

TECHNO-ECONOMIC ASSESSMENT FOR ROBOTICS-DRIVEN INSPECTION OF FLOATING OFFSHORE WIND FARMS

OLLSCOIL NA HÉIREANN, CORCAIGH

NATIONAL UNIVERSITY OF IRELAND, CORK



**Techno-economic assessment for robotics-driven
inspection of floating offshore wind farms**

Thesis presented by

Omer Khalid

for the degree of

Doctor of Philosophy

University College Cork
School of Engineering and Architecture

&

MaREI Centre, Environmental Research Institute

Supervisors: Prof. Guangbo Hao, Dr. Cian Desmond, Dr. Hamish Macdonald, Dr. Fiona Devoy McAuliffe

April, 2025

To my parents.

CONTENTS

List of Figures	xi
List of Tables	xiii
Declaration	xv
Acknowledgements	xvii
Abstract	xix
List of Outputs	xxi
Nomenclature	xxiii
1 Introduction	1
1.1 Background to the thesis	1
1.2 Rationale behind the thesis	2
1.3 Thesis objectives and scope	3
1.4 Thesis structure and the link between the chapters	5
1.4.1 Chapter 2	5
1.4.2 Chapter 3	5
1.4.3 Chapter 4	5
1.4.4 Chapter 5	7
1.4.5 Chapter 6	7
1.4.6 Chapter 7	7
2 Applications of robotics in floating offshore wind farm operations and main- tenance: Literature review and trends	9
2.1 Abstract	10
2.2 Introduction	10
2.3 O&M of Floating Offshore Wind Farms	11
2.3.1 Turbine O&M	13
2.3.2 Balance-of-Plant O&M	14
2.3.3 Logistics	15
2.4 Robotics for O&M of FOWFs	15
2.4.1 Climbing robots	20
2.4.2 Unmanned aerial vehicles	23
2.4.3 Subsea robots	24
2.4.4 Autonomous surface vessels	25

2.5	Potential areas of research	31
2.5.1	Future robotic systems	31
2.5.2	Design challenges	32
2.5.3	Market challenges	35
2.6	Conclusion	36
3	Cost-benefit assessment framework for robotics-driven inspection of floating offshore wind farms	39
3.1	Abstract	40
3.2	Introduction	40
3.3	Methodology	42
3.3.1	Cost estimation	42
3.3.2	O&M model	45
3.3.3	Residual risk	46
3.4	Application to a floating offshore wind farm	47
3.5	Results	47
3.5.1	Sensitivity analysis	50
3.5.2	Correlation matrix	51
3.6	Conclusion	53
4	Informed decision-making for investment in robotics-driven inspection of floating offshore wind farms: A real options approach	55
4.1	Abstract	56
4.2	Introduction	56
4.3	Methodology	58
4.3.1	Simulation	60
4.4	Results	64
4.5	Conclusion	65
5	UAV-based automated detection of wind turbine blade damages: Sequential evaluation of model training with thermal analysis	67
5.1	Abstract	68
5.2	Introduction	68
5.3	Methodology	69
5.3.1	Case study overview	70
5.3.2	Data collection	70
5.3.3	Model training	71
5.3.4	Thermal analysis	72
5.4	Results	75
5.5	Conclusion	77
6	Development of a systems engineering framework for the deployment of robotics-driven inspection of floating offshore wind farms	81
6.1	Abstract	82
6.2	Introduction	82
6.3	MBSE model	84
6.3.1	System definition	84

6.3.2	System design	84
6.3.3	Failure modes and effects analysis	91
6.4	Conclusion	91
7	Conclusion	95
7.1	Conclusions to the thesis objectives.	95
7.2	Critical reflection	97
7.3	Recommendations and future research	98
	Bibliography	101
	Appendix	117

LIST OF FIGURES

1.1	Thesis outline and the link between the chapters.	6
2.1	Illustration of the multi-robot platform based inspection of FOWE	15
2.2	Number of publications and patents granted in the domain of robotics in the oil and gas sector [38].	17
2.3	Publication trends of ROVs and UAVs for offshore O&M.	18
2.4	Research pertaining to robotics for O&M, rectangular areas (grayed): widely investigated. Elliptical areas (with filled color): possible research gaps. . .	19
2.5	Sensors needed to control a typical robotic system and those needed to conduct the O&M task.	20
2.6	An illustration of the size and mass of the climbing robots, UAVs, and ROVs. All the values are indicative and serve only as a guide to scale different systems. Images courtesy: ROVCO and Creative commons.	21
2.7	ALFUS framework applied to the UAV-based inspection of turbine blades.	22
2.8	Climbing robot from Rope Robotics [117]. A similar system is offered by BladeRobots from Vestas [172].	22
2.9	Class II ROV from [94].	26
2.10	Class I ROV from [71].	26
2.11	Research outlook for the adoption of robotics in O&M.	32
2.12	Sea-kit Maxlimer ASV recovering the HUGIN AUV. From [116].	33
2.13	SCAMP as proposed by [105].	34
3.1	Illustration of the multi-robot platform based inspection of a FOWE. Typical damages on the FOWF components are exhibited in green blocks. . . .	43
3.2	O&M model methodology. WOMBAT simulation adjusted from [129]. . . .	46
3.3	Component-wise OPEX breakdown. The category 'cables' include both array and export cables.	49
3.4	Residual risk plot. The dashed and dotted lines show the range where the MRP is a net positive and a net negative investment, respectively.	49
3.5	Sensitivity analysis for the OPEX metric. The dashed line show the preliminary OPEX which is selected as the reference for the sensitivity analysis. . .	52
3.6	Sensitivity analysis for the time-to-completion metric. The dashed line show the preliminary time-to-completion which is selected as the reference for the sensitivity analysis.	52
3.7	Correlation matrix of five key parameters. The red colours correspond to a positive correlation and the blue colours correspond to a negative correlation.	53

4.1	Decision tree diagram showing the relationships between the selected scenarios. For instance, the lines in red show a decision path for the full-autonomy scenario.	61
4.2	A box diagram showing overview of the real options analysis methodology.	62
4.3	Categorization of the autonomy levels (elaborated from [149]. The boxes in blue pertain to the four scenarios selected for this study.	62
4.4	Visualisation of the OREC O&M simulation model methodology.	62
5.1	Bellacorick Wind Farm in County Mayo, Republic of Ireland with the four inspected turbines highlighted in red.	71
5.2	A subset of the RGB images acquired from the UAV with various types of damages boxed in red.	74
5.3	Methodology for sequential evaluation.	75
5.4	ROI based thermal profile of the erosion on the blade shows a temperature differential of more than 1°C.	78
5.5	ROI based thermal profile of the discoloration on the rotor hub shows a relatively smaller temperature differential of 0.5°C.	78
5.6	ROI based thermal profile of the vent hole on the rotor hub shows a relatively smaller temperature differential of 0.4°C.	79
6.1	Visualisation of the software architecture for robotics-driven inspection of FOWFs.	87
6.2	Risk matrix capturing relationships among the system size and the 14 cost drivers.	90

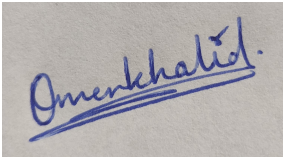
LIST OF TABLES

2.1	Classification of ROVs	25
2.2	Autonomy level classification as presented by [82]	27
2.3	Application of robotics for key FOWF-specific O&M activities	29
3.1	Estimation of day-rate for the multi-robot platform (MRP)	45
3.2	Specification of the FOWF	48
3.3	WOMBAT simulation input parameters	50
3.4	OPEX and time-to-completion variation between baseline and MRP cases	51
4.1	Simulation input parameters.	59
4.2	FOWF parameters.	63
4.3	Calculation of option values for the three decision paths of full autonomy, full autonomy - staged and semi-autonomy.	63
4.4	Option values for the cases of learning rates variation and biannual inspection.	64
5.1	Specification of the wind farm.	72
5.2	Hardware and software specification of the computer system.	72
5.3	Performance metrics for the DL-based model training.	77
6.1	Identification of the system requirements and approaches with respect to the major building blocks pertaining to the robotics-driven inspection of floating offshore wind farms.	85
6.2	Expert elicitation group's professional composition and area of expertise.	88
6.3	FMEA table with RPN calculation.	93

DECLARATION

This is to certify that the work presented in the thesis chapters is conceptualized, investigated, and written by me. The supervisors provided guidance and reviewed the submitted work. Dr. Aubryn Cooperman provided administrative and research support for my secondment at the National Renewable Energy Laboratory (NREL) in the United States. Dr. Cian Desmond supported me by arranging meeting with Bord na Mona, and by procuring the services of a supplier for imagery data acquisition from the Bellacorick wind farm.

This is to certify that the work I am submitting is my own and has not been submitted for another degree, either at University College Cork or elsewhere. All external references and sources are clearly acknowledged and identified within the contents. I have read and understood the regulations of University College Cork concerning plagiarism and intellectual property.

A handwritten signature in blue ink, reading "Omenkhatid.", is written on a light-colored, textured surface. The signature is underlined with two parallel blue lines.

10/04/2025

ACKNOWLEDGEMENTS

Firstly, a heartfelt thank you goes to my family, whose consistent support has been the backbone of my journey. Their unconditional love, understanding, and encouragement have provided me with the strength and resilience needed to overcome the many challenges faced during this endeavor.

The completion of this PhD thesis would not have been possible without the unwavering support and encouragement from numerous individuals who have guided and assisted me throughout this journey.

I would like to extend my deepest gratitude to my academic supervisor, Professor Guangbo Hao, whose expert guidance, insightful feedback, and persistent encouragement have been pivotal in shaping this research. His dedication towards pursuing excellence and his patience in addressing my numerous questions have been invaluable. It would not have been possible to complete this arduous, at times unassailable yet rewarding journey, without your consistent support.

I am equally indebted to my industrial supervisors, Cian Desmond and Hamish Macdonald, whose expertise and practical insights have significantly enriched this work. Their support has not only enhanced the quality of this research but has also shaped up my professional ethos.

I would also like to thank Aubryn Cooperman for facilitating my visit to the National Renewable Energy Laboratory (NREL) in Denver, U.S., and giving me valuable feedback on the manuscript preparation.

I would like to thank my STEP4WIND fellows for being a constant source of encouragement throughout the course of the PhD. The time we spent together made the otherwise onerous journey a valuable and pleasant experience.

Lastly, I would like to thank the European Union Horizon 2020 Research and Innovation Programme for making this PhD possible under the Grant Agreement No. 860737.

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Wind Energy Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

ABSTRACT

The floating offshore wind farm (FOWF) industry is poised for substantial growth, necessitating efficient operations and maintenance (O&M) practices. There is an ever-evolving need to overcome operational challenges such as restricted weather windows, long-distance logistical strategies, and the need for cost-effective and feature-rich data acquisition. This thesis explores the integration of robotic systems into the FOWF-specific O&M activities from a techno-economic perspective, revealing several key insights. Robotic systems such as unmanned aerial vehicles (UAVs) and remotely operated vehicles (ROVs) can provide several benefits in terms of enhancing the O&M vector. These include improved safety and efficiency for longer duration missions and operability under harsh weather conditions, while advanced sensors and data acquisition technologies, such as thermographic cameras, provide feature-rich data as compared to the traditional manned visual inspections. AI and data-driven approaches can improve resource management and asset availability through automated data gathering and retrieval, and modular designs of climbing robots and UAVs equipped with mission-specific sensors can further aid in carrying out various inspection tasks.

This thesis explores the use of the WOMBAT tool, and devises a cost estimation framework for an offshore multi-robot platform (MRP) inspecting a large-scale FOWF highlighting potential cost and inspection time reductions. Furthermore, key variables are identified that impact operational expenditure (OPEX) and time-to-completion, suggesting initial utilization of fewer MRPs to balance costs and the inspection duration. Furthermore, simulations incorporating unmanned surface vehicles (USVs), ROVs, and UAVs for FOWF inspections indicate long-term cost savings from early adoption of higher autonomy levels, with real options analysis (ROA) emphasizing flexible investment approaches to adapt to market dynamics. The ROA demonstrates the strategic advantage of adopting higher autonomy levels earlier in a project's lifecycle, emphasizing the importance of flexible investment approaches in the face of market and technological uncertainties.

The cost-benefit analysis has been complemented with assessing the technical feasibility of UAV-based automated detection of wind turbine blade damages. Performance evaluation using visible and thermal imaging shows significant benefits, with thermal imaging identifying deeper structural erosion on the blades and combined imaging modalities effectively assessing damage severity. Lastly, a model-based systems engineering (MBSE) framework for deploying robotics-driven FOWF inspections is presented. This framework integrates system requirements with software and hardware design, facilitating end-to-end traceability and coherence. Identifying potential deployment roadblocks, such as system requirements and architecture, along with prioritizing risk mitigation efforts through failure modes and effects analysis (FMEA), inculcates the importance of incorporating advanced robotic systems in the FOWF sector, in a holistic manner. This thesis supports the integration of these methodologies to enhance the integrity

and reliability of the FOWF infrastructure, and hence, contributes towards the overall economical and environmental sustainability efforts.

LIST OF OUTPUTS

Journal Publications:

1. Chapter 2:

O. Khalid, G. Hao, C. Desmond, H. Macdonald, FD. McAuliffe, G. Dooly, W. Hu, *Applications of robotics in floating offshore wind farm operations and maintenance: Literature review and trends*, [Wind Energy](#). 2022;25(11):1880-1899.

- Publication selected for the cover image of the Issue 11 of the *Wind Energy* journal.
- Top Downloaded Article among work published in an issue between 1 January 2022 and 31 December 2022.

2. Chapter 3:

O. Khalid, G. Hao, H. Macdonald, A. Cooperman, FD. McAuliffe, C. Desmond, *Cost-benefit assessment framework for robotics-driven inspection of floating offshore wind farms*, [Wind Energy](#). 2024;27(2):152-164.

3. Chapter 4:

O. Khalid, G. Hao, H. Macdonald, FD. McAuliffe, C. Desmond, *Informed decision-making for investment in robotics-driven inspection of floating offshore wind farms: A real options approach*, prepared for submission to the NAWEA/WindTech Conference 2025.

4. Chapter 5:

O. Khalid, G. Hao, H. Macdonald, FD. McAuliffe, C. Desmond, *UAV-based automated detection of wind turbine blade damages: Sequential evaluation of model training with thermal analysis*, prepared for submission to the special issue *Operations and Maintenance (O&M) of Offshore Renewable Energy (ORE) Devices Using Marine Vehicles and Drones* of the *Drones* journal of MDPI.

5. Chapter 6:

O. Khalid, G. Hao, H. Macdonald, FD. McAuliffe, C. Desmond, *Development of a systems engineering framework for the deployment of robotics-driven inspection of floating offshore wind farms*, prepared as a policy paper for presentation to the *Offshore Wind Conference 2025* by Wind Energy Ireland on 27 May, 2025.

Presentations:

1. **O. Khalid**, G. Hao, C. Desmond, H. Macdonald, *Applications of robotics in floating offshore wind farm operations and maintenance*, Wind Energy Science Conference, Hannover, Germany, 26th May, 2021.

2. **O. Khalid**, G. Hao, C. Desmond, H. Macdonald, *Development of a cost modelling framework for robotics-driven inspection of floating offshore wind farms*, Wind Energy Ireland, Annual Conference, Dublin, Ireland, 13th April, 2022.
3. **O. Khalid**, G. Hao, C. Desmond, H. Macdonald, A. Cooperman, *Cost-benefit analysis of robotics-driven operations and maintenance for a floating offshore wind farm*, NAWEA WindTech Conference, Delaware, USA, 28th September, 2022.

Industrial reports:

1. **O. Khalid**, *UK Offshore Wind 2023 Round-up and 2024 Outlook*, <https://ore.catapult.org.uk/blog/uk-offshore-wind-2023-round-up-and-2024-outlook/>.
2. B. Jenkins, **O. Khalid**, C. Twaddle, *PR43: Application of Remote and Autonomous Systems (RAS) for FOW Construction, Installation, Operations and Maintenance Activities*, <https://fowcoe.co.uk/wp-content/uploads/2024/04/PN000614-DOC-008-Rev-1-PR43-Public-Summary-Report.pdf>

NOMENCLATURE

AEP	Annualized Energy Production
ASV	Autonomous Surface Vessel
AUV	Autonomous Underwater Vehicle
BoP	Balance of Plant
BVLOS	Beyond Visual Line Of Sight
CAPEX	Capital Expenditure
CNN	Convolutional Neural Network
CRL	Commercial Readiness Level
CTV	Crew Transfer Vessel
FMEA	Failure Modes and Effects Analysis
FOWF	Floating Offshore Wind Farm
H&S	Health and Safety
LCOE	Levelized Cost Of Energy
MBSE	Model-Based Systems Engineering
MRP	Multi-Robot Platform
O&M	Operations and Maintenance
OPEX	Operational Expenditure
OREC	Offshore Renewable Energy Catapult
PBA	Production Based Availability
RAS	Robotics and Autonomous Systems
ROA	Real Options Analysis
ROV	Remotely Operated Vehicle
RPN	Risk Priority Number
SOV	Service Operations Vessel

TRL	Technology Readiness Level
UAV	Unmanned Aerial Vehicle
USV	Unmanned Surface Vehicle
VLOS	Visual Line Of Sight
WOMBAT	Windfarm Operations and Maintenance cost-Benefit Analysis Tool
WTG	Wind Turbine Generator

1

INTRODUCTION

1.1. BACKGROUND TO THE THESIS

This thesis is conducted as part of the **STEP4WIND (Novel deSign, production and operation approaches for floating WIND turbine farms)** project. STEP4WIND is a European Industrial Doctorate programme, granted under the H2020 Marie-Curie Innovative Training Network initiative (H2020-MSCA-ITN-2019, grant agreement 860737). The overarching objective of the project is to address both technological and economical challenges related to the development of floating offshore wind farms (FOWFs). The work contained in this thesis pertains to the Work Package 3: Operations and Scalability, wherein the aim is to assess the incorporation of robotics for operations and maintenance (O&M) of FOWFs from a technical and commercial perspective. The thesis also presents the work carried out at the Offshore Renewable Energy Catapult (OREC), UK's leading technology innovation and research centre for offshore renewable energy sector. OREC, as a beneficiary, has supported the work by providing with supervisory, software and cost modeling support during the course of the PhD. Furthermore, the PhD included a four months visiting researcher stint to the National Renewable Energy Laboratory (NREL) in the U.S., which provided support with the cost modeling tool and research manuscript preparation.

The deployment of FOWFs is gaining traction as it provides an opportunity to not only exploit stronger winds and larger farm sizes but also contribute towards the Net Zero ambitions [1]. Compared to the bottom-fixed offshore wind turbines which are limited to shallow coastal waters, floating turbines can be located further offshore and in deeper waters with stronger and more consistent winds. This allows for large-scale wind farms to be developed, as there are fewer spatial constraints [2]. Additionally, the farther offshore locations mitigate concerns over visual pollution and disruption to coastal activities like shipping or fishing. While floating offshore wind is still an industry in its infancy, rapid technological innovations and cost reductions are making it an increasingly viable option. With the potential for higher energy yields and minimized conflicts with competing interests, FOWFs have the opportunity to make major contributions to the renewable energy sector worldwide [3].

However, conducting O&M of FOWFs poses unique technical and commercial challenges. Periodic turbine maintenance and repairs require dispatching technicians and equipment over long distances offshore, via crew transfer vessels (CTVs) and service operation vessels (SOVs). This leads to higher O&M costs compared to onshore or nearshore wind farms [4]. Furthermore, the replacement of defective components and their transport from offshore sites to the port results in even higher costs. Redundancy of critical electrical and control systems and their continuous monitoring is important to minimize losses from unexpected failures. Advanced condition monitoring and predictive maintenance coupled with remote access can optimize O&M scheduling and reduce costs. With proactive planning, innovation and systems engineering, O&M strategies can be designed to maximize time-based and production-based availability along with the profitability of FOWFs [5].

The incorporation of Robotics and Autonomous Systems (RAS) for conducting O&M of offshore energy assets have been the center of research in recent years [6]. Studies have shown the impact of robotics-driven inspection wherein the benefits of feature-rich data extraction along with improved health and safety (H&S) aspects can be reaped [7]. The use of unmanned aerial vehicles (UAVs) and remotely operated underwater vehicles (ROVs) has great potential to make O&M of FOWFs more efficient and cost-effective [8]. UAVs equipped with cameras and sensors can regularly inspect blades, while ROVs can monitor subsea components including hard-to-access areas such as cable spans and foundations. Drones and underwater robots can expedite repairs and mitigate the risks of sending human technicians and divers offshore [9]. Moreover, advancements in autonomy levels, control systems and swarm robotics can enable continuous inspection and remote monitoring of offshore components. By reducing the need for offshore transport vessels and manual labor, RAS are poised to transform O&M in floating wind farms.

1.2. RATIONALE BEHIND THE THESIS

In order to assess the challenges pertaining to the automation of O&M for FOWFs with an emphasis on cost reduction, this thesis primarily sets out to investigate and advance upon the techno-economic viability of the incorporation of robotic systems. Furthermore, this thesis aims to develop a framework for cost-benefit analysis of robotics-driven O&M with a focus on identifying key cost and performance metrics along with devising recommendations for the commercialization of such systems.

As research and growth of the large-scale FOWF's advances on, conducting a comprehensive techno-economic evaluation of robotic systems tailored for FOWF inspection and maintenance is of paramount importance. Firstly, it enables a thorough understanding of the technological readiness and maturity of these systems, identifying their capabilities, limitations, and potential for adaptation or advancement [10, 11]. By meticulously analyzing the current state of robotic technologies applicable, researchers can identify areas requiring further development or innovation, facilitating targeted efforts to enhance system performance, robustness, and reliability. Moreover, this assessment paves the way for the identification of optimal deployment strategies, ensuring seamless integration of robotic systems with existing offshore infrastructure and operations. Secondly, a rigorous techno-economic assessment is crucial for quantifying the economic viability and potential cost savings associated with the adoption of robotic

systems [12, 13]. The offshore wind industry operates in a highly capital-intensive environment, where minimizing operational expenditure and maximizing asset utilization are paramount. By conducting a comprehensive cost-benefit analysis, researchers can evaluate the financial implications of deploying robotic systems, including potential cost savings achieved through reduced downtime, enhanced maintenance efficiency, and extended asset lifecycle. This analysis can provide valuable insights for stakeholders such as O&M vendors, enabling informed decision-making and facilitating the development of business cases that justify the investment in robotic technologies. Furthermore, the incorporation of robotic systems holds the promise of significantly enhancing safety standards in FOWF operations. Traditional human-centric inspections and maintenance activities in the harsh offshore environment expose personnel to numerous risks, including hazardous weather conditions, working at heights, and the potential for accidents or injuries. Robotic systems can mitigate these risks by performing tasks autonomously or remotely, reducing the need for human intervention in high-risk scenarios [14, 15]. This not only safeguards the well-being of personnel but also minimizes the potential for costly operational disruptions resulting from accidents or injuries.

Additionally, the potential for reduction in operational downtime by deploying robotic solutions and the cumulative effect on costs needs to be thoroughly investigated [16]. By enabling more frequent and comprehensive inspections, robotic systems can facilitate early detection of potential issues or defects, allowing for proactive maintenance and preventive measures. This proactive approach can extend the lifecycle of critical components, minimizing the need for reactive maintenance and unplanned shutdowns, which can be costly and disruptive [17]. Moreover, robotic systems can be designed to operate in adverse weather conditions, enabling continuous monitoring and maintenance activities even during periods when human intervention may be impractical or unsafe. Lastly, the lessons learned from this research can contribute to technology de-risking and pave the way for the broader commercialization of robotic systems in the floating offshore wind sector. By identifying and addressing technical and economic challenges, perceived risks associated with adopting these innovative technologies can be mitigated, fostering confidence among industry stakeholders. The development of a framework for cost-benefit analysis and the formulation of recommendations tailored to the commercialization of robotic systems can serve as a guiding resource, facilitating the widespread adoption of these technologies and driving the industry towards more efficient, safer, and sustainable operations.

1.3. THESIS OBJECTIVES AND SCOPE

The binding thread of the thesis aims to assess the incorporation of robotics for the O&M of FOWFs from a techno-economic perspective. Based on the rationale presented in the previous section, the following research questions have been devised for this study:

- **RQ-1.** What is the state-of-the-art in the incorporation of robotics-based O&M of FOWFs and what are the key enablers and barriers pertaining to it?
- **RQ-2.** What are the techno-economic benefits and limitations in automating the inspection of FOWFs?

- **RQ-3.** How the costs associated with deploying robotic systems can be captured, and what are the key parameters that affect these costs?
- **RQ-4.** What is the feasibility for UAV-based damage detection on wind turbine blades?
- **RQ-5.** What techno-economic insights can be gained to aid the the policy making vector and enhance the robotic systems' adoption in the FOWF domain?

Accordingly, the thesis objectives and the scope has been identified as follows:

- Investigate the state-of-the-art in the incorporation of robotics for O&M of FOWFs (**RQ-1, RQ-5**).
 - Analyze different types of offshore marine robotic systems such as climbing robots, UAVs, and ROVs, and compare them in terms of their techno-economic performance.
 - Identify main challenges and limitations associated with using robotics for the inspection of FOWFs.
 - Conduct an extensive literature review and identify potential areas of research from a technical and commercial perspective.
- Conduct cost-benefit assessment for robotics-driven inspection of FOWFs (**RQ-2, RQ-3**).
 - Develop a methodology for the estimation of cost parameters of a multi-robot platform inspecting various components of a FOWF
 - Compare the performance metrics of MRP with those of the traditional manned inspection method.
 - Conduct sensitivity analysis in order to identify key cost drivers.
- Develop a methodology for investment in robotics-driven inspection of FOWFs to inform decision-making (**RQ-2, RQ-3**).
 - Capture the uncertainty in cost estimation considering technical and commercial factors.
 - Develop a decision-making framework based upon different autonomy levels of the robotic systems.
 - Examine different investment scenarios and assess their feasibility.
- Investigate the feasibility of UAV-based automated damage detection on turbine blades based upon operational wind farm data (**RQ-4**).
 - Acquire and post-process visible and thermal imagery data from an operational wind farm.
 - Devise a model training and thermal analysis methodology to detect damages on the blades.

- Evaluate performance parameters for the damage detection.
- Evaluate the policy-making vector for RAS in the floating offshore wind domain from a systems engineering perspective (**RQ-5**).
 - Identify system requirements for the marine based RAS.
 - Investigate barriers for the adoption of robotic systems based upon expert elicitation.
 - Conduct system-level risk assessment.
 - Derive insights from the analysis and make recommendations to aid the policy-making vector.

1.4. THESIS STRUCTURE AND THE LINK BETWEEN THE CHAPTERS

This has been set up as a publication-based thesis wherein the next five chapters consists of research papers that pertain to the aforementioned thesis objectives. A flow chart delineating the thesis structure is shown in Figure 1.1. A summary the thesis chapters is given below, describing their content and the links between them.

1.4.1. CHAPTER 2

This research paper, published in the *Wind Energy* journal and presented as Chapter 2 of the thesis, investigates the state-of-the-art in the applications of robotics for operations and maintenance of floating offshore wind farms. Four different kinds of robotic systems have been presented namely climbing robots, unmanned aerial vehicles, sub-sea robots and autonomous surface vessels. Furthermore, challenges pertaining to the system design and commercialization have been investigated with an aim to identify potential areas for future research.

1.4.2. CHAPTER 3

Having reviewed the start-of-the-art, Chapter 3 focuses on the development of a cost-benefit assessment framework for robotics-driven inspection of FOWFs wherein a detailed methodology for estimating the costs of a multi-robot platform is presented. This is followed by the full lifecycle simulation conducted in the WOMBAT model, where the metrics of the incurred operational expenditure (OPEX) and inspection time are calculated and compared with those of a baseline case. Furthermore, sensitivity analysis is conducted to identify the key cost drivers affecting the performance metrics. This paper is published in the *Wind Energy* journal.

1.4.3. CHAPTER 4

This work builds up upon the Chapter 3 and delves deeper into the robotics-driven inspection of FOWFs from a decision-making lens. In order to assess the variation in OPEX under different autonomy scenarios and project's temporal duration, real options analysis has been leveraged with an aim to identify optimal scenarios under which the invest-

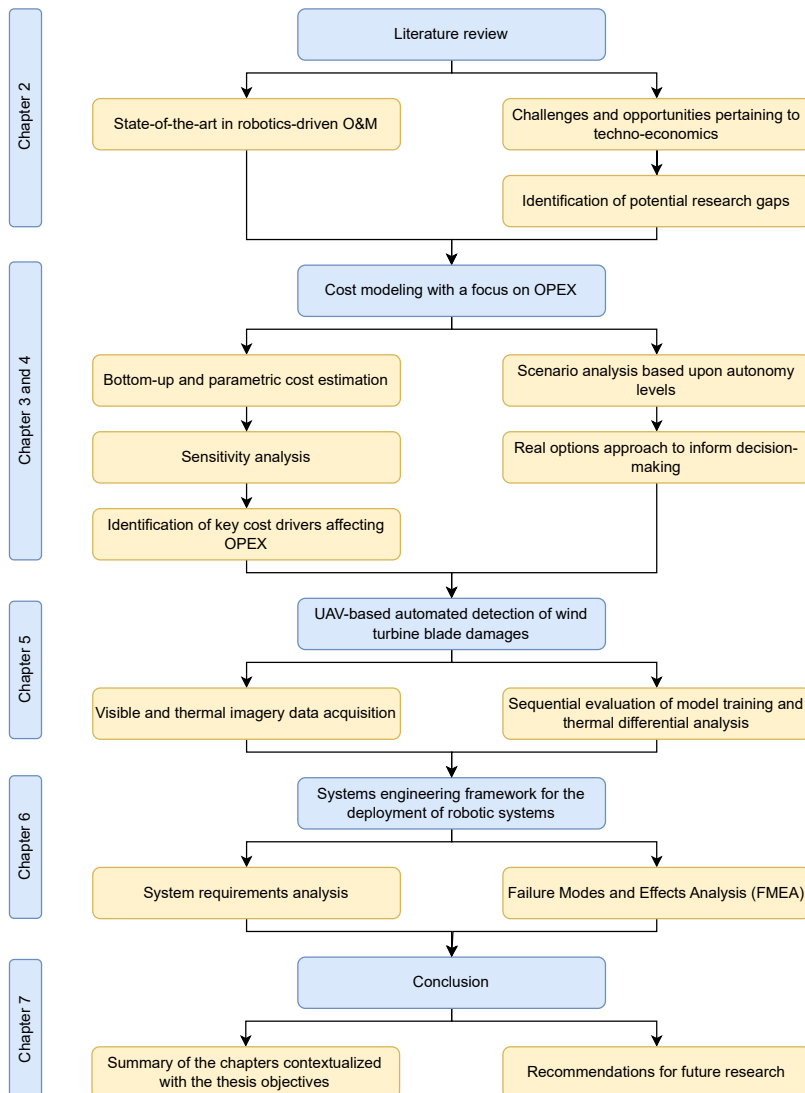


Figure 1.1: Thesis outline and the link between the chapters.

ment in capital-intensive robotic systems would yield the maximum return. This paper will be submitted to the *Energies* journal by MDPI.

