario 46 follows a comparable pattern, though with slightly fewer tasks in the same period and therefore experiences slightly less delay.

In contrast, Scenario 5 shows one of the shortest average delays (approximately 10 days). Most of its tasks were completed by December 2001, and the next round did not begin until mid-June 2002, thus avoiding the harshest weather periods. This contrast illustrates how both task timing and weather exposure play a crucial role in the variability of delay outcomes across different schedules.

5.3.2. Task cancellations

In some cases, the probabilistic optimized model (Case 2) determines that a task should not be executed, either due to high risk of seasickness and unsuccessful transfer, or because the cost-loss ratio cannot be justified even with the maximum allowable crew size. Figure 5.6 compares the frequency of task cancellations in Case 2 to the deterministic industry case in Case 1, which assumes that all tasks can be executed when vessel operability limits are met.

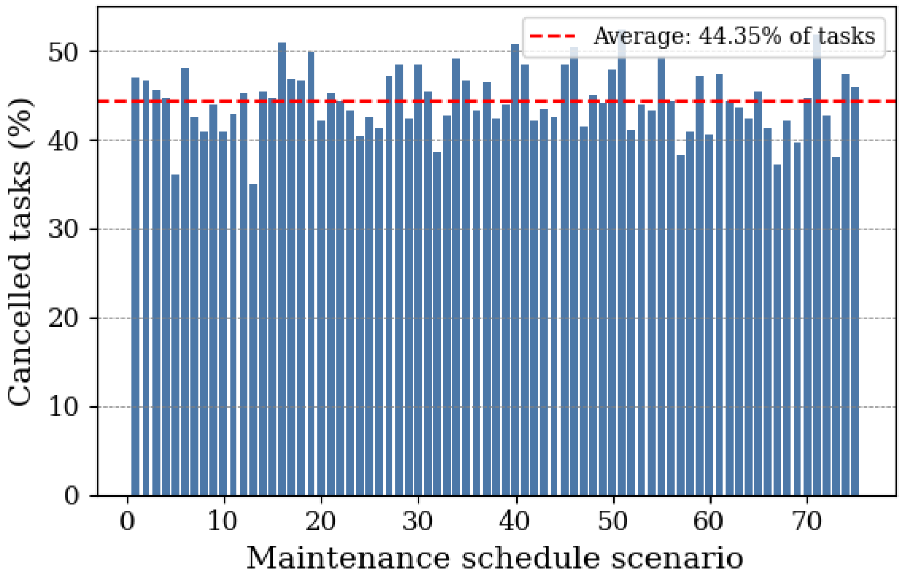

Figure 5.6: Percentage of maintenance tasks initially scheduled by Case 1 that were later cancelled by Case 2 due to low feasibility

In total, 8,375 out of 19,090 tasks, which is more than 44%, were cancelled under Case 2 approach. These cancellations are not failures of the model, but reasonable decisions to avoid economically inefficient or operationally risky attempts. In contrast, Case 1 would proceed with these tasks, potentially incurring full operational costs despite the high likelihood of failure.

This comparison shows how the proposed model works as a filter that not only evaluates feasibility but also weighs the economic and operational implications of attempting a task under environmental conditions that are not ideal. By predicting technician performance after transit and estimating both transit and transfer success probabilities, the model can identify maintenance attempts that are likely to fail or incur excessive costs. In these cases, recommending cancellation is a strategic action that aims to avoid unnecessary mobilization, technician exposure to unsafe metocean conditions, and financial losses from failed missions. In this way, the model supports better planning by focusing efforts on days when the chances of success are significantly higher and economically justified.

5.3.3. Technician deployment

In some cases, Case 2 determines that a task should be executed if more than two technicians are deployed. Figure 5.7 illustrates the percentage of maintenance tasks that required more than the default two-technician crew under the proposed model (Case 2). This reflects the proportion of cases where the model recommended increasing the number of technicians to improve mission feasibility.

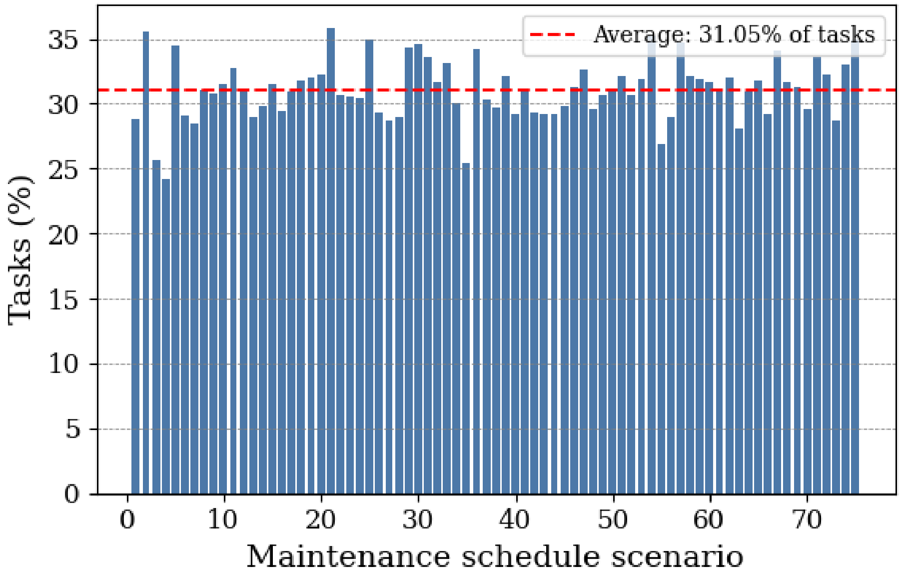

Figure 5.7: Percentage of tasks for which Case 2 recommended deploying more than two technicians, across all maintenance schedule scenarios

Out of the 19,090 tasks analyzed, 5,932 required a team larger than two technicians, which is approximately 31% of the tasks. This adjustment is driven by the need to mitigate the risk of seasickness during vessel transit. In rougher sea conditions, the model expects a higher probability that one or more technicians may become unfit to work upon arrival at the OWF. By sending a larger team of technicians, the likelihood that at least two technicians remain healthy and capable of executing the task increases significantly.

In contrast, approximately 69% of the tasks were suggested to be performed with the standard two-technician crew, aligning with current industry practices. The model selectively increases team size only when necessary, balancing the cost of additional technicians against the improved probability of success. Unlike the fixed-crew strategy used in Case 1, which treats all conditions the same, the adaptive approach in Case 2 adjusts to the weather conditions for each task. By accounting for technician health and safety risks in real time, Case 2 offers a more robust and cost-efficient framework for offshore maintenance planning. A detailed breakdown of deployed crew sizes for each maintenance schedule is provided by Table B.1 in Appendix B.

5.4. Performance and economic impact comparison

This Section compares the overall effectiveness of the two maintenance strategies, Case 1 and Case 2 in terms of success probability and economic outcomes.

5.4.1. Combined probability of mission success

While Case 1 follows deterministic scheduling logic, the combined probability of mission success for this case is estimated retrospectively using the probabilistic framework developed in this thesis. Specifically, it reflects the likelihood that a mission scheduled under standard weather thresholds (with a fixed crew size of two technicians) will succeed, accounting for both transit and technician transfer risks. This probability is computed using the same equations used for Case 2, applied to the Case 1 schedule, without any optimization of crew size.

As illustrated in Figure 5.8, the average combined probability of mission success differs significantly between the two strategies. Case 1, which reflects standard industry practice achieves a combined success probability of 0.433 (43.3%). In contrast, Case 2, which employs the developed probabilistic model and dynamically adjusts crew size based on prevailing conditions and a cost-loss threshold, achieves a substantially higher combined success probability of 0.687 (68.7%). This corresponds to a relative improvement of approximately 58.7%.

To better understand the contribution of the crew size optimization itself, the bar for Case 2 is divided into two components. The dark green portion represents the performance of the probabilistic model when constrained to a fixed crew of two technicians (that is, excluding the optimization component), which achieves a success rate of approximately 62.6%. The light green segment illustrates the additional gain attributable solely to optimizing the number of technicians, which increases the probability by approximately 9.7%.

These results highlight that while the probabilistic framework itself provides a substantial improvement over deterministic scheduling, the added flexibility of optimizing crew size further enhances operational performance by improving the likelihood of mission success, particularly under marginal weather conditions.

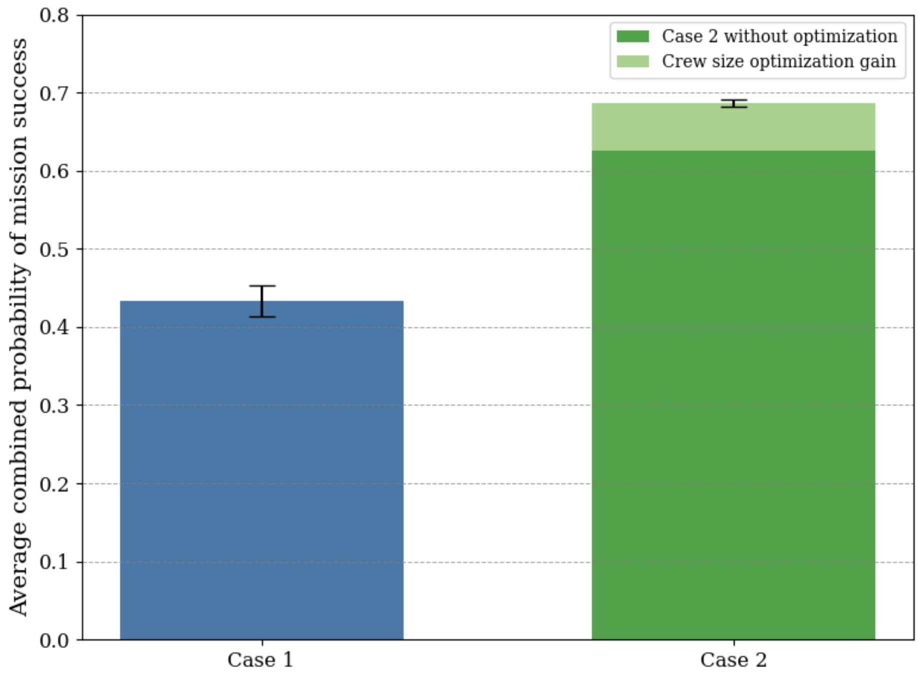

Figure 5.8: Combined probability of mission success for task execution for Case 1, and Case 2. Error bars represent variability across maintenance schedule scenarios

5.4.2. Cost-benefit analysis

In addition to improving operational feasibility, the proposed Case 2 approach demonstrates strong financial performance compared to conventional planning methods. One of the cost-related distinctions of Case 2 is the possibility of recommending more than two technicians for certain tasks when this leads to better economic outcomes. The average additional technician cost incurred over the 10-year horizon is calculated using Equation 3.19 and is approximately $53,000.

Despite these extra personnel expenses, the optimized model still delivers a clear net financial advantage, which is estimated by the difference in expected costs of the two cases. Compared to Case 1, Case 2 achieves an average expected cost saving of approximately $540,000 (see Table B.1 for expected operational costs for each schedule). This improvement is primarily due to the model's ability to avoid failed missions and minimize unnecessary mobilizations by proactively adapting crew size and scheduling decisions.

Relative to Case 2 with a fixed two-technician crew, the dynamic crew sizing strategy offers an additional cost benefit of around $75,000. These values are derived from the expected cost formulation as defined by Equation 3.15, where both the probability of success and the cost-loss trade-off are jointly considered. In all cases, the cost of adding extra technicians is fully accounted for in the expected cost of Case 2.

In summary, the optimized approach balances risk and cost more effectively than fixed-crew alternatives. Its ability to adapt to sea conditions and technician health in real time translates into smarter, more efficient maintenance planning, delivering both reliability and financial value.

5.5. Environmental impact assessment

This Section evaluates the environmental performance of each maintenance scheduling strategy by quantifying the expected CO_2 emissions resulting from failed maintenance attempts. As explained in Chapter 3, emissions are driven by re-attempted vessel trips, which occur when a mission is unsuccessful.

To quantify this impact, CO_2 emissions are estimated for each scheduling strategy (Case 1 and Case 2) based on the number of expected task re-attempts due to failure. These failures are determined by the average combined probability of mission success achieved in each case. As outlined in Section 5.1, a total of 19,090 tasks across the 75 schedules were assessed over the 10-year planning horizon. Each maintenance schedule covers the full 10-year operational period and includes an average of 255 minor repair tasks.