1.4.4. CHAPTER 5

In order to assess the operational feasibility of UAV-based inspection of wind turbines, Chapter 5 presents the development of an innovative methodology for the automated detection of blade damages. Imagery data including visible and thermal images is acquired from the turbines of an operational wind farm. Two detection approaches based upon model training and thermal analysis have been employed in a sequential manner, and results are evaluated based upon their respective detection performance. This paper will be submitted to the special issue *Operations and Maintenance (O&M) of Offshore Renewable Energy (ORE) Devices Using Marine Vehicles and Drones* of the *Drones* journal by MDPI.

1.4.5. CHAPTER 6

Chapter 6 delves into the policy-making domain, wherein a model-based systems engineering framework, underpinned by the expert elicitation, is presented for the deployment of robotics-driven inspection of FOWFs. A high-level concept including system definition, design and risk assessment is presented wherein, the key enablers and blockers for the development and commercialisation of such a system have been highlighted, based on the findings from the techno-economic analysis conducted in the previous chapters. This policy paper is prepared for submission to the *Cleaner Energy Systems* journal by Elsevier.

1.4.6. CHAPTER 7

Lastly, Chapter 7 presents the conclusions drawn from the preceding chapters of the thesis. The concluding remarks from all the previous chapters have been presented in an overall summary format. Furthermore, key recommendations and directions for future research in this domain have been highlighted.

2

APPLICATIONS OF ROBOTICS IN FLOATING OFFSHORE WIND FARM OPERATIONS AND MAINTENANCE: LITERATURE REVIEW AND TRENDS

Omer Khalid ^{1,2,3}, Guangbo Hao ², Cian Desmond ⁴, Hamish Macdonald ³, Fiona Devoy McAuliffe ¹, Gerard Dooly ⁵, Weifei Hu ⁶

¹ MaREI Centre, Environmental Research Institute, University College Cork, Cork, Ireland

² School of Engineering and Architecture-Electrical and Electronic Engineering, University College Cork, Cork, Ireland

³ Offshore Renewable Energy Catapult, Glasgow, UK

⁴ Gavin and Doherty Geosolutions, Dublin, Ireland

⁵ Centre for Robotics and Intelligent Systems (CRIS), University of Limerick, Limerick, Ireland

⁶ State Key Laboratory of Fluid Power and Mechatronic Systems, School of Mechanical Engineering, Zhejiang University, Hangzhou, China

CHAPTER OVERVIEW

This chapter consists of a research manuscript which has been published in the Wind Energy journal by Wiley. The publication can be accessed on the following link: <https://doi.org/10.1002/we.2773>. In this publication, an extensive study has been conducted to understand the state-of-the-art in the incorporation of different kinds of robotic systems for conducting O&M of FOWFs, with a focus on identifying key enablers and barriers from a technical perspective.

CONTRIBUTION

Omer Khalid: Conceptualization, Investigation, Methodology, Formal analysis, Writing – original draft, Visualization. **Guangbo Hao:** Supervision, Validation, Writing – review & editing. **Cian Desmond:** Writing – review & editing, Project administration, Funding acquisition. **Hamish Macdonald:** Writing - review & editing, Project administration, Resources, Supervision. **Fiona Devoy McAuliffe:** Writing - review & editing, Supervision. **Gerard Dooly:** Writing - review & editing. **Weifei Hu:** Writing - review & editing.

2.1. ABSTRACT

Marine operations required to transfer technicians and equipment represent a significant proportion of the total cost of offshore wind. The profile of sites being considered for floating offshore wind farms (FOWFs), e.g., further from the shore and in harsher environments, indicates that these costs need to be assessed by taking into account the maintenance requirements and restricted weather windows. There is an immediate need to investigate the potential use of robotic systems in the wind farm's operations and maintenance (O&M) activities, to reduce the need for costly manned visits. The use of robotic systems can be critical, not only to replace repetitive activities and bring down the levelised cost of energy but also to reduce the health and safety risks by supporting human operators in performing the desired inspections. This paper provides a review of the state of the art in the applications of robotics for O&M of FOWFs. Emerging technology trends and associated challenges and opportunities are highlighted, followed by an outline of the agenda for future research in this domain.

2.2. INTRODUCTION

The deployment of floating offshore wind turbines is gaining traction as their potential installation locations provide the opportunity to exploit stronger winds and larger farm sizes, while also reducing the prevailing conflicts of interests with other factors such as societal acceptance and visual impact [18]. However, maintaining floating offshore wind farms (FOWFs) to allow them to perform at their optimal level for over 25 years of service can account for 29.5% of the total lifecycle cost [19]. It has been estimated that the operations and maintenance (O&M) of onshore wind turbines account for about 25–30% of the total lifecycle cost of wind turbines, and in the case of offshore turbines, the costs are even higher, in the range of 30–35% [19, 20].

The O&M activities for FOWFs involve inspecting and maintaining components of the wind turbines and their subsystems to prevent and address faults. O&M activities on the turbine blades are typically performed by rope-access technicians, often working in extreme conditions and during restricted weather windows. The duration of turbine downtime and hence the lost energy production can be considerable, while the use of crew transfer vessels (CTVs) and service operation vessels (SOVs) also makes up a significant proportion of the wind farm O&M costs [21]. The O&M of FOWFs poses significant technological and economical challenges pertaining to asset downtime, operational expenditure (OPEX) incurred, data quality, and fault diagnosis and prognosis.

Recent advances in the development of offshore robotics have opened up new opportunities for deploying semi or fully autonomous systems for the O&M of offshore

wind farms [22]. Incorporating robotic systems offshore can not only improve the assets' reliability but could also reduce costs and mitigate the health and safety (H&S) risks associated with deploying human operators to offshore sites with harsh weather conditions. In recent years, a host of new projects has focused on the autonomous inspection and maintenance of offshore wind turbines [23].

While robotic systems are predominantly relevant to the O&M activities, their applications are not limited to this domain. These systems are also being utilised in the manufacturing of turbine components, although this falls outside the scope of this thesis. Robotic systems in manufacturing offer potential in processes such as blade assembly, painting, and coating [24]. For example, precision-tooled manipulator systems can be deployed to manufacture intricate components inside turbine blades along with polishing the blade surfaces. These systems can improve production efficiency, ensure consistency, and reduce manual labor costs [25, 26]. More complex systems such as automated fiber placement (AFP) robots can precisely lay down composite materials following predetermined paths, ensuring consistent material distribution and structural integrity [27]. These robots can work in confined spaces within the blade structure, accessing areas that would be challenging for human workers to reach consistently.

This review paper gives an overview of the state-of-the-art in the application of robotics-driven O&M for FOWFs with the objectives of the following:

1. Identifying O&M tasks that could be performed or supported by the robots.
2. Determining the technical feasibility of incorporating different types of robots in the FOWF environment.
3. Discussing challenges and future trends to make the robotics-based O&M commercially viable.

The paper is structured as follows: Section 2 gives an overview of the O&M activities associated with FOWFs. Section 3 presents the applications of robotics for conducting O&M and an overview on the existing use-cases. Four robotic systems are presented here, namely, climbing robots, aerial robots, subsea robots, and autonomous vessels. In Section 4, potential areas of future research are presented and segmented into future robotic systems, design, and market challenges. This is followed by the conclusion in Section 5.

2.3. O&M OF FLOATING OFFSHORE WIND FARMS

In the wind power industry, the expression O&M is often used in reference to a broad set of activities including, but not limited to, administration, insurance, land leasing, civil works, and the wider asset management. In the context of this review paper, a slightly narrower definition is employed which pertains to activities associated with enhancing the performance and reliability of components and assets with an overall aim of increasing the production-based availability of FOWF. These activities include performing preventive and corrective maintenance, inspection, surveys, and conducting condition monitoring of various components and assets. Such activities are typically included in the scope of O&M contracts for wind farm operators with an aim to maintain the asset

following its installation and during its entire operational phase [28]. The primary objectives of O&M are to ensure asset availability for smooth energy production and preserve equipment lifetime, while also taking into consideration the H&S aspects of the employees involved.

FOWF-specific O&M activities: Industry-wide studies [29, 30] have identified different FOWF-specific O&M activities. It is pertinent to mention that the floating wind industry is still in its infancy, as compared with bottom-fixed, and these activities may be adapted as lessons are learned from more installations. These activities are associated with not only maintaining the wind turbine generator but also the floating platforms, mooring lines, anchors, and dynamic cables. For instance, annual surveys need to be conducted to inspect the condition of catenary moorings and drag anchors. Around once in every 5 years, moorings are raised to the surface for a detailed inspection. Furthermore, dynamic cables require regular visual inspection of bending stiffeners, transition joints, buoyancy modules, and marine growth. Floating platforms are designed to withstand weather conditions without failure for the duration of a turbine's lifetime; however, as with any other offshore structure, dynamic sea conditions may result in the occurrence of cracks. A number of factors exist that can affect the implementation strategies for O&M in the case of FOWFs. A few of them are summarized below:

1. Limited accessibility and dependance on weather windows: In order to reap the maximum benefits pertaining to energy generation, FOWFs are being deployed farther into the sea. The wind conditions at such locations are more suitable for higher and more consistent energy generation [31]. But this also brings about a host of challenges such as the difficulty to access the turbines for conducting preventive or corrective maintenance due to sparse availability of weather windows. The higher values of significant wave height at FOWF sites also constrain the O&M scheduling and logistics.
2. Increased loads: FOWF turbines are subjected to higher cyclic loads due to dynamic response of the turbine to wind and wave profiles. Hence, they are prone to more structural damage as compared to their onshore or bottom-fixed counterparts. The sub-systems such as foundation and mooring lines will also be subjected to harsher wave conditions which may have an effect on the individual component's lifecycle. Consequently, the inspection and maintenance activities need to be considered more often for these turbines.
3. Resource constraints: The resources needed to access FOWFs for conducting maintenance may be limited owing to further distances from the onshore facilities and depots. These include procuring and replacing spare components, and the vessel logistics of transporting them to the offshore sites within the available weather windows. Furthermore, harsher environmental conditions and the floating foundations make the tasks more complex and time-consuming that can be challenging and risky for the personnel involved.
4. O&M costs: While the fixed O&M cost of a FOWF can be predetermined, the variable costs associated with transferring personnel and equipment to the offshore sites are subjected to the availability of weather windows, the type and duration of

repair, and the significant wave height. This brings about a corresponding increase in the costs associated with leasing of CTVs and SOVs. Furthermore, the risks associated with safety and well-being are higher at these locations, and as such, the insurance costs are dearer [32]. These factors culminate in an overall higher OPEX for the wind farm.

In case of a FOWF, the O&M activities can be divided into the three broader categories, namely, turbine, balance of plant (BoP), and the offshore logistics-related activities. The turbine includes the tower and the rotor-nacelle assembly, while the BoP constitutes the supporting structure needed to generate and export electricity from the turbine. The offshore logistics is an important aspect in a FOWF as there is a need to account for the transportation of equipment and personnel to offshore sites under restricted weather windows. These three categories are discussed in detail below.

2.3.1. TURBINE O&M

The O&M activities associated with the turbine are centered around the tower, rotor blades, and the nacelle along with its mechatronic components. With the increasing capacity of wind farms in locations farther into the sea, the loading cycles on turbine and its sub-systems are envisaged to increase. Hence, the components are prone to be deteriorated frequently due to wear, corrosion, and fatigue. Various research studies have focused on both designing robust and motion-compensated platforms to access offshore wind turbines, and optimizing the scheduling and planning of maintenance activities, in order to maximise turbine availability and reduce costs [33]. In general, maintenance is defined to be either proactive or reactive in nature. The former relates to the preventive maintenance that is performed to mitigate the occurrence of a component or system failure in the future. Reactive or corrective maintenance is based on the repairing or replacement of a component or system when the damage, fault, or failure has already occurred. These can further be categorized as follows:

1. Scheduled / Preventive maintenance:

- Calendar based: a fixed number of inspections or repairs per a specified interval of time, conducted by the operator irrespective of the damage state of the components or system.

2. Corrective maintenance:

- Deferred: when a failure is expected to happen, and the maintenance is planned and conducted in advance of the failure occurrence.
- Immediate: when a failure occurs without any prior knowledge and the component or system needs to be put into idle mode or shut down for maintenance.

3. Predictive maintenance:

- Condition based: a repair or replacement is conducted based on the observed health of the component or system.

The prediction of faults before they occur through robust condition monitoring approaches can lead to significant reduction in the O&M costs. These approaches are based on analyses of specific measurements and aspects of operations such as fatigue analysis, strain measurement, thermal, and acoustic data. Recent advancements in sensors, data analytics, and the improvements in machine learning algorithms have opened up new opportunities for integrated and in-depth system analytics, whereby different types of data can facilitate informed and reliable decision-making.

In FOWF conditions, the rotor blades and tower are continuously stressed by the environmental conditions, such as temperature changes and structural degradation. Example maintenance activities in this case include visual inspection for damage detection on lightning receptors, blade cleaning, and resident sensors' installation. The nacelle houses the drivetrain along with its components such as the gearbox. Although the advent of direct drive generators has mitigated the typical gearbox related faults, the need to continuously monitor the components is still required. Here, the aim is to predict the faults in due time so that the Mean-Time-To-Repair (MTTR) can be minimized. Next to this, the health of the tower needs to be monitored continuously in order to reduce the occurrence of worst-case scenarios. This is important as the floating platform is subjected to increased stochastic loads due to dynamic response of the turbine to wind and wave profiles, which results in structural fatigue. Another region is the splash zone; section of the turbine that is intermittently in or out of seawater during the turbine's life-cycle. This results in increased cyclic wave loading and hence, corrosion related effects are prone to occur especially in high wave conditions [34]. Based on a structural health monitoring system, such effects can be visually observed in advance, and repairs can be arranged before they become catastrophic failures.

2.3.2. BALANCE-OF-PLANT O&M

In the context of FOWF-specific O&M, the term BoP includes the activities of the wind farm that do not pertain to the wind turbine. These include inspecting the turbine substructure, laying out and maintenance of mooring lines and power export cables, conducting site surveys, and attaining metocean data. An illustration of these activities in the context of the entire FOWF is shown in Figure 2.1. In principle, the O&M strategy for wind turbine and BoP is executed similarly, but the maintenance processes are considered differently. The impacts on performance, costs, and reliability for a wind turbine system or component failure are more localized, in contrast to the BoP related failure. The latter can result in significantly reduced availability of the wind farm, along with a resultant increased cost of energy [35]. With the advent of larger wind farms in more remote offshore conditions, the maintenance of BoP systems is even more crucial for the effective operation of wind farm, and ensuring the export of generated power.

For large-scale FOWF applications, it is important to achieve maneuverability in a congested subsea space in order to deploy and inspect subsea structures such as mooring lines. Offshore regulations require subsea inspection at a minimum of every 2–5 years, depending on the specific system. Apart from that, new mooring lines and anchors may need to be procured and installed over time. Some industry figures indicate that one in every 100 mooring lines needs to be replaced in a year. On a farm of 100 turbines with four to five mooring lines each, this would mean between four and five

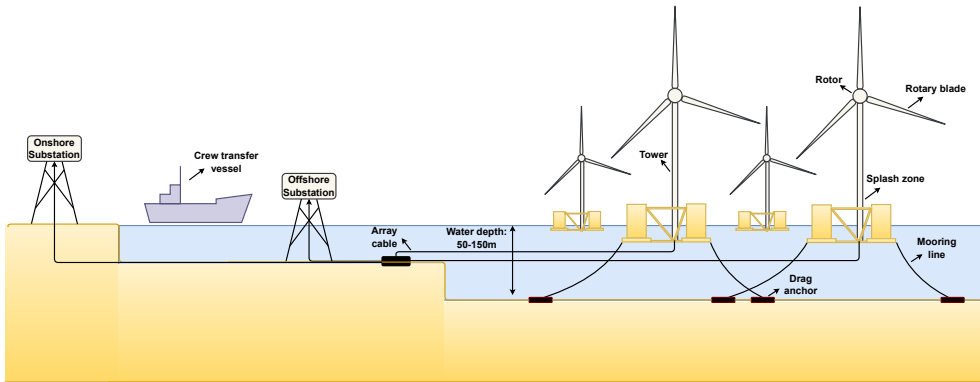


Figure 2.1: Illustration of the multi-robot platform based inspection of FOWE

mooring line replacements per year [36]. Finally, a robust maintenance strategy must be in place for emergency repair/replacement in response to worst case scenarios such as a mooring line breakage. Furthermore, geophysical and visual surveys need to be conducted after specific time intervals to comply with industrial and environmental standards.

2.3.3. LOGISTICS

In addition to the O&M activities related to the turbine and BoP, the transport of goods and personnel from onshore to the offshore sites and vice versa needs to be taken into account. Currently, most of these activities are based on CTVs which are used to transfer spare components, goods, and personnel to wind turbines and substations to perform both preventive and corrective maintenance. These are also utilized to perform asset protection and security operations for the wind farm. As the offshore developments are moving farther into the sea, SOVs are becoming increasingly relevant. In comparison to CTVs, they are larger in size and can carry heavier payloads along with staying at offshore locations for a longer duration of time. If larger or heavier components require installation or removal, then heavy lift vessels (HLVs), also known as jack-up vessels may be required. These are essentially crane barges that are towed to the desired site using tugboats. Jack-up vessels have higher day rates as compared to CTVs and SOVs, and are used for one-off charters to conduct corrective maintenance and repair of large components, e.g., turbine blades or generators. Recently, the use of helidecks is gaining traction on the offshore installations. These are mounted on turbines or the offshore vessels. The addition of offshore helidecks comes at higher financial expense but have benefits in terms of reducing transit times, providing greater accessibility, and complementing the vessel-based O&M activities [37].

2.4. ROBOTICS FOR O&M OF FOWFs

A significant increase in the adoption of robotics in the oil and gas sector has been witnessed in recent years. This has been motivated by the advanced automation capabili-

ties provided by the modern robots along with a reduction in the number of manhours needed in the rigs. This trend, obtained from GlobalData Patent Analytics [38], is depicted in Figure 2.2, where the number of publications and patents granted over the past 20 years show rising interest for robotics in the oil and gas sector. This could provide with an approximation of the future growth in robotic systems in FOWFs and other marine renewables, as the O&M facets of the two domains are similar.

Robotic systems offer various opportunities to significantly change the nature of the offshore operations, ranging from efficiently executing the otherwise repetitive tasks to attaining continuous and high-resolution data. Furthermore, the potential financial advantages and H&S-related benefits for the personnel onboard at offshore installations necessitate the need to minimize the manual human intervention. In recent years, the concept of remote inspection in industrial processes has also been gaining traction, whereby unmanned aerial vehicles (UAVs) and remotely operated vehicles (ROVs) are being utilized to access the machines and sites that are otherwise difficult or dangerous for humans to operate in. Prototype systems have been developed and tested for fault detection in pipelines [15, 39], subsea survey and repairs [40], and more recently for wind turbine inspections [41].

To conduct this review and to gain a holistic overview of the trends related to the applications of robotics for offshore wind farms, articles were retrieved from Web of Science (Clarivate Analytics) using the key search terms “offshore,” “O&M,” “UAV,” and “ROV” and filtered by year (>2000), access, citations, and relevancy. In order to extract key trends, a network visualization of these papers was created which is shown in Figure 2.3. Furthermore, three distinct clusters were observed where majority of the publications were related to optimization of maintenance activities for offshore wind farms. This was followed by a cluster of fault detection, and condition monitoring based on SCADA. The third cluster was focused on the control system design of UAVs for acquisition and analysis of imagery data. A visualization of the robotics-based O&M for FOWF and the potential research gaps is shown in Figure 2.4. Apart from the key highlights, it was observed that more focus is being diverted towards costs, investments, data analytics, and proactive fault detection of turbine and its sub-systems. While the asset management and condition monitoring have been extensively studied, more recently, the applicability of remote inspection and big data management have started gaining attention. This elaborates that the trends have been moving towards devising innovative O&M solutions with an aim to achieve higher efficiency and safety while reducing the levelized cost of energy (LCOE). Although there are different types of robotic systems present, they all need to fulfill certain requirements in order to successfully complete their mission given the FOWF-related site constraints previously stated in Section 2. These requirements are as follows:

1. **Mobility:** Mobility pertains to the motion of the robot in unstructured environments under difficult operating conditions and at speeds that allow for efficient acquisition of inspection data. For instance, the thruster technology of a subsea robot should be reliable and controllable where it should be able to do the required task in an efficient manner while also minimizing the possibility of a crash into the asset. For subsea robots, the propulsive efficiency remains a challenge. This is highlighted by [42] where it is shown that the subsea robots have to considerably

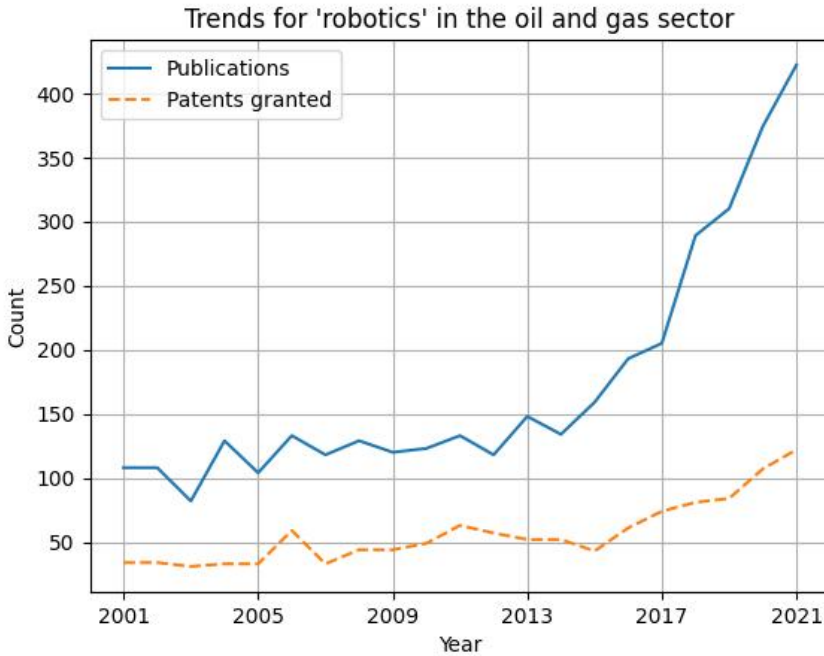


Figure 2.2: Number of publications and patents granted in the domain of robotics in the oil and gas sector [38].

increase their propulsive efficiency in order to navigate the waters like marine animals do. Simultaneously, the operational range of subsea robots also needs to increase for them to be useful for longer duration underwater monitoring activities. The design optimization on these two fronts has improved in recent years. For instance, [43] have demonstrated that a resonance-based squid-like robot can enhance the swimming speed and efficiency to an extent that is comparable to that of an aquatic organism. Moreover, the robot should be able to steer itself and maneuver to access the required part of the asset. For instance, the dexterity of the manipulator arm of a turbine climbing robot is a key aspect. In case of a UAV, the beyond-visual-line-of-sight (BVLOS) system is a crucial determinant in enhancing its operational capability.

2. Sensing capabilities: Another important requirement is the sensing capability of the robot. The sensors not only aid in navigation and control of the robot itself but also determine its operational capability in terms of conducting the remote or in-situ inspection of the asset, attaining feature-rich information, and performing non-destructive testing (NDT). Here, it is also important to assess the functionality of the sensors with respect to their operation in dynamic wind and wave conditions such as during foggy weather and in turbid sea water. Figure 2.5 illustrates

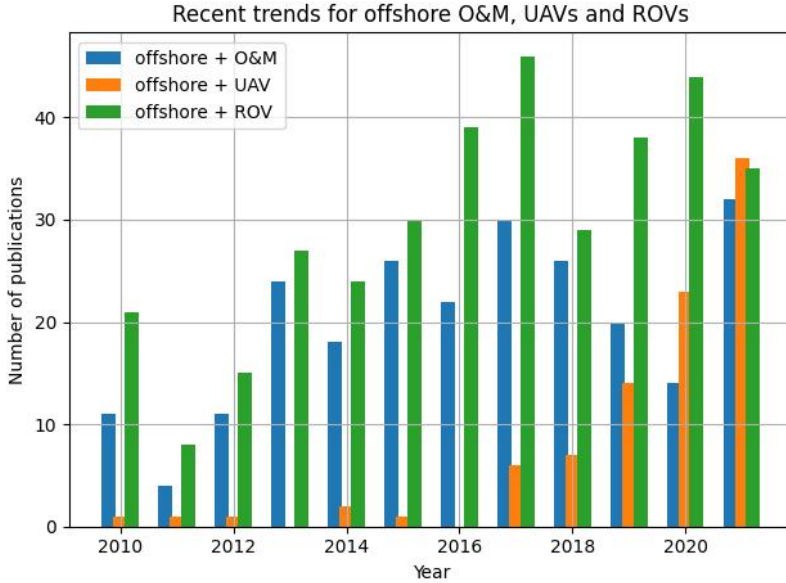


Figure 2.3: Publication trends of ROVs and UAVs for offshore O&M.

the key sensors needed to control a typical robotic system and those needed to conduct an O&M task by gathering data from a FOWF asset.

3. **Size and weight:** An important aspect of the offshore robots is their cumulative size and weight. The size of the robot should be large enough to accommodate the resident sensors and actuators/manipulators. Although keeping the robot small and light is desirable, it is also crucial to maximize the payload for various diagnostic instruments while maintaining ample power storage. This has ramifications in terms of power requirements and operational endurance of the mission. Hence, the cumulative weight of the robotic structure and its payload should be within the specified bounds where a trade-off has to be made between the operational requirements of the robot and weight bearing capacity of the entire system. Furthermore, there exist country-specific regulatory considerations for the particular sizes and weights of unmanned aerial systems [44]. In Figure 2.6, an illustration of the generic size and mass of different prototypes of climbing robots, UAVs, and ROVs is presented. While the actual values depend upon a variety of factors such as the operational requirements and the type of payload, the figure gives an indication about the relatively larger size of ROVs as compared to that of UAVs and climbing robots. This is partly due to the fact that ROVs have to navigate stronger currents and as such, require higher propulsive and power requirements, although the higher weight of ROVs becomes positively buoyant in the water.
4. **Level of autonomy:** The level of autonomy of the robot describes the automa-



Figure 2.4: Research pertaining to robotics for O&M. rectangular areas (grayed): widely investigated. Elliptical areas (with filled color): possible research gaps.

tion capability of the robot. For instance, Pilot Authorisation and Control of Tasks (PACT) framework distinguishes between the range of human support needed for various piloted systems [45]. Another framework is ALFUS [46], shorthand for Autonomy Levels for Unmanned Systems, which is a generic framework and applicable to multiple unmanned system domains. The key components of this framework are the metrics along the three established axes or aspects. An illustration of these aspects for the UAV-based inspection of turbine blades is shown in Figure 2.7. This scenario represents a relatively high complexity of the operational environment, while the human independence and mission complexity aspects are in the middle. The aspects of mission complexity, environmental complexity, and human independence together characterize the autonomy of a specific robotic system. Different commercially available robotic systems can lie along the three axes, the autonomy profile of which can be assessed for a specific O&M activity. The objective for an autonomous operation is to achieve the missions as assigned by its human operator(s) through the designated human-robot interaction mechanism. While the state of the art includes remote operation of UAVs and tethered control of subsea robots under human supervision, the focus has increasing been moving towards highly autonomous robotic systems. These robots are capable to

carry out asset inspection for extended duration of time and without active human intervention. Such systems need to acquire data, store it on their onboard computer, and send it to the onshore control system. Moreover, it is likely that the autonomy will be tuned for different scenarios. For example, transit out to the windfarm could be heavily automated but an inspection task may require more approval or input from a remote operator.

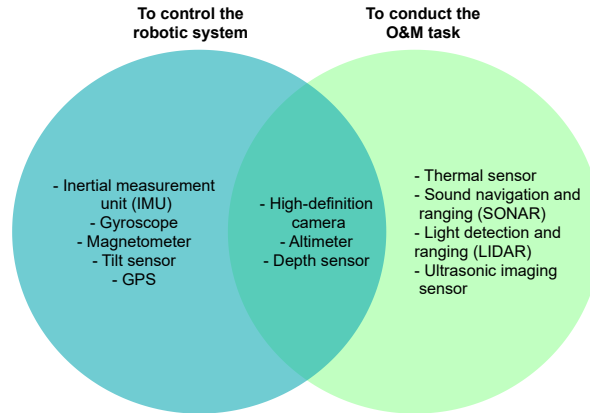


Figure 2.5: Sensors needed to control a typical robotic system and those needed to conduct the O&M task.

2.4.1. CLIMBING ROBOTS

In general, human operators with rope-access to the wind turbine conduct O&M tasks such as cleaning blades and inspecting structural defects in windy, high, and harsh environments. It is envisaged that a climbing robotic mechanism could replace some of these O&M tasks, improving efficiency in the process while also addressing the H&S aspects. In literature, different types of climbing robots are discussed based upon their design specification and functional requirements [23, 47]. For this paper, the definition of climbing robots is restricted to be the machines that can move vertically or around the tower and blades of a wind turbine. The robot's access to the entire circumference of the tower and to the surface of the blade is imperative as it would determine the range of the O&M tasks that could be conducted. An example of such a climbing robot is shown in Figure 2.8. Based on their locomotion ability, climbing robots can be classified into the following two types:

1. **Legged locomotion:** The key benefit of legged climbing robots is that they are highly adaptable to the surface structure, can clear obstacles and steps, and can transition from ground to wall with ease. In literature, various robots can be found with different number of legs and for different degrees of freedom. However, in terms of a smooth gait control, a large number of degrees of freedom contribute to a complicated mechanical structure and the associated control system. Consequently, the weight and torques are also increased. Hence, the robots with two [48] and four [49, 50] legs are more common in literature.

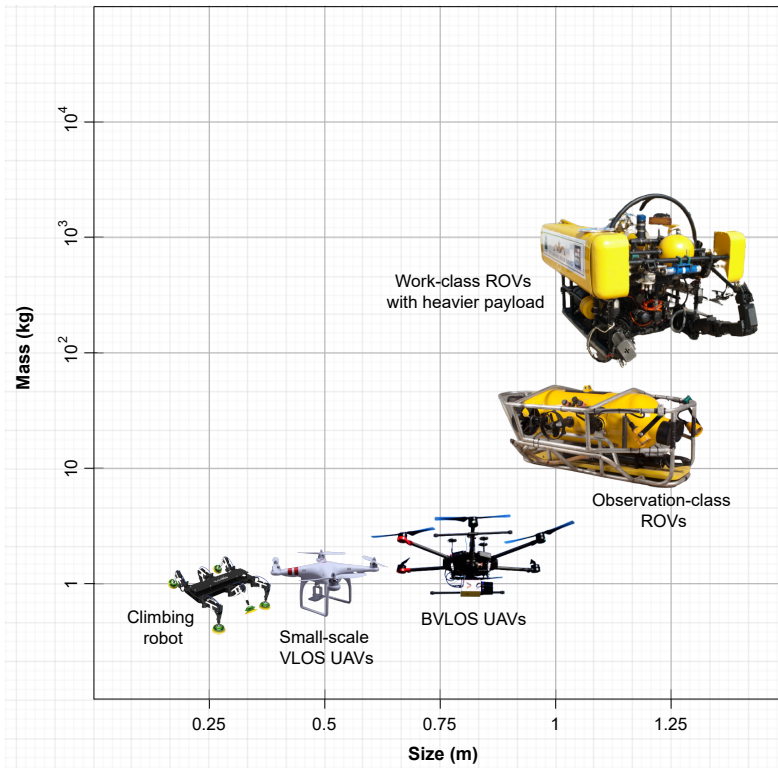


Figure 2.6: An illustration of the size and mass of the climbing robots, UAVs, and ROVs. All the values are indicative and serve only as a guide to scale different systems. Images courtesy: ROVCO and Creative commons.

2. Wheeled or chain-driven locomotion: In case of a relatively smooth surface, climbing robots based on wheels and chains are used. The quick and continuous movement, as well as a simpler mechanical structure and control design, are significant advantages of wheeled or chain-driven robots. However, since these robots are unable to manage large steps or obstacles, they are less adaptable to varying surface characteristics and are limited to specific use-cases.

A comprehensive overview of climbing robots for inspection of vertical structures is presented by [23] where a conclusion is drawn that although various prototypes exist for specific environments, very often the contradicting requirements of achieving a light-weight structure along with high maneuverability and dexterity capability, hinders their universal applicability. A maintenance robot for blade cleaning is presented by [51] where both motion of the mechanism of the robot and the cleanup mechanism based on water-jet can be controlled. A wire-tethered climbing robot is presented by [52] where the applications of water-jet based cleaning and phased array ultrasonic testing (PAUT) are studied. The height and attitude control system are validated by conducting field experiments of the prototype. The results show that a robust control performance in terms

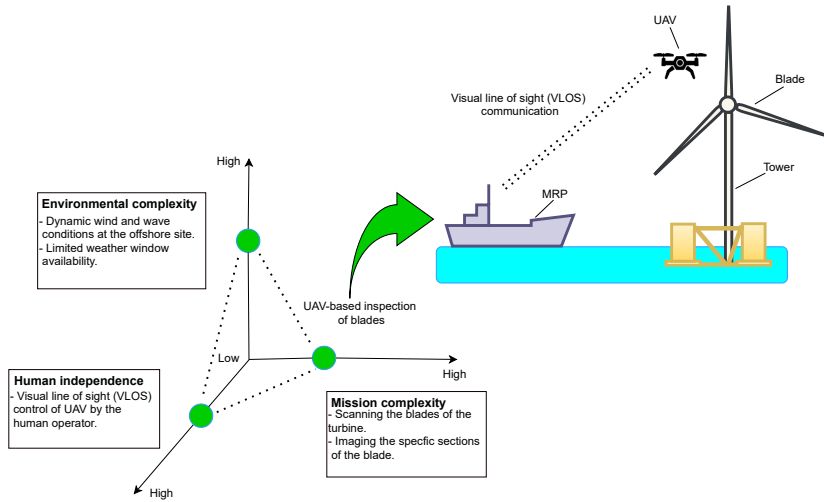


Figure 2.7: ALFUS framework applied to the UAV-based inspection of turbine blades.

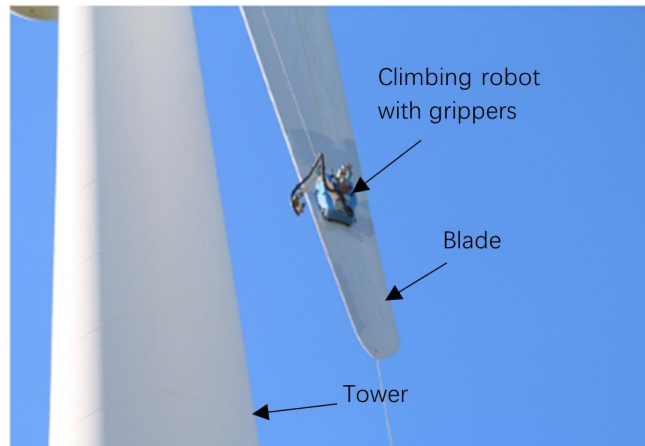


Figure 2.8: Climbing robot from Rope Robotics [117]. A similar system is offered by BladeRobots from Vestas [172].

of the motion of the robotic system is achieved. A modular robotic design is proposed in [53] where the robot is able to move vertically and rotate around the circumference of the tower. The robot scans the surface and conducts in situ X-ray tomography. This work was extended by [54] where permanent magnets were used as an adhesion force for the robot. Experimental results show that the robot is able to adapt to the tapering diameter of the tower and the scanning arm was able to conduct NDT of the blade.

2.4.2. UNMANNED AERIAL VEHICLES

While relatively fewer studies have focused on climbing robots for O&M, aerial robots are gaining increased interest for conducting inspection and other remote sensing applications ranging from surveillance and infrastructure inspection to data acquisition, and aerial mapping [41, 55, 56]. The automated inspection of energy assets based on UAVs have gained significant attention in recent years. For instance, dust on solar panels in a large-scale solar farm can affect the power generation. In this case, UAVs can be utilized to monitor the condition of the solar panels [57]. Another use of UAVs in power systems that has been studied is automatic meter reading [58] along with the inspection of damage to the transmission lines [59]. In the case of FOWFs, a mature commercial offering is available where UAVs fitted with data acquisition technology are used to scan the surface of the turbine tower and blades. Advancements in UAV technology have led to increased automation of the task, reducing the onus on the pilot to manually maneuver the UAV. The data are then recorded and wirelessly transmitted back to the onshore control station. Post-processing is done to acquire imaging details, acoustic emissions, and the sensor measurements. Main benefits of using UAVs to inspect FOWF assets include (1) a more frequent and spatially larger access to the wind farm in a shorter interval of time, (2) the possibility to mount a variety of imaging and acoustic sensors onto the UAV for feature-rich data acquisition, and (3) the improvement in H&S aspects regarding manned access to the FOWFs. A few characteristics of UAVs in terms of remote inspection are as follows:

1. **Specifics of motion:** UAVs are able to move in 3D space. The autopilot of UAVs is able to control the steady state flight along with the autonomous takeoff and landing of the UAV. Furthermore, vertical take-off and landing (VTOL) technology allows to control fixed-wing UAVs without the need for a runway. Nevertheless, certain aspects of the UAV motion need to be taken into account such as the range and endurance of the aircraft along with spatially covering the maximum area within a shorter interval of time. In case of a fixed-wing aircraft, the minimum turning radius restriction needs to be accounted for when considering flight paths with many curvatures. While most UAVs can adapt to variable weather environments, the offshore conditions such as strong winds need to be considered before the flight of the UAV.
2. **Payload limitation:** The factors affecting a UAV's payload primarily include its design weight, onboard power storage unit, and the type of sensing equipment. The heavier the sensing equipment will be, the more thrust would be needed by the UAV, and hence, the power requirements would increase.
3. **Specifics of communication:** UAVs have to maintain communication with the operators and in some cases, with the control station. A swarm of UAVs with BVLOS capability has the benefit in terms of an efficient control and larger swept area [60]. Furthermore, the acquired data need to be stored onboard and then transmitted to the control station. Here, sufficient data storage and transmission bandwidth need to be taken into account. Other connectivity challenges such as obstacle avoidance, GPS denial, and signal fading also need to be considered.

Recent research has benefitted from the advancements in machine learning algorithms for autonomous navigation and guidance of UAVs [61, 62]. This is complemented by the use of imagery sensors such as LIDAR to acquire feature-rich data and send it to the onshore computers. [63] proposed the use of UAVs to detect the cracks on wind turbine blades based on image data acquisition. A typical control strategy entails directing the UAV such as a quadcopter to a position where it can concentrate on a reference object or feature using GPS signals [64]. After that, a high-definition or thermal camera is used to assess the target. It is pertinent to mention that the environmental conditions such as foggy and rainy weather can cause problems in the imaging, resulting in reduced usability and a limited detection of faults.

2.4.3. SUBSEA ROBOTS

Recent advancements in subsea survey and inspection technology have allowed more detailed studies of the oceans and underwater structures [65, 66]. Marine scientists and companies also have access to a wide range of underwater technologies, which are increasingly being used for a variety of purposes. However, owing to the increased offshore developments with varied scientific requirements, deep sea research remains expensive in terms of logistics and personnel requirements. Subsea technology is routinely used by the offshore oil and gas, and renewable energy industries for inspection, monitoring, and maintenance of assets in areas that are otherwise inaccessible to the marine personnel. In recent years, ROVs are increasingly being used at windfarms for conducting O&M activities along with de-risking offshore operations. The industry is developing new technologies for both underwater and topside applications in order to minimize the O&M costs and manpower requirements while also improving the safety and reliability aspects. For the case of a FOWF, two primary applications for ROVs pertaining to O&M are cited: (1) export/array cable surveys and repairs and (2) scour and structural scans [67].

While the uptake of ROVs for inspection and monitoring has seen progress in recent times, significant challenges impede their full-scale exploitation in offshore sites. ROVs have very limited autonomy and must be tethered to the surface to receive power and be controlled from a technician. Higher operating costs for battery power and acquisition of trained technicians are stumbling blocks. On the other hand, autonomous underwater vehicles (AUVs), self-propelled underwater robotic systems powered and piloted by an on-board power source and computer, provide benefits in terms of higher mission capabilities, such as autonomous mapping and inspection of subsea structures. The drawbacks include limited operational range and increased on-board power requirements in case of longer duration missions. Both types of these subsea robots have attracted research and development efforts [40]. ROVs are classified into different types based upon their operational capabilities, as shown in Table 2.1. Classes I and II constitute observation vehicles with the ability to mount various sensors such as SONAR, high-definition camera, and lights. Class III is work-class vehicles with the ability to mount small manipulators in addition to more advanced sensors. Class IV vehicles are pulled through the water by a surface craft. These are heavier vehicles and are normally designed to carry out a specific underwater task such as burial of cables. Class V includes AUVs that are untethered, have higher autonomy and maneuverability, and can carry out mapping

tasks for a longer duration of time.

Table 2.1: Classification of ROVs

Class	Description	O&M activity
I	Observation ROVs	Visual survey
II	Observation ROVs with pay-load option	Visual survey and light intervention
III	Work-class vehicles	Heavier payload with manipulators
IV	Towed and tracked vehicles	Cable burial, marine growth removal
V	AUVs	Autonomous inspection, spatial mapping

2

An iterative design process of an inspection-class ROV prototype is presented by [68] where it is concluded that the final design of an ROV has to be based on the optimization of a series of trade-offs such as manufacturing cost, dry weight, power, and aerodynamic drag. Sole emphasis on maximum thrust can lead to a corresponding increase in power requirements, tethering cross-section, and costs while also increasing the drag. Furthermore, aspects related to portability need to be taken into account as the deployment and recovery of sophisticated ROVs can be manually challenging and expensive. [69] have proposed the dynamic positioning of an ROV based on a nonlinear model predictive control. Results from hardware-in-the-loop simulation show that the controller is able to track the reference while rejecting external disturbances. Similar studies [70, 71, 72] show that the onset of advanced work-class ROVs coupled with robust control algorithms has resulted in their increased usage across different marine applications. The ROV prototypes Kaxan and PoseiBot are depicted in Figures 2.9 and 2.10, respectively. In terms of ROVs for FOWF, it is pertinent to mention that a vast majority of these systems would be deployed in shallow water along with experiencing rough wave and tidal conditions as opposed to deeper waters where the disturbances are minimal. Here, the highly dynamic and non-linear nature of the marine environment makes it critical that control aspects pertaining to disturbance rejection be considered. In this regard, typical approaches include disturbance estimation and rejection from in situ observations [73] or rejecting disturbances arising from steady or impulse perturbations rather than dynamic wave disturbances [74]. [75] presents experimental validation of the estimation of hydrodynamic forces acting on an ROV under regular and irregular waves of different significant wave heights.

2.4.4. AUTONOMOUS SURFACE VESSELS

Autonomous surface vessels (ASVs), also known as unmanned surface vessels (USVs), have been the focus of significant research in recent years [76, 77]. While the use of CTVs and SOVs bring flexibility in terms of payload and personnel capacity, their dependence on weather windows and higher leasing costs makes their use for longer duration of time less than optimal. Moreover, the typical cut-off point where CTVs can no longer be used and offshore accommodation is needed is 40 nautical miles (74 km) from the port [78]. With the anticipated construction of wind farms farther from the coast, a considerable reduction in O&M vessel costs could be possible by eliminating the need for

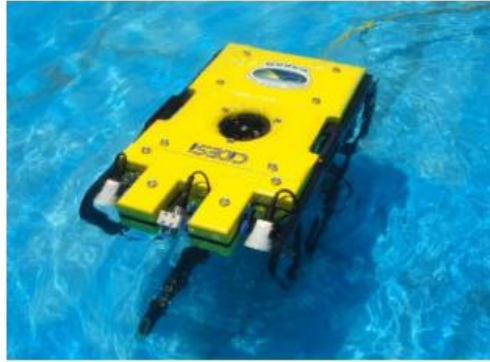


Figure 2.9: Class II ROV from [94].



Figure 2.10: Class I ROV from [71].

large inspection vessels [79]. While the use of ASVs in defense and security domain has seen significant development [80], their usage in offshore wind energy operations is still nascent. The use of ASVs has benefits in terms of conducting marine O&M for extended duration of time and without the need for enhanced crew deployment. ASVs typically utilize catamaran hulls for higher stability and have a modular design, whereby different types of payloads can be mounted based on the specific mission requirements. It is important to consider the varying degrees of autonomy for the ASVs and their effects on the O&M activities and task allocation. A classification of autonomy levels is provided by the Lloyd's Register where the tasks are divided into decision making, action taking and exceptions handling [81]. A more recent classification is presented by [82] as shown in Table 2.2.

ASVs have demonstrated their ability to conduct mapping and obtain accurate models of the terrain above and below the sea level. This is done by combining laser scanning data with bathymetric data and then geo-referencing both data sets. In this way,

Table 2.2: Autonomy level classification as presented by [82]

Autonomy level	Description
0	Human is alone
1	Human is helped by systems
2	Human is helped by systems and agents
3	Autonomous path following vessel
4	Autonomous trajectory tracking vessel
5	Human in the loop
6	Human supervises the decisions making system
7	Human supervises the actions making system
8	Human supervises the exceptions handling system
9	Human supervises actions, decision, and exceptions
10	Fully autonomous

a 3D model synchronized with temporal and spatial characteristics information is generated. Furthermore, ASVs have high maneuverability, can mount sensors of different types and weight, and have higher communication bandwidth which are pivotal in conducting large-scale bathymetry and surveying. Finally, removing the human operator from the offshore vessels allows to enhance human safety on the command-and-control operational framework in the offshore environment. ASVs also pose significant challenges in terms of their use in the wind industry owing to larger distances to the FOWFs and limited weather window availability. Of particular interest is the certification requirements for the use of ASVs in conjunction with manned vessels [83], coordinated control of multiple ASVs, and devising command-and-control framework for ASVs to accomplish complex O&M tasks using real-time navigation and perception.

The deployment of robotic systems such as UAVs, ROVs, and USVs in FOWF operations can enhance the safety related aspects by eliminating or drastically reducing the need for human technicians and divers to work in extreme offshore environments. For example, subsea inspections of turbine foundations, cables, and mooring systems in FOWFs often require divers to operate in low-visibility conditions, strong currents, and depths exceeding 60 meters, where even minor human errors or equipment failures can prove fatal. By contrast, ROVs equipped with advanced sensors and cameras can perform these tasks autonomously or via remote control, navigating complex subsea environments while transmitting real-time data to onshore operators. The shift towards robotic systems also minimizes the logistical challenges associated with crewed vessels. For instance, innovations like Fugro's "RoboDock" enable USVs and ROVs to recharge and transfer data autonomously at sea, eliminating the need for frequent returns to port and further reducing human exposure [173]. Furthermore, ORE Catapult estimates that integrating USVs into a 2GW wind farm could reduce annual operating costs by £850,000, partly by slashing the need for crewed vessels implicated in 60–65% of O&M accidents [174]. By combining real-time data acquisition, collision-avoidance algorithms, and resilient communication systems, robotic systems can create a closed-loop safety framework where risks are identified and mitigated proactively, long before they escalate into

emergencies.

A categorization of robotics-based O&M for the turbine, BoP and logistics is shown in Table 2.3. The feasibility for a selection of O&M activities is highlighted in terms of low, medium, and high. Low feasibility refers to systems being in nascent stages of development, while the medium feasibility refers to systems that have been validated in scenarios representative of the actual FOWFs. High feasibility pertains to systems already in use with the future potential of upscaling the technology along with enhancing their usability in the FOWF domain. It is observed that the UAV- and ROV-based systems are more commercially developed and can conduct a range of tasks while the use of ASVs is relatively nascent and subject to extensive regulatory requirements.

Table 2.3: Application of robotics for key FOWF-specific O&M activities

O&M activity	Robotic System	Typical Payload	Feasibility	References
Turbine				
Blade inspection	UAVs	photogrammetry, video assessment and thermographic camera	High - UAVs widely used in industrial applications, high TRL	[63, 84, 85]
	climbing robots	ultrasonic imaging, NDT	Low - mounting and control remains challenging, low TRL for wide-scale adoption	[53, 54]
Tower inspection	climbing robots	photogrammetry, ultrasonic sensors	Medium - benefits in terms of fatigue testing, grout and structural health monitoring	[86]
Nacelle O&M	resident robots	grippers, visual imaging	Low - resident systems inside the nacelle can perform minor inspections	[87]
	UAVs	visual and thermal imaging	Medium - UAVs can do external surveys, deploy small payload to assist personnel	
Balance-of-plant				
Bathymetry mapping	ROV	SONAR	High - widely used in marine operations	[88]
	ASV	SONAR, GPS/IMU for autonomous navigation	Low - challenging in terms of large-scale command and navigation of ASVs	61, 80, 89
Inspection of array/export cables	ROV, AUV	camera, grippers	High - increased usage of ROVs for fault detection and fatigue inspection in sub-components	[40, 90]

O&M activity	Robotic System	Typical Payload	Feasibility	References
Burial of cables	ROV	camera, grippers	High - burial of cables is done using work-class ROVs, inspection of defects and fatigue in components	[91]
Marine growth on subsea structures	ROV	SONAR, videography	High - widely used in marine operations	[92, 93]
Metocean survey	ROV	camera, lights	Medium - widely used in marine operations, marine regulations need to be taken into account	[71, 94]
Logistics				
Transportation of components	ASV	data link, battery-powered	Low - deployment of higher autonomy level ASVs are subject to marine regulations and zone approvals, advanced navigation requirements for fleet control and coordination	[95]
Offshore operations center	ASV	data link, battery-powered	Low - autonomous mother vessels can deploy UAVs and ROVs, limited applications due to navigation and data communication requirements	[41, 96]

2.5. POTENTIAL AREAS OF RESEARCH

As the floating wind industry grows, there is a need to address research gaps pertaining to the incorporation of robotics and automation in this sector. In particular, the futuristic robotic systems capable of inspecting offshore assets under dynamic weather conditions along with conducting advanced sensing and actuation tasks need to be investigated. Furthermore, the associated design challenges and market adoption aspects need to be addressed. An illustration of this potential research outlook is shown in Figure 2.4, and the key identified areas are further discussed below.

2.5.1. FUTURE ROBOTIC SYSTEMS

The development of advanced robotics for inspections is an ever-evolving process. Significant challenges remain in terms of autonomy, operational range, actuation, and capability of robots to perform the complicated O&M tasks under extreme marine conditions. To this end, many emerging robotic systems have been in development, leaning in on the advancement in industrial automation, control engineering, and artificial intelligence (AI). One such example is the use of soft robotics based on compliant and versatile materials. This results in an increased dexterity which aids in bio-inspired locomotion and navigation of the robot to access the otherwise unreachable and unknown subsea regions and structures [97]. An important aspect pertaining to soft and compliant materials is that they can protect the core electronic components and also mitigate the damage in case of collision with the asset. Although soft robots are cheaper to manufacture as compared to the traditional rigid structures, there exist challenges that hinder their large-scale adoption in the FOWF sector. These include navigating the rough waters, acquiring balance between the softness and load-bearing capacity of the robot, and the mounting of complex sensors and actuators for data acquisition and manipulation, respectively. Nevertheless, soft robotic systems provide promising potential for conducting O&M in the FOWF environment. Based on their functionality, these systems can generally be classified into two groups: (1) deterministic systems which achieve macroscale compliance through the force transition between truss-like structure [98, 99] and (2) fluid-elastomer composites which are composed of soft materials to achieve mesoscale deformability in different loading directions [100]. Both systems could be utilized to conduct wind farm O&M especially the subsea components like mooring lines, array, and export cables. Another future trend is the deployment of resident subsea inspection platforms that are capable of conducting inspection for a longer duration of time, and without the active need of intervention. These platforms can be utilized for environmental surveillance and monitoring of the subsea infrastructure. For instance, [101] have proposed a station keeping mechanism based on a legged robot which has shown to have higher station keeping efficiency (28%) than that of the commercial propeller based ROVs.

An emerging area of research is the development of hybrid systems where different types of robots are combined onto a single platform and work in unison to perform complicated tasks [102]. For instance, [103] have proposed a cooperative platform consisting of an ASV that can launch an ROV. Experimental results show that the ROV can autonomously navigate and track a target and send continuous video stream to the ASV. A similar system is shown in Figure 2.12. Another interesting example is the use of UAVs

to carry and mount climbing robots on the turbine blade. While the UAVs can inspect the turbine from a distance, the mounted climbing robots can be more dexterous and achieve higher functionality in close proximity to the asset. CAROS (Climbing Aerial Robot System) is proposed by [104] which consists of a quadcopter equipped with four wheels. The quadcopter can adhere itself to a wall using aerodynamic adhesion force generated by the tilting of rotors. The control algorithm manages to regulate the orientation and landing speed of the quadcopter onto the wall. A similar system is proposed by [105] named as SCAMP (Stanford Climbing and Aerial Maneuvering Platform), which is a quadcopter capable to fly, perch, climb, and take-off again, as shown in Figure 2.13. It consists of carbon-fiber-based feet and tendons that control the gait of the platform as it climbs up a wall. Such robots can address the challenges associated with reaching different regions of the turbine tower and blades [106]. By mounting imaging sensors, the usability of these robots can be improved along with enhancing the scale of turbine inspections while removing the need for rope-access.

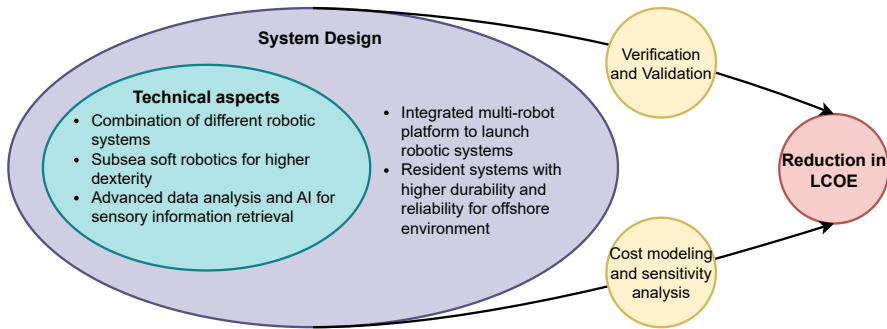


Figure 2.11: Research outlook for the adoption of robotics in O&M.

Recent advances in AI and machine learning have provided benefits in terms of enhanced sensor functionality and post-processing of big data. In particular, the development of autonomous vehicles industry has resulted in LIDAR-based navigation sensors that have higher operational range and collision detection technology. This has also culminated in the use of LIDAR on UAVs for metocean mapping [107]. The availability of feature-rich data and higher processing power bodes well for the adoption of robotics-driven O&M. Furthermore, the modularization of design has resulted in low-cost robotic structures that can be retrofitted with the required sensors and actuators based on the mission-specific requirements. This results in cost reduction and greater operational flexibility of the robots. The acquisition of real-time sensor data is critical for the continuous monitoring of FOWF assets, which is then combined with the historical data to form a complete information flow. The high-speed processing and analysis of this data is becoming a key factor in planning and decision-making for O&M of FOWFs, along with the ability to deal with unforeseen situations and make efficient resource allocation [108].

2.5.2. DESIGN CHALLENGES

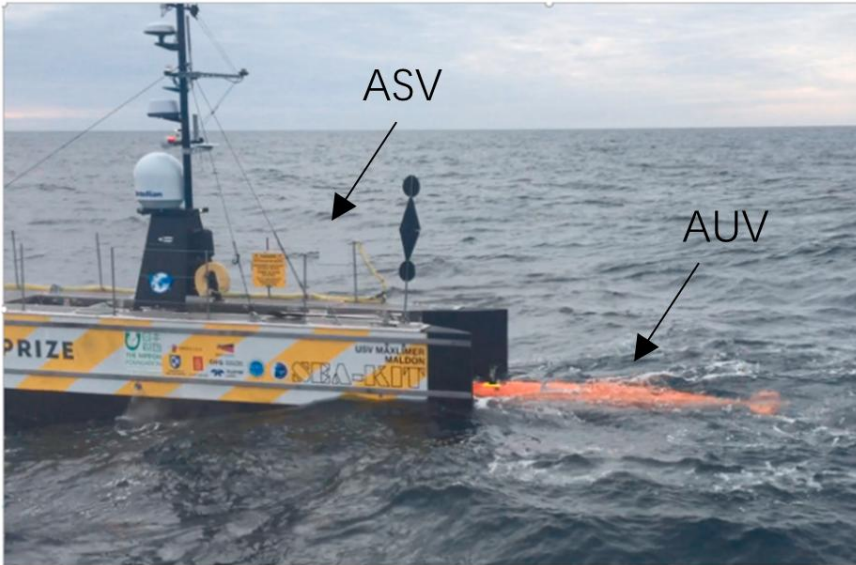


Figure 2.12: Sea-kit Maxlimer ASV recovering the HUGIN AUV. From [116].

INTEGRATED PLATFORM

One of the opportunities pertaining to wide-scale adoption of robotics in the FOWF sector is an integrated platform which can assist with the deployment of different robotic systems for O&M of assets. This integrated platform envisages both the design of a mother vessel that can launch daughter robots and a decision support framework for O&M task allocation and scheduling. Furthermore, the control and coordination of multi-agent systems such as a fleet of UAVs remain challenging in terms of meeting the standard marine regulations. In literature, there are recent examples of small platforms that have been devised to assess the costs and benefits associated with the usage of UAVs and ROVs. The conceptual design of a multi-robot platform named as Multi-platform Inspection, Maintenance, and Repair in extreme environments (MIMRee) is presented in [41]. The platform includes an autonomous mothership, equipped with a fleet of drones and crawling robots that sails to the offshore assets and carry out inspection and repairing. More recently, the Atlantis project [109] aims to develop a pilot infrastructure in order to demonstrate key enabling technologies for the use of robotics in the offshore sector. This also includes developing a certification roadmap for the deployment of robotics and to measure the impact of it on the entire offshore wind life cycle.