To estimate the environmental impact of each maintenance strategy, the expected number of task re-attempts per schedule is calculated using the average combined probability of mission success. Based on the corresponding success rates, the expected number of task re-attempts is calculated as follows:

- Case 1, with a 43.3% average combined probability of mission success, leads to an expected percentage of failed attempts of 56.7%, leading approximately to 145 expected task re-attempts.
- Case 2, with a 68.7% average combined probability of mission success, leads to an expected percentage of failed attempts of 31.3%, leading approximately to 80 expected task re-attempts.

Hence, using Equation 3.21, the total emissions in tons by each strategy due to re-attempts are the following:

$$E_{\text{total}(Case\ 1)} = 1.66 \cdot 145 = 240.7 \text{ tons } CO_2$$

$$E_{\text{total}(Case\ 2)} = 1.66 \cdot 80 = 132.8 \text{ tons } CO_2$$

These results can be seen in Figure 5.9. Compared to Case 1, Case 2 results in a reduction of 107.9 tons of CO_2, which represents a 44.8% decrease in emissions from task re-attempts. This comparison underscores the environmental benefit of adopting more effective planning approaches.

While these reductions reflect the overall performance of Case 2, it is worth noting that a portion of the improvement is specifically attributable to the crew size optimization mechanism. If Case 2 had used a fixed crew size of two technicians, its total emissions would have been moderately higher, at 158.3 tons. This value was estimated using Equation 3.21 and the corresponding combined probability of mission success without crew optimization (62.6%).

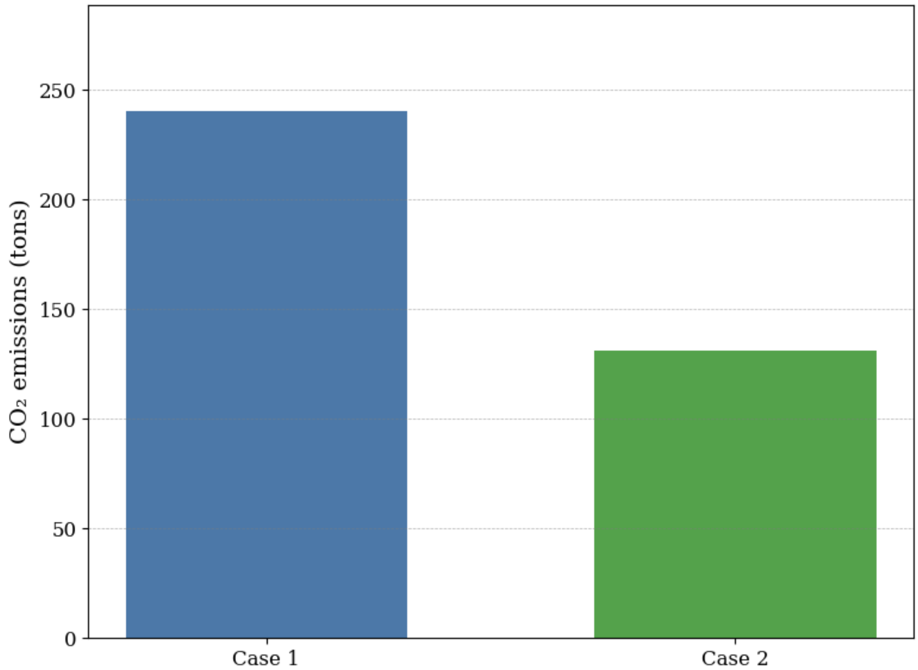

Figure 5.9: Total estimated CO_2 emissions in tons resulting from task re-attempts under each strategy during the 10-year planning horizon

These findings highlight an important environmental advantage of adopting safer, risk-informed planning strategies, such as the probabilistic model used in Case 2. By accounting for factors like the risk of seasickness, unsuccessful technician transfers, and by optimizing the number of technicians assigned to each task, this approach improves the likelihood of successful maintenance execution. While the model was primarily developed to enhance operational efficiency and reduce costs, its ability to minimize avoidable vessel trips also leads to a significant reduction in CO_2 emissions. This added environmental benefit strengthens the case for wider industry adoption, especially as the offshore wind sector continues its efforts to decarbonize maritime operations.

In addition to lowering CO_2 emissions, reducing unnecessary vessel trips also helps minimize other environmental impacts. Fewer transits can lead to a decrease in underwater noise pollution, which is known to disrupt marine life by interfering with communication, increasing stress levels, and in some cases, causing hearing damage [71], [72]. Moreover, because marine animals are often difficult to detect from vessels, especially in poor visibility, there may not be enough time to avoid a collision, increasing the risk of vessel strikes. Reduced vessel activity therefore also lowers the likelihood of such incidents, a growing concern with increasing offshore traffic, particularly for vulnerable species like marine mammals [73]. These additional environmental benefits further support the adoption of smarter, risk-informed maintenance planning strategies.

5.6. Sensitivity analysis results

To assess the robustness of the proposed decision-support model, two weather-modified scenarios were tested alongside the baseline conditions. In Scenario 1, harsher sea states were simulated by increasing wave height and wind speed by 20% and reducing wave period by 20%. In contrast, Scenario 2 applied better weather conditions with exactly the opposite adjustments. The goal was to evaluate how the model's recommendations change when environmental uncertainty increases or decreases.

5.6.1. Combined probability of mission success

The impact of varying environmental conditions on the combined probability of mission success is shown in Figure 5.10. The comparison highlights how each strategy responds to changes in wave height, wind speed, and wave period, and how robust each is to such deviations.

Under the harsher sea-state scenario (Scenario 1), both strategies experience reduced performance. Case 1, which does not account for technician condition after transit or cost-based optimization, drops to an average combined probability of mission success of 40.1%. In contrast, Case 2, which adapts both scheduling and crew size based on feasibility and cost-effectiveness, achieves the highest success probability of 67.4%.

In the baseline hindcast scenario, as seen before, Case 1 improves slightly to 43.3%, while Case 2 again leads with an average combined probability of mission success of 68.7%, showing that its dynamic decision-making framework consistently boosts reliability. Under the favorable weather scenario (Scenario 2), both strategies benefit from the improved weather. Case 1 reaches a combined probability of 51.8%, indicating that weather alone can affect execution feasibility, even when transit and transfer risks are overlooked, while Case 2 peaks at 69.5%.

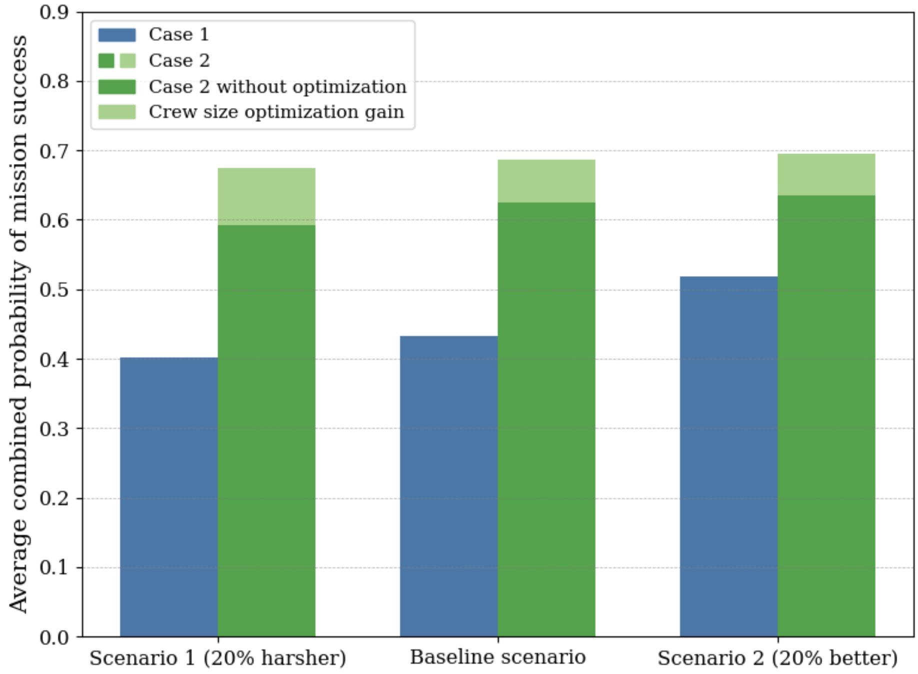

Figure 5.10: Average combined probability of mission success for Case 1 and Case 2 under three weather scenarios: 20% harsher weather, baseline hindcast conditions, and 20% more favorable weather.

These results confirm that Case 1 is more sensitive to weather variability, with its performance declining sharply under harsher conditions. This is due to its static nature, which does not account for technician well-being or dynamic decision-making. In contrast, Case 2 demonstrates consistently higher reliability, with average mission success rates remaining close to 70% across all scenarios. Notably, part of this improved performance stems from dynamic crew sizing.

The dark green bars in Figure 5.10 indicate the performance of Case 2 if it used a fixed crew size of two technicians. Even under this constraint, Case 2 would still outperform Case 1, achieving success probabilities of 59.2% in Scenario 1, 62.6% in the baseline, and 63.6% in Scenario 2. However, by optimizing the number of technicians based on risk and cost-loss trade-offs, Case 2 achieves even higher probabilities: 67.4%, 68.7%, and 69.5%, accordingly.

This highlights the dual advantage of the proposed model: it not only incorporates environmental and transit-transfer risks, but also dynamically allocates resources to further enhance reliability. This makes Case 2 a more robust and reliable strategy for offshore maintenance planning.

5.6.2. Cost-benefit analysis

Figure 5.11 presents the average additional technician costs incurred by Case 2 due to dynamic crew size optimization across the three environmental scenarios. As expected, these costs increase under harsher sea-state conditions, rising from approximately $53.3K in the baseline scenario to $74.1K in Scenario 1. Interestingly, in Scenario 2, which represents more favorable weather, technician costs are slightly higher than in the baseline ($58.1K). This may initially appear unexpected, as improved sea-state conditions typically reduce the need for larger crews. However, this outcome can be attributed to the probabilistic nature of the model. Even with overall better conditions, some maintenance tasks may fall within short periods of less favorable weather. In such cases, the model might recommend deploying additional technicians to slightly boost the combined probability of mission success above the cost–loss threshold to avoid unnecessary cancellations.

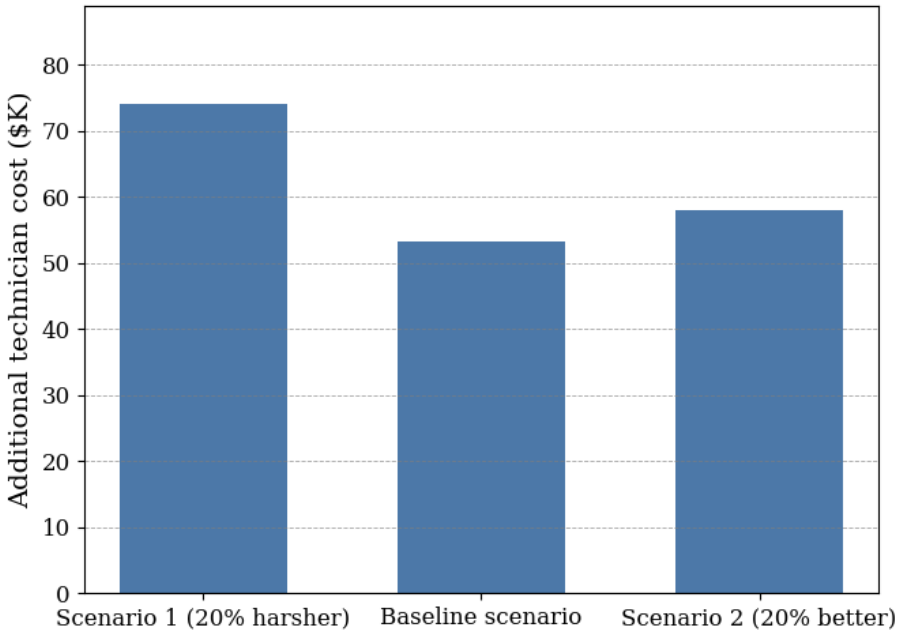

Figure 5.11: Additional technician costs for Case 2 under the three weather scenarios

Despite these added costs, the overall financial performance of Case 2 remains consistently favorable. Figure 5.12 presents the expected cost savings of Case 2 over Case 1 across all three weather scenarios. The stacked bars in the plot separate the base savings achieved by using Case 2 schedule with a fixed crew size from the additional gain due to crew size optimization. In other words, the dark blue bar represents the cost savings Case 2 would achieve if it used a fixed crew size of two technicians. The light blue bar shows the additional benefit gained by enabling crew size optimization based on weather risk and cost–loss thresholds.