VERIFICATION AND VALIDATION

Compared with the onshore assets, remote and in-situ inspection of FOWFs is a long and potentially challenging undertaking. To this end, it is difficult to do extensive testing, verification, and validation of the O&M robotic systems. This is especially important

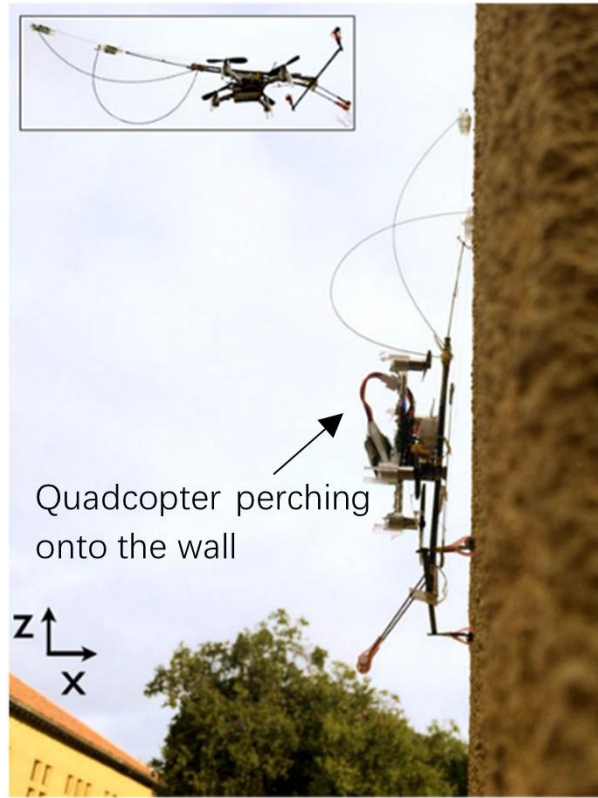


Figure 2.13: SCAMP as proposed by [105].

for systems where robots have to work in unison with humans, and hence need to meet H&S and certification standards. In order to assess the operation of robotic systems for FOWFs, a number of verification and validation techniques [110] may be employed such as the following:

1. Extensive experimental and scaled testing of the robotic systems on representative FOWF platforms.
2. Iterative validation including developing and improving system design based upon the continuous feedback from industrial end-users.
3. Simulation-based testing and training of the robotic systems and their operators, respectively.
4. Formal verification methods to ascertain the logistics and temporal functionalities of the robotic systems and their limitations.

Along with specifying the hardware and software performance, formal verification also includes aspects related to the explainability of AI-based systems. Remote operation of robots in marine environment poses several complex challenges. The lack of access to the local system, in case of a centralized control system, leaves the human operator reliant on sensory information and feedback to navigate. This can hamper the operator's situational awareness. On the other hand, in case of automation complacency, the operator can become too reliant on the robotic system that can lead to reduced perception of threats. The precision required to remotely operate a robot and if done for longer duration of time could lead to an increase in stress responses, which, if not mitigated, could lead to accidents. Moreover, insufficient training and a lack of transparency in system design could result in confidence and trust issues between the human operator and the robot, especially in the case of unforeseen and critical situations.

2.5.3. MARKET CHALLENGES

O&M COST MODELING

In order to assess the O&M costs associated with the robotic systems and to identify the key cost drivers, it is imperative to forecast the OPEX for O&M activities. Variable O&M costs constitute the majority of the wind farm's OPEX as opposed to the fixed costs, which pertains to factors such as human resources, insurance, and leasing costs. In literature, various O&M cost models have been presented and their benefits assessed, although most of these models are developed in-house and their detailed description remains confidential. Typically, the models accept inputs in terms of the turbine and BoP specifications, failure rates, weather conditions, weather window availability, and the O&M strategy. The outputs are given in terms of the OPEX costs, with some indications on the vessels and personnel required, energy production, capacity factor, and time- and energy-based availability. The overall objective is to improve performance metrics such as a reduction in asset downtime and the LCOE. An overview of the existing cost models prior to 2011 is presented in [33] with more recent reviews presented by [111] and [112]. A cost-benefit assessment of remote inspection of nacelle is presented by [87] where NOWIcob tool is used to simulate the O&M costs. It is demonstrated that for an offshore wind farm, a remote inspection system combined with condition monitoring improves availability and reduces the LCOE, as compared to the condition monitoring alone.

VALUATION METHODOLOGY

Robotic systems with low-to-medium technology readiness levels (TRLs) are characterized by the uncertainty of projected costs (e.g., capital and operational expenditure) and benefits (e.g., return on investment, reduction in LCOE). This is because investors often forego capital intensive investments into robotics and automation systems that could bring benefits in the long term. To this end, investors need a comprehensive product valuation to aid in the decision making. An important aspect in OPEX forecasting is the valuation methodology used. In general, net present value and discounted cash flow analysis is used to determine the price required for an investment to breakeven. While this is a widely used methodology, there are other aspects pertaining to future investments in innovative systems that need to be accounted for [113]. A valuation methodology based on options theory is presented in [114] where the mathematical framework

for single-stage and multi-stage investments is developed. Real options analysis is the methodology used to capture the inherent complexity and uncertainty in innovation-driven investments [115]. Real options allow to model different scenarios such as the timeframe of making investments and the resultant effect on long-term value creation. The refinement of the valuation methodology aids in incorporating the policy making vector in the early-stage design process, whereby investors can forecast the value of their investments before the final investment decision can be granted.

2.6. CONCLUSION

The FOWF industry is destined to grow in the future, and as such, the demand for efficient O&M practices with lower expenditures is expected to be more pronounced. Restricted weather windows, long-distance logistics, and the need to ably maneuver, gather high quality data, and conduct O&M of FOWF assets are challenging tasks for which the traditional methods are not sustainable. In this paper, a range of robotic systems and their applications for the FOWF-specific O&M are presented. While the adoption of robots in industrial sector has seen significant traction in recent years, various challenges remain for their wide-scale incorporation into the FOWF domain. Hereby, a non-exhaustive list of discussion points include the following:

1. In terms of autonomous offshore logistics, the advancement in battery technology augurs well for the use of battery powered ROVs which will allow tether-free access along with increasing the endurance of UAVs.
2. The usage of ROVs for burial and inspection of underwater cables have seen considerable progress. The challenge remains in terms of increasing the TRL of existing systems, and enhancing the operational range of ROVs, which can eliminate the need for divers and expensive tether management system.
3. While the use of ASVs is still in nascent stage, benefits in terms of improved safety and higher efficiency can be reaped by their usage in longer-duration missions and especially under harsh weather conditions.
4. The development of autonomous industrial robots has culminated in the availability of advanced yet low-cost sensors for data acquisition. For instance, thermographic cameras and ultrasonic sensors can greatly aid in gathering feature-rich data from the FOWF assets in comparison to traditional manned methods of visual inspection.
5. The automated gathering and retrieval of data are ushering in the usage of AI and data-driven approaches for continuous maintenance and inspection. This could aid in better management of available resources and increased availability of the FOWF assets.
6. The modular design and low-cost versions of climbing robots and UAVs aid in their applicability for various O&M tasks. Sensors and payload of different characteristics can be mounted as per the specific mission requirements.

For the FOWF industry, the benefits of enhancing O&M through robotic systems range from efficiency in terms of cost and resource management to enhanced and accurate data gathering. Furthermore, the long-term impacts of FOWF infrastructure in oceans can be assessed and understood. With this knowledge comes improved decision-making for conducting continuous O&M at FOWFs deeper into the sea. The robotic system providers need to be cognizant of the emerging trends in O&M while also taking into account the regulatory and certification barriers. This can improve the TRLs of the robots and provide a viable commercial roadmap along with enhancing the value-chain in the robotics-based O&M sector.

3

COST-BENEFIT ASSESSMENT FRAMEWORK FOR ROBOTICS-DRIVEN INSPECTION OF FLOATING OFFSHORE WIND FARMS

Omer Khalid ^{1,2,3}, Guangbo Hao ², Hamish Macdonald ³, Aubryn Cooperman ⁴, Fiona Devoy McAuliffe ¹, Cian Desmond ⁵

¹ MaREI Centre, Environmental Research Institute, University College Cork, Cork, Ireland

² School of Engineering and Architecture-Electrical and Electronic Engineering, University College Cork, Cork, Ireland

³ Offshore Renewable Energy Catapult, Glasgow, UK

⁴ National Renewable Energy Laboratory (NREL), Golden, Colorado, United States

⁵ Gavin and Doherty Geosolutions, Dublin, Ireland

CHAPTER OVERVIEW

This chapter consists of a research manuscript which has been published in the Wind Energy journal by Wiley. The publication can be accessed on the following link: <https://doi.org/10.1002/we.2881>. In this publication, cost modelling is conducted for robotics-driven inspection of FOWFs. The simulation is conducted in the WOMBAT cost model and the outputs are analysed which is followed by the sensitivity analysis.

CONTRIBUTION

Omer Khalid: Conceptualization, Investigation, Methodology, Formal analysis, Writing – original draft, Visualization. **Guangbo Hao:** Supervision, Validation, Writing – review

& editing. **Hamish Macdonald**: Project administration, Resources, Supervision. **Aubryn Cooperman**: Secondment supervision, Project administration, Resources. **Fiona Devoy McAuliffe**: Supervision. **Cian Desmond**: Writing – review, Project administration, Funding acquisition.

3.1. ABSTRACT

Operations and maintenance (O&M) of floating offshore wind farms (FOWFs) poses various challenges in terms of greater distances from the shore, harsher weather conditions and restricted mobility options. Robotic systems have the potential to automate some parts of the O&M leading to continuous feature-rich data acquisition, operational efficiency, along with health and safety improvements. There remains a gap in assessing the techno-economic feasibility of robotics in the FOWF sector. This paper investigates the costs and benefits of incorporating robotics into the O&M of a FOWF. A bottom-up cost model is used to estimate the costs for a proposed multi-robot platform (MRP). The MRP houses unmanned aerial vehicle (UAV) and remotely operated vehicle (ROV) to conduct the inspection of specific FOWF components. Emphasis is laid on the most conducive O&M activities for robotization, and the associated technical and cost aspects. The simulation is conducted in WOMBAT, where the metrics of the incurred operational expenditure (OPEX) and inspection time are calculated and compared with those of a baseline case consisting of crew transfer vessels, rope-access technicians and divers. Results show that the MRP can reduce the inspection time incurred but this reduction has dependency on the efficacy of the robotic system and the parameterization (e.g., cost elements, inspection rates) of the FOWF. Conversely, the increased MRP day-rate results in a higher annualized OPEX. Residual risk is calculated to assess the net benefit of incorporating the MRP. Furthermore, sensitivity analysis is conducted to find the key parameters influencing the OPEX and the inspection time variation. A key output of this work is a robust and realistic framework which can be used for cost-benefit assessment of the MRP systems for specific FOWF activities.

3.2. INTRODUCTION

The development of offshore wind energy has continued to expand over the last couple of decades [118]. In particular, the focus has been shifting towards floating offshore wind farms (FOWFs) wherein the benefits of greater capture of the wind resource and water depth along with lower carbon footprint can be reaped [2]. Floating wind energy, still in its infancy, has a core place in the green energy transition, and a host of pressing challenges are being addressed by researchers to aid its wide-scale adoption. One such challenge is to improve the operational efficiency of FOWF components and to reduce the associated costs of operations and maintenance (O&M) [5]. O&M costs can account for over 29.5% of the total lifecycle costs of a FOWF [19]. FOWF components such as turbine blades, tower, floating platform, array and export cables are subjected to varying and extreme loads during the course of their operation. This leads to reduced structural integrity of the component, which if not rectified in due time, can result in failure and a subsequent loss of power production. Furthermore, deeper waters and harsh weather conditions can hinder the inspection activities especially where

rope-access technicians and divers need to be involved, making it more time- and cost-intensive. It is also pertinent to mention that the costs associated with inspection activities can have a direct impact on the levelized cost of energy (LCOE) while the downtime incurred affects the annualized power production (AEP). Hence, there is an opportunity for automation and robotics-based inspection of FOWFs with the goal of improving the operational efficiency, while also reducing the downtime and the costs incurred [119]. Furthermore, these robotic systems can reduce the need for manual inspections, therefore minimizing human risk, and collect and stream continuous high-quality data for better decision-making [7]. As FOWFs continue to grow in size and scale, robotics-based inspection could become increasingly attractive not only to ensure the reliability and safety of offshore assets but also due to economies of scale and perceived shortages of competent O&M labour. While many robotic systems in the offshore oil and gas operations have been in operation [15, 39, 120], their usage in the offshore wind farm industry has been relatively explored less. Previous studies in this domain have focused on exploring robotics-based inspection from various angles. For instance, [87] have proposed the use of a robot inside the nacelle. The proposed robot moves on a rail, is able to conduct inspection with high resolution camera, thermal sensor and microphones. Simulation results show that the remote inspection leads to increased time- and production-based availability and a lower cost of energy. Such turbine-mounted robots, while assisting remote inspection, have limitations in terms of navigating certain parts of the internal turbine due to their limited range of motion and manoeuvrability. Furthermore, they may have limited payload capacity and flexibility in carrying diverse equipment and attaining feature-rich inspection data [23].

The use of unmanned aerial vehicles (UAVs) for inspecting wind turbines has gained traction in recent years [84, 121]. The turbine blades are prone to damage over the course of the project lifecycle. Timely inspection using UAVs can lead to early detection and maintenance that can increase the assets' lifecycle [17]. UAV-assisted videography can lead to identification and classification of damages, and determine the structural integrity of the asset [64]. The coordinated control of multiple UAVs, and route optimization [55] can lead to a reduction in the inspection time of turbine blades. A cost estimation for a drone service provider is provided by Kabbabe Poleo *et al.* [13], where it is shown that using drones for inspecting offshore wind farms can result in cost reduction of up to 70%, when compared with that of a rope-access case. Furthermore, revenue lost due to downtime is reduced by up to 90%. For the subsea components of the offshore wind farms, remotely operated vehicles (ROVs) have been in commercial operations with an aim to reduce the need for time-intensive diving operations, improve inspection efficiency and reduce downtime [40, 68, 93]. Based on site and task-specific mobility and reliability considerations, ROVs can either be tethered to the launching vessel or un-tethered, where they can autonomously navigate underwater, inspect the asset, and return to the vessel for retrieval. Different classes of offshore ROVs exist ranging from low-cost observation class to advanced ROVs with increased automation and cable burial capabilities [82]. In the case of a FOWF, the most relevant use-case is observation and work-class ROVs with visual sensors and light intervention capability for inspection of mooring lines, array cables, export cables and turbine foundations. An extensive survey on the technical feasibility of ROVs is presented by McLean *et al.* [122]. The develop-

ment of a prototype ROV designed to be launched from an autonomous surface vessel (ASV) is presented by Gray *et al.* [96]. Similarly, the hydrodynamic modeling and control strategy for an ROV that is launched from an ASV is presented by Zhao *et al.* [102], where the feasibility for such a cooperative system is established. ROVs have also been shown to cost less and reduce deployment time for the inspection of wave energy converters as compared to that of the diver-assisted methods [123].

While significant research has focused on the control, sensing and data communication from UAVs and ROVs, there is a need to develop a framework to conduct cost-benefit assessment in order to analyze the financial implications of incorporating robotic systems in the floating offshore wind energy sector. Previous studies in this domain have focused on the feasibility of singular systems [13, 123], but there remains a gap in assessing the cost-benefit impact of incorporating a multi-robot platform (MRP) in a large-scale FOWF environment. To this end, the objective of this work is to develop a cost-benefit assessment framework to estimate the cost of an MRP, and assess its impact on the OPEX and key performance metrics of a FOWF. The proposed MRP consists of a commercially available UAV and ROV with the functionality of inspecting assets on the turbine and underwater, respectively.

This paper is organized as follows: Section 3.3 describes the methodology employed in this study which includes the cost estimation and the details of the O&M model. Section 3.4 presents the application of the cost estimation to a FOWF. The results obtained from the O&M model simulation are discussed in Section 3.5 along with the sensitivity analysis and the correlation matrix. This is followed by the conclusion in Section 3.6.

3.3. METHODOLOGY

This section outlines the methodology employed in this study, beginning with an introduction to the cost estimation of robotics-based inspection of a FOWF. The operational cost of an MRP that could inspect different components of a FOWF is estimated. This cost is then taken as an input for an O&M cost model where different inspection scenarios are simulated for the lifecycle of the FOWF, which forms the basis of our work. The simulation methodology is described followed by a formulation of the residual risk curve.

3.3.1. COST ESTIMATION

There exists different methods in literature to estimate costs for various offshore operations [124, 125]. The top-down method, also known as analogous or parametric estimation, relies on historical data and comparisons with similar operations to derive an approximate cost estimate. In contrast, the bottom-up method involves breaking down an operation into smaller, manageable tasks or components followed by estimating costs at the task or component level. The former method is advantageous for providing quick and preliminary cost estimates, while the latter estimation is preferred for detailed and precise cost analysis. In this work, a combination of both methods is utilized wherein top-down costs of equipment have been estimated from available data while bottom-up cost modeling is utilized in order to capture the various cost elements of an MRP inspecting a FOWF.

Recently, various conceptualizations of an MRP have been proposed in literature and industrial discourse with a focus towards their systems design, engineering and commercial adoption [41]. In order to inspect different components of the FOWF, the proposed MRP in this work consists of a UAV with remote communication capability, and an ROV with tethered access to the MRP for effective and safe deployment. The vessel would have a typical payload capacity of up to 70 kg. The UAV would inspect the blades and rotor hub on the turbine with a high-definition camera and a thermal sensor. The ROV would conduct inspection of the foundation, mooring lines, array and export cables with videography. This is to mimic a simplified inspection scenario for the main components of a FOWF. The MRP serves as a hub, centralizing the inspection process by storing the acquired data onboard. It is assumed that the MRP is equipped with collision avoidance system, emergency shut-down mechanism, and fail-safe protocols. A visual illustration of such a scenario is shown in Figure 3.1.

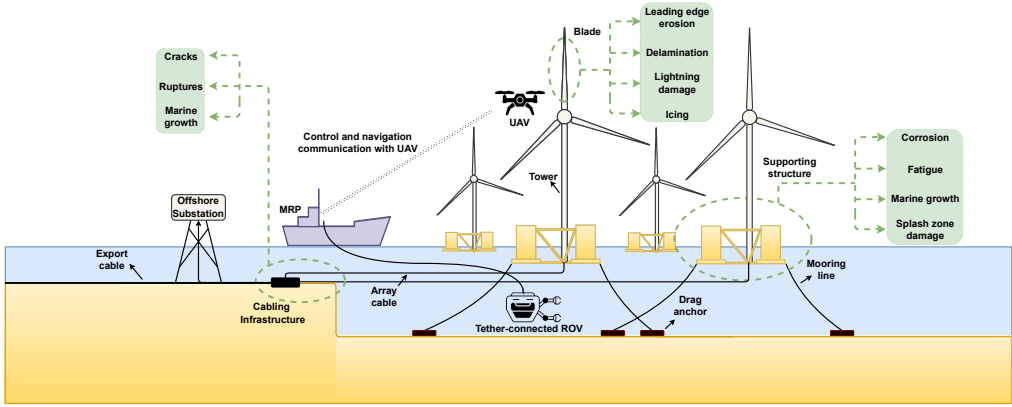


Figure 3.1: Illustration of the multi-robot platform based inspection of a FOWF. Typical damages on the FOWF components are exhibited in green blocks.

A generalized formulation of the LCOE is stated in Equation 3.1 where r stands for the specified interest rate. t and n denote the time interval and the lifetime of the FOWF, respectively. The relevant metrics to be assessed are the OPEX and AEP. While the capital expenditure (CAPEX) pertains to the procurement and the installation of different components of the FOWF, the OPEX along with the AEP, need to be forecasted for the total lifecycle of the FOWF, and hence, are dependent on the forecasting variables.

$$LCOE = \frac{CAPEX + \sum_{t=1}^n \frac{OPEX_t}{(1+r)^t}}{\sum_{t=1}^n \frac{AEP_t}{(1+r)^t}} \quad (3.1)$$

The OPEX consists of cost-contributing factors during the operational phase of the wind farm, where it primarily relates to the day-rate of the vessel hired and any equipment needed to do the inspection, repairs or replacement. In order to estimate the day-rate of the MRP, contributing factors need to be defined that would be representative of the actual costs incurred during the inspection of the FOWF components. The formula-

tion of OPEX for the MRP is shown by Equation 3.2:

$$\text{Day-rate} = \sum_{k=1}^m (wf, eq, scd) k \quad (3.2)$$

where wf , eq , and scd stands for workforce, equipment and secondary costs, respectively. k is the time unit pertaining to the duration of inspecting a certain component. These variables are further discussed below.

3

WORKFORCE COSTS

The workforce cost element consists of the salaries of the MRP operators and constitutes a major part of the total cost along with that of the MRP infrastructure. For this work, it is envisaged that the MRP would be based at an offshore support base in the vicinity of the FOWF from where it would transit to the turbine for inspection. The role of the operators would be to launch the UAV and ROV from the offshore support base along with acquisition and processing of the inspection data.

Estimating the workforce costs for offshore vessels can be achieved using various methods, each with its advantages and limitations. One commonly used method is the traditional "labour day-rate", which calculates the cost per operator per day worked. Another approach is the use of "fixed pricing", which involves a fixed price for the entire team of operators for a specified period, regardless of the number of days worked. Additionally, some researchers have proposed a "task-based pricing" method, which accounts for the different tasks and activities performed by the operators during their shift. In this work, fixed pricing in terms of monthly salaries of the MRP operators is utilized where a fixed number of workforce comes as part of the MRP and remains available for the duration of the inspection. As offshore operations are typically longer in duration owing to the weather window availability, hence fixed pricing mechanism can be utilized to hire MRP and conduct the inspection tasks during a certain period of the year.

EQUIPMENT COSTS

The equipment costs relate to the UAVs, ROVs, and their sub-systems such as sensors and spare parts. The UAV consists of an RGB and a thermal camera with which it would be able to scan the turbine blades. It would have remote communication capability where the operator of the MRP would fly it from the offshore support base. The ROV would be tethered to the MRP whilst inspecting the foundation, mooring lines and cabling infrastructure.

While most of the relevant cost data from actual operations is confidential, estimation is done based on available literature, commercial quotations and expert elicitation. The readily available models of UAV and ROV, with visual inspection functionality have been selected as listed in the Table 3.1.

SECONDARY COSTS

The secondary costs include soft costs such as administration, consumables and insurance costs. While these are dependent upon the type of equipment utilized and the specific inspection scenarios, an estimation based on annual contract length is conducted using available data [126]. Furthermore, indirect costs to the tune of 10% of the total

operating costs have been included to account for any additional expenditure. A breakdown of the total cost estimation is shown in Table 5.3.

Table 3.1: Estimation of day-rate for the multi-robot platform (MRP)

Cost element	Cost (\$)	Notes
UAV	8,000	Based on the quote of a DJI™ Matrice 300 UAV
Thermal sensor for UAV	600	Based on the quote of a FLIR™ thermal camera
ROV	55,000	Based on the quote of a VideoRay™ Pro4 ROV
Workforce	375,000	Based on 2020 nominal U.S. salary rate†
MRP soft costs‡	150,000	Estimated from Kaiser <i>et al.</i> [127] and Ioannou <i>et al.</i> [126]
Other consumables	50,000	Adjusted from Kabbabe Poleo <i>et al.</i> [13]
Total operating cost	638,600	Sum of the preceding costs
Anticipated revenue	159,650	Revenue rate of 25% for the O&M operator
Indirect costs	63,860	10% of the total operating cost
MRP vessel infrastructure	2,500	Day-rate of the vessel excluding any capital costs, adjusted from [128]
Estimated MRP day rate	5,815	Calculated for 260 annual working days

† A workforce of 5 MRP operators is assumed with 75,000\$ annual rate per person.

‡ Including administration costs.

3.3.2. O&M MODEL

There exists different O&M models in literature [111] with a focus on understanding the underlying O&M mechanism along with using such models as decision-making tools to arrive at the right design choices. In this work, WOMBAT (Windfarm Operations and Maintenance cost-Benefit Analysis Tool) [129] is used as the O&M tool to simulate the lifecycle of the FOWF. WOMBAT is a discrete-event simulation tool with the function to analyze the O&M phase of a wind farm from a technical and financial viewpoint. It has high component-level granularity, where the *repair manager* assigns equipment such as MRP or crew transfer vessel based on the failure rates and maintenance intervals of a specific component. The way the simulation runs is that when a component sends request for inspection then the time needed to reach the site and the time needed to conduct the inspection is calculated. If this time falls within the next weather window availability, then the inspection is conducted. If not, then the MRP waits until the weather window becomes available. This is done in order to make sure that the vessel does not have to go back to the port in the middle of the inspection. Furthermore, after conducting one inspection, the loop for the next component inspection is run again to find the next weather window availability. The weather window availability can affect the accrued costs and process time of an inspection task. An illustration of the complete simulation methodology employed in this work is shown in Figure 3.2 and is detailed in the steps below:

- 1) Day-rate of the MRP is estimated based on bottom-up cost modeling.
- 2) Parameters pertaining to the FOWF site, inspection components and the MRP are

added as inputs into the WOMBAT model.

- 3) After initialization, the simulation is run based on the site-specific wind-wave time series.
- 4) When an inspection interval is reached, a request is passed by the asset to the *repair manager*. The *repair manager* sends on the MRP which conducts inspection conditional to the weather window availability. After the inspection is completed, the component returns to the normal operation.
- 5) The outputs in terms of OPEX and process time are calculated for post-processing.
- 6) The steps 1 to 5 are repeated for the baseline case and the difference in the logged outputs is determined.
- 7) Next, sensitivity analysis is conducted by varying the key parameters in step 2 and the resultant effect on OPEX and process time is analyzed.

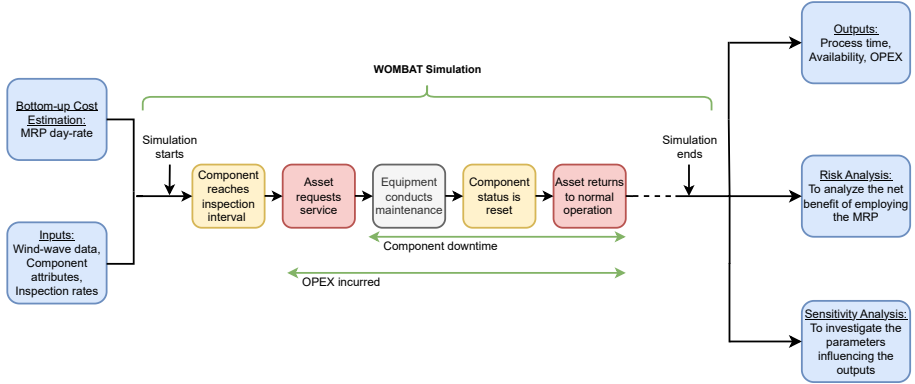


Figure 3.2: O&M model methodology. WOMBAT simulation adjusted from [129].

3.3.3. RESIDUAL RISK

The cost-benefit ramifications of the MRP are further assessed by calculating the residual risk, which is defined as follows:

$$R_r = P(L_b - L_{MRP}) - C_o \quad (3.3)$$

where P relates to probability of attaining a certain loss. The losses are defined as L_b and L_{MRP} where the former pertains to the baseline OPEX and the latter is the OPEX incurred by the MRP. In general, the risk is defined as the product of probability and consequence. Here, the consequence is defined as the OPEX incurred while the probability takes into account the inherent uncertainty of the OPEX estimation from the WOMBAT simulation and hence, gives a broader indication into the feasibility of incorporating MRP for the inspection as compared to the baseline manned inspection. C_o is the operating cost of

the MRP/CTV which the product of day-rate of the MRP/CTV and the total number of yearly working days. In Equation 3.3, the residual risk is defined in a way that the MRP is a net benefit if the residual risk is positive and vice versa.

3.4. APPLICATION TO A FLOATING OFFSHORE WIND FARM

The cost estimation presented in this work is applied to a hypothetical FOWF located in the West coast of Ireland. The West coast has been mapped extensively and computations have shown that it incurs the lowest LCOE for floating wind as compared to the other Irish coasts [130]. The hourly wind-wave data for the site is obtained from Copernicus ERA5 database [131]. The specification of the proposed 1.5GW FOWF is listed in Table 3.2 where the IEA 15MW turbine has been selected as the reference [132]. In order to analyze the O&M phase of the FOWF, inspection time and duration for the selected components needs to be specified. Typically, the O&M contractor sets a schedule for one or two inspections per year. By increasing the frequency of inspections, unplanned failures can be minimized. However, planning for more frequent inspections based on fixed time intervals or a specific reliability threshold may entail higher expenses [133]. In this study, we consider the annual inspection of five components namely: a) wind turbine blades, b) supporting structure which includes the foundation and the splash zone, c) mooring lines, d) array cables and e) export cables. The UAV launched by the MRP would inspect the blades while the observation-class ROV would inspect the remaining subsea components. The inspection is restricted to visually capture the external surface of the components and store the imaging and videography data onboard. The time required to inspect a certain component is included in the simulation where the initial values are taken from the available data [13, 123] which are then varied in the sensitivity analysis to make the findings more robust. Failure rates and resource requirements for 350 offshore wind turbines have been presented in [134], where three different O&M operations have been highlighted: minor and major repair, and major replacement which gives an overview of the costs and time duration associated with conducting component-wise O&M tasks. In this work, only annual inspection of these components has been considered as it includes the most relevant activities that could be replaced by the proposed MRP.

The baseline scenario is represented by inspecting the components by rope-access technicians and divers from a crew transfer vessel (CTV). Different reference studies on the validation of O&M tools have detailed the cost estimation of CTVs [136]. The initial day-rate of the CTV is obtained from the recent [128] which amounts to be £2000. This is converted into dollars with a base conversion rate of 2023 and the day-rate of the technicians and divers is added to it. For the CTV, a total of 8 crew members are considered for one inspection operation. The final day-rate for the CTV is estimated to be \$4100. The selected values pertaining to the inspection and the WOMBAT simulation parameters are listed in Table 3.3.