Under harsher conditions (Scenario 1), Case 2 achieves the highest cost savings at approximately $562K, including $97K attributable to crew size optimization. In the baseline scenario, total savings reach $540K, with a crew gain of $75K. Even in favorable conditions (Scenario 2), Case 2 outperforms Case 1 by $346K, of which $63K stems from crew optimization.

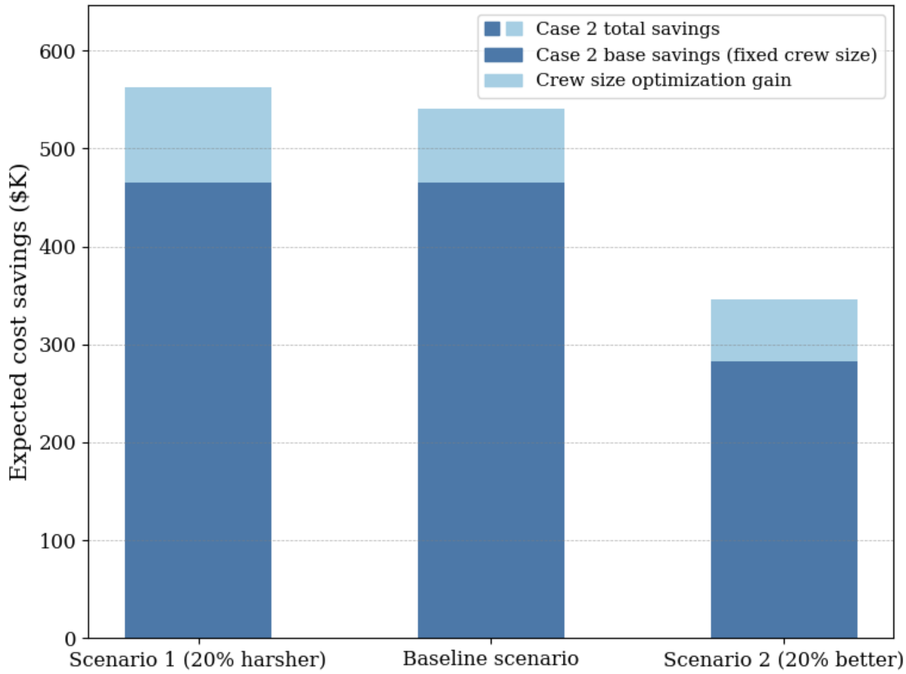

Figure 5.12: Average expected cost savings of Case 2 over Case 1, across harsh, baseline, and favorable weather scenarios

In summary, Case 2 consistently outperforms Case 1 by leveraging risk-informed planning and dynamic crew deployment. The benefits are most pronounced under harsher sea conditions, but remain substantial across all weather scenarios. These results clearly demonstrate the value of adaptive resource planning. The model transforms operational uncertainty into opportunity, by minimizing failed attempts, reducing vessel mobilizations, and delivering substantial financial gains.

5.6.3. Technician deployment

Figure 5.13 shows the percentage of tasks for which the optimized strategy (Case 2) recommends deploying more than two technicians, across the three weather condition scenarios. These values reflect how environmental conditions influence the model's decision to increase crew size in order to meet the required threshold for mission success.

In the harsh weather scenario (Scenario 1), the model recommends sending more than two technicians for approximately 41.5% of tasks, which is substantially higher than the 31.1% observed in the baseline scenario and the 30.2% in the favorable weather scenario (Scenario 2). This trend illustrates the model's sensitivity to more challenging sea-state conditions. As significant wave height and wind speed increase, and wave period decreases, the likelihood of technicians experiencing seasickness rises, along with the risk of unsuccessful transfers. To mitigate these risks and maintain feasibility, the model compensates by assigning larger crews to a greater number of tasks.

In contrast, when sea conditions improve (Scenario 2), the likelihood of successful technician transfer and health during transit rises. Consequently, two technicians are often sufficient, and the model suggests additional personnel only when necessary to ensure success under marginal conditions. Overall, the results highlight the model's ability to adapt technician deployment, avoiding overstaffing in favorable conditions while increasing crew size only when it is operationally necessary and economically justified.

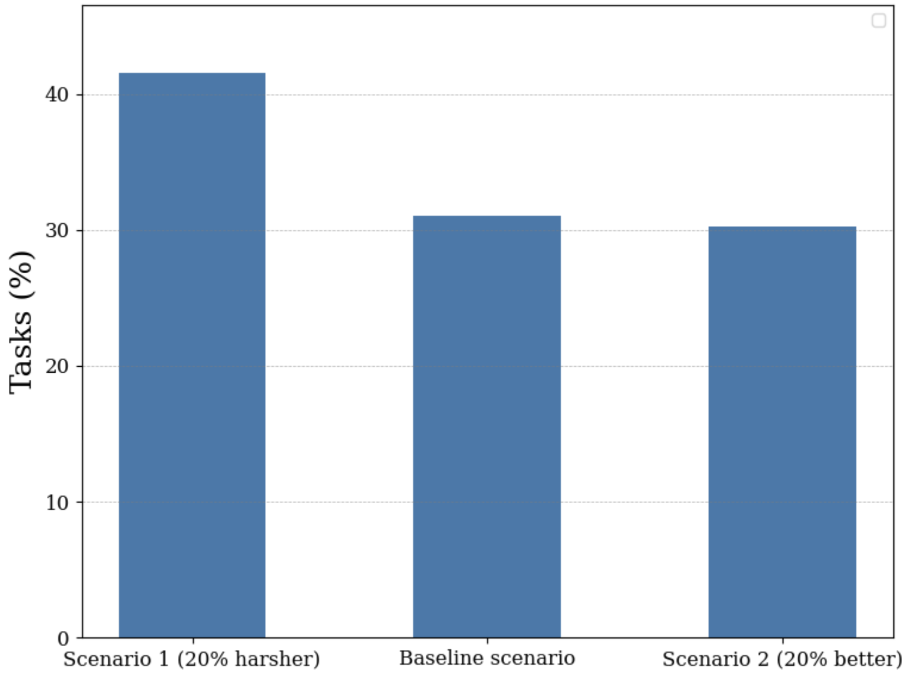

Figure 5.13: Percentage of tasks that require more than two technicians across harsh, baseline, and favorable weather scenarios

5.6.4. Task cancellations

Figure 5.14 presents the percentage of maintenance tasks that were initially scheduled for execution under Case 1 but were ultimately cancelled under the optimized strategy of Case 2. These cancellations occur when the probabilistic assessment determines that the expected probability of success does not meet the cost-loss threshold, even after exploring all crew size options.

Under harsh weather conditions (Scenario 1), the model recommends cancelling approximately 45.8% of tasks. This is slightly higher than the 44.3% observed in the baseline scenario and significantly greater than the 27.9% in the favorable weather scenario (Scenario 2). These findings show the model's ability to identify maintenance tasks that may appear feasible under traditional scheduling (as in Case 1), but in reality include considerable operational or financial risk. Unlike Case 1, which bases feasibility only on vessel operability, Case 2 incorporates technician health and the probability of successful transfer. In adverse sea states, the likelihood of seasickness or failed transfers increases, and the model often determines that attempting the task would not be economically justified. In such cases, cancellation becomes the safest and most cost-effective recommendation.

In contrast, under favorable sea conditions, Case 2 recommends significantly fewer task cancellations. This reflects the wider availability of suitable time windows for safe and economically viable operations, allowing a greater number of tasks to proceed with a high probability of success. Overall, the model dynamically evaluates not only technician deployment but also the feasibility of task execution, ensuring that maintenance activities are carried out only when justified by both safety considerations and economic thresholds.

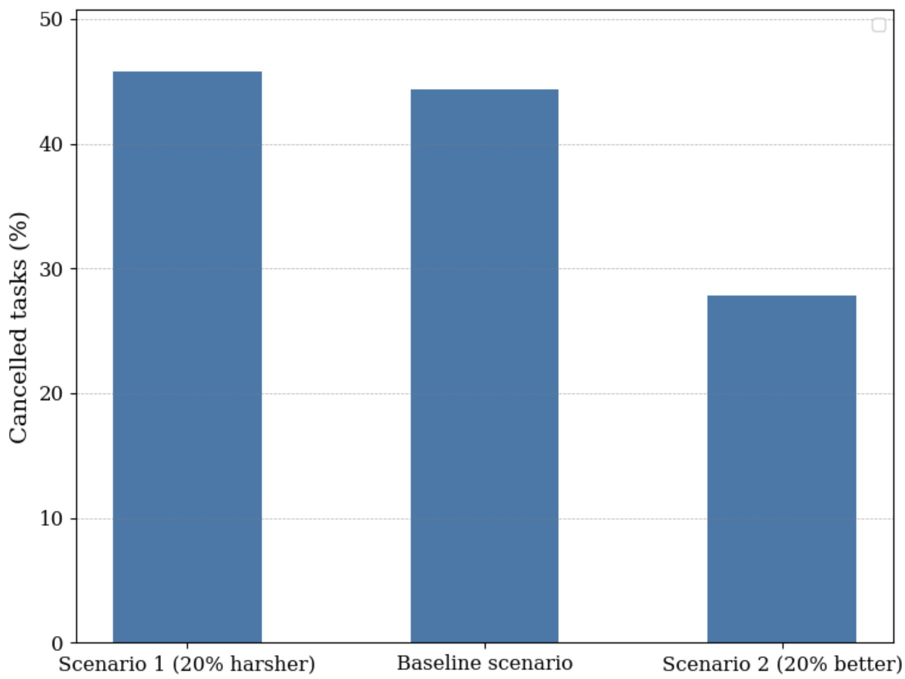

Figure 5.14: Percentage of tasks cancelled by Case 2 despite being scheduled under Case 1, across harsh, baseline, and favorable weather scenarios

5.6.5. Task execution delay - Case 2 vs. Case 1

Figure 5.15 illustrates the average delay introduced by the probabilistic model scheduling (Case 2) compared to the deterministic industry scheduling (Case 1), across the three weather condition scenarios, in order to observe how often tasks are postponed from their original scheduling due to the feasibility constraints that the Case 2 model looks at.

As expected, the results show that in harsher weather conditions (Scenario 1), the model introduces significantly higher delays, on average 111 days, compared to the baseline scenario, where the average delay is approximately 35 days. In favorable weather (Scenario 2), delays are minimal, averaging around 11 days. This trend reflects the model's conservative and risk-aware approach. Under poor metocean conditions, it postpones tasks until a sufficiently safe and economically viable window becomes available. These delays result from the model's effort to avoid sending technicians under unsafe or high-risk conditions. In this way, the model ensures that operations are carried out only when there is a high probability of success and when the cost is justified by the expected benefit.

However, this approach also introduces a potential drawback. In scenarios with persistent bad weather, extended delays are possible. Even though this helps avoid failed missions, it also increases the risk that initially minor repairs may worsen over time, potentially evolving into more serious faults or requiring more costly interventions later. This trade-off highlights the challenge of ensuring operational feasibility in the short term while minimizing long-term risks to asset condition and performance. In summary, although the model maintains high success rates even under challenging sea conditions, this reliability often comes at the cost of longer scheduling delays.

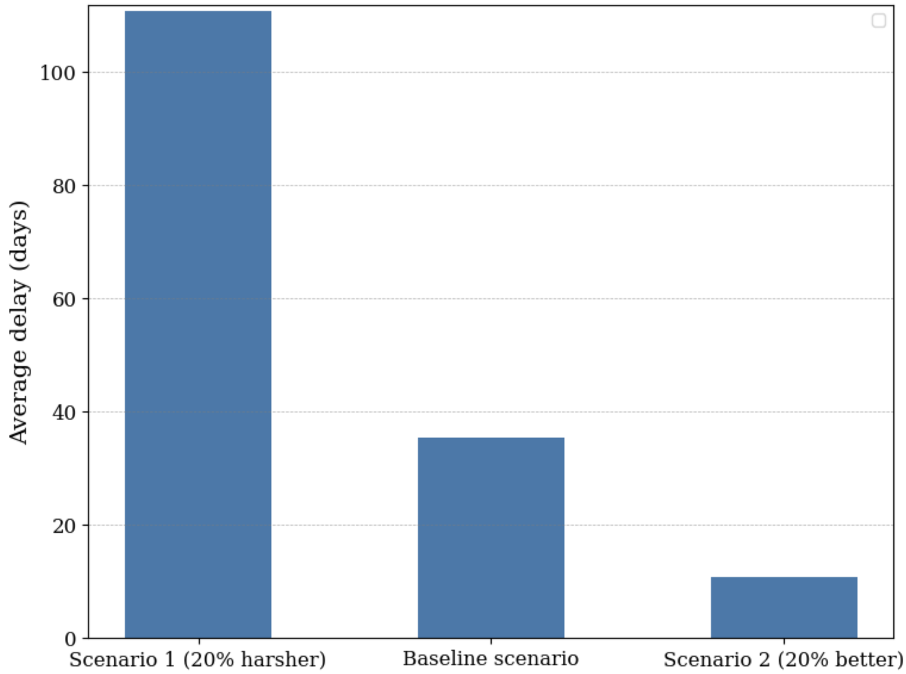

Figure 5.15: Average delay in maintenance task execution under Case 2 compared to Case 1, across harsh, baseline, and favorable weather scenarios

5.6.6. Environmental impact assessment

This section evaluates how weather variability influences the environmental performance of each maintenance scheduling strategy by quantifying the expected CO_2 emissions resulting from failed maintenance attempts across the three weather scenarios examined in the sensitivity analysis. These emissions are driven by the number of re-attempted vessel trips, which occur when maintenance missions are unsuccessful. Consequently, emissions are directly influenced by the combined probability of mission success achieved under each scenario.

Table 5.5 summarizes the expected number of re-attempts and the resulting CO_2 emissions for Case 1 and Case 2, across harsh, baseline, and favorable weather conditions. These values are derived using the combined probabilities of mission success presented in Section 5.6.1, and the emissions calculation methodology introduced by Equation 3.21 in Chapter 3.

Table 5.5: Estimated CO_2 emissions (in tons) from task re-attempts under different weather scenarios

Scenario	Strategy	Re-attempts	CO_2 Emissions (tons)
Scenario 1	Case 1	153	253.98
	Case 2	83	137.78
Baseline	Case 1	145	240.7
	Case 2	80	132.8
Scenario 2	Case 1	123	204.18
	Case 2	78	129.48

Figure 5.16 visualizes these results. Across the three scenarios, Case 2 consistently achieves lower CO_2 emissions than Case 1. The most significant reduction is observed under harsh conditions (Scenario 1), where emissions decrease by 116.2 tons, representing an improvement of 45.8%. Even under favorable conditions (Scenario 2), Case 2 achieves a notable reduction of 74.7 tons, equivalent to a 36.6% decrease.

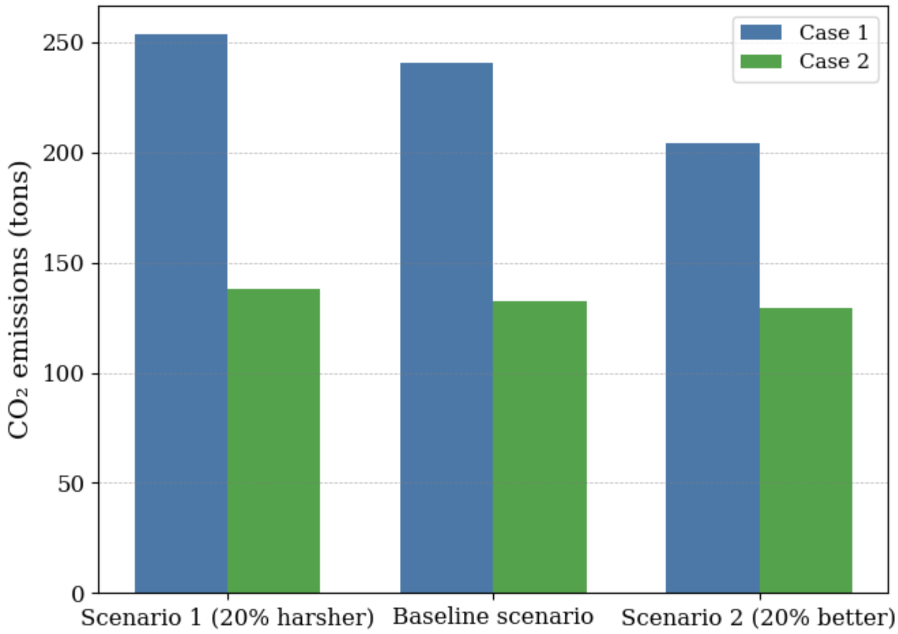

Figure 5.16: Total estimated CO_2 emissions (tons) from task re-attempts under each weather scenario and case

These findings confirm that the environmental benefits of adopting a probabilistic, optimized scheduling approach (Case 2) are robust across a wide range of operating conditions. By reducing the number of failed missions, and thus unnecessary vessel trips, Case 2 contributes consistently to emission reduction, supporting offshore wind decarbonization goals.

While the figure presents total emissions per strategy, it is worth noting that a portion of Case 2's emission reductions is specifically attributable to the crew size optimization mechanism. Without it, emissions would be slightly higher across all scenarios. If Case 2 were executed with a fixed crew size of two technicians, its total CO_2 emissions under the three scenarios would rise to 172.7 tons (Scenario 1), 158.3 tons (Baseline), and 154.1 tons (Scenario 2). This reinforces the added environmental value of dynamically adjusting crew size in response to operational risk.

6
Discussion

This Chapter reflects on the performance and broader implications of the proposed decision-support model for offshore wind maintenance. It evaluates the model's contribution to improving maintenance planning through enhanced reliability, cost-efficiency, and environmental performance.

Section 6.1 summarizes and interprets the key results of the case study, highlighting the model's strengths and operational benefits. Section 6.2 then outlines the main assumptions and limitations of the study, providing critical context for understanding the scope and potential of the model.

6.1. Main findings

This study introduced a probabilistic decision-support model for offshore wind maintenance planning, aiming to improve task feasibility, cost-efficiency, and operational reliability by accounting for short-term weather forecasts and human factors. The case study analyzed in Chapter 4 leads to some key findings.

First, compared to standard industry practices (Case 1), the proposed model (Case 2) significantly reduced the number of failed maintenance attempts. Case 2 achieved an average combined probability of mission success of 68.7%, compared to 43.3% for Case 1. That means that the developed model can lead to up to 58% increase in the probability of success. A key reason for this improved performance is that the model incorporates technician transfer risks and the likelihood of seasickness during transit, which are factors often overlooked in traditional planning approaches. By capturing these human-related uncertainties, the model provides a more realistic assessment of mission feasibility.

Second, by integrating a cost-loss decision framework, the model ensured that maintenance was only attempted when the estimated probability of success outweighed the economic risk of failure. This supported more economically justifiable decision-making under uncertainty.

Financially, Case 2 resulted in an average improvement of approximately $540,000 over the 10-year simulation period when compared to the standard approach (Case 1). These cost savings result from the model's ability to balance crew deployment costs with the risks and consequences of unsuccessful missions.

Another important finding is the model's dynamic crew allocation. Approximately 70% of all tasks could still be performed with the standard two-person crew, while additional technicians were added only when necessary to meet the cost-loss condition. This approach avoids overstaffing while maintaining a high probability of task success.

However, the model also introduces task delays. On average, Case 2 postponed task execution by 35 days compared to Case 1. This delay results from the model avoiding risky or low-success missions and waiting for better conditions. Sensitivity analysis showed that delays varied with weather, with just 11 days in favorable weather, and up to 111 days in harsh conditions. Despite this, the model maintained a success probability close to 70% across all weather scenarios, demonstrating strong robustness. However, long delays under harsh conditions may pose scheduling and operational challenges, especially when urgent tasks are involved. Thus, smart planning of maintenance activities to avoid seasons with high risk of harsh weather conditions, such as between late autumn and early spring, could lead to lower delays and improved success.

Finally, improved success rates translate into fewer failed attempts and, consequently, fewer unnecessary vessel trips. As shown in Section 5.6.6, Case 2 consistently achieves substantial reductions in CO_2 emissions compared to Case 1 across all weather scenarios. In the baseline hindcast weather scenario, emissions are reduced by approximately 44.8%. Similar trends are observed under both favorable and harsh conditions, with reductions ranging from 36.6% to 45.8%, respectively. These results emphasize the environmental benefits associated with risk-aware and optimized scheduling. By reducing vessel mobilizations, the proposed model not only enhances operational and financial performance but also contributes meaningfully to the sector's decarbonization efforts.

In general, these findings demonstrate that shifting from more traditional industry scheduling to a probabilistic and cost-aware approach can increase operational success, reduce costs, and reduce emissions, contributing to more sustainable and efficient offshore maintenance planning.

6.2. Limitations

This study presents a probabilistic decision-support model for offshore wind maintenance planning. While the model demonstrates added value and promising results, several limitations and simplifying assumptions must be acknowledged.

Lack of historical validation data
Due to confidentiality constraints, it was not possible to obtain real-world maintenance records from industry operators. As a result, the model could not be validated against historical cases to assess how well its recommendations align with actual mission outcomes. This limits the ability to evaluate the model's predictive performance under real-world scenarios.

Simplified estimation of seasickness
Technician well-being during transit is modelled using the MSI metric. However, seasickness is a highly complex phenomenon influenced by many factors such as fatigue, personal tolerance, experience in similar environments, and medication. Even large-scale industry initiatives like the SPOWTT project, which used real-time motion data and technician feedback over several years, did not manage to develop a robust predictive seasickness metric. Given the constraints of a 30-week MSc thesis, the objective here was not to develop a new seasickness model. Instead, the study used average MSI values from historical CTV-based maintenance records to estimate the likelihood that some technicians may become unfit for work during transit. While this approach is simplified, it offers a reasonable starting point. However, it is quite important to mention that the model is fully adaptable, since MSI can be replaced with any other metric if the operator has a more accurate or customized way of estimating seasickness.

Limitations in vessel motion modelling
At the beginning of the project, modelling vessel motions and accelerations was considered to estimate seasickness more precisely, similar to what has been done in the SPOWTT project [49] and related PhD studies [6], [7]. However, feedback from industry experts made it clear that such detailed modelling is highly complex. It typically requires collaboration across multiple disciplines, real-time vessel monitoring systems, and long-term support from industry partners. Given these challenges, and the limited time and scope of this MSc project, it was not reasonable to follow this approach. Instead, based also on industry feedback, the project focused on developing a simplified probabilistic approach that could still offer valuable operational insights. This method provides meaningful operational insights while staying feasible within the academic and resource constraints of the project.

Assumed vessel operability thresholds
The developed model applies vessel operability thresholds for wave height and wind speed based on values found in the literature. However, in practice, these thresholds vary between operators depending on operators' and technicians' experience, and internal safety policies. Some operators may choose to operate beyond the assumed limits, while others adopt more conservative standards. Thus, these variations would affect the results of the model.

Single vessel and task focus
The developed model assumes that only one task is performed per day using a single CTV, and does not consider the possibility of parallel tasks or multiple vessels operating at the same time. This simplification was intended to keep technician shifts within reasonable limits and to manage model complexity. However, in actual offshore operations, it is common to coordinate several tasks across different vessels in a single day. Expanding the model to handle multi-task and multi-vessel scheduling would improve its applicability to large OWF.

Fixed shift start time assumption
The model assumes that all maintenance shifts begin at 08:00, a realistic working starting time. This fixed start time ensures that vessel transit (in this case study is two hours round-trip) and the minimum six-hour task duration can be completed within standard daily working hours. However, this assumption may limit the model's flexibility. In practice, some tasks might be feasible if shifts started slightly earlier or later, particularly on days when weather conditions improve or get worse within the day. As a result, this constraint might lead to conservative feasibility assessments in marginal weather windows.