3.5. RESULTS

Table 3.4 corresponds to the incurred inspection-based OPEX during the lifecycle of the FOWF which increases by 51.1% in the case of utilizing 3 MRPs as compared to that of

Table 3.2: Specification of the FOWF

Description	Value
FOWF location	West Coast, IE
FOWF size	1.5 GW
Project Lifecycle	20 years
Number of turbines	100
WT Model	IEA 15MW RWT
WT Rated power	15 MW
Cut-in Wind Speed	3 m/s
Cut-out Wind Speed	25 m/s
WT Rotor diameter	240 m
WT Rated wind speed	10.6 m/s
Floating platform	DeepCwind [135]
Floating platform type	Semi-submersible
Number of mooring lines	3
Unstretched mooring line length	835.5 m [135]
Water depth	70m

the baseline case. A value of 4,200.28\$ per MW per year is obtained which includes inspection of the five components of the FOWF. On the other hand, this leads to a 58.3% improvement in the time-to-completion which pertains to the total number of hours from the time of inspection request by a component to the time-of-completion of the inspection. The OPEX reduces by 50.6% if only one MRP is utilized but this leads to a slightly higher time-to-completion i.e., an increment of 17.2%. This is due to fact that a single MRP has to conduct inspection of each component on a first-in-first-out basis as compared to multiple MRPs which can transit to multiple sites as the requests come in. The OPEX breakdown, as shown in Figure 3.3, shows that inspection of the blades and mooring lines constitute a major proportion of the OPEX, while inspection of the supporting structures, array and export cables are not as costly. It is pertinent to mention here that only *inspection* of the components is simulated in this study and hence, this OPEX is not reflective of major repairs and expensive replacements of components that could correspond to that of an actual FOWF.

Figure 3.4 shows the residual risk curve where it can be seen that the MRP is a net benefit up until the probability of 0.73 which is the breakeven point. If we reduce the day-rate by 20% then this breakeven point moves further to the right to the value of 0.57, which is depicted by the blue line in the plot. This shows that the residual risk increases for lower values of the MRP day-rates which means that further net benefit can be attained if any of the values of the cost elements in Table 3.1 are to reduce. This bodes well for the future developments in this domain where innovation leading to further depreciation in the prices of robotic systems and the associated vessel costs can make the MRP a net positive investment.

Results can differ based on the choice of cost parameters in Table 3.1. In this work, a simplified scenario with the most readily available cost elements is chosen, but there re-

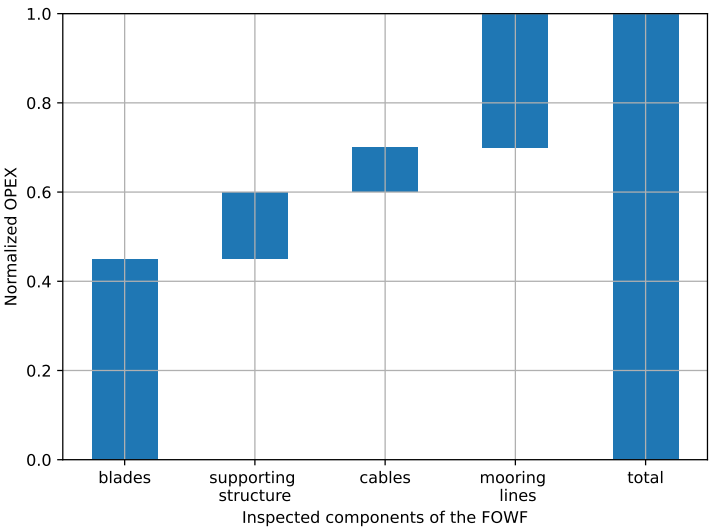


Figure 3.3: Component-wise OPEX breakdown. The category 'cables' include both array and export cables.

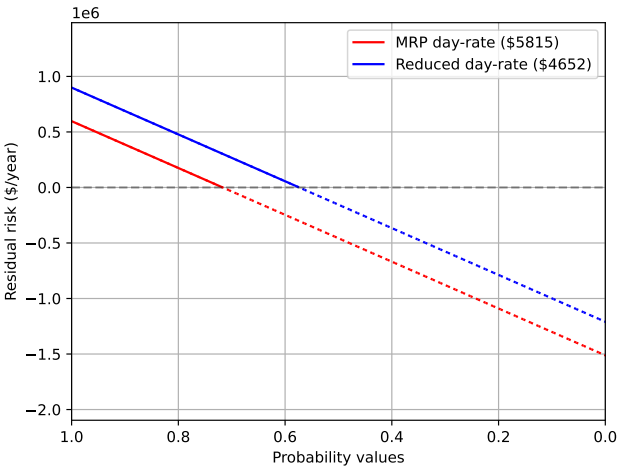


Figure 3.4: Residual risk plot. The dashed and dotted lines show the range where the MRP is a net positive and a net negative investment, respectively.

Table 3.3: WOMBAT simulation input parameters

Description	Units	CTV	MRP	Notes
Start year	-	1996	1996	Start year of the simulation (inclusive)
End year	-	2015	2015	Final year of the simulation (inclusive)
Work day start	AM	07:00	07:00	Starting hour for a typical work shift (inclusive)
Work day end	PM	19:00	19:00	Ending hour for a typical work shift (inclusive)
Inflation rate	%	1	1	Varied between 0.5 and 2
Significant wave height	m	2.5	2.5	Maximum wave height for safe operations
Maximum operating wind speed	m/s	20	20	Maximum wind speed limit for safe operations
Number of crew	-	8	5	These values are taken for preliminary day-rate estimation. These are further increased by 35% in the sensitivity analysis.
Time required to inspect components	-			Adjusted from [123] and [13]. Varied by $\pm 50\%$ in the sensitivity analysis.
Blades	hr	3	0.75	
Supporting structure	hr	3	0.75	
Array cables	hr	4.5	1	
Export cable	hr	4.5	1	
Mooring lines	hr	3	1	

mains possibility of extending the bottom-up model by including more detailed cost elements. Furthermore, the increase in OPEX also corresponds to higher CAPEX incurred on the type and functionality of the selected UAV and ROV. In future, this CAPEX could decrease with the advent of systems with higher technology readiness levels (TRLs) and economies of scale, which can result in further improvement in the metrics of OPEX and time-to-completion.

3.5.1. SENSITIVITY ANALYSIS

The sensitivity analysis represents a crucial aspect of evaluating the impact of variations in the different parameters on key performance metrics i.e., inspection-based OPEX and the time-to-completion. In the depicted graph in Figure 3.5, OPEX (\$/MW/year) is plotted on the x-axis, while inflation rate, MRP day rate, design life, port distance and number of MRPs are displayed on the y-axis. This is done to assess the effect on OPEX by varying the key parameters. For instance, a 35% increase in the MRP day-rate, from a baseline value of \$5,815 to \$7,850.25, results in more than \$1,500/MW/year increase

Table 3.4: OPEX and time-to-completion variation between baseline and MRP cases

Metric	Baseline (3 CTVs)	MRPs (3)	MRPs (1)
OPEX (\$/MW/year)	2,779.83	4,200.28	1,373.11
OPEX variation	-	+51.1%	-50.6%
Time-to-completion variation	-	-58.3%	+17.2%

in OPEX. Similarly, an increase in the number of MRPs from an initial value of 3 to 12 leads to a drastic rise in the OPEX. It is pertinent to mention that this rise is not proportional as more components are inspected in a shorter duration of time by utilizing the weather window availability which reduces the number of transit days needed. On the other hand, prolonging the design life from 20 to 25 years, corresponds to a relatively minor increase in the OPEX. It can be seen that the number of MRPs, day rate and the inflation rate have the largest impact on the OPEX. This shows that the cost elements associated with the MRP account for a significant proportion of the overall increase in the inspection-based OPEX.

Similarly, Figure 3.6 shows the sensitivity analysis results for the time-to-completion metric. It can be seen that the number of MRPs is indirectly proportional to the time-to-completion metric. This means that an increase in the number of MRPs can result in quicker inspection but this comes at an expense of higher OPEX, as shown in Figure 3.5. Further reduction in time-to-completion can be attained by reducing the inspection time of components. The mobilization time also results in an increase in the metric while the port distance has a relatively minor effect on the time-to-completion.

3.5.2. CORRELATION MATRIX

The correlation matrix analysis is a powerful statistical tool that measures the strength and direction of linear relationships between multiple variables, in this case OPEX and the MRP attributes. It is essential to conduct such an analysis to identify potential patterns, dependencies, and redundancies, which can help improve efficiency, reduce costs, and optimize overall operations. The correlation matrix for a selected number of parameters is shown in Figure 3.7.

Starting from the top left, a negative correlation can be seen between the number of MRPs and the time-to-completion. This relates to the fact that a large number of MRPs can conduct inspection in a shorter duration of time. A positive correlation of 1 between OPEX and MRPs implies that an increase in the number of MRPs typically corresponds with a higher OPEX which is a function of the day-rate of the MRP. Similarly, the positive correlation of 0.88 between task completion rate and MRPs indicates that a higher number of MRPs is associated with increased task completion rate. This corresponds to the monthly average tasks completed which reduces if the number of MRPs are reduced where some of the tasks initiated in one month are completed in the next month. This also highlights the operational benefits of increasing the number of MRPs but at the expense of a corresponding increase in OPEX.

Lastly, there is a strong positive correlation of 1 between number of MRPs and the 'no requests' cost, which pertains to the cost incurred when the MRPs are available but

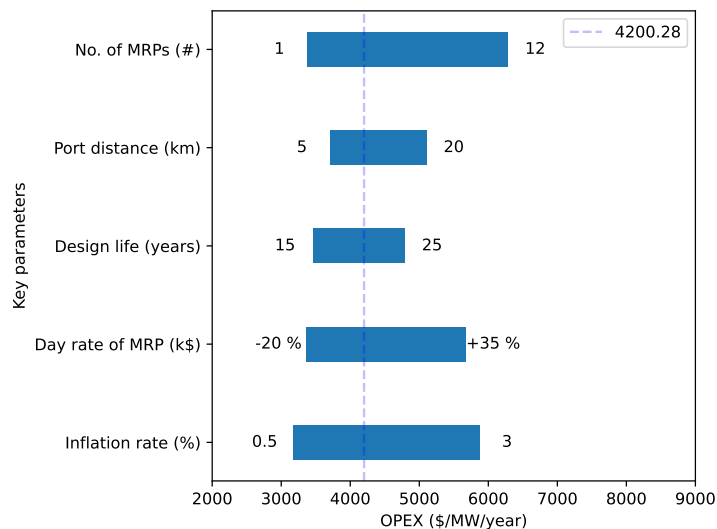


Figure 3.5: Sensitivity analysis for the OPEX metric. The dashed line show the preliminary OPEX which is selected as the reference for the sensitivity analysis.

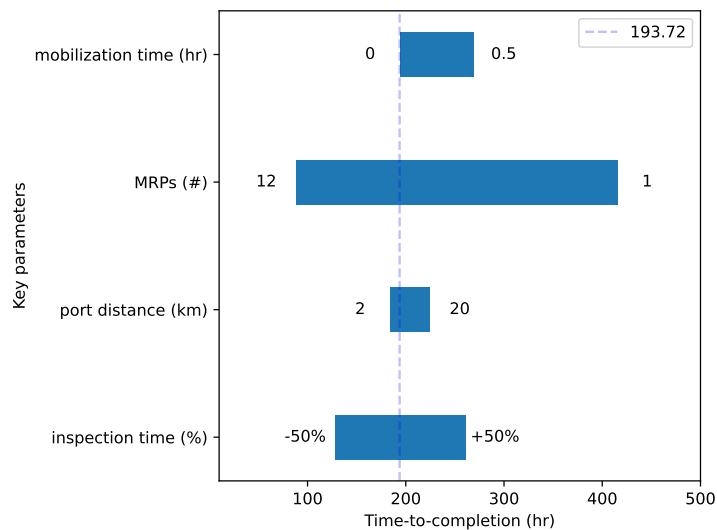


Figure 3.6: Sensitivity analysis for the time-to-completion metric. The dashed line show the preliminary time-to-completion which is selected as the reference for the sensitivity analysis.

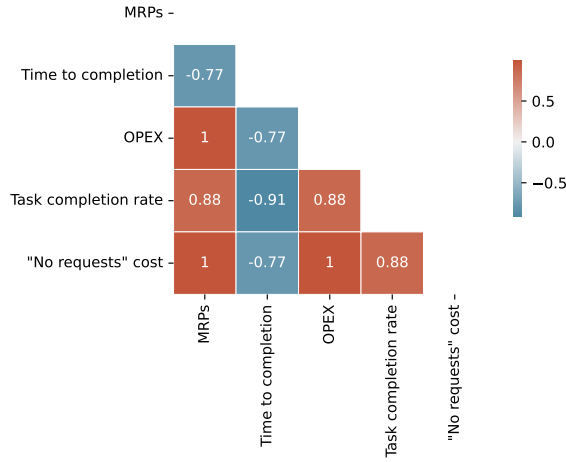


Figure 3.7: Correlation matrix of five key parameters. The red colours correspond to a positive correlation and the blue colours correspond to a negative correlation.

there are no inspection tasks to be completed. This indicates that 'no requests' costs can result in higher OPEX values when it is a function of the day-rate which corresponds to a fixed number of working days simulated in this study. Instead of day-rate, a fixed term inspection contract could result in a lower overhead in the 'no requests' element. The power production remains the same for all cases as only the inspection scenarios are considered in this study.

In summary, the correlation matrix analysis unveils valuable insights into the relationships between inspection time, OPEX and the MRP attributes. It suggests that efforts to minimize the day rate could lead to a lower OPEX, thereby improving MRP competitiveness. It also demonstrates that optimizing the number of MRPs can lead to both increased task completion rate and decreased time-to-completion, which are critical factors for devising an optimal O&M strategy. By understanding these relationships and adjusting the parameters accordingly, decision-makers can optimize resource allocation and drive operational improvements.

3.6. CONCLUSION

This study presents cost estimation for an offshore MRP and its impact on the OPEX and process time of inspecting specific components of a 1.5GW FOWF consisting of 100 turbines. The newly developed WOMBAT is employed as the O&M simulation tool. The outputs pertaining to various techno-economic performance metrics are analyzed and sensitivity analysis is conducted to identify the variables that have a key effect on these metrics. The analysis shows that there is a potential for inspection time reduction by the use of MRP. This reduction has dependency on the day-rate of the MRP and the time taken by the UAV or ROV to conduct inspection. Considering that incurred cost, inspection time, and data resolution are the main enablers of adoption of the MRP, further re-

finement of cost estimation and its validation could pave way for wide-scale adoption of robotics in the floating wind energy sector. In future, the perceived CAPEX depreciation in prices of UAV and ROV could also result in lower values of the day rates.

In comparison with CTV-based inspection, the MRP incurs a higher OPEX of 51.1% but accumulates a lower time-to-completion rate by 58.3%. The OPEX reduces by 50.6% if only one MRP is used with a relatively lower increase of 17.2% in the time-to-completion metric. This shows that initially smaller number of MRPs could be utilized which would reduce the OPEX but at an expense of increased inspection duration. Sensitivity analysis shows that the metrics of number of MRPs, day-rate and the inflation rate have the highest impact on the OPEX. On the other hand, the number of MRPs and the component inspection duration have the highest impact on the overall time-to-completion. Furthermore, correlation analysis shows that transitioning from the industrial standard of specified annual working days to fixed term O&M contracts can reduce the OPEX as well.

Such a cost-benefit framework can be used by MRP or FOWF developers to assess and optimise the suitability of robotics based inspections. In future, conducting sensitivity analysis of the cost estimation variables by including O&M term contracts and analyzing its effect on the OPEX could result in attaining useful insights regarding the MRP use cases. The inherent flexibility of the WOMBAT tool could be leveraged to simulate a variety of FOWF scenarios and across a large parameter horizon in order to arrive at a generalized framework for the MRP cost estimation. Furthermore, extending this analysis by including major repairs, replacements, and CAPEX data resulting in a realistic value of the LCOE should make the results more resourceful, and representative of an actual FOWF.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

4

INFORMED DECISION-MAKING FOR INVESTMENT IN ROBOTICS-DRIVEN INSPECTION OF FLOATING OFFSHORE WIND FARMS: A REAL OPTIONS APPROACH

Omer Khalid ^{1,2,3}, Guangbo Hao ², Hamish Macdonald ³, Fiona Devoy McAuliffe ¹, Cian Desmond ⁴

¹ MaREI Centre, Environmental Research Institute, University College Cork, Cork, Ireland

² School of Engineering and Architecture-Electrical and Electronic Engineering, University College Cork, Cork, Ireland

³ Offshore Renewable Energy Catapult, Glasgow, UK

⁴ ESB, Dublin, Ireland

CHAPTER OVERVIEW

This chapter consists of a research manuscript prepared for submission to the *Energies* journal by MDPI. In this publication, real options analysis has been utilized to conduct an assessment of the investment and operational costs of different robotic systems with varying levels of autonomy. The option values for different temporal nodes have been calculated and concluding remarks regarding the optimal decision paths that can result in the maximum return on investment have been discussed.

CONTRIBUTION

Omer Khalid: Conceptualization, Methodology, Formal analysis, Writing – original draft, Visualization. **Guangbo Hao:** Supervision, Validation, Writing – review & editing. **Cian Desmond:** Writing – review, Project administration, Funding acquisition. **Hamish Macdonald:** Project administration, Resources, Supervision. **Fiona Devoy McAuliffe:** Supervision.

4.1. ABSTRACT

The inspection and maintenance of floating offshore wind farms presents significant challenges due to their remote locations and harsh environments. Utilizing robotics can be an effective solution for enhancing the efficiency and safety of these operations. There is an increased focus on the deployment of autonomous robotic systems for inspecting the critical components of floating offshore wind farms, such as the turbine blades, mooring lines, and export cables. However, the integration of robotic systems for offshore inspection involves significant upfront investments, extended deployment timelines, and uncertainties arising from the technology readiness levels of such systems. An informed investment approach based on the insights derived from extensive cost assessment can allay these concerns. This research focuses on the devising of an informed investment decision-making process, leveraging real options analysis as the basis. Four different scenarios ranging from no autonomy to full-scale autonomy have been simulated in a cost model and the option values associated with various decision paths have been calculated. The model aims to determine the optimal investment approach and timing for the deployment of robotic inspection systems in a way to lower the incurred costs for each decision path. Results show that the transition to full-scale autonomy earlier in the project's lifecycle can save up to 24% in the incurred costs.

4.2. INTRODUCTION

The levelized cost of energy (LCOE) is a key metric used to evaluate and compare renewable energy technologies and projects. The LCOE calculation includes estimation of capital expenditures (CAPEX), operating expenditures (OPEX), additional risk premiums, and annual energy production (AEP) over the lifecycle of a floating offshore wind farm (FOWF) [137]. OPEX can make up to 20-30% of the total costs for a FOWF [19]. Therefore, accurately estimating the costs incurred during the operations and maintenance (O&M) phase is critical for evaluating a FOWF's financial viability and supporting long-term logistical and strategic decisions in this regard. Several of the largest sources of uncertainty that impact O&M costs and strategies include weather conditions and accessibility which affect the ability to access turbines for maintenance based on wave height, wind speeds as well as the scheduling of logistics that must adapt to weather windows and financial limitations [138, 139]. Additionally, failure rates and component reliability introduce uncertainties, especially with new floating platform designs making failure rates harder to predict. There are also uncertainties around vessel availability, pricing volatility, suitable ports and the broader supply chain over a project's lifetime [4]. Furthermore, electricity prices and ensuing revenue streams impact profitability available to fund O&M activities and are subject to volatility from markets and regulatory policies.

Traditionally, the net present value (NPV) and discounted cash flow (DCF) methods have been used for the cost analysis of industrial and operational processes. However, these methods have limitations in incorporating risk and uncertainty [140]. OPEX can have high variability due to weather delays, uncertain failure rates, logistic complexities, and other stochastic factors - especially for FOWFs which lie in sites farther from shore and in deeper waters. Static NPV analysis relying on deterministic inputs can be poorly equipped to model the flexibilities available to adapt to emerging information about cost drivers over a FOWF's nominal lifecycle of 25 years. Real options analysis (ROA) has emerged as a valuable supplement to NPV/DCF analysis that can better incorporate uncertainty and provide more realistic valuation. ROA treats investments as analogous to financial options, using similar valuation techniques [141]. Just as financial options confer the right but not the obligation to take certain actions contingent on how uncertainties are resolved, many infrastructure investments have similar flexibilities or "real options" embedded within them [142]. Unlike traditional NPV analysis, which assumes a fixed set of parameters, ROA allows for the incorporation of flexibility and the ability to adapt to changing conditions over time [143]. This is particularly relevant in the context of FOWFs, where factors such as technological advancements, regulatory changes, and market conditions can introduce substantial uncertainty into project planning and decision-making [144]. O&M strategies for a FOWF can be adapted based on revealed information about failure rates, vessel constraints, etc. In this regard, ROA provides quantification and valuation of such operational and managerial flexibilities.

Different research studies have shown that incorporating robotic systems for inspecting assets of a renewable energy system can reduce human deployment in harsh conditions, make operations more efficient, and optimize inspection of assets, ultimately reducing costs, improving reliability and cutting the carbon footprint as well [119], [6]. While the upfront capital costs of advanced robotic systems like unmanned aerial vehicles (UAVs) and remotely operated vehicles (ROVs) can be high, the long-term operational efficiencies, safety benefits, reliability improvements, and emissions reductions can often outweigh the initial investment costs [7]. As such, increased robotic integration represents a valuable pathway toward optimizing the inspection process. By applying real options analysis to the estimation of costs for robotics-based inspection of FOWFs, decision-makers can account for the value of flexibility in responding to unforeseen developments. For instance, the ability to delay investment in new inspection technologies until their effectiveness is better understood can be quantified as a real option, providing a more comprehensive view of the project's potential costs and benefits [145]. This approach aligns with the dynamic nature of financial viability, where the ability to defer, expand, or abandon certain activities based on evolving conditions can significantly impact the overall project economics [146].

[147] presents a case study where the inclusion of hydrogen powered gantry cranes over a long time period is assessed. Different technological scenarios were considered and the expected values for each of them were estimated. The optimal investment strategy was assessed wherein, it is concluded that the port will obtain more profits than the other strategies, but bear more capital pressure. Therefore, ports should flexibly adjust the investment strategy based on their development status and future planning.

There are various quantitative models and methods that have been developed to implement real options analysis, with different complexities and data requirements. Common models include decision trees with simple discrete scenarios and probabilities; dynamic programming which optimizes sequential decisions through backwards recursion; Monte Carlo simulation that requires probability distributions as inputs; binomial lattices that discretize uncertainty into up/down movements over time; and the Black-Scholes option pricing formula which is a closed-form solution assuming geometric Brownian motion and constant volatility. Each model has pros and cons relating to computational intensity, mathematical complexity, data availability, and accuracy. O&M decisions for FOWFs have multiple sources of uncertainty that interact in complex ways, without nice closed-form solutions. Therefore, lattice-based methods are often best suited for capturing the advent of innovation pertaining to different robotic systems and estimating the present value of the associated options.

In this work, we devise an ROA methodology wherein incorporating different robotic systems for the inspection of FOWF assets is considered. At first, the scenarios under the decision tree are established. This is followed by the formulation of the option value equation. The lifecycle of the FOWF is simulated in a cost modeling tool and the option values are calculated, which is followed by the analysis and interpretation of the obtained results.

4.3. METHODOLOGY

The decision tree for the robotics-driven inspection of a FOWF is shown in Figure 4.1. The horizontal axis pertains to the time period considered ranging from 2026 up until 2040 with increments of five years in each period. Four different scenarios are presented on the vertical axis starting from "no autonomy" to "full autonomy". These scenarios are considered considering the innovation aspects and technological trends in this regard along with an extensive literature study [119]. The decision tree consists of a binomial lattice where each node represents an instance in a time period. Two options of "increment" and "deferral" are considered for each node. Increment option enables to increase the investment into robotic systems and scale the innovation along the four scenarios. Deferral options allows to delay the investment in the higher autonomy level until costs are better known and more feasible. This scheduling of investments support re-optimising of decisions if initial assumptions differ from expectations, along with facilitating O&M vendors and investors to adapt their decisions as new information emerges and the technology readiness level (TRL) of robotic systems increases. By modeling such options explicitly and understanding the effects of triggering each option, the ROA can provide insights into the costs associated with each scenario and optimize strategies to maximize the overall project value. An overview of the methodology is presented in Figure 4.2. The methodology is further enumerated as follows:

- 1) At first, four scenarios pertaining to the roll-out of robotics-based inspection are identified based on literature review and stakeholder engagement.
- 2) Next to this, a decision tree is established outlining the four proposed scenarios and the relationship between them is presented. The categorization of the four

Table 4.1: Simulation input parameters.

Description	Value	Notes
Scenario 1		
Vessel day rate ^a (\$)	2,500	Value adjusted from [128].
Initial investment (\$)	-	Baseline scenario.
Inspection time (hrs.)		Mobilisation time ^b of 1.5 hours. Adjusted from [128].
Blades	3	
Mooring lines	3	
Export cable	4.5	
Scenario 2		
Vessel day rate (\$)	2,500	Same as Scenario 1.
Initial investment (\$)	8,600	Based upon analysis conducted in the author's previous study [148].
Inspection time (hrs.)		Mobilisation time of 1 hour. Adjusted from [13].
Blades	0.75	
Mooring lines	3	
Export cable	4.5	
Scenario 3		
Vessel day rate (\$)	2,500	Same as Scenario 1.
Initial investment (\$)	63,600	Based upon analysis conducted in the author's previous study [148].
Inspection time (hrs.)		Mobilisation time of 1 hour. Adjusted from [123] and [13].
Blades	0.75	
Mooring lines	1	
Export cable	1	
Scenario 4		
Vessel day rate (\$)	5,815	Based upon analysis conducted in the author's previous study [148].
Initial investment (\$)	-	Incorporated in the vessel day rate.
Inspection time (hrs.)		Mobilisation time of 0.5 hour. Adjusted from [123] and [13].
Blades	0.75	
Mooring lines	1	
Export cable	1	

^a 12 personnel are considered for the Scenarios 1,2 and 3, while 5 are considered for Scenario 4. Annual rate of \$75,000 per person is assumed.

^b Includes port-side and asset-side mobilisation time.

scenarios is elaborated in Figure 4.3. Three time periods are chosen from 2025 until 2040 with five years of increment in each period. The four scenarios are devised

as follows:

- (a) The first scenario pertains to no automation. This includes the use of a crew transfer vessel (CTV) with technicians and divers onboard to inspect the blades and subsea components of the FOWF, respectively.
 - (b) In the second scenario, a semi-automated system is considered where the blades are inspected using UAV.
 - (c) In the third, ROV is employed to inspect the subsea components in addition to the use of UAV. The technicians onboard the CTV are assumed to be responsible for launching and retrieving the UAV and ROV.
 - (d) The fourth scenario represents a fully autonomous system where an unmanned surface vessel (USV) is utilized with a launch and recovery mechanism for UAV and ROV. The system is also equipped with beyond visual-line-of-sight (BVLOS) capability. The technicians are located at the onshore O&M base, or at the offshore support base, and are responsible for inspection coordination and post-processing of the acquired data.
- 3) In the third step, simulation is run in the cost model with the defined parameters and the present value of the option is calculated at each decision node.
 - 4) The optimal decision strategy is evaluated by assessing the calculated option values.

The generic formulation of the present value is given in Equation 4.1 where PV refers to the present value and FV refers to the future value. The rate of return and the number of time periods is represented by r and n , respectively. The option value is formulated by taking into account the initial investment costs of a robotic system pertaining to a specific scenario, the operational costs as calculated by the cost model and the associated PBA. This is shown in Equation 4.2. The investment cost based upon the learning curve is further given by Equation 4.3, where a refers to the cost of a singular robotic system, x is the number of systems and b is the specified learning curve coefficient.

$$PV = FV \frac{1}{(1 + r)^n} \quad (4.1)$$

$$\text{Option value} = \frac{(I_{S_0} + O_{S_0})}{PBA_{S_0}} \quad (4.2)$$

$$I_l = a \sum_{x=1}^n x^b \quad (4.3)$$

4.3.1. SIMULATION

The lifecycle simulation of the FOWF is conducted in the Offshore Renewable Energy Catapult's (OREC) in-house cost model, and the option values at each decision node are calculated. The OREC model is a discrete-event prescriptive simulation tool dependent upon a variety of user inputs pertaining to the FOWF and the O&M strategy. An overview

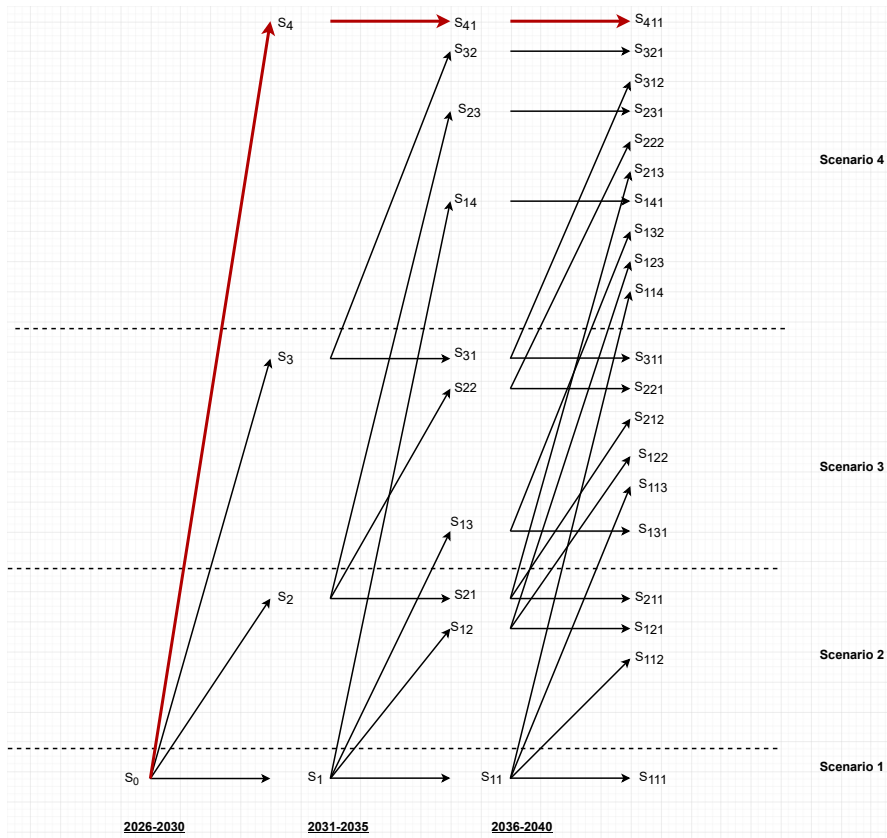


Figure 4.1: Decision tree diagram showing the relationships between the selected scenarios. For instance, the lines in red show a decision path for the full-autonomy scenario.

of the model is shown in Figure 4.4. In this study, only scheduled inspection of blades, mooring lines and export cables is considered on an annual basis. The parameters of the FOWF and those of the simulation are listed in Table 4.2 and Table 4.1, respectively. The significant wave height, H_s , is considered to be 1.75m for Scenarios 1, 2 and 3 while for Scenario 4, the value is taken to be 3m as it is more representative of the commercially available USVs.