Scope of case study
Although the methodology is designed to support both CTV and SOV operations, the case study focused only on CTV-based missions and minor repairs. This focus was chosen because more data and relevant research were available for CTVs. In contrast, SOV-related data and studies remain limited. As a result, the findings and insights of this study are primarily applicable in the context of CTV-based minor maintenance tasks.

Assumed flexibility in technician deployment
The developed approach dynamically determines the number of technicians to deploy for each task, selecting the smallest crew size that meets the cost-loss ratio. This supports more cost-effective and risk-informed planning. However, in real-world operations, crew sizes are often fixed and might not be easy to be adjusted due to logistical logistical constraints or existing contracts. As a result, applying this model in practice would require a degree of flexibility from operators to adjust crew size based on forecasted risks and economic considerations.

Tasks assumed equally critical
While task duration and cost were component-specific in the case study, all tasks were treated as equally critical in terms of urgency and impact on turbine performance. In practice, some tasks may carry higher priority due to factors such as safety issues, planned maintenance schedules, or the risk of performance degradation if delayed. Introducing task-specific criticality levels would enhance the model's ability to support prioritization and improve real-world applicability.

CTV speed set to match weather data resolution
The CTV speed was selected as 22 knots to ensure a one-way transit time of approximately 1 hour. This choice aligns with the hourly resolution of the weather data used in the study, allowing a clear separation between the transit phase and the technician transfer phase when calculating success probabilities.

Full transit for each failed attempt
The model assumes that each failed attempt results in a complete round-trip journey between the port and the OWF. This includes cases where the mission could be aborted before reaching the OWF, such as if more technicians than allowed are already seasick before reaching the site. This assumption simplifies emissions estimation, but might slightly overestimate fuel consumption and emissions in practice.

Fixed fuel consumption rate
The model assumes a constant fuel consumption rate for the CTV, regardless of the number of technicians on board. In reality, the weight of the vessel might affect consumption, but this effect is expected to be minor for small changes in the size of the crew.

Simplified downtime assumptions
The developed model includes financial losses due to downtime in its cost-loss calculations. However, the case study that was based on maintenance plans obtained from another study assumes no downtime

between a failed minor repair attempt and its re-attempt. This is a reasonable assumption for minor tasks that can be rescheduled without major disruption. However, in the case of major repairs or replacements, downtime could be much longer and significantly increase the economic loss. This would affect the cost-loss ratio and could change the model's decision about whether to proceed with maintenance or the optimal number of technicians.

7
Conclusions

This thesis developed a probabilistic, same-day decision-support model to improve offshore wind maintenance planning under uncertain conditions. By integrating short-term weather forecasts, technician health risks, and cost-based optimization, the model supports more informed, safer, sustainable, and economically justified operational maintenance decisions.

This Chapter concludes the thesis by addressing the research sub-questions and the main research question in Section 7.1, as introduced in Section 1.4. Section 7.2 offers recommendations for future research and development to enhance the model's applicability in real-world offshore operations.

7.1. Answer to research questions

Sub-question 1:

What environmental, operational, and human factors influence the probability of successful offshore maintenance execution?

The probability that an offshore maintenance mission will be executed successfully is shaped by a combination of environmental conditions, vessel capabilities, and technician readiness, each interacting in complex ways. First of all, environmental factors play a fundamental role. The model specifically considers significant wave height, wind speed, and peak wave period, as the weather parameters that directly influence two critical operations:

- The transfer of technicians from vessel to turbine.
- The onboard experience during transit, which affects the likelihood of seasickness.

Harsher metocean conditions increase the risk of seasickness and reduce both transfer and transit success probabilities, thus reducing the overall feasibility of performing the task. On the operational side, vessel constraints, such as maximum allowable wave height and wind speed for safe operation, serve as the initial feasibility check. Additionally, technician scheduling constraints, such as shift duration, transfer safety, and the requirement of having at least the minimum number of technicians able to work on site, also influence whether a task can be realistically completed.

To account for this, the model estimates seasickness risk using the MSI and calculates the probability that a sufficient number of technicians will remain fit for work after transit. This approach captures a critical source of uncertainty that is often overlooked in traditional planning models.

In summary, mission success depends not only on whether a vessel can operate, but on the combined probability that technicians can arrive safely and remain capable of performing the task. This highlights the importance of incorporating both seasickness and transfer risks into offshore maintenance planning.

Sub-question 2:

How can short-term weather forecasts be integrated with vessel and technician constraints to assess the probability of mission success?

The model is designed to support same-day maintenance planning by integrating short-term weather forecasts with operational and human constraints. Although hindcast data were used in the case study, the model's intended real-world application assumes the use of short-term wave and wind forecasts, which literature suggests are reliable for up to five days. The idea is that each morning, operators would update the model with forecasted conditions to evaluate whether planned maintenance activities should proceed.

To do this, the model processes key forecasted environmental parameters, including significant wave height, wind speed, and peak wave period and translates them into probabilities for two critical factors:

- Transfer success probability, which reflects the likelihood that technicians can safely move from the vessel to the turbine. This is primarily influenced by vessel motions that happen due to sea-state conditions.
- Transit success probability, which reflects the likelihood that technicians will not experience seasickness during transit. This is quantified using MSI values, which estimate the proportion of technicians likely to become unfit for work due to seasickness.

These probabilities are then combined to compute an overall probability of successful task execution. It is also important to note that vessel type plays a role in transfer feasibility. In CTVs, high vessel motion during rough seas makes transfers particularly risky, as technicians must step directly from the vessel bow onto the turbine ladder. In contrast, SOVs often employ W2W systems, which provide a more stable gangway platform and allow safer transfers even in harsher conditions.

By integrating weather forecasts with both vessel operational limits and human factors, the model moves beyond simple operational thresholds and provides a probabilistic assessment of feasibility. This allows operators to make more informed decisions, reduce unnecessary mobilizations, and align daily planning with both safety and cost-efficiency goals.

Sub-question 3:

How can it be determined when maintenance is economically justified, based on the probability of success and associated costs?

In this study, economic justification for offshore maintenance is assessed using a cost-loss decision model, a well-established framework for evaluating decisions under uncertainty. The developed model applies a cost-loss ratio to determine the minimum required probability of mission success that justifies attempting maintenance. The condition that is used to make the decision of attempting maintenance is:

$$P_{\text{s,combined}} > \frac{\sum C_i}{L} \tag{7.1}$$

Where:

- $P_{\text{s,combined}}$ is the combined probability of mission success, incorporating both transfer feasibility and the likelihood that technicians remain fit for work after transit.
- $\sum C_i$ represents the total cost of attempting maintenance, including vessel charter, fuel, technician wages, and spare parts.
- L is the economic loss incurred if the mission fails, which includes lost energy production and the cost of re-attempting maintenance.

If the combined probability of mission success is higher than the cost-loss ratio, the model considers the maintenance task economically viable and recommends proceeding. If not, delaying or cancelling the task is seen as the more cost-effective and safer choice.

This approach captures the key trade-offs involved in same-day offshore maintenance planning by considering both the uncertainty of success and the financial consequences of failure. By accounting for risks such as technician unavailability due to seasickness and the possibility of unsuccessful transfers, the model helps avoid missions that are unlikely to succeed or could result in unnecessarily high costs. This ensures that resources are used efficiently and safely, and that maintenance activities are only carried out when they are both operationally and economically justified.

Sub-question 4:

How can technician deployment be optimized to minimize costs while maintaining an acceptable probability of success?

To address this challenge, the model integrates a technician deployment optimization routine within the broader cost-loss decision framework. The goal is to determine the minimum number of technicians needed for a given task so that the combined probability of mission success exceeds the economic threshold defined by the cost-loss ratio. The model begins by evaluating the task's feasibility with the required minimum of two technicians. If this crew size fails to satisfy the economic condition of Equation 7.1, the model incrementally increases the crew size until the inequality is met. This ensures that the number of deployed technicians is just sufficient to meet both operational feasibility and cost-effectiveness, without spending more money than needed for additional technicians.

This optimization accounts for the probabilistic impact of seasickness on technician availability. A larger crew increases the likelihood that at least two technicians will remain fit for duty upon arrival. However, it also increases technicians' costs. By balancing these competing effects, the model selects the smallest crew size that still ensures a mission is worthwhile from both a safety and financial perspective.

In practice, this dynamic technician allocation leads to smarter use of resources. In favorable conditions, the baseline team of two technicians is often sufficient. Under harsher sea states, however, the model may recommend sending additional technicians to address the increased risk of failure. As demonstrated in the case study, this strategy consistently outperforms fixed-crew approaches, offering better reliability and stronger cost performance across various weather scenarios.

Main research question:

How can offshore wind maintenance operations be scheduled more effectively by incorporating seasickness risk, transfer safety, and cost-efficiency into decision-making?

This study highlights that offshore wind maintenance operations can be scheduled more effectively by integrating environmental, operational, and human factors into a probabilistic decision-support model. Traditional scheduling approaches often rely on deterministic thresholds and ignore the dynamic and highly uncertain offshore environments. In contrast, the model developed in this thesis incorporates:

- Transfer safety, by estimating the probability that technicians can safely move from vessel to turbine under forecasted sea conditions.
- Seasickness risk, through the application of the MSI metric, which quantifies the likelihood that technicians may become unfit for work during transit.
- Cost-efficiency, using a cost-loss framework that compares the cost of attempting maintenance to the potential financial loss if the mission fails.

By combining these elements, the model calculates the combined probability of mission success and determines whether maintenance is economically justified. Moreover, it includes an optimization step that dynamically adjusts technician deployment, ensuring that just enough technicians are deployed to satisfy both operational feasibility and cost-effectiveness.

The model's effectiveness was demonstrated through a case study using hindcast weather data and a set of realistic operational constraints. Results showed that the optimized approach (Case 3) consistently achieved the highest probability of success and delivered significant financial benefits across a range of environmental scenarios. It also proved robust under harsh conditions by recommending appropriate crew sizes and scheduling adjustments, while avoiding unnecessary risk and cost.

In summary, this study demonstrates that offshore maintenance scheduling can be significantly enhanced by moving beyond standard industry approaches that rely only on vessel operational limits and fixed crew sizes. The proposed model takes into account important sources of uncertainty, including the risk of failed technician transfers due to rough sea conditions and the possibility that technicians may become unable to work because of seasickness. It compares these risks with the potential financial losses that could result from a failed maintenance attempt. This allows operators to make more informed decisions that reflect real-world operating conditions, leading to safer and more cost-effective offshore wind maintenance planning.

7.2. Recommendations for future work

Undoubtedly, there are several areas where the model could be expanded, improved, or validated further. These suggestions aim to enhance the model's real-world applicability and address some of the limitations discussed in the previous Chapter.

First, due to confidentiality constraints, the model could not be validated against real-world data. Future research could focus on establishing collaborations with offshore wind operators to obtain records of past maintenance attempts. This would allow for a direct comparison between model recommendations and actual outcomes, improving trust in the model's predictive capability.

Second, future work could aim to develop a more refined metric for estimating seasickness. Given the complexity of human response to vessel motion, this would likely require collaboration with industry stakeholders and potentially include collecting technician feedback through post-transit questionnaires. Correlating this input with environmental conditions could lead to the creation of a more robust model for technician well-being, based on operator's and technicians' experience.

Third, future studies could allow more flexibility in the starting time of technician shifts. This would make it possible to take advantage of short weather windows that occur outside of the fixed 08:00 start time. By adjusting the shift timing within safe and realistic working hours, the model could identify more opportunities to perform maintenance tasks, especially on days when conditions improve or worsen throughout the day. This would make planning more effective and flexible while still respecting operational limits and crew safety.

Additionally, while the current case study focused on minor repairs using CTVs, the methodology is applicable to any maintenance operation. Future work should explore the model's application to SOV missions and more complex repair tasks to assess its adaptability and performance in those contexts.

Finally, the current model assumes that only one maintenance task is performed per day using a single vessel. In practice, offshore maintenance cycles could involve multiple vessels and parallel operations. Expanding the model to support scheduling for multiple vessels and tasks on the same day would improve its ability to support real-world planning scenarios, especially for large OWF and high-demand periods.

References

[1] International Energy Agency. *Offshore Wind Outlook 2019 – Analysis - IEA*. 2019. URL: https://www.iea.org/reports/offshore-wind-outlook-2019.