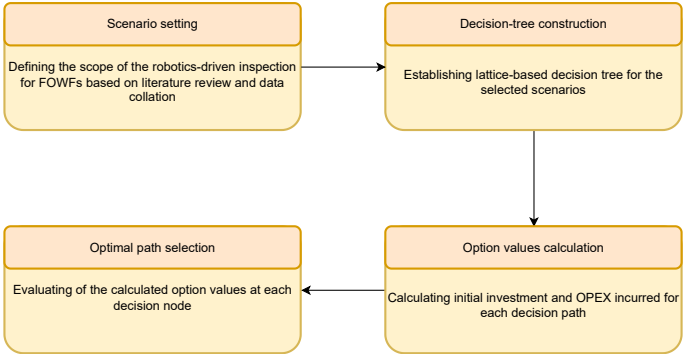


Figure 4.2: A box diagram showing overview of the real options analysis methodology.

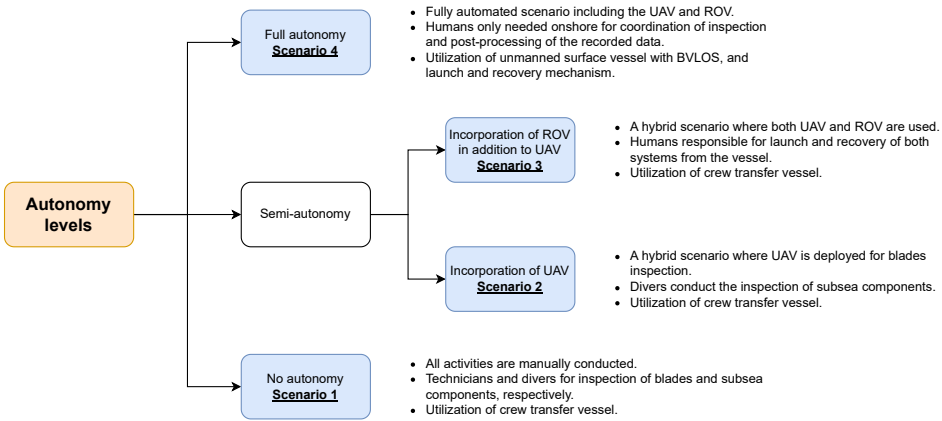


Figure 4.3: Categorization of the autonomy levels (elaborated from [149]). The boxes in blue pertain to the four scenarios selected for this study.

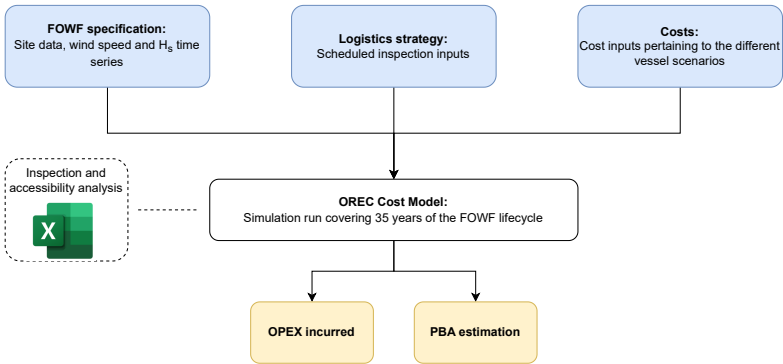


Figure 4.4: Visualisation of the OREC O&M simulation model methodology.

Table 4.2: FOWF parameters.

Description	Value
FOWF location	West Coast, IE
FOWF size	1.5 GW
Number of turbines	100
WT Model	IEA 15MW RWT [150]
WT Rated power	15 MW
Hub height	150m
Floating platform	DeepCwind [135]
Floating platform type	Semi-submersible
Number of mooring lines	3
Water depth	70m
Distance to O&M port	50km

Table 4.3: Calculation of option values for the three decision paths of full autonomy, full autonomy - staged and semi-autonomy.

Decision path	Time period	Decision path route	Option Value (Million \$)
Full autonomy	2026-2030	$S_0 - S_4$	2.7
	2031-2035	$S_4 - S_{41}$	2.3
	2036-2040	$S_{41} - S_{411}$	1.9
Full autonomy - staged	2026-2030	$S_0 - S_2$	2.7
	2031-2035	$S_2 - S_{22}$	2.2
	2036-2040	$S_{22} - S_{222}$	2.3
Semi-autonomy	2026-2030	$S_0 - S_2$	2.7
	2031-2035	$S_2 - S_{22}$	2.2
	2036-2040	$S_{22} - S_{221}$	2.5

4.4. RESULTS

Table 4.3 outlines the optimal decision paths and the corresponding option values across three distinct scenarios for conducting inspection of the FOWF over three 5-year time periods spanning from 2026 to 2040. These values reflect the costs associated with pursuing each path, considering the flexibility inherent in each decision, such as deferring investment or scaling up to a higher autonomy level based on the prevailing market conditions and technological advancements. The first case, termed "full autonomy," depicts decision paths labeled as $S_0 - S_4$, $S_4 - S_{41}$, and $S_{41} - S_{411}$, for the respective time frames of 2026-2030, 2031-2035, and 2036-2040, yielding option values of 2.7, 2.3, and 1.9 million dollars, respectively.

Table 4.4: Option values for the cases of learning rates variation and biannual inspection.

Case	Full autonomy - Option values (Million \$)		
	2026-2030	2031-2035	2036-2040
Learning rate - 0.1	2.7	2.6	2.4
Learning rate - 0.2	2.7	2.3	1.9
Learning rate - 0.4	2.7	1.8	1.3
Biannual inspection	5.8	4.9	4.6

In the second case, "full autonomy - staged," denoted by paths $S_0 - S_2$, $S_2 - S_{22}$, and $S_{22} - S_{222}$, the option values for the same time periods are 2.7, 2.2, and 2.3 million dollars, respectively. This scenario introduces a staged approach to the higher autonomy levels, enhancing the risk profile as compared to the full autonomy scenario. It can be inferred that even a staged approach can result in 21% increase in the final option value, signifying the importance of inspection profile associated with each scenario.

The third case of "semi-autonomy" presents decision paths labeled as $S_0 - S_2$, $S_2 - S_{22}$, and $S_{22} - S_{221}$, with associated option values of 2.7, 2.2, and 2.5 million dollars, respectively. This case involves staying at the semi-autonomy level of Scenario 3, and not opting for Scenario 4. This results in the highest final option value for the 2036-2040 period. This is due to the non-incurment of lower OPEX associated with Scenario 4.

Overall, this ROA provides valuable insights into the strategic decision-making process for managing FOWF inspections, highlighting the importance of considering flexibility and uncertainty in investment decisions. It can be inferred that the decision path pertaining to the full autonomy results in the lowest option value for the final time period of 2040. This path also remains optimal if the cumulative option values are considered for the three time periods.

Furthermore, Table 4.4 presents four cases, a comparison of learning rates across three distinct time periods along with the effect of biannual inspection. The simulations are carried out for three learning rates of 10%, 20% and 40%. The corresponding values in the table denote the option values associated with each case. As the learning rate increases, the option values decrease consistently across the three time periods, indicating a negative correlation between the learning parameter and performance. In case of biannual inspection, the option value rises in the initial time period to \$5.8M but then settles at \$4.6M in the final time period. It is pertinent to mention that the higher val-

ues associated with biannual inspection also accounts for the smaller weather window availability as the inspection window slides into the winter season with less favourable operating conditions.

4.5. CONCLUSION

In this work, we considered the incorporation of USV, ROV and UAV for inspecting various components of a FOWF. Simulations are conducted for four scenarios pertaining to different autonomy levels. Results based upon the option value calculations show that the transition to a higher autonomy level earlier in the project's lifecycle can save costs in the long term. The varied option values associated with the simulated scenarios reflect the strategic advantage of adopting a flexible investment approach, enabling decision-makers to adapt to changing market dynamics and maximize project value over the long term. The findings from learning rate variation suggests that the higher values of learning rates lead to accelerated reduction in option values over time, highlighting the importance of technological innovation and economies of scale in shaping long-term decision-making processes.

The utilization of ROA for assessing innovation-driven costs such as the incorporation of robotic systems of varying autonomy levels for inspection of FOWFs can support improved industry practices and decision making in several ways. It can provide insights into how costs can spread out over long time periods under different pre-defined scenarios. While the definition of scenarios is prone to assumptions and top-down estimation, the ROA can nevertheless capture the uncertainty present in the costs over a FOWF's lifecycle. Different stakeholders such as O&M vendors can integrate ROA into their cost modeling, logistics planning and decision making processes. Furthermore, by spreading out investment costs, decision-makers can mitigate risks and capitalize on future opportunities while maintaining financial flexibility.

In conclusion, ROA can provide with a modern quantitative valuation approach for estimating lifecycle O&M costs and making strategic decisions around FOWF maintenance under financial and technical uncertainty. Further adoption of ROA techniques in research, policy, and industry practices will ultimately enable more realistic cost projections, reduced risks, increased cost efficiencies, and enhanced reliability for FOWF infrastructure critical to overall net zero efforts. By analyzing various decision paths and their associated option values, stakeholders can better understand the trade-offs and opportunities inherent in different scenarios and devise optimal strategies to enhance project value and long-term sustainability, particularly in industries characterized by uncertainty and evolving market conditions, such as the offshore wind energy sector.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

5

UAV-BASED AUTOMATED DETECTION OF WIND TURBINE BLADE DAMAGES: SEQUENTIAL EVALUATION OF MODEL TRAINING WITH THERMAL ANALYSIS

Omer Khalid ^{1,2,3}, Guangbo Hao ², Hamish Macdonald ³, Fiona Devoy McAuliffe ¹, Cian Desmond ⁴

¹ MaREI Centre, Environmental Research Institute, University College Cork, Cork, Ireland

² School of Engineering and Architecture-Electrical and Electronic Engineering, University College Cork, Cork, Ireland

³ Offshore Renewable Energy Catapult, Glasgow, UK

⁴ ESB, Dublin, Ireland

CHAPTER OVERVIEW

This chapter consists of a research manuscript slated for submission to the special issue *Operations and Maintenance (O&M) of Offshore Renewable Energy (ORE) Devices Using Marine Vehicles and Drones* of the *Drones* journal by MDPI. This publication focuses on the demonstration of UAV-based automated detection of wind turbine blade damages. Imagery data consisting of visible and thermal images has been acquired from an operational wind farm. Two detection approaches based on model training and thermal analysis have been employed in a sequential manner, and results are evaluated based upon their respective detection performance.

CONTRIBUTION

Omer Khalid: Conceptualization, Methodology, Formal analysis, Writing – original draft, Visualization. **Guangbo Hao:** Supervision, Validation, Writing – review & editing. **Cian Desmond:** Writing – review, Project administration, Funding acquisition. **Hamish MacDonald:** Project administration, Resources, Supervision. **Fiona Devoy McAuliffe:** Supervision.

5.1. ABSTRACT

Automated inspection of wind turbine blades using unmanned aerial vehicles have been gaining traction in recent years. It can help to identify defects at an earlier stage resulting in preventive maintenance and mitigating risks of turbine downtime and catastrophic failures. In this work, we present a sequential evaluation of model training with thermal analysis applied on the imagery dataset acquired from an operational wind farm. A convolutional neural network has been trained to conduct binary classification on the visible (RGB) images while temperature differential analysis is conducted on the thermal images. The outputs from the two techniques are evaluated in terms of their detection performance and computational cost. Results demonstrate that the model training can result in effective detection with a precision of up to 76%, although a sparse training dataset can limit the performance of the model. Furthermore, applying thermal differential analysis on the detected damaged regions can help in identifying most of the defects that have penetrated the blade surface.

5.2. INTRODUCTION

Automated inspection of wind turbine blades using unmanned aerial vehicles (UAVs) or drones has been a key area of academic research and technology development in recent years [151, 152]. This includes both the acquisition of the imagery data from the blades and the post-processing of it, with an aim to assess the structural health of the blades based upon pre-defined classification categories. As the onshore and offshore wind energy industry continues to grow at a rapid pace, the inspection of turbine blades would continue to remain relevant and critical in the future. Preventive maintenance of blades by taking images at regular intervals helps in detecting damages and defects along with the opportunity to rectify them in due time. This reduces the risk of damages turning into potential failures or catastrophic events along with enhancing the production-based availability and the cumulative lifecycle of the wind turbines.

Several studies have focused on the detection and classification of damages on wind turbine blades [153, 154]. This includes leveraging image processing algorithms in order to detect the presence of damages along with classifying them into different categories based upon the type or extent of damages [155, 156]. [157] discussed the use of supervised machine learning algorithms for wind turbine blade damage detection based on statistical features extracted from acoustics. This study emphasized the importance of selecting appropriate features and devised a deep learning (DL) algorithm for effective damage identification. [158] presented the application of transfer learning to improve the generalisation ability of the DL-based model, which results in successful binary classification of defective and non-defective blades. [159] explored the identifica-

tion of de-bonding damage in wind turbine blades using artificial neural networks and natural frequency key features, showcasing the potential of machine learning techniques in detecting specific types of damage in composite wind turbine structures. Further to this, various studies have looked at utilizing thermal images for detection of damages based on temperature differentials. Infrared (IR) thermography is a non-contact, remote non-destructive testing (NDT) method capable of rapidly inspecting large areas by capturing thermal images of the structure [160]. The thermographic detection of defects is grounded in the disruption of heat transfer dynamics caused by structural anomalies within composite materials, such as fiber-reinforced polymers. These materials exhibit predictable thermal conductivity and emissivity under normal conditions, but defects like delamination, cracks, or moisture ingress introduce localized variations in thermal properties. Typically, defects cause variations in surface temperature, which are detected by the IR cameras. In [161] and [162], an automated quantification of damages based on thermal imagery is presented with an aim to assess its costs and benefits. It is shown that an estimated levelized cost of energy (LCOE) reduction of 1%–2% can be achieved compared to the baseline using conventional inspection methods. This work is further elaborated by [163] wherein a graphical user interface has been developed to aid with the thermal analysis of videos in addition to the imagery datasets.

While a lot of work has centered on the machine learning based damage detection and quantification algorithms, there has been a lack of focus on complementing model-based approach with thermal analysis. Furthermore, there exists a need to demonstrate the effectiveness of employing such techniques on extensive imagery dataset acquired from an operational wind farm. In this work, we present a best practices approach for automated detection of damages on wind turbine blades based upon a sequential evaluation of DL-based model training on the visible (RGB) images, complemented with thermal differential analysis on the corresponding thermal images. The primary objectives of this work are to: (i) conduct UAV-based acquisition of blade imagery data from operational wind turbines, (ii) develop DL-based model training and thermal differential algorithms for damage detection on the acquired dataset, and (iii) conduct sequential evaluation by inferring results in terms of detection performance and computational cost.

5.3. METHODOLOGY

The methodology for the damage detection based upon the two techniques is visualized in Figure 5.2. At first, an extensive RGB and thermal imagery dataset is acquired from an operational wind farm. This is further discussed in Section 5.3.2. Next, two sequential work streams based upon DL and thermal differential analysis have been created to detect damage utilizing RGB and thermal images, respectively. A convolutional neural network (CNN) is trained to detect damage in the images based upon binary categories of "defective" and "non-defective". Once the defective images are detected, thermal analysis based upon passive temperature differential is conducted in order to identify the type of defect present. The results from the two approaches are collated and an evaluation in line with detection performance and computational cost has been presented. The detection performance is further divided into the metrics of Precision, Recall and F1 score [164]. The Precision, as shown in Equation 5.1, is defined as how good the model is at

predicting a certain category, where *TP* and *FP* stand for *True Positive* and *False Positive*, respectively. Recall is a measure of the proportion of the *Positive* samples that were correctly identified as *Positive* to all of the *Positive* samples. This is calculated by Equation 5.2, where *FN* stands for *False Negative*. Finally, a single metric which weighs the two ratios in a balanced way, the harmonic mean of recall and precision, is given by the F1-score, as shown in Equation 5.3.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (5.1)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5.2)$$

$$\text{F1-score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5.3)$$

5

5.3.1. CASE STUDY OVERVIEW

The rationale of the work presented in this study centers around the need to demonstrate the applicability of automated damage detection on blades imagery data from an operational wind farm, along with investigating the trade-offs between the performance of RGB and thermal data sources. While prior research has demonstrated the feasibility of automated damage detection using lab-controlled datasets, the translation of these methods to operational wind farms remains underexplored. Lab-based datasets often aggregate meticulously annotated images under controlled conditions, enabling precise feature extraction. In contrast, real-time operational data is inherently heterogeneous, requiring adaptive models capable of generalizing across diverse scenarios without overfitting. A secondary focus lies in evaluating the comparative efficacy of RGB and thermal imaging modalities, each presenting distinct trade-offs. The training of damage detection model requires access to extensive feature-rich RGB data, which is difficult to attain based upon real-time operational data as compared to the lab-based data acquisition. On the other hand, thermal analysis can provide with simpler assessment as it is dependent upon the observed thermal gradient and the model does not need to be trained, but the relationship between the gradient and the type or the nature of the defect is difficult to assess.

5.3.2. DATA COLLECTION

The imagery data acquired for the purpose of this work comprises of over 3500 RGB and thermal images acquired from four turbines located at the Bellacorick Wind Farm in County Mayo, Republic of Ireland as shown in Figure 5.1. These four turbines were selected with an aim to target the blades with the highest proportion and types of defects present at the time of inspection. In order to obtain clear images, the data acquisition was performed at noon on 28 October 2022. The weather at the time of inspection was partly sunny and the temperature was recorded to be 13 °C. The specifications of the wind farm along with those of the UAV used for the acquisition of images are presented in Table 5.1. External surfaces of the blade root, Leading Edge (LE), Trailing Edge (TE),

and rotor hub are inspected. A sample of these images including the various types of defects present on the blades is shown in Figure 5.2.

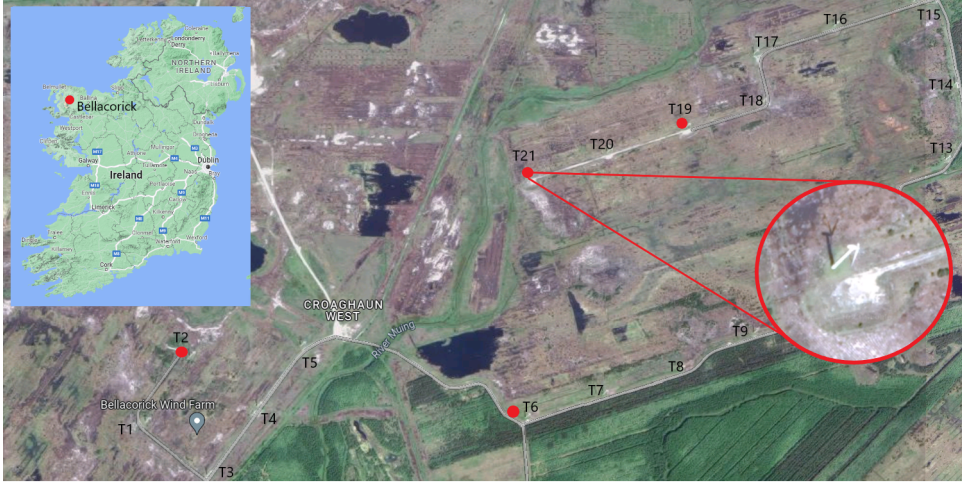


Figure 5.1: Bellacorick Wind Farm in County Mayo, Republic of Ireland with the four inspected turbines highlighted in red.

5.3.3. MODEL TRAINING

The automated damage detection is conducted based upon a convolutional neural network (CNN) model which is trained using TensorFlow [175] and Keras [176]. The specifications of the computer system are listed in Table 5.2. The model consists of multiple convolutional layers, max-pooling layer, and a final dense layer with a sigmoid activation function for binary classification. Notably, initial experiments with multi-class classification yielded suboptimal accuracy (below 50% on validation data), as the model struggled to discern subtle distinctions between defect categories with insufficient training examples. For instance, cracks and surface erosion, often visually similar in low-resolution or noisy images, were frequently misclassified due to overlapping features and limited per-class samples. In contrast, the binary model achieved markedly higher performance, underscoring its suitability for operational scenarios where the primary objective is reliable damage detection rather than granular defect categorization. This pragmatic approach aligns with the constraints of field-acquired data, where blade defects are sporadic, heterogeneous, and rarely conform to standardized laboratory defect typologies. During pre-processing, the input shape is set to (180, 180, 3), re-sizing the input images to a size of 180x180 pixels with 3 color channels (RGB). The imagery data is then split into training, validation and test datasets. This partition ensures that the model can be trained, validated, and tested on distinct data, allowing for accurate performance evaluation. Furthermore, as the damages present on the available dataset of blades are sparse, data augmentation is applied by creating a sequential model that applies random flips, rotations, and zooms to the input images. This step is useful for in-

Table 5.1: Specification of the wind farm.

Wind farm specifications	Value
Farm location	Bellacorick, Mayo, IE
Farm capacity	6.45 MW
Turbine Model	Nordtank NTK300/31
Rated power	300 kW
Rotor diameter	31 m
Rated wind speed	15 m/s
Turbines inspected	T2, T6, T19, T26
UAV and sensor specifications	Value
Model	DJI Matrice M300
Maximum flight time	55 min
Battery capacity	5935 mAh
RGB camera zoom	20 MP
RGB camera wide	12 MP
Thermal camera model	FLIR Hadron 640 Series
Thermal camera resolution	640 X 512 pixels
Temperature accuracy	± 5 °C less, over 0 °C to 100 °C range
Thermal camera size (L x W x H)	35 x 49 x 45 mm
Standoff distance	5-10 m

Table 5.2: Hardware and software specification of the computer system.

Specification	Details
Processor	Intel Core i7-10610U @ 1.80GHz
Memory (RAM)	32GB
Operating System	Microsoft Windows 10, Build 19045

creasing the diversity of the training data and improving the model's generalization ability. After applying augmentation, the data is loaded into the CNN model. An overview of the methodology is presented in Figure 5.3 while the pseudo-code for the DL-based model training is presented in Algorithm 1.

5.3.4. THERMAL ANALYSIS

In order to detect damages based upon thermal imaging, temperature differential calculation and region of interest (ROI) scaling is leveraged with an aim to identify defective regions in the blade images. Area marking allows to select a ROI on the thermal image and calculate the minimum, maximum, and average temperatures within that region. This allows for the removal of extraneous regions and is beneficial for inspecting larger areas of the blade and identifying potential defects or anomalies based on temperature variations across the selected region. The pseudo-code for the thermal analysis methodology is presented in Algorithm 2, while the key steps are presented as follows:

Algorithm 1 Pseudo-code for detection based upon DL.

```
1: Set Up Directories
2: Define paths for base directories
3: function MAKE_SUBSET(subset_name, start_index, end_index)
4:   for all category in ("defective", "non-defective") do
5:     Create directory for the subset and category
6:   end for
7: end function
8: Create training, validation, and test subsets using make_subset
9: Apply Data Augmentation
10: Define data augmentation with random flip, rotation, and zoom
11: Build Convolutional Neural Network (CNN)
12: Initialize input layer with shape (180, 180, 3)
13: Apply data augmentation to inputs
14: Add rescaling layer
15: Add a series of Conv2D and MaxPooling2D layers
16: Flatten the output
17: Add a Dense layer with sigmoid activation for binary classification
18: Compile the model with binary crossentropy loss and RMSprop optimizer
19: Display model summary
20: Prepare Data
21: Load training, validation, and test datasets from directories with image size (180, 180)
    and batch size 32
22: Train Model
23: Define model checkpoint callback to save the best model based on validation loss
24: Train the model with training dataset for 30 epochs, validating on validation dataset,
    using defined callbacks
25: Plot training and validation accuracy
26: Plot training and validation loss
27: Evaluate Model
28: Load the saved model
29: Evaluate the model outputs
```



Figure 5.2: A subset of the RGB images acquired from the UAV with various types of damages boxed in red.

- 1) **Data pre-processing:** Pre-processing of the data is critical so that the results can be accurately interpreted. The thermal images are adjusted for emissivity, a property that varies with material and surface conditions, using a predefined emissivity value (typically 0.95 for composite materials commonly used in wind turbine blades). This adjustment compensates for the variability in thermal radiation emission and ensures that the temperature readings reflect true surface temperatures accurately.
- 2) **ROI selection:** The next step is defining ROIs on the thermal image. ROIs are specific areas on the wind turbine blade that are suspected to be susceptible to damage or require detailed inspection. These regions are manually selected based on structural features and potential stress concentration areas such as the leading edge of the blades. The selection of ROIs is guided by knowledge of wind turbine blade design and typical failure points, ensuring that the analysis focuses on the most critical areas.
- 3) **Calculation of temperature differentials:** Once the ROIs are defined, temperature measurement and profiling are conducted within these regions. For each ROI, a temperature profile is measured along specific lines or areas. This is achieved by drawing a line across the ROI and sampling the temperature data points along this line. The temperature values along these lines provide a profile that reflects the thermal gradient and distribution across the ROI. This step is essential for identi-

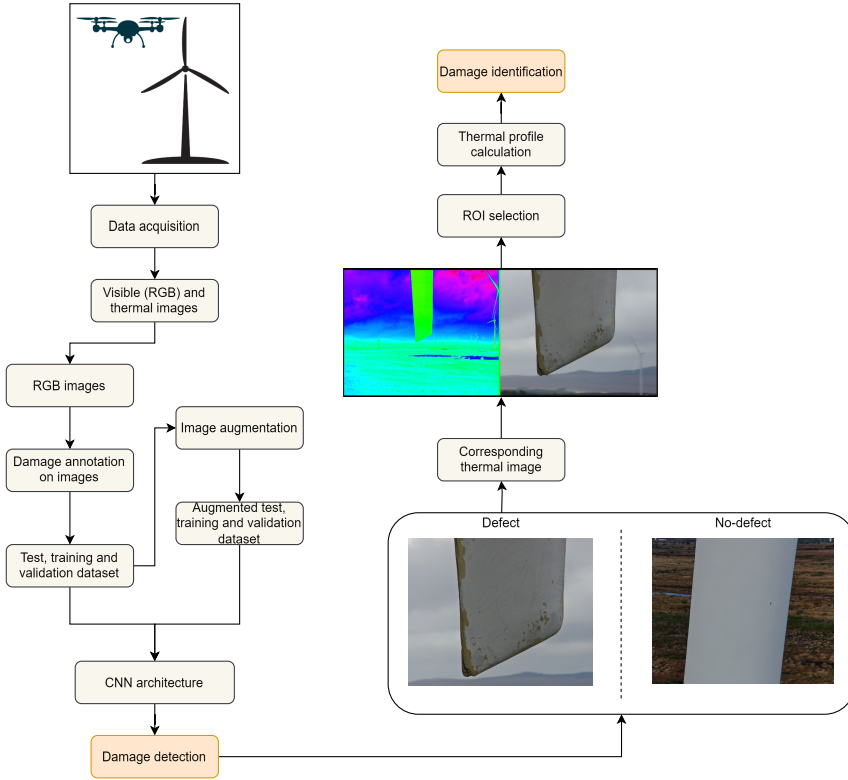


Figure 5.3: Methodology for sequential evaluation.

fying localized temperature anomalies that could indicate subsurface damage or defects.

- 4) **Damage detection:** Finally, the algorithm processes the temperature differential data and applies a predefined threshold to identify significant deviations. This threshold is manually specified by as part of the temperature differential calculation, as its value is dependent upon different types of damages and on different parts of the blades. ROIs exhibiting temperature differentials above this threshold are flagged as potentially damaged.