[2] Nuobei Zhang et al. "Strategies for sustainable development of offshore wind power in regions with limited resources". In: *Energy* 311 (Dec. 2024), p. 133345. ISSN: 0360-5442. DOI: 10.1016/J.ENERGY.2024.133345.

[3] Rebecca Martin et al. "Sensitivity analysis of offshore wind farm operation and maintenance cost and availability". In: *Renewable Energy* 85 (Jan. 2016), pp. 1226–1236. ISSN: 0960-1481. DOI: 10.1016/J.RENENE.2015.07.078.

[4] Yannis Hadjoudj and Ravi Kumar Pandit. "Improving OM decision tools for offshore wind farm vessel routing by incorporating weather uncertainty". In: *IET Renewable Power Generation* 17 (6 Apr. 2023), pp. 1488–1499. ISSN: 1752-1424. DOI: 10.1049/RPG2.12689. URL: https://onlinelibrary.wiley.com/doi/full/10.1049/rpg2.12689%20https://onlinelibrary.wiley.com/doi/abs/10.1049/rpg2.12689%20https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/rpg2.12689.

[5] A. Kolios et al. "Effect of weather forecast uncertainty on offshore wind farm availability assessment". In: *Ocean Engineering* 285 (Oct. 2023), p. 115265. ISSN: 0029-8018. DOI: 10.1016/J.OCEANENG.2023.115265.

[6] Tobenna D. Uzuegbunam, Rodney Forster, and Terry Williams. "Assessing the Welfare of Technicians during Transits to Offshore Wind Farms". In: *Vibration 2023, Vol. 6, Pages 434-448* 6 (2 May 2023), pp. 434–448. ISSN: 2571-631X. DOI: 10.3390/VIBRATION6020027. URL: https://www.mdpi.com/2571-631X/6/2/27/htm%20https://www.mdpi.com/2571-631X/6/2/27.

[7] Pietro D. Tomaselli et al. "A Decision-Making Tool for Planning OM Activities of Offshore Wind Farms Using Simulated Actual Decision Drivers". In: *Frontiers in Marine Science* 7 (Jan. 2021), p. 588624. ISSN: 22967745. DOI: 10.3389/FMARS.2020.588624/BIBTEX.

[8] Miguel de Matos Sá et al. "Optimising OM scheduling in offshore wind farms considering weather forecast uncertainty and wake losses". In: *Ocean Engineering* 301 (June 2024). ISSN: 00298018. DOI: 10.1016/J.OCEANENG.2024.117518.

[9] Vestas. *V236-15.0 MW™*. URL: https://www.vestas.com/en/energy-solutions/offshore-wind-turbines/V236-15MW.

[10] Siemens Gamesa. *Wind turbine sg 14 236 dd*. URL: https://www.siemensgamesa.com/global/en/home/products-and-services/offshore/wind-turbine-sg-14-236-dd.html.

[11] RenewEconomy. *Siemens Gamesa claims world's most powerful wind turbine with new offshore behemoth | RenewEconomy*. URL: https://reneweconomy.com.au/siemens-gamesa-claims-worlds-most-powerful-wind-turbine-with-new-offshore-behemoth/.

[12] Core Marine. "The what, why and how of offshore wind: Australia edition". In: (2023).

[13] Anthony Gray. "WHAT ARE OPERATIONS AND MAINTENANCE SIMULATION TOOLS?" In: (2020).

[14] B Maples et al. "Installation, Operation, and Maintenance Strategies to Reduce the Cost of Offshore Wind Energy". In: (2013). URL: www.nrel.gov/publications..

[15] Thomas Michael Welte et al. "Operation and Maintenance Modelling". In: *Offshore Wind Energy Technology* (Feb. 2018), pp. 269–303. DOI: 10.1002/9781119097808.CH7. URL: https://onlinelibrary.wiley.com/doi/full/10.1002/9781119097808.ch7%20https://onlinelibrary.wiley.com/doi/abs/10.1002/9781119097808.ch7%20https://onlinelibrary.wiley.com/doi/10.1002/9781119097808.ch7.

[16] M. Borsotti, R. R. Negenborn, and X. Jiang. "Model predictive control framework for optimizing offshore wind OM". In: *Advances in Maritime Technology and Engineering* 1 (2024), pp. 533–546. DOI: 10.1201/9781003508762-65. URL: https://research.tudelft.nl/en/publications/model-predictive-control-framework-for-optimizing-offshore-wind-o.

[17] J. McMorland et al. "Opportunistic maintenance for offshore wind: A review and proposal of future framework". In: *Renewable and Sustainable Energy Reviews* 184 (Sept. 2023), p. 113571. ISSN: 1364-0321. DOI: 10.1016/J.RSER.2023.113571.

[18] M. Li. "Towards Closed-loop Maintenance Logistics for Offshore Wind Farms". In: (2023). DOI: 10.4233/BD895C0F-043B-43F0-A2A3-6E2D3DF18121. URL: https://repository.tudelft.nl/record/uuid:bd895c0f-043b-43f0-a2a3-6e2d3df18121.

[19] Vinit V Dighe, Loris Pergod, and Chen Yung. "Offshore Wind Access Report 2022". In: (2022). URL: www.tno.nl.

[20] B Hu and C Yung. "OFFSHORE WIND ACCESS REPORT OFFSHORE WIND ACCESS REPORT 2020 Offshore Wind Access Report 2020 Date". In: *1.1.1.1.1.1.1* 1 (1 2020). URL: www.tno.nl.

[21] G.C.A. Uppenkamp. *Design space exploration of Mother-Daughter Concepts for Far Offshore Wind Farm Oamp;M | TU Delft Repository*. URL: https://repository.tudelft.nl/record/uuid:eb790f24-b948-4a16-9a85-897f947b8c71.

[22] Offshore Magazine. *NYK, Van Oord team up for offshore wind installation vessels in Japan | Offshore*. URL: https://www.offshore-mag.com/vessels/article/14074898/nyk-van-oord-team-up-for-offshore-wind-installation-vessels-in-japan.

[23] Amports. *Windcat Workboats. Pionering, innovating and growing - Amports*. URL: https://www.amports.nl/magazine/windcat-workboats-pionering-innovating-and-growing/.

[24] Ulstein. *WINDEA La Cour | Ulstein*. URL: https://ulstein.com/references/windea-la-cour.

[25] Offshore-Energy.biz. *Ventus Marine SATV starts working on Formosa 1 offshore wind farm - Offshore Energy*. URL: https://www.offshore-energy.biz/ventus-marine-satv-starts-working-on-formosa-1-offshore-wind-farm/.

[26] Airbus. *Airbus Helicopters focuses on the wind turbine growth market | Airbus*. URL: https://www.airbus.com/en/newsroom/press-releases/2018-09-airbus-helicopters-focuses-on-the-wind-turbine-growth-market.

[27] State of Green. *Powering vessels at sea in offshore wind farms*. URL: https://stateofgreen.com/en/solutions/powering-vessels-at-sea-in-offshore-wind-farms/.

[28] Anders Arvesen, Christine Birkeland, and Edgar G. Hertwich. "The importance of ships and spare parts in LCAs of offshore wind power". In: *Environmental Science and Technology* 47 (6 Mar. 2013), pp. 2948–2956. ISSN: 0013936X. DOI: 10.1021/ES304509R/SUPPL_FILE/ES304509R_SI_001.PDF. URL: https://pubs.acs.org/doi/abs/10.1021/es304509r.

[29] Anthony Gray. "SETTING A BENCHMARK FOR DECARBONISING OM VESSELS OF OFFSHORE WIND FARMS". In: (2021).

[30] J. T. Reason. "Motion sickness adaptation: a neural mismatch model". In: *Journal of the Royal Society of Medicine* 71 (11 1978), p. 819. ISSN: 01410768. DOI: 10.1177/014107687807101109. URL: https://pmc.ncbi.nlm.nih.gov/articles/PMC1436193/.

[31] Vestas. *Vestas pioneers world's first hydrogen-powered offshore service vessel*. URL: https://www.vestas.com/en/media/company-news/2022/vestas-pioneers-world-s-first-hydrogen-powered-offshore-c3596070.

[32] Offshore-Energy.biz. *New pilot project looking to decarbonise floating wind by using green ammonia-fuelled vessels - Offshore Energy*. URL: https://www.offshore-energy.biz/new-pilot-project-looking-to-decarbonise-floating-wind-by-using-green-ammonia-fuelled-vessels/.

[33] Damen. *Service Operation Vessel 7017 Electric - Damen*. URL: https://www.damen.com/vessels/offshore/service-operation-vessels/sov-7017-electric.

[34] Damen. *The next step in crew transfer vessels - Damen*. URL: https://www.damen.com/insights-center/articles/the-next-step-in-crew-transfer-vessels.

[35] Mahmood Shafiee. "Maintenance logistics organization for offshore wind energy: Current progress and future perspectives". In: *Renewable Energy* 77 (1 May 2015), pp. 182–193. ISSN: 0960-1481. DOI: 10.1016/J.RENENE.2014.11.045.

[36] G. J.W. van Bussel and W. A.A.M. Bierbooms. "The DOWEC Offshore Reference Windfarm: Analysis of Transportation for Operation and Maintenance". In: *http://dx.doi.org/10.1260/030952403322770986* 27 (5 Sept. 2003), pp. 381–392. ISSN: 0309524X. DOI: 10.1260/030952403322770986. URL: https://journals.sagepub.com/doi/10.1260/030952403322770986.

[37] Matti Scheu et al. "Maintenance Strategies for Large Offshore Wind Farms". In: *Energy Procedia* 24 (Jan. 2012), pp. 281–288. ISSN: 1876-6102. DOI: 10.1016/J.EGYPRO.2012.06.110.

[38] Matthias Hofmann and Iver Bakken Sperstad. "NOWIcob – A Tool for Reducing the Maintenance Costs of Offshore Wind Farms". In: *Energy Procedia* 35 (Jan. 2013), pp. 177–186. ISSN: 1876-6102. DOI: 10.1016/J.EGYPRO.2013.07.171.

[39] Iver Bakken Sperstad et al. "A Comparison of Single- and Multi-parameter Wave Criteria for Accessing Wind Turbines in Strategic Maintenance and Logistics Models for Offshore Wind Farms". In: *Energy Procedia* 53 (C Jan. 2014), pp. 221–230. ISSN: 1876-6102. DOI: 10.1016/J.EGYPRO.2014.07.231.

[40] Mingkang Wu. "Numerical analysis of docking operation between service vessels and offshore wind turbines". In: *Ocean Engineering* 91 (Nov. 2014), pp. 379–388. ISSN: 0029-8018. DOI: 10.1016/J.OCEANENG.2014.09.027.

[41] Yalcin Dalgic et al. "Advanced logistics planning for offshore wind farm operation and maintenance activities". In: *Ocean Engineering* 101 (June 2015), pp. 211–226. ISSN: 0029-8018. DOI: 10.1016/J.OCEANENG.2015.04.040.

[42] Ole Erik V. Endrerud, Jayantha P. Liyanage, and Nenad Keseric. "Marine logistics decision support for operation and maintenance of offshore wind parks with a multi method simulation model". In: *Proceedings - Winter Simulation Conference* 2015-January (Jan. 2015), pp. 1712–1722. ISSN: 08917736. DOI: 10.1109/WSC.2014.7020021.

[43] J. Browell, I. Dinwoodie, and D. McMillan. "Forecasting for day-ahead offshore maintenance scheduling under uncertainty". In: *Risk, Reliability and Safety: Innovating Theory and Practice - Proceedings of the 26th European Safety and Reliability Conference, ESREL 2016* (2017), p. 182. DOI: 10.1201/9781315374987-171.

[44] Chandra Ade Irawan et al. "Optimisation of maintenance routing and scheduling for offshore wind farms". In: *European Journal of Operational Research* 256 (1 Jan. 2017), pp. 76–89. ISSN: 0377-2217. DOI: 10.1016/J.EJOR.2016.05.059.

[45] B Cheung. "Chapter 8-Seasickness: Guidelines for All Operators of Marine Vessels, Marine Helicopters and Offshore Oil Installations". In: (2007). URL: https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=50a95ed5ec25c1315dd16e021fe056d825e3831c.

[46] Sathishkumar Nachimuthu. "Decision Models for Operation and Maintenance of Offshore Wind Farms Considering Uncertainties". In: (2020).

[47] Guojin Si et al. "Maintenance scheduling and vessel routing for offshore wind farms with multiple ports considering day-ahead wind-wave predictions". In: *Applied Energy* 379 (Feb. 2025), p. 124915. ISSN: 0306-2619. DOI: 10.1016/J.APENERGY.2024.124915.

[48] Ravi Kumar Pandit, Athanasios Kolios, and David Infield. "Data-driven weather forecasting models performance comparison for improving offshore wind turbine availability and maintenance". In: *IET Renewable Power Generation* 14 (13 Oct. 2020), pp. 2386–2394. ISSN: 17521424. DOI: 10.1049/IET-RPG.2019.0941.

[49] "SPOWTT: Improving the safety and productivity of offshore wind technician transit". In: *Wind Energy* 25 (1 Jan. 2022), pp. 34–51. ISSN: 1099-1824. DOI: 10.1002/WE.2647. URL: https://onlinelibrary.wiley.com/doi/full/10.1002/we.2647%20https://onlinelibrary.wiley.com/doi/abs/10.1002/we.2647%20https://onlinelibrary.wiley.com/doi/10.1002/we.2647.

[50] S Pfaffel, S Faulstich, and S Sheng. “Recommended key performance indicators for operational management of wind turbines”. In: *Journal of Physics: Conference Series* 1356 (1 Oct. 2019), p. 012040. ISSN: 1742-6596. DOI: 10.1088/1742-6596/1356/1/012040. URL: https://iopscience.iop.org/article/10.1088/1742-6596/1356/1/012040%20https://iopscience.iop.org/article/10.1088/1742-6596/1356/1/012040/meta.

[51] Andrew Stormonth-Darling. “SPOWTT FINAL PROJECT REPORT”. In: (2020). URL: https://cms.ore.catapult.org.uk/wp-content/uploads/2020/06/SPOWTT-Project-Report.pdf.

[52] Li Li Zhang et al. “Motion Sickness: Current Knowledge and Recent Advance”. In: *CNS neuroscience therapeutics* 22 (1 Jan. 2016), pp. 15–24. ISSN: 1755-5949. DOI: 10.1111/CNS.12468. URL: https://pubmed.ncbi.nlm.nih.gov/26452639/.

[53] Samson C. Stevens and Michael G. Parsons. “Effects of Motion at Sea on Crew Performance: A Survey”. In: *Marine Technology and SNAME News* 39 (01 Jan. 2002), pp. 29–47. ISSN: 0025-3316. DOI: 10.5957/MT1.2002.39.1.29.

[54] James F. O’Hanlon and Michael E. McCauley. “MOTION SICKNESS INCIDENCE AS A FUNCTION OF THE FREQUENCY AND ACCELERATLION OF VERTICAL SINUSOIDAL MOTION”. In: (1973).

[55] A. H. Wertheim, J. E. Bos, and W. Bles. “Contributions of roll and pitch to sea sickness”. In: *Brain Research Bulletin* 47 (5 Nov. 1998), pp. 517–524. ISSN: 0361-9230. DOI: 10.1016/S0361-9230(98)00098-7.

[56] Hassan Khalid et al. “Application of the subjective vertical–horizontal-conflict physiological motion sickness model to the field trials of contemporary vessels”. In: *Ocean Engineering* 38 (1 Jan. 2011), pp. 22–33. ISSN: 0029-8018. DOI: 10.1016/J.OCEANENG.2010.09.008.

[57] Laurel Marie Ritmiller. “EFFECTS OF VESSEL MOTION AND FATIGUE ON HUMAN PERFORMANCE IN MARINE OPERATIONS”. In: (1994).

[58] International Organization for Standardization. *ISO 2631-1:1997 - Mechanical vibration and shock — Evaluation of human exposure to whole-body vibration — Part 1: General requirements*. URL: https://www.iso.org/standard/7612.html.

[59] S. Faulstich, B. Hahn, and P. J. Tavner. “Wind turbine downtime and its importance for offshore deployment”. In: *Wind Energy* 14 (3 2011), pp. 327–337. ISSN: 10991824. DOI: 10.1002/WE.421.

[60] James Carroll et al. “Availability, operation and maintenance costs of offshore wind turbines with different drive train configurations”. In: *Wind Energy* 20 (2 Feb. 2017), pp. 361–378. ISSN: 10991824. DOI: 10.1002/WE.2011.

[61] James Carroll, Alasdair McDonald, and David McMillan. “Failure rate, repair time and unscheduled OM cost analysis of offshore wind turbines”. In: *Wind Energy* 19 (6 June 2016), pp. 1107–1119. ISSN: 10991824. DOI: 10.1002/WE.1887.

[62] Nora Tangen Raknes et al. “Marine Science and Engineering Scheduling of Maintenance Tasks and Routing of a Joint Vessel Fleet for Multiple Offshore Wind Farms”. In: (2017). DOI: 10.3390/jmse5010011. URL: www.mdpi.com/journal/jmse.

[63] B. Hu, S. Krishna Swamy, and K.W. Hermans. *Including Realistic Vessel and Human Behaviour in Simulations of Offshore Wind Farm Operations*. 2018.

[64] Marco Taboga. *Beta distribution | Properties, proofs, exercises*. URL: https://www.statlect.com/probability-distributions/beta-distribution.

[65] Masashi Sugiyama. “Examples of Continuous Probability Distributions”. In: *Introduction to Statistical Machine Learning* (2016), pp. 37–50. DOI: 10.1016/B978-0-12-802121-7.00015-7.

[66] ScienceDirect. *Binomial Distribution - an overview | ScienceDirect Topics*. URL: https://www.sciencedirect.com/topics/engineering/binomial-distribution.

[67] J. C. Thompson and G. W. Brier. *THE ECONOMIC UTILITY OF WEATHER FORECASTS in: Monthly Weather Review Volume 83 Issue 11 (1955)*. URL: https://journals.ametsoc.org/view/journals/mwre/83/11/1520-0493_1955_083_0249_teuowf_2_0_co_2.xml.

[68] Frances Judge et al. “A lifecycle financial analysis model for offshore wind farms”. In: *Renewable and Sustainable Energy Reviews* 103 (Apr. 2019), pp. 370–383. ISSN: 1364-0321. DOI: 10.1016/J.RSER.2018.12.045.

[69] Lin Li, Zhen Gao, and Torgeir Moan. “Joint Distribution of Environmental Condition at Five European Offshore Sites for Design of Combined Wind and Wave Energy Devices”. In: *Journal of Offshore Mechanics and Arctic Engineering* 137 (3 June 2015). ISSN: 1528896X. DOI: 10.1115/1.4029842/377037. URL: https://dx.doi.org/10.1115/1.4029842.

[70] Zulqarnain Ali, Ahmad Hassan, and Yung-Chang Chan. *Crew Transfer Vessel for Offshore Wind Farm*. Technical Report EMSHIP_CTV_Project_2024. Accessed via ResearchGate June 16, 2025. Liège, Belgium: University of Liège, 2024. DOI: 10.13140/RG.2.2.13752.97282. URL: https://www.researchgate.net/publication/383862936_Crew_Transfer_Vessel_for_Offshore_Wind_Farm.

[71] A. Abramic, V. Cordero-Penin, and R. Haroun. “Environmental impact assessment framework for offshore wind energy developments based on the marine Good Environmental Status”. In: *Environmental Impact Assessment Review* 97 (Nov. 2022), p. 106862. ISSN: 0195-9255. DOI: 10.1016/J.EIAR.2022.106862. URL: https://www.sciencedirect.com/science/article/pii/S0195925522001287.

[72] NOAA Fisheries. *Ocean Noise | NOAA Fisheries*. URL: https://www.fisheries.noaa.gov/national/science-data/ocean-noise.

[73] NOAA Fisheries. *Assessing the Impacts of Offshore Wind Energy on Marine Life | NOAA Fisheries*. URL: https://www.fisheries.noaa.gov/topic/offshore-wind-energy/assessing-impacts-to-marine-life.

A

Illustrative maintenance cycle - detailed results

This appendix complements Section 5.2.2 by providing the full set of visualizations for the 11 tasks introduced in Table 4.3. Each figure illustrates how the developed model (Case 2) scheduled the task under weather, cost, and human constraints.