5.4. RESULTS

With respect to the model training, the outputs in terms of the performance metrics of precision, recall, F1-score and computational cost are presented in Table 5.3. Four DL-based algorithmic techniques have been compared, starting from the base CNN architecture VGG19 without any augmentation. This results in a moderate precision and recall of 0.56 and 0.72, respectively, resulting in an F1-score of 0.63. This indicates that while the model was fair at identifying damaged blades, it also had a significant num-

Algorithm 2 Pseudo code for thermal differential analysis.

```

1: procedure THERMAL_IMAGE_ANALYSIS(thermal_image, threshold)
2:   thermal_data, metadata  $\leftarrow$  Load_Thermal_Images()
3:   roi_coords  $\leftarrow$  Get_ROI_Vertices()
4:   roi_data, roi_min, roi_max  $\leftarrow$  Scale_ROI(thermal_data, roi_coords)
5:   temperature_differentials  $\leftarrow$  Calculate_Temperature_Differentials(roi_data)
6: end procedure
7: procedure SCALE_ROI(thermal_data, roi_coords)
8:   roi_indices  $\leftarrow$  Get_ROI_Indices(roi_coords, thermal_data.shape)
9:   roi_data  $\leftarrow$  thermal_data[roi_indices]
10:  roi_min  $\leftarrow$  np.min(roi_data)
11:  roi_max  $\leftarrow$  np.max(roi_data)
12:  scaled_data  $\leftarrow$  np.clip(thermal_data, roi_min, roi_max)
13:  return scaled_data, roi_min, roi_max
14: end procedure
15: procedure CALCULATE_TEMPERATURE_DIFFERENTIALS(roi_data)
16:   threshold  $\leftarrow$  {}
17:   for roi_data  $\in$  temperature_differentials do
18:     if roi_data > threshold then
19:       defects.append()
20:     end if
21:   end for
22:   return roi_data
23: end procedure

```

ber of false positives. The computational time was relatively low at 0.8 hours, making it efficient but less accurate. Augmenting the dataset for the VGG19 model significantly improved all performance metrics. The precision increased to 0.67, recall to 0.80, and F1-score to 0.73. This improvement suggests that data augmentation helped the model to generalize better and reduce false positives. However, the computational time doubled to 1.6 hours. The ResNet 50 model with augmentation showed a precision of 0.68 and recall of 0.74, resulting in an F1-score of 0.71. While its precision was slightly better than VGG19 with augmentation, its recall was lower. The computational time remained at 1.6 hours, indicating that ResNet 50 is computationally efficient given its performance. Inception V3 with augmentation achieved the best performance among all models. With a precision of 0.76 and recall of 0.77, it resulted in an F1-score of 0.76. This model had the highest computational time at 1.7 hours but provided the best trade-off between precision and recall, making it the most reliable for detecting damages. It is inferred that the relatively lower F1-score of the trained models is due to the sparse dataset containing damages. While the augmentation resulted in better performance, further improvement is dependent upon enhancing the size and quality of the dataset. Once, the defective and non-defective images have been detected, the corresponding thermal images of the defective images are selected for the thermal profile analysis.

The majority of the defects present on the blades and the rotor hub are of lighter

nature ranging from discoloration, light erosion and presence of vents and lightning receptors. A sample of these defects with their thermal profiles is presented in Figures 5.4, 5.5 and 5.6. For instance, Figure 5.4c shows a close-up RGB image of the blade's leading edge, where a visible erosion along the edge, appearing as a rough, irregular surface instead of a smooth contour, can be observed. The corresponding thermal image is shown in Figure 5.4b where the horizontal line pertains to the ROI. The thermal profile of the ROI is shown in Figure 5.4a, where it can be seen that there is a temperature differential of more than 1°C indicating the presence of erosion. The graph in Figure 5.5a shows thermal profiles based on three ROIs on the rotor hub, labeled as l1, l2, and l3. It can be seen that the l1 profile results in the largest thermal differential of about 0.5°C, while the l2 and l3 profiles results in relatively smaller differentials. It can be inferred that the structural discoloration, as shown in Figure 5.5c, results in smaller temperature differentials as compared to damages such as erosion which has a higher structural depth. Similarly, Figure 5.6a shows the thermal profile pertaining to the vent hole present on the lower segment of the rotor hub. This also results in a smaller differential of 0.4°C. Based on the available damages on the dataset, it is inferred that the deeper structural erosion results in a differential of over 1°C, while minor structural damages and discoloration results in fairly smaller differential in the range of 0.5°C.

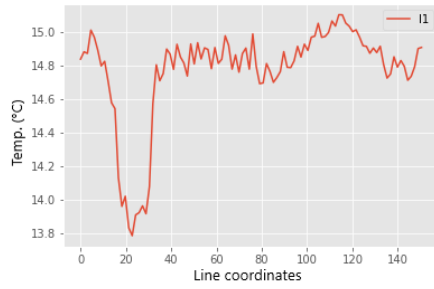
Table 5.3: Performance metrics for the DL-based model training.

Technique	Precision	Recall	F1-score	Computational time (hrs)
CNN (VGG19)	0.56	0.72	0.63	0.8
CNN (VGG19) + augmentation	0.67	0.80	0.73	1.6
CNN (ResNet 50) + augmentation	0.68	0.74	0.71	1.6
CNN (Inception V3) + augmentation	0.76	0.77	0.76	1.7

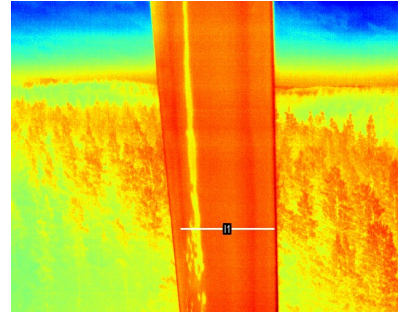
5.5. CONCLUSION

The work conducted in this study explored the performance evaluation based upon the visible and thermal imaging for detecting damages on WTG blades and the rotor hub. A sequential approach is considered where initially a model is trained for binary classification of defective and non-defective regions. Next to it, the corresponding thermal images of the defective regions are analysed with an aim to quantify the type of defect present. The following concluding remarks have been inferred from the analysis:

- 1) The integration of thermal and visible imaging captured by the visible and the FLIR cameras provides benefits in terms of utilizing the complementary features of RGB and thermal images.
- 2) While data augmentation can significantly improves the performance, the relatively lower F1-scores across all DL-based models suggest that the dataset is sparse



(a) Thermal profile based upon the ROI.

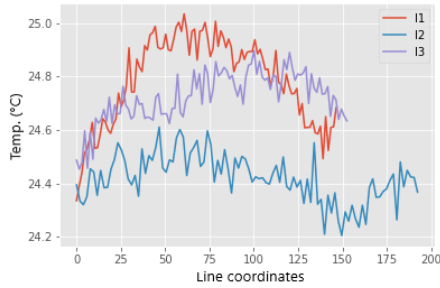


(b) Thermal image of the blade with the line-based ROI selection.

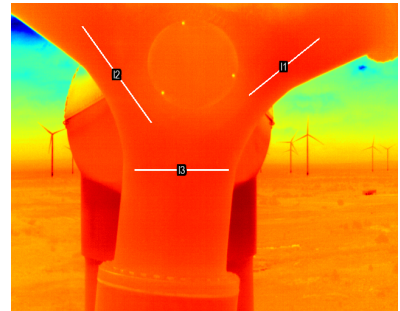


(c) RGB image of the blade's leading edge.

Figure 5.4: ROI based thermal profile of the erosion on the blade shows a temperature differential of more than 1°C .



(a) Thermal profile based upon the ROI.

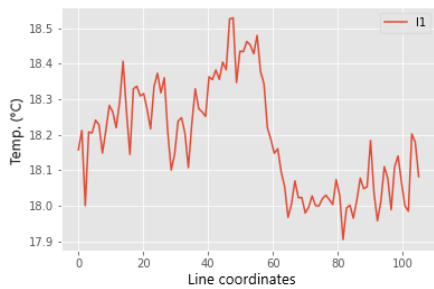


(b) Thermal image of the rotor hub with the line-based ROI selection.

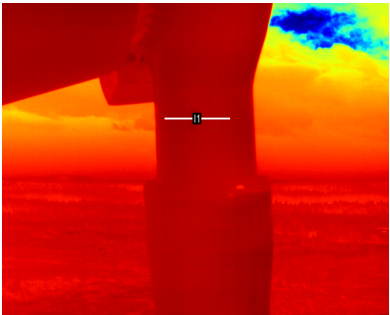


(c) RGB image of the rotor hub.

Figure 5.5: ROI based thermal profile of the discoloration on the rotor hub shows a relatively smaller temperature differential of 0.5°C .



(a) Thermal profile based upon the ROI.



(b) Thermal image of the rotor hub with the line-based ROI selection.



(c) RGB image of the rotor hub.

Figure 5.6: ROI based thermal profile of the vent hole on the rotor hub shows a relatively smaller temperature differential of 0.4°C.

or imbalanced, indicating a need for more diverse and comprehensive training data.

- 3) The time required for training the model depends upon on a number of factors such as the size of the dataset and the images, depth of the CNN layers and the selected hyperparameters. The computational time for the VGG19 is 0.8 hours which increases to up to 1.7 hours in case of Inception V3 with augmentation. It is pertinent to mention that this pertains to a training, validation and test dataset of 1000 images each. It is inferred that this can increase substantially if the dataset grows bigger, or if further augmentation of images is applied.
- 4) Thermal imaging successfully identified erosion on the blade's leading edge, with a temperature differential of more than 1°C. This indicates that deeper structural erosion can be reliably detected through significant thermal differentials.
- 5) Significant erosion on blade regions tends to produce larger temperature differentials (>1°C) compared to surface discoloration or minor structural damages (0.5°C). This correlation highlights the potential of thermal imaging as a diagnostic tool for assessing the severity of structural damages on the WTG blades.
- 6) The motion of floating offshore wind turbine blades, while dynamic due to wave-induced platform movement and rotor rotation, is unlikely to significantly impede data acquisition from drones equipped with stabilization systems and target-locking sensors. Modern drones leverage advanced inertial stabilization, gimbal systems, and real-time tracking algorithms to maintain precise focus on moving targets, compensating for both blade motion and the drone's own positional fluctuations. Thermal and RGB cameras can lock onto blade surfaces, capturing high-resolution imagery even during moderate blade oscillations. However, extreme motion amplitudes or high-frequency vibrations—common in harsh offshore conditions—could introduce motion blur in RGB images or smeared thermal gradients, potentially degrading defect detection accuracy. Thermal imaging, which relies on relative heat patterns rather than fine spatial details, may be less affected by minor motion as compared to the RGB data.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

6

DEVELOPMENT OF A SYSTEMS ENGINEERING FRAMEWORK FOR THE DEPLOYMENT OF ROBOTICS-DRIVEN INSPECTION OF FLOATING OFFSHORE WIND FARMS

Omer Khalid ^{1,2,3}, Guangbo Hao ², Hamish Macdonald ³, Fiona Devoy McAuliffe ¹, Cian Desmond ⁴

¹ MaREI Centre, Environmental Research Institute, University College Cork, Cork, Ireland

² School of Engineering and Architecture-Electrical and Electronic Engineering, University College Cork, Cork, Ireland

³ Offshore Renewable Energy Catapult, Glasgow, UK

⁴ ESB, Dublin, Ireland

CHAPTER OVERVIEW

This chapter consists of a policy manuscript slated for submission to the *Cleaner Energy Systems* journal by Elsevier. In this publication, the utilisation of model-based systems engineering framework has been explored for the deployment of robotics-inspection of floating offshore wind farms from a policy-making perspective. Furthermore, risk assessment based upon failure modes and effect analysis has been conducted with an aim to identify potential barriers for the adoption of autonomous inspection systems.

CONTRIBUTION

Omer Khalid: Conceptualization, Methodology, Formal analysis, Writing – original draft, Visualization. **Guangbo Hao:** Supervision, Validation, Writing – review & editing. **Cian Desmond:** Writing – review, Project administration, Funding acquisition. **Hamish Macdonald:** Project administration, Resources, Supervision. **Fiona Devoy McAuliffe:** Supervision.

6.1. ABSTRACT

Technological innovations in the marine sector often suffer from a slow uptake and struggle to achieve the technical and commercial readiness required for mass scale adoption. The use of robotic systems for the inspection of floating offshore wind farms is one such example. This paper aims to leverage model based systems engineering (MBSE) to conceptualise and assess the risks associated with such systems. The paper demonstrates how MBSE facilitates end-to-end traceability and coherence from system requirements through design, deployment, and operations. The methodology encompasses the identification of system requirements, relating them to software and hardware aspects of system design, and leveraging expert elicitation for estimating cost drivers based upon the COSYSMO model. Additionally, a Failure Mode and Effects Analysis (FMEA) is conducted to capture the inherent uncertainty at the sub-system level. Key findings highlight the holistic nature of system requirements, the effectiveness of MBSE in delineating software-hardware interfaces, and the identification of potential deployment roadblocks. The FMEA results provide crucial insights for prioritizing risk mitigation efforts and enhancing system reliability. This framework offers a structured approach to addressing the complex challenges in developing and deploying autonomous inspection systems for FOWFs, potentially leading to more cost-effective and efficient strategies.

6.2. INTRODUCTION

The growth of offshore wind energy is a critical part of the global transitioning towards renewable energy resources and achieving net zero targets [1]. Offshore wind farms offer several advantages over their onshore counterparts, including higher wind speeds, lower spatial turbulence, and the ability to deploy turbines of larger sizes over greater areas [118]. Floating offshore wind farms (FOWFs), where the turbines are mounted on buoyant platforms tethered to the seabed, are particularly well-suited for deep water sites that are unfeasible for fixed-bottom technology [2]. Many floating projects are in development worldwide, driven by the growth potential of this technology to unlock deep water offshore wind resources. However, operating these utility-scale facilities in the harsh maritime environment presents unique challenges in terms of installation, maintenance, and ultimately decommissioning of the wind turbine generators (WTGs) and the associated infrastructure.

A key aspect of operating FOWFs over their lifecycle is developing robust processes and strategies for regular inspection and maintenance of different assets in a cost effective manner [4, 139]. Periodic inspection is required to monitor the structural integrity and biological fouling of the surface and submerged components, including the turbine towers, blades, mooring lines, anchors, and export cables. These inspections must be

carried out regularly throughout the multi-decade operational life of the wind farm with an overarching aim of increasing the production-based availability (PBA) of the turbines.

Manual inspection techniques, such as using personnel on crew transfer vessels (CTVs) and service operation vessels (SOVs) can be challenging and expensive in FOWF environments, especially as these farms scale up to hundreds of turbines distributed over large areas. There are also potential safety risks pertaining to presence of human technicians in offshore locations for long periods of time. In this regard, robotic and autonomous systems (RAS) offer a compelling solution for conducting affordable, frequent, and safe inspections while minimizing manual intervention and operational disruption [7]. This has driven research into using unmanned aerial vehicles (UAVs) or drones and underwater remotely operated vehicles (ROVs) integrated with data acquisition sensors to automate inspection tasks. UAVs can provide aerial imaging of topside components, while ROVs can inspect subsurface components such as mooring lines, export cables and anchors. Key technical capabilities include autonomous navigation, visual sensing, automated defect detection, and managing robust communications with the control and coordination team over long ranges offshore. Developing an integrated automated inspection system for inspection of FOWFs is an inherently complex, multi-disciplinary challenge that spans domains such as robotics, sensing, data analytics, communications, and control systems. It requires close coordination between diverse engineering disciplines as well as deep integration of hardware and software components into a holistic system [11].

Model-Based Systems Engineering (MBSE) is an emerging methodology that uses descriptive models as the primary means of information exchange between engineers and various stakeholders, rather than relying on traditional methods [165]. In MBSE, a system model provides a coherent single source of data that captures the complete system across multiple views and levels of abstraction. This allows different engineering domains to concurrently contribute their perspectives in a unified model. MBSE based approaches are gaining traction across industries that develop complex cyber-physical systems [166]. By shifting the paradigm to descriptive models, MBSE aims to enhance transparency, consistency, knowledge capture, and efficiency across all stages of a system's lifecycle. In the context of robotic inspection systems for FOWFs, MBSE offers a comprehensive framework for integrating all aspects of system definition, analysis, design, deployment, and operational scenarios. By capturing the full system model from the outset, the MBSE process ensures end-to-end traceability between customer needs, engineering requirements, component implementations, and system verification.

The application of MBSE to the design and development of robotic inspection systems for FOWFs can yield significant practical benefits. A well-designed MBSE model provides clear allocation of responsibilities across engineering teams, streamlines project management, and seamlessly connects to downstream deliverables like technical documentation, and operational status of the wind farm. The model can be readily leveraged for follow-on activities and technology transition along with reusing the model for similar tasks due to its modular structure. Most critically, the MBSE process can instill a *design-for-X* mindset from the outset - designing robustness, affordability, safety, and operability into the system architecture rather than retroactively addressing these cross-cutting concerns downstream. For mission-critical systems like effective inspection of

high-value offshore assets, this focus on designing in system resiliency and managed operational complexity is paramount. On the commercialization and business strategy front, the MBSE design process and the model offer advantages in terms of facilitating logistical studies, sensitivity analysis, and what-if exploration to rapidly evaluate O&M scenarios, and value propositions.

This paper examines the specific application of MBSE to the engineering and commercialization of robotic systems comprising UAVs, ROVs and unmanned surface vessels (USVs) for inspection of FOWFs. It focuses on establishing a tailorable MBSE approach, underpinned by the expert elicitation, covering system definition including system requirements, architecture design, and risk assessment. The aim is to provide a holistic framework for streamlining development of these inherently complex robotic systems, while enhancing quality, safety, and commercial viability. Ultimately, this can enable the deployment of affordable, autonomous inspection solutions that can allow FOWFs to operate at peak efficiency over their multi-decade lifecycle.

6.3. MBSE MODEL

6.3.1. SYSTEM DEFINITION

Establishing a rigorous system definition using MBSE principles is the critical foundation for developing an understanding of the robotics-driven inspection system for FOWFs. The MBSE process begins by elaborating a coherent model of the operational context, use cases, and stakeholder needs that drive the eventual system requirements. In this regard, Table 6.1 highlights the identified building blocks and the system requirements associated with characterization of the FOWF, assets to be inspected, robotic vehicle capabilities and constraints, and data outputs needed to satisfy inspection objectives. The underlying context includes conducting above-the-waterline and below-the-waterline inspection of FOWF components e.g., WTG blades, foundation, inter-array cables, mooring lines, and foundations with the aid of robotic systems such as UAVs, ROVs, USVs, and their associated subsystems for mobility, sensing, navigation, and communication.

6.3.2. SYSTEM DESIGN

After capturing the system definition in a descriptive manner, MBSE shifts to assign the system requirements to functional modules. For robotic systems, this involves modeling the functional modules of mission/task decomposition, data communication, autonomy levels, system coordination, and the role of human supervision. In general, this is done by devising an understanding of the software and physical architecture underlying the system [169]. On the software or computational architecture side, the MBSE model focuses on its decomposition into logical components, runtime infrastructure, data acquisition, and external interface relationships. This also includes capturing the control system of the UAV, ROV or ASV and its autonomous inspection algorithm, localization and navigation, communications protocols, and other key robotic subsystems. A visualisation of the software architecture of such a system is shown in Figure 6.1. At its core is a Control and Coordination Center, which attains inspection inputs from either a n Operations Control Room or an offshore support base connected to the FOWF. The robotic system is then launched, the control system of which is depicted as either a

Table 6.1: Identification of the system requirements and approaches with respect to the major building blocks pertaining to the robotics-driven inspection of floating offshore wind farms.

Building blocks	System requirements	Approaches	Reference
Level of autonomy	Technical assessment of various autonomy levels (e.g., BVLOS, semi-autonomous, fully-autonomous) of robotic systems with respect to conducting different O&M activities.	Human-in-the-loop simulation, human factors engineering	[82], [11]
Performance	Typically assessed in terms of the accuracy and quality of imagery and sensory data.	Data post-processing, automated anomaly detection	[151]
Coordination and control	Logistics and remote control aspects of the robotic systems in the FOWF environment.	Control systems design, vessel management system	[17]
Price	Commercial viability and bankability of the robotic systems.	Market analysis	[87], [148]
Environmental sustainability	Incorporation of carbon emissions accounting in the marine environment is becoming increasingly relevant.	Emissions accounting	[167], [168]
Customers	Operations of the robotic systems from the customer's/user's perspective including the health and safety aspects.	H&S quantification, Marketing strategy	[7]
De-risking	Potential for de-risking of offshore O&M activities for the FOWFs.	Prototype testing, system verification and validation	[122]

model-based or model-free controller. The system considers various operational dependencies such as power systems, fail-safe mechanisms, weather conditions, and marine coordination. Data flows from the controller to the sensory infrastructure unit which is divided into acoustic, imagery, radio, and health monitoring application layers, collecting diverse data types. This information is transmitted via internet on to the Control and Coordination Center or stored onboard for eventual post-processing. The key building blocks of the software architecture are enumerated as follows:

- 1) **Control system design:** This pertains to the physical control and manipulation of the offshore robotic systems while conducting O&M activities. This includes

autonomous navigation and persistent control of the robotic systems using techniques such as the simultaneous localization and mapping (SLAM), model-based methods such as model predictive control, or model-free approaches such as machine learning.

- 2) **Remote coordination:** The remote coordination of robotic systems is an important task in this regard as the continuous monitoring of offshore marine systems is deemed necessary for regulatory compliance. Furthermore, incorporation of human supervision from the offshore support base or from the port-side control and coordination center, acts as a fail-safe mechanism which can mitigate the occurrence of offshore hazards. Such a coordination in the offshore domain requires sufficient latency, deployment of radio masts along with satellite-based communication capability in case of FOWFs farther from the shore.
- 3) **Data acquisition:** This includes aspects such as data acquisition from the imagery sensors, its communication with the remote operations team and its on-board storage.
- 4) **Data post-processing:** The final step is the post-processing of the acquired data based upon techniques such as data mining and computer vision. The outputs include trends analysis, forecasting and structural health monitoring.

6

In parallel, the physical architecture facilitates defining aspects like safety, weight, human factors, and technical feasibility of conducting below-the-waterline and above-the-waterline inspection. This also includes capturing regulatory certification constraints such as incorporating safety requirements, failure scenarios, and contingency responses. The key building blocks of the physical architecture are enumerated as follows:

- 1) **Hardware design:** The hardware design of the systems such as UAV, ROV and USV primarily takes into account the sensors and manipulators required for data acquisition such as visible and thermal cameras, and SONAR. This also includes the main power and the auxiliary system.
- 2) **Launch and recovery mechanism:** This pertains to an efficient launch of the robotic systems from the onshore O&M base or an offshore support base along with the retrieval and docking of it. The choice of the launch base depends on factors such as system endurance, site weather conditions, and frequency and duration of the inspection task.

In order to ascertain the complexity involved in designing and deploying such as autonomous system, Constructive Systems Engineering Cost Model, also known as COSYSMO [170] is utilised, which is a widely recognised parametric cost model used to estimate the end-to-end systems engineering effort required to develop and deploy a project. The main formulation of the model is shown in Equation 6.1, where PM stands for effort in Person Months, A is the calibration constant derived from historical project data, and E represents the economies of scale. EM stands for the effort multipliers, also known as cost drivers as discussed later, while w_x and Φ_x represents weight and quantity of the system size represented by k . The system size is an aggregate of the following inputs scored on a metric of *easy*, *nominal* or *difficult*:

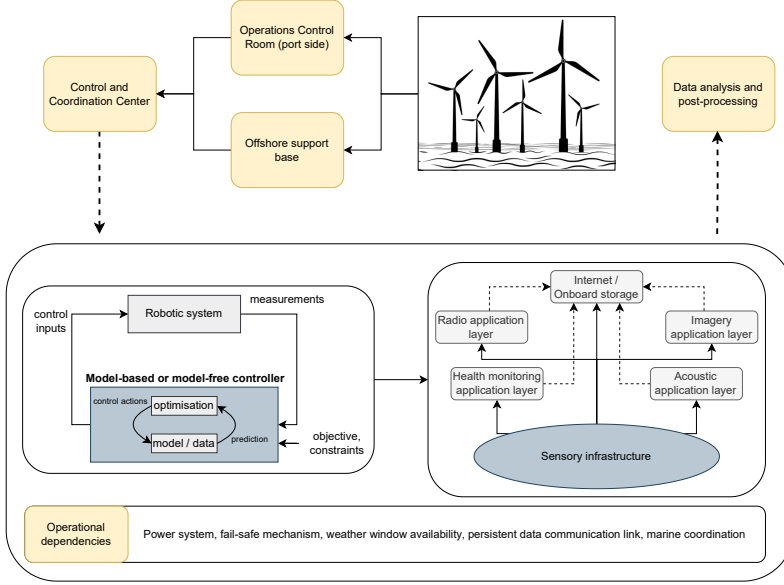


Figure 6.1: Visualisation of the software architecture for robotics-driven inspection of FOWFs.

- 1) System requirements (REQ)
- 2) System interfaces (INT)
- 3) Critical system algorithms (ALG)
- 4) Operational scenarios (SCN)

$$PM = A \cdot \left(\sum_k (w_{e,k} \Phi_{e,k} + w_{n,k} \Phi_{n,k} + w_{d,k} \Phi_{d,k}) \right)^E \cdot \prod_{j=1}^{14} EM_j \quad (6.1)$$

In order to gain insights into the complexity of system size and cost drivers in the context of robotics-driven inspection of FOWFs, we conducted a comprehensive expert elicitation process. This approach was chosen due to specialized nature of the data and its sparse availability in the public domain, which required insights from professionals across various disciplines. Our expert panel consisted of 27 individuals with diverse professional backgrounds, including project engineers, project managers, commercial analysts, and O&M professionals. The panel members were carefully selected based on their experience in the relevant fields and familiarity with either the O&M, offshore robotics, or cost estimation techniques. The composition of the panel in terms of their profession and area of expertise is shown in Table 6.2.

The elicitation process was structured in three phases:

Table 6.2: Expert elicitation group's professional composition and area of expertise.

Profession	Number of experts	Area of expertise	Number of experts
Project Manager	5	Floating Wind	9
Project Engineer	6	Offshore Wind O&M	6
Analyst	2	Robotics	4
O&M Engineer	4	Offshore Wind	8
Research Engineer	6		
Post-doctorate	4		

1) **Preparatory Phase:** We began by providing the experts with background information, including the specific challenges of autonomously inspecting FOWFs using USVs that can launch ROVs and UAVs, and the potential challenges of deploying such an end-to-end system. The level of autonomy considered is Level 5 which pertains to a scenario where a human operator can assign a robot a mission and the robot can ensure the mission is achieved in a safe and self-optimized manner [7]. This includes the robot overcoming unforeseen challenges and events, which may otherwise impact the capacity of the robot to complete the specified task. We also offered a refresher on the COSYSMO model and its inputs to ensure all participants had a common understanding of the task at hand.

2) **Individual Assessment Phase:** Each expert was asked to provide their initial estimates for the COSYSMO inputs independently. This approach helped to avoid groupthink and capture a wide range of perspectives. Experts were encouraged to provide rationales for their estimates and highlight any areas of particular uncertainty. The inputs requested included relationships among the system size and the following 14 cost drivers:

- Understanding factors:
 1. **Requirements Understanding:** The clarity of end-to-end system requirements for the robotics-driven inspection, including environmental constraints, inspection methodologies, and data communication needs.
 2. **Architecture Understanding:** The complexity of the overall system architecture, including the robotic platforms, sensors, communication systems, and data processing infrastructure.
- Complexity factors:
 3. **Technology Risk:** The maturity and reliability of technologies used in the robotic systems, such as autonomous navigation in marine environments and advanced sensing capabilities.
 4. **Level of Service Requirements:** The performance expectations for the robotic inspection system, such as inspection frequency and duration, coverage area, and data quality.

5. **Recursive Levels in the Design:** The complexity of subsystems within the robotic platform, such as propulsion, sensor integration, and data processing layers.
 6. **Documentation:** The extent and quality of documentation required for conducting inspection based upon varying autonomy levels, including operational procedures, maintenance manuals, and regulatory compliance documentation.
- Environmental factors:
 7. **Multisite Coordination:** The complexity of coordinating development efforts across different locations, such as port-side control and coordination center, and asset-side offshore support base.
 8. **Tool Support:** The availability and sophistication of tools used in the development process, such as simulation environments, systems modeling tools, and project management software.
 - Operational factors:
 9. **Migration Complexity:** The difficulty of transitioning from manned inspection methods to the autonomous, including integration with existing wind farm operations.
 10. **Diversity of Installations/Platforms:** The variety of FOWF turbine designs including larger WTG sizes, foundation platforms and environmental conditions the robotic systems must accommodate in order to conduct inspection in an efficient and safe manner.
 - Personnel factors:
 11. **Stakeholder Team Cohesion:** The alignment and cooperation between various stakeholders, including FOWF developers, operators, technology providers, and regulatory bodies.
 12. **Personnel/Team Capability:** The expertise and experience of the team deploying the robotic inspection system, particularly in areas like marine robotics and operations management.
 13. **Personnel Experience/Continuity:** The team's familiarity with similar projects and the stability of the development team throughout the project lifecycle.
 14. **Process Capability:** The maturity and effectiveness of the systems engineering processes with regards to deploying and operating the robotic systems. This also incorporates the technological and commercial readiness levels of such systems.

We requested the relationships to be scored on the metric ranging from 0 to 10, with the former pertaining to the low risk and the latter to the high risk category. The risk in this regard captures the technological readiness and commercial readiness of a relationship wherein high risk refers to the scenarios requiring higher techno-economic maturity.

3) **Analysis Phase:** We then collated the results in a risk matrix populated with the averaged risk values based upon the survey responses, as depicted in Figure 6.2.

	Size	Req.	Arch.	LSR.	MC.	TR.	Doc.	DIP.	RLD.	STC.	PTC.	PEC.	PC.	MC.	TS.
Size (REQ, INT, ALG, SCN)		9	9	7	4	8	5	7	6	7	8	8	7	6	4
Requirements Understanding			8	6	4	8	6	8	7	5	8	7	6	5	5
Architecture Understanding				8	5	7	7	7	6	5	7	7	7	4	4
Level of Service Requirements					5	6	5	7	5	6	7	7	5	5	5
Migration Complexity						6	6	8	7	8	7	6	6	7	6
Technology Risk							6	9	8	7	7	8	7	8	7
Documentation								5	5	3	3	3	5	4	8
Diversity of Installations/Platforms									5	7	6	6	7	7	4
Recursive Levels in the Design										6	7	7	6	7	5
Stakeholder Team Cohesion											5	6	6	8	2
Personnel/Team Capability												8	8	7	7
Personnel Experience/Continuity													7	6	5
Process Capability														5	3
Multisite Coordination															2
Tool Support															

Figure 6.2: Risk matrix capturing relationships among the system size and the 14 cost drivers.

The statistical analysis of the risk correlation matrix provides key insights into the relationships between various risk factors in system architecture and project management. The data consists of 105 values, ranging from 2 to 9, with a mean of 6.36 and a standard deviation of 1.34, indicating a moderate level of variability. The most frequently occurring value is 7, followed by 6 and 5, suggesting that most risk factors exhibit a moderate to high degree of correlation. Higher correlations (8s and 9s) are observed in areas such as system size vs. requirements/architecture, and technology risk vs. diversity of installations/platforms, indicating critical dependencies that could significantly impact project complexity. Conversely, lower correlations (2s and 3s) are seen in areas like tool support vs. migration complexity, reflecting weaker dependencies. These findings highlight the importance of prioritizing high-correlation risks while recognizing the lower-impact relationships, allowing for a more targeted risk mitigation strategy in complex system design.