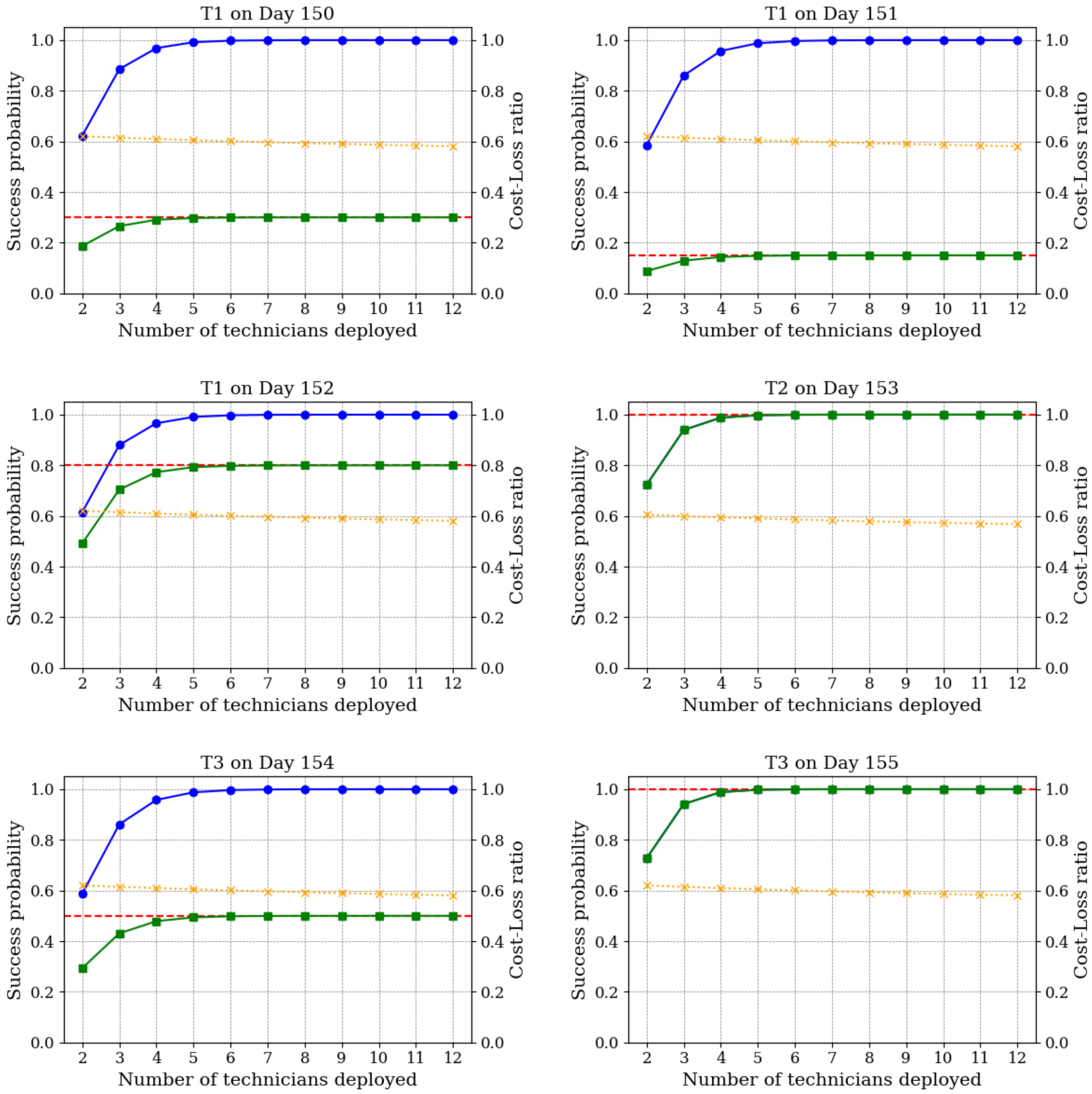

Figure A.1: Illustrative maintenance cycle: Days 150–155

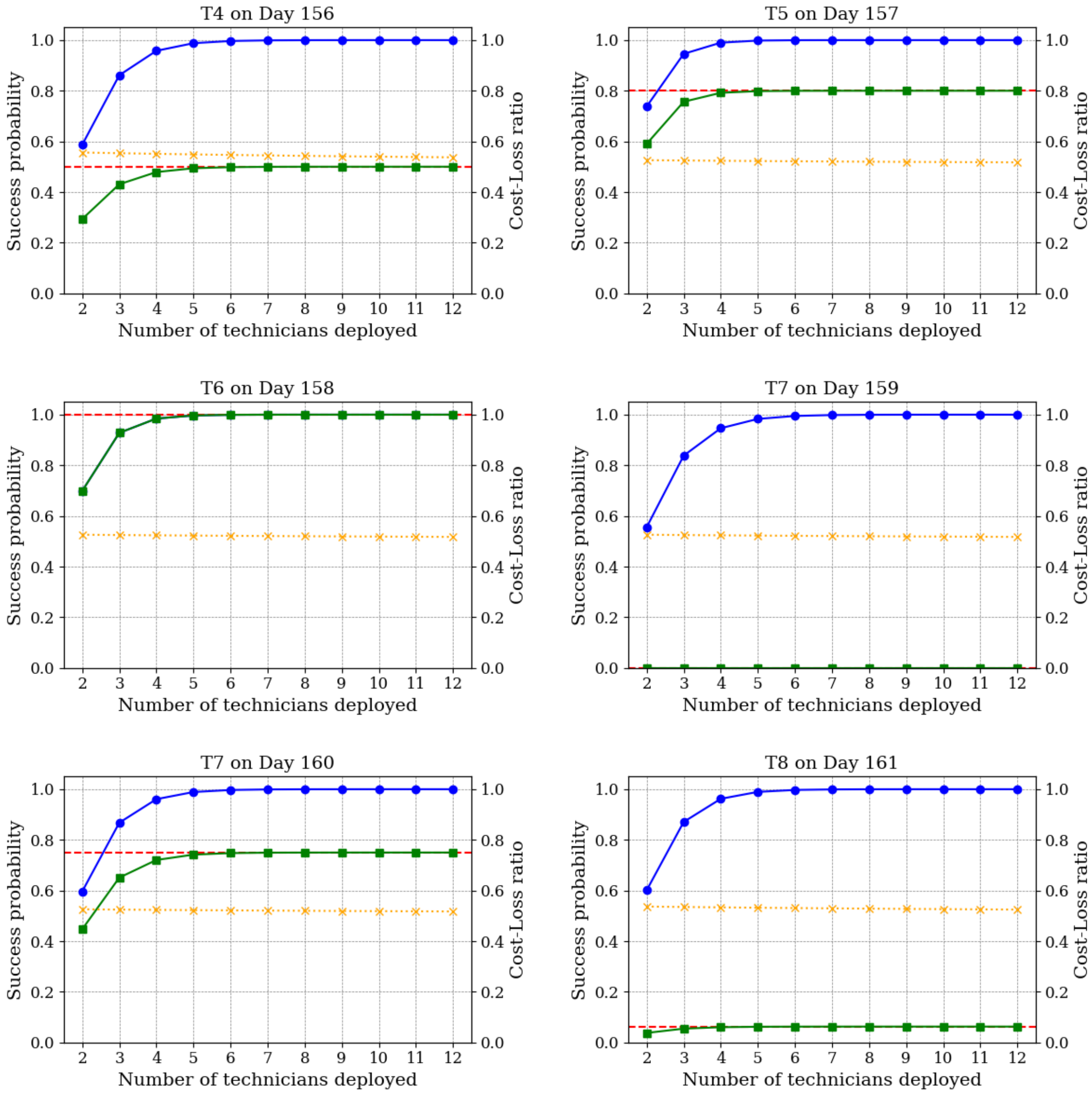

Figure A.2: Illustrative maintenance cycle: Days 156–161

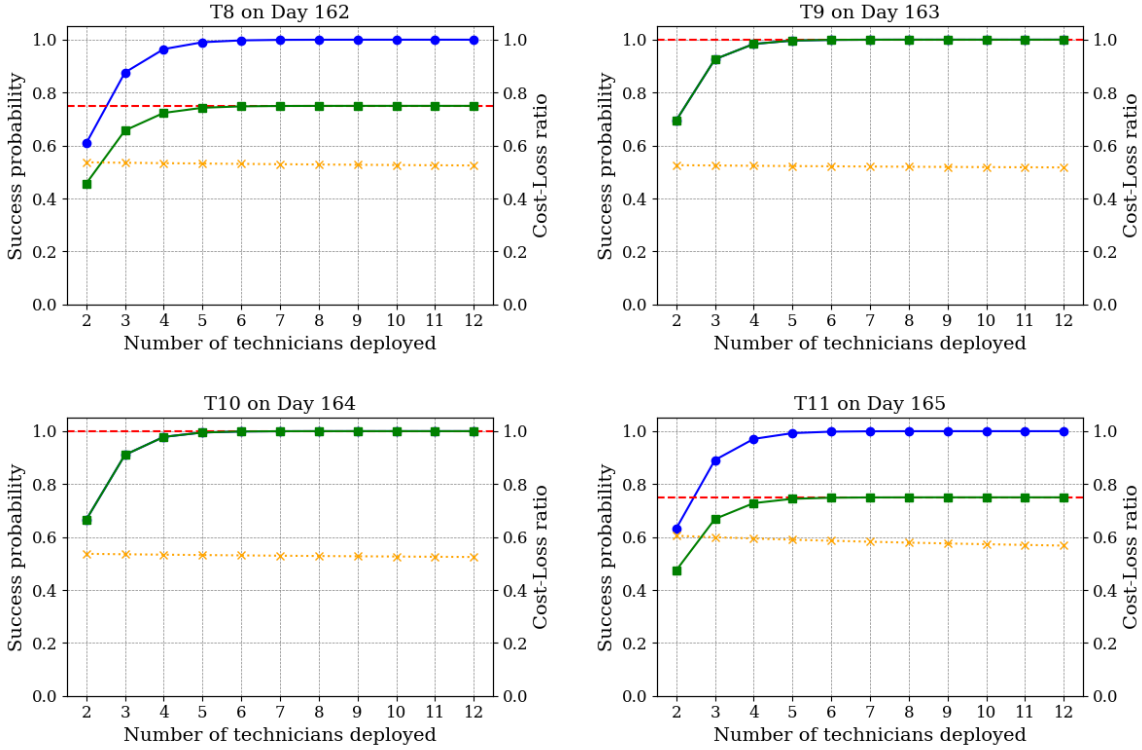

Figure A.3: Illustrative maintenance cycle: Days 162–165

B
Maintenance schedule summary and deployment statistics

This appendix provides additional details on the 75 maintenance schedules analyzed in this study. For each schedule, Table B.1 reports the total number of minor repairs, the number of maintenance cycles over the 10-year planning horizon, the frequency of technician crew sizes deployed under Case 2, and the expected operational costs associated with both Case 1 and Case 2. For compactness, $N_{T,\text{deployed}}$ is abbreviated as N_T in the table.

Table B.1: Summary of maintenance schedule characteristics: Number of tasks, maintenance cycles, technician crew size distribution in Case 2, and expected operational costs for Case 1 and Case 2

Schedule	Minor repairs	Cycles	$N_T = 2$	$N_T = 3$	$N_T = 4$	$N_T = 5$	$N_T = 6$	$N_T = 7$	Case 1 Expected costs ($M)	Case 2 Expected costs ($M)
1	277	17	197	69	5	4	0	2	4.88	4.26
2	286	18	196	80	7	1	1	1	5.03	4.46
3	226	15	152	65	6	1	0	2	3.96	3.50
4	263	16	181	79	1	0	1	1	4.69	4.09
5	214	15	152	53	5	1	0	3	3.67	3.31
6	275	17	193	74	6	2	0	0	4.92	4.30
7	302	19	207	85	6	1	0	3	5.36	4.69
8	228	14	161	56	7	1	2	1	4.10	3.55
9	239	16	165	66	3	0	2	3	4.30	3.77
10	290	19	198	81	8	1	0	2	5.20	4.52
11	231	15	157	65	5	2	1	1	4.20	3.66
12	225	13	145	71	7	1	1	0	4.06	3.55
13	192	12	130	52	8	2	0	0	3.41	3.01
14	226	13	145	71	6	3	1	0	4.05	3.54
15	235	16	163	61	8	1	0	2	4.12	3.62
16	236	16	164	65	2	2	1	2	4.14	3.67
17	233	17	162	65	4	1	1	0	4.03	3.60
18	169	11	110	51	2	2	2	2	2.99	2.66
19	286	19	202	76	5	1	0	2	5.00	4.42
20	244	14	174	61	5	2	0	2	4.25	3.70
21	256	16	182	66	4	1	1	2	4.54	3.95
22	239	16	157	73	5	1	0	3	4.18	3.72
23	261	20	194	61	4	1	0	1	4.54	3.98
24	211	14	138	64	6	1	1	1	3.75	3.26
25	315	18	209	92	7	5	0	2	5.67	4.98
26	259	14	177	70	6	3	0	3	4.54	4.05
27	302	19	202	86	9	4	1	0	5.23	4.63
28	279	20	195	75	5	3	1	0	4.94	4.29
29	240	15	179	52	4	3	0	2	4.22	3.70
30	222	15	146	66	8	0	0	2	3.94	3.47
31	291	20	203	77	6	4	1	0	5.08	4.44
32	293	20	206	76	8	1	1	1	5.10	4.51
33	243	17	165	65	7	3	1	2	4.30	3.79
34	244	17	185	51	6	1	0	1	4.34	3.79
35	302	18	214	74	4	3	1	6	5.43	4.71
36	209	12	144	61	2	1	1	0	3.76	3.29
37	266	16	188	66	6	3	2	1	4.64	4.13

Schedule	Minor repairs	Cycles	$N_T = 2$	$N_T = 3$	$N_T = 4$	$N_T = 5$	$N_T = 6$	$N_T = 7$	Case 1 Expected costs ($M)	Case 2 Expected costs ($M)
38	226	14	160	59	3	1	1	2	3.95	3.49
39	278	19	197	65	8	4	1	3	4.88	4.32
40	221	13	155	58	3	2	1	2	3.97	3.43
41	317	21	218	90	6	1	1	1	5.66	4.89
42	258	14	174	72	9	3	0	0	4.51	4.01
43	304	18	214	83	3	3	0	1	5.40	4.75
44	238	14	165	66	5	1	0	1	4.20	3.68
45	247	18	162	68	10	3	1	3	4.26	3.85
46	236	18	163	65	5	1	0	2	4.18	3.65
47	290	19	197	80	6	3	1	3	5.15	4.46
48	300	20	208	79	8	2	1	2	5.24	4.62
49	307	18	209	86	8	2	0	2	5.42	4.76
50	236	16	153	71	6	4	0	2	4.21	3.73
51	276	17	202	63	6	3	2	0	4.91	4.27
52	273	19	194	73	6	0	0	0	4.78	4.20
53	196	12	128	59	4	2	1	2	3.41	3.06
54	218	13	148	60	5	2	1	2	3.82	3.39
55	257	16	175	75	2	3	1	1	4.60	4.02
56	241	17	171	59	5	2	3	1	4.34	3.78
57	256	16	175	74	5	1	0	1	4.52	4.00
58	249	16	172	69	3	2	1	2	4.41	3.87
59	294	19	200	85	4	3	1	1	5.24	4.63
60	278	20	200	68	5	2	1	2	4.86	4.28
61	217	12	150	61	1	2	3	0	3.85	3.41
62	198	13	135	55	5	2	0	1	3.52	3.08
63	247	14	175	62	5	3	0	2	4.29	3.80
64	258	15	170	77	6	1	0	4	4.53	4.08
65	266	17	182	77	6	0	0	1	4.68	4.12
66	278	17	191	80	4	2	1	0	4.82	4.30
67	249	16	178	65	5	0	0	1	4.38	3.85
68	298	20	210	76	7	3	0	2	5.25	4.63
69	247	15	164	68	7	2	1	5	4.52	3.92
70	239	15	162	69	4	1	2	1	4.22	3.74
71	258	18	184	66	4	0	2	2	4.49	4.03
72	258	17	173	73	7	3	2	0	4.59	3.98
73	209	13	136	69	1	2	0	1	3.78	3.32
74	310	20	214	80	5	4	2	5	5.47	4.87
75	253	20	175	70	4	3	0	1	4.51	3.99