Results show that the *system size*, along with the *requirements* and *architecture understanding* correlate with higher risk values as respondents opined that the complexity of the system is the main driver of the deployment of such systems. Furthermore, *technology risk* and *diversity of installations/platforms* also show higher risk values. Respondents highlighted that the WTGs of larger sizes and different design considerations of the floating foundation platforms can hinder the rapid deployment of robotic systems. When estimating the *recursive levels in the design*, experts considered the hardware interactions within the robotic systems but also the interaction between the deployed system and the WTGs, as well as data transmission interfaces for remote operation and monitoring. Hence, this factor also scored higher as compared to the more generic ones of *multisite coordination* and *tool support*. For the *migration complexity* factor, experts weighed the challenges of transitioning from traditional manual inspection methods to a robotic system and highlighted that the cost-benefit aspects of such systems need to be explicitly identified. Although, the health and safety benefits are observed to be widely understood in the industry. Similarly, *process capability* estimates were influenced by the nascent state of standardized procedures for the deployment and operation of autonomous systems, in particular USVs, in the offshore marine sector.

6.3.3. FAILURE MODES AND EFFECTS ANALYSIS

An additional part of the expert elicitation included conducting risk assessment based upon the failure modes and effects analysis (FMEA). FMEA is a systematic approach that can enable the engineers and operators to identify potential failure modes, their causes, and consequences across the complex array of systems involved in autonomous inspection processes [171]. By applying, stakeholders can proactively mitigate risks and enhance the reliability of these critical operations. In the context of USVs that launch ROVs and UAVs for conducting above-the-waterline and below-the-waterline inspection, different systems and functional aspects were highlighted, and the respondents were asked to identify potential failure modes and their effects against these aspects. Furthermore, respondents were asked to identify the failure modes based on three critical parameters: severity of impact, likelihood of occurrence, and ease of detection. This evaluation led to the calculation of Risk Priority Numbers (RPNs) for each failure mode, providing a quantitative measure for risk prioritization. The complete FMEA analysis is presented in Table 6.3. UAV and ROV launch systems also demonstrated high RPNs, 140 and 135 respectively, due to the complexity of autonomously deploying these systems in offshore marine environments. Communication system failures, particularly satellite link loss, showed a high severity and occurrence, underscoring the importance of maintaining remote control capabilities with the operations control room or the offshore support base. Cybersecurity concerns were highlighted with a high severity rating of 9, although the occurrence was rated lower. These high-risk areas point to the complex interplay between mechanical, electrical, and software systems in the harsh offshore environment, emphasizing the need for redundancy, robust design, and proactive maintenance strategies.

6.4. CONCLUSION

This paper presented the development of a systems engineering framework for the deployment of robotics-driven inspection of FOWFs. A methodology based upon MBSE is adopted wherein the conceptualisation of such a system is discussed along with delving in its risk assessment aspects. In summary, the emerging discipline of MBSE offers a powerful framework for developing the multi-faceted autonomous systems required for cost-effective inspection and monitoring of FOWFs. By tightly integrating descriptive models across disciplines, MBSE facilitates end-to-end traceability and coherence from system requirements through system design, deployment, and operations. At first, the system requirements are identified which are then related to the software and hardware aspects of the system design. An expert elicitation approach has been leveraged to estimate the inputs pertaining to the cost drivers for the COSYSMO model. Furthermore, FMEA is conducted in order to capture the elements of uncertainty on a sub-system level. The concluding remarks from the conducted study are enumerated as follows:

- 1) The system requirements pertaining to the robotics-driven inspection of FOWFs, as listed in Table 6.1, are of a holistic nature ranging from the performance aspects to the commercial viability considerations. As such, they need to be inculcated early into the design process, underpinned by the *design-for-X* methodology.
- 2) An MBSE approach can delineate the interfaces between the software and hard-

ware architecture of the system. This can aid in the analysis of the design requirements, functions, and logic along with the development and validation of the complete system. Furthermore, a high-level conceptualisation of the system, such as shown in Figure 6.1, can help in creating a roadmap of the deployment, which can further feed into the inspection workflow process.

- 3) The evaluation of the system size and cost drivers, based upon the COSYSMO model and underpinned by the expert elicitation, identified potential roadblocks with respect to the deployment of such systems. These primarily included the factors of system requirements and architecture understanding, which pertains to the complexity of the inspection scenario. These are followed by the factors such as level of autonomy, incorporation of different FOWF design considerations, and regulatory compliance requirements.
- 4) FMEA results provided with crucial insights for prioritizing risk mitigation efforts on a sub-system level, and enhancing the reliability of robotics-driven inspection systems for FOWFs. UAV and ROV launch systems exhibited the highest RPN values, while the communication and sensing systems resulted in the lowest values. It can be inferred that FOWF-agnostic sub-systems such as imaging cameras and legacy data communication are risk-averse, while the sub-systems associated with autonomous launch and recovery mechanism are more prone to the occurrence of failure modes.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table 6.3: FMEA table with RPN calculation.

System/Function	Potential failure mode	Potential failure effect	Severity	Occurrence	Detectability	RPN
Power supply	Lack of power supply to the propeller(s)	Loss of propulsion, inability to complete mission	5	2	9	90
Propulsion system	Propeller(s) damage	Reduced propulsion, slower transit speed	5	1	9	45
GPS	Malfunction	Loss of precise positioning, potential for collision or drifting off course	8	2	3	48
Inspection Sensors	Camera malfunction	Reduced visual inspection capabilities	6	3	2	36
Inspection Sensors	SONAR system failure	Loss of underwater mapping and object detection	8	2	3	48
Tethering system	Loss of communication and/or power supply	USV/ROV running aground	8	2	5	80
Station keeping mechanism	Dynamic positioning system failure	Time delays, increased MTTR	8	2	4	64
Data Storage and Processing	Data corruption	Inaccurate inspection results, potential for missed defects	8	3	4	96
Command and control system	On-board computer failure	Loss of autonomous functions, potential mission abort	9	2	2	36

System	Potential failure mode	Potential failure effect	Severity	Occurrence	Detectability	RPN
Communication System	Satellite link loss	Loss of remote monitoring and control capabilities	8	4	2	64
Communication System	Internal network failure	Loss of coordination between USV subsystems	7	2	3	42
UAV Launch System	Launch mechanism malfunction	Unable to deploy UAV, incomplete inspection	7	4	5	140
UAV Launch System	UAV battery failure	Shortened flight time, incomplete inspection	6	3	2	36
ROV Launch System	Winch malfunction	Unable to deploy or retrieve ROV	8	3	4	96
ROV Launch System	ROV tether damage	Loss of ROV control or communication	9	3	5	135
Collision Avoidance System	LIDAR sensor malfunction	Reduced obstacle detection capability, increased collision risk	8	3	3	72
Cybersecurity	Intrusion detection system failure	Increased vulnerability to cyber attacks, potential loss of control	9	2	6	108
Automatic Identification System (AIS)	AIS transponder signal loss	Reduced visibility to other vessels, increased collision risk	8	2	3	48

7

CONCLUSION

7.1. CONCLUSIONS TO THE THESIS OBJECTIVES

The main conclusions drawn from the thesis are as follows:

- The FOWF industry is destined to grow in the future, and as such, the demand for efficient O&M practices with lower expenditures is expected to be more pronounced. In this regard, robotic systems such as UAVs, ROVs and USVs have a greater role to play with benefits in terms of conducting remote O&M in an effective manner, while also improving the H&S aspects. In this regard, a detailed study from the technical, operational and commercial standpoint is presented in Chapter 2.
- Advancements in robotics are revolutionizing O&M practices for FOWFs. Improved battery technology is enabling tether-free ROVs and longer-endurance UAVs, while progress in ROV capabilities for underwater cable inspection and burial focuses on increasing operational range and reducing reliance on divers. The emerging use of ASVs can result improved safety and efficiency, especially in harsh conditions and long-duration missions. Concurrently, the availability of advanced, low-cost sensors, such as thermographic cameras and ultrasonic sensors, is enhancing asset structural integrity. These developments are facilitating the implementation of AI and data-driven approaches for continuous maintenance and inspection, leading to better resource management and increased asset availability. Furthermore, the advent of modular, low-cost climbing robots and UAVs with customizable payloads is expanding the range of possible O&M tasks that can be performed in-situ, mitigating the need for expensive crane setups. Collectively, these innovations are driving more efficient, safer, and cost-effective O&M practices.
- The study conducted in Chapter 3 assesses the cost and impact of an offshore MRP on OPEX and inspection time for a 1.5GW FOWF, using the WOMBAT simulation tool. Results show that MRP use can potentially reduce inspection time,

but its effectiveness depends on the MRP's day-rate and UAV/ROV inspection duration. Compared to CTV-based inspection, using multiple MRPs increases OPEX by 51.1% but reduces completion time by 58.3%, while using a single MRP reduces OPEX by 50.6% with a 17.2% increase in completion time.

- Sensitivity analysis reveals that the number of MRPs, day-rate, and inflation rate significantly impact OPEX, while the number of MRPs and the component inspection duration greatly affect the overall inspection completion time.
- Cost-benefit analysis pertains to looking at a small number of scenarios with a high degree of granularity. On the other hand, front-end engineering design requires to map the design space by running a lot of scenarios. The real-options analysis framework presented in Chapter 4 aids in the decision-making in this regard. The simulation of scenarios ranging from semi-autonomy to full-scale autonomy and the calculation of associated option values gave insights into cost savings of up to 24% during the lifecycle of the FOWF.
- It is also inferred from the simulation that the learning rates have a higher effect in cost reduction. Doubling the learning rate can result in cost savings of up to 31%.
- The study conducted in Chapter 5 evaluates the performance of visible and thermal imaging for detecting damages on WTG blades and rotor hub, using a two-step approach: binary classification of defective regions followed by thermal image analysis to quantify defect types.
- Integration of visible and thermal imaging provides complementary features, enhancing damage detection capabilities. However, relatively low F1-scores across deep learning models suggest a need for more diverse and comprehensive training data.
- Model training time varies based on factors such as dataset size, image dimensions, CNN layer depth, and hyperparameters. Training time ranged from 0.8 hours for VGG19 to 1.7 hours for Inception V3 with augmentation, using datasets of 1000 images each.
- Thermal imaging successfully identified blade erosion, with temperature differentials exceeding 1°C indicating deeper structural erosion. Significant erosion produced larger temperature differentials (>1°C) compared to surface discoloration or minor structural damages (approx. 0.5°C), highlighting thermal imaging's potential as a diagnostic tool for assessing damage severity.
- Chapter 6 consists of a policy paper delving into systems engineering framework for deploying robotics-driven inspection of FOWFs, using a Model-Based Systems Engineering (MBSE) methodology to conceptualize the system and assess risks. System requirements for robotics-driven FOWF inspection are holistic, covering performance aspects and commercial viability considerations, and need to be integrated early in the design process using a design-for-X methodology.

- The expert elicitation process also yielded valuable qualitative insights. Experts highlighted potential risk factors and areas requiring further research, such as the need for extensive prototype testing and advanced control algorithms for autonomous navigation in dynamic offshore conditions.
- Evaluation of system size and cost drivers using the COSYSMO model identified potential roadblocks, primarily related to system requirements and architecture understanding, level of autonomy, FOWF design considerations, and regulatory compliance requirements.
- FMEA provided insights for risk mitigation, revealing that UAV and ROV launch systems had the highest risk priority numbers, while communication and sensing systems had the lowest, suggesting that FOWF-agnostic sub-systems are less risky than autonomous launch and recovery mechanisms.

7.2. CRITICAL REFLECTION

The thesis set out with an overarching objective to assess the incorporation of robotics into the O&M of FOWFs from a techno-economic perspective. This was articulated through a series of research questions and specific objectives aimed at exploring the state-of-the-art in robotics-based O&M, evaluating techno-economic benefits and limitations, developing cost estimation methodologies, investigating UAV-based damage detection, and ultimately providing insights to guide policy-making in the FOWF domain. Reflecting on the original objectives alongside the conclusions drawn, it is clear that while the study made significant strides in addressing many of the research aims, several areas invite further discussion regarding both successes and potential shortcomings.

One of the core strengths of the study is its multidisciplinary approach, integrating technical, economic, and policy dimensions. However, the complexity inherent in combining these perspectives can sometimes lead to an imbalance in depth. For instance, while the technological advancements and economic assessments were explored in considerable detail, the policy implications—though well-conceived through expert elicitation and systems engineering frameworks, might have benefited from a more in-depth exploration of regulatory challenges and industry-specific case studies. A deeper dive into policy analysis could have further strengthened the link between technical findings and their practical implications for industry standards and regulatory practices. The use of simulation tools like WOMBAT provided a controlled environment to test various scenarios, yet simulations inherently involve assumptions and model-mismatch that may not fully capture real-world variability. The conclusions drawn regarding OPEX reduction and inspection times are promising, but they would gain further credence if complemented by field trials or pilot/prototype projects in actual FOWF environments. This gap highlights an area for future research: moving from simulation-based insights to practical, on-site implementations that can validate and potentially adjust the simulation models used.

The research into UAV-based damage detection is particularly forward-looking, but it also reveals a limitation in the current state of data availability. The modest F1-scores achieved by the deep learning models point to the necessity for more extensive and diverse datasets. While the study acknowledges this need, it raises a broader question

about the pace at which data collection and model training can keep up with technological advances. Future work in this area should prioritize the establishment of comprehensive databases that can improve the robustness and accuracy of AI-driven inspection models. The thesis provides a robust framework for economic assessment and risk mitigation, yet the sensitivity analysis indicates that small changes in key parameters can lead to significant variations in outcomes. This sensitivity underscores the importance of continuous monitoring and recalibration of models as real-world conditions evolve. The inclusion of FMEA and COSYSMO models was a strong methodological choice, but integrating these risk assessments into a dynamic, iterative decision-making process would further enhance the utility of the findings for industry stakeholders.

7.3. RECOMMENDATIONS AND FUTURE RESEARCH

The following recommendations have been produced for conducting future research in this domain:

- **Technical validation of the proposed approach:** A prototype field testing or hardware-in-the-loop simulation based upon USV, ROV and UAV is the first recommended next step to validate the proposed robotics-driven inspection approach. After an extensive simulation phase, it is important to do real-world testing in order to evaluate the operational performance of the robotic systems. In this way, real-time aspects and limitations can be studied such as the asset accessibility, operational efficiency along with the data communication requirements.
- **Commercial readiness:** In addition to the technical validation, an important aspect would be to conduct extensive stakeholder engagement with current technology providers and O&M vendors to ascertain the commercial readiness of different robotic systems in relation to the FOWF aspects such as distance to shore, O&M scope, operational limits, technology acceptance, etc. Of particular interest would be the sourcing of component-wise failure rates that would be representative of an operational wind farm.
- **Communication protocols:** The study of data communication requirements and protocols was beyond of the scope of this work. However, in real-world applications, the aspects such as remote communication with the robotic systems, data latency, storage and privacy cannot be negated. Hence, during implementation, the design of a systematic communication workflow taking into account all the stakeholders and data regulatory requirements should be conducted.
- **Regulatory aspects:** One major area of future work is the study of regulatory aspects both from an implementation and a policy-making perspective. The understanding of regulatory requirements specific to a robotic system such as a USV is necessary in order to safely deploy it to a FOWF location. Furthermore, from a policy-making perspective, it would be pertinent to identify the regulatory barriers and how they can be addressed from a technical and commercial standpoint, in order to speed up the roll out of robotic systems.

- **Data post-processing:** In this thesis, we have provided best practices approach with respect to the damage detection on WTG blades based upon DL and thermal analysis. It would be useful to extend the future work by incorporating different types of defects on subsea components such as marine growth, along with advanced damage detection and classification methodologies. The metrics of detection and classification accuracy along with the computational expense can be evaluated with an aim to increase confidence in the outputs and scale up the data post-processing process.
- **Environmental sustainability:** Future work can also focus on the evaluation of emissions pertaining to the use of robotics and how they fare as compared to the use of CTVs and SOVs. Furthermore, the electrification of daughter vessels launching UAVs and ROVs can be incorporated, and their effects on the overall O&M emissions profile can be assessed.
- **Optimal allocation:** In Chapter 3 and 4, modeled scheduled maintenance of different components of the FOWF is modeled. Future research should focus on defining the objective functions such as maximising the PBA and minimizing the downtime, while optimising the allocation of robotic systems and CTVs. This optimal allocation could provide insights such as the relationship between failure rates and the scheduling of inspection activities utilising robotic systems and CTVs, along with the concurrent effect on OPEX.
- **Human factors:** Finally, it is pertinent to conduct research on the interaction between robotic systems and their operators from an operational viewpoint. This interaction can affect performance, operability and safety in dynamic ways. Human factors considerations such as coordination and collaboration with robots of different autonomy levels, fail-safe mechanism, redundancy and complacency need to be investigated with an aim to devise best practices regarding the deployment and utilization of remote robotic systems in an efficient and safe manner.

BIBLIOGRAPHY

- [1] D. Greaves, S. Jin, P. Wong, D. White, H. Jeffrey, B. Scott, and R. Wigg, *UK perspective research landscape for offshore renewable energy and its role in delivering Net Zero*, Progress in Energy, IOP Publishing, vol. 4, 2022.
- [2] N. Bento and M. Fontes, *Emergence of floating offshore wind energy: Technology and industry*, Renewable and Sustainable Energy Reviews, Elsevier Ltd, vol. 99, pp. 66–82, 2019.
- [3] B. M. Smith, R. Clayton, A. H. van der Weijde, and P. R. Thies, *Evaluating technical and financial factors for commercialising floating offshore wind: A stakeholder analysis*, Wind Energy, Wiley, vol. 25, pp. 1959–1972, 2022.
- [4] J. McMorland, M. Collu, D. McMillan, and J. Carroll, *Operation and maintenance for floating wind turbines: A review*, Renewable and Sustainable Energy Reviews, Elsevier BV, vol. 163, p. 112499, 2022.
- [5] G. Rinaldi, P. R. Thies, and L. Johannning, *Current status and future trends in the operation and maintenance of offshore wind turbines: A review*, Energies, MDPI, vol. 14, no. 9, p. 2484, 2021.
- [6] K. Zhang, V. Pakrashi, J. Murphy, and G. Hao, *Inspection of Floating Offshore Wind Turbines Using Multi-Rotor Unmanned Aerial Vehicles: Literature Review and Trends*, Sensors, MDPI AG, vol. 24, no. 3, p. 911, 2024.
- [7] D. Mitchell, J. Blanche, S. Harper, T. Lim, R. Gupta, O. Zaki, W. Tang, V. Robu, S. Watson, and D. Flynn, *A review: Challenges and opportunities for artificial intelligence and robotics in the offshore wind sector*, Energy and AI, Elsevier BV, vol. 8, p. 100146, 2022.
- [8] S. Brown, *Families of Robotic Systems Solving Offshore Wind Inspection Challenges*, Day 1 Mon, May 06, 2024, OTC, 2024.
- [9] S. Sivčev, E. Omerdić, G. Dooly, J. Coleman, and D. Toal, *Towards Inspection of Marine Energy Devices Using ROVs: Floating Wind Turbine Motion Replication*, Advances in Intelligent Systems and Computing, Springer International Publishing, pp. 196–211, 2017.
- [10] A. Aminzadeh, M. Dimitrova, M. S. Meiabadi, S. S. Karganroudi, H. Taheri, H. Ibrahim, and Y. Wen, *Non-Contact Inspection Methods for Wind Turbine Blade Maintenance: Techno-Economic Review of Techniques for Integration with Industry 4.0*, Journal of Nondestructive Evaluation, Springer Science and Business Media LLC, vol. 42, no. 2, 2023.

- [11] D. Mitchell, J. Blanche, O. Zaki, J. Roe, L. Kong, S. Harper, V. Robu, T. Lim, and D. Flynn, *Symbiotic System of Systems Design for Safe and Resilient Autonomous Robotics in Offshore Wind Farms*, IEEE Access, IEEE, vol. 9, pp. 141421–141452, 2021.
- [12] E. E. Ambarita, A. Karlsen, O. Osen, and A. Hasan, *Towards fully autonomous floating offshore wind farm operation & maintenance*, Energy Reports, Elsevier BV, vol. 9, pp. 103–108, 2023.
- [13] K. Kabbabe Poleo, W. J. Crowther, and M. Barnes, *Estimating the impact of drone-based inspection on the Levelised Cost of electricity for offshore wind farms*, Results in Engineering, Elsevier Ltd, vol. 9, p. 100201, 2021.
- [14] W. Zuo, J. Allen, J. B. Dabney, and R. Krishnamoorti, *Robotics Workforce Training, Offshore Energy Transformation*, Day 1 Mon, May 01, 2023, OTC, 2023.
- [15] A. Shukla and H. Karki, *Application of robotics in offshore oil and gas industry-A review Part II*, Robotics and Autonomous Systems, Elsevier B.V., vol. 75, pp. 508–524, 2016.
- [16] Z. Jiang, F. Jovan, P. Moradi, T. Richardson, S. Bernardini, S. Watson, A. Weightman, and D. Hine, *A multirobot system for autonomous deployment and recovery of a blade crawler for operations and maintenance of offshore wind turbine blades*, Journal of Field Robotics, vol. 40, no. 1, pp. 73–93, 2022.
- [17] M. Nordin, S. Sharma, A. Khan, M. Gianni, S. Rajendran, and R. Sutton, *Collaborative Unmanned Vehicles for Inspection, Maintenance, and Repairs of Offshore Wind Turbines*, Drones, MDPI AG, vol. 6, no. 6, p. 137, 2022.
- [18] P. Veers, K. Dykes, E. Lantz, S. Barth, C. L. Bottasso, O. Carlson, A. Clifton, J. Green, P. Green, H. Holttinen, D. Laird, V. Lehtomäki, J. K. Lundquist, J. Manwell, M. Marquis, C. Meneveau, P. Moriarty, X. Munduate, M. Muskulus, J. Naughton, L. Pao, J. Paquette, J. Peinke, A. Robertson, J. Sanz Rodrigo, A. M. Sempreviva, J. C. Smith, A. Tuohy, and R. Wiser, "Grand challenges in the science of wind energy," *Science*, vol. 366, no. 6464, pp. 1–18, 2019. doi:10.1126/science.aau2027.
- [19] T. Stehly, P. Beiter, and P. Duffy, 2019 Cost of Wind Energy Review, Office of Scientific and Technical Information (OSTI), Dec. 2020. doi:10.2172/1756710.
- [20] W. Hu, R. J. Barthelmie, F. Letson, and S. C. Pryor, "A new seismic-based monitoring approach for wind turbines," *Wind Energy*, vol. 22, no. 4, pp. 473–486, 2018. doi:10.1002/we.2300.
- [21] T. Brink, S. O. Madsen, and S. Lutz, "Perspectives on how operation maintenance (OM) innovations contribute to the reduction of Levelized Cost of Energy (LCOE) in offshore wind parks," University of Southern Denmark, 2015.
- [22] K. Pfeiffer, M. Bengel, and A. Bubeck, "Offshore Robotics - Survey, Implementation, Outlook," in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2011, pp. 241–246. doi:10.1109/iros.2011.6094661.

- [23] D. Schmidt and K. Berns, "Climbing robots for maintenance and inspections of vertical structures - A survey of design aspects and technologies," *Robotics and Autonomous Systems*, vol. 61, no. 12, pp. 1288-1305, 2013. doi:10.1016/j.robot.2013.09.002.
- [24] J.-H. Ohlendorf, M. Richrath, J. Franke, M. Brink, and K.-D. Thoben, "Towards automation of wind energy rotor blade production: a review of challenges and application examples," *Advanced Manufacturing: Polymer Composites Science*, vol. 6, no. 4, pp. 173-190, Oct. 2020. doi:10.1080/20550340.2020.1838224.
- [25] Z. Chong, F. Xie, X.-J. Liu, J. Wang, and H. Niu, "Design of the parallel mechanism for a hybrid mobile robot in wind turbine blades polishing," *Robotics and Computer-Integrated Manufacturing*, vol. 61, p. 101857, Feb. 2020. doi:10.1016/j.rcim.2019.101857.
- [26] P. Yang, M. Zhang, L. Sun, and X. Li, "Design and Control of a Crawler-Type Wall-Climbing Robot System for Measuring Paint Film Thickness of Offshore Wind Turbine Tower," *Journal of Intelligent Robotic Systems*, vol. 106, no. 2, Oct. 2022. doi:10.1007/s10846-022-01750-w.
- [27] R. Harik, J. Halbritter, D. Jegley, R. Grenoble, and B. Mason, "Automated fiber placement of composite wind tunnel blades: process planning and manufacturing," in *Society for Advancement of Material and Process Engineering (SAMPE) 2019 Conference*, 2019, no. NF1676L-31791.
- [28] M. A. Sanz-bobi, *Use, Operation and Maintenance of Renewable Energy Systems*, Springer, 2016. doi:10.1007/978-3-319-03224-5.
- [29] BVG Associates, "A Guide to an Offshore Wind Farm Updated and extended," Published on behalf of The Crown Estate and the Offshore Renewable Energy Catapult, 2019. [Online]. Available: <http://www.thecrownestate.co.uk/guidetooffshorewindfarm.pdf>.
- [30] A. Gray, H. Macdonald, and N. Avanessova, "O&M Case Study Report," *Periscope Network*, 2021.
- [31] R. Fairgrieve, K. Wellard, and C. Trigg, "Floating Offshore Wind Development and Consenting Process - Risks and Opportunities," *ORE Catapult*, 2021.
- [32] A. Myhr, C. Bjerkseter, A. Ågotnes, and T. A. Nygaard, "Levelised cost of energy for offshore floating wind turbines in a lifecycle perspective," *Renewable Energy*, vol. 66, pp. 714-728, 2014. doi:10.1016/j.renene.2014.01.017.
- [33] M. Hofmann, "A review of decision support models for offshore wind farms with an emphasis on operation and maintenance strategies," *Wind Engineering*, vol. 35, no. 1, pp. 1-16, 2011. doi:10.1260/0309-524X.35.1.1.
- [34] R. Rolfes, S. Tsiapoki, and M. W. Hackell, "Sensing solutions for assessing and monitoring wind turbines," 2014. doi:10.1533/9781782422433.2.565.

- [35] M. Maness, B. Maples, and A. Smith, "NREL Offshore Balance-of-System Model NREL Offshore Balance-of-System Model," Jan. 2017. [Online]. Available: <https://www.nrel.gov/docs/fy17osti/66874.pdf>.
- [36] MAERSK, "The Right Questions to Ask Before Installing a Floating Wind Farm," 2020.
- [37] B. Maples, G. Saur, M. Hand, R. van Pietermen, and T. Obdam, "Installation, Operation, and Maintenance Strategies to Reduce the Cost of Offshore Wind Energy," Technical Report Nrel/Tp-5000-57403, Jul. 2013. [Online]. Available: <http://www.nrel.gov/docs/fy13osti/57403.pdf>.
- [38] "Offshore Technology, Robotics in Oil and Gas Dashboard," [Online]. Available: <http://offshore-technology.com>. Accessed: Jun. 4, 2022.
- [39] A. Shukla and H. Karki, "Application of robotics in onshore oil and gas industry-A review Part I," *Robotics and Autonomous Systems*, vol. 75, pp. 490-507, 2016. doi:10.1016/j.robot.2015.09.012.
- [40] L. Fahrni, P. R. Thies, L. Johanning, and J. Cowles, "Scope and feasibility of autonomous robotic subsea intervention systems for offshore inspection, maintenance and repair," in *Advances in Renewable Energies Offshore - Proceedings of the 3rd International Conference on Renewable Energies Offshore, RENEW 2018*, 2018, pp. 771-778.
- [41] S. Bernardini, F. Jovan, Z. Jiang, S. Watson, P. Moradi, T. Richardson, R. Sadeghian, and S. Sareh, "With the increasing scale of offshore," in *Proceedings of the International Joint Conference on Autonomous Agents and Multiagent Systems, AAMAS*, 2020.
- [42] A.B. Phillips, M. Haroutunian, S.K. Man, A.J. Murphy, S.W. Boyd, J.I.R. Blake, and G. Griffiths, "Nature in Engineering for Monitoring the Oceans: Comparison of the energetic costs of marine animals and AUVs," *The Institution of Engineering and Technology*, pp. 373-405, 2012.
- [43] T. Bujard, F. Giorgio-Serchi, and G.D. Weymouth, "A resonant squid-inspired robot unlocks biological propulsive efficiency," *Science Robotics*, vol. 6, no. 50, 2021. doi: 10.1126/SCIROBOTICS.ABD2971.
- [44] Maritime Autonomy Regulation Lab (MARLab) Report. 2021. Available: <https://www.gov.uk/government/publications/maritime-autonomy-regulation-lab-marlab-report>. Accessed on: Nov. 22, 2021.
- [45] M. Bonner, R. Taylor, K. Fletcher, and C.A. Miller, "Adaptive automation and decision aiding in the military fast jet domain," *Proceedings of the Human Performance, Situation Awareness and Automation: User-Centered Design for the New Millennium*, vol. 2000, pp. 154-159, 2000.

- [46] H.M. Huang, "Autonomy Levels for Unmanned Systems (ALFUS) framework: Safety and application issues," *Performance Metrics for Intelligent Systems (PerMIS) Workshop*, pp. 48-53, 2007.
- [47] R. Bogue, "Climbing robots: recent research and emerging applications," *Industrial Robot*, vol. 46, no. 6, pp. 721-727, 2019. doi: 10.1108/IR-08-2019-0154.
- [48] Q. Hong, R. Liu, H. Yang, and X. Zhai, "Wall climbing robot enabled by a novel and robust vibration suction technology," *Proceedings of the 2009 IEEE International Conference on Automation and Logistics, ICAL 2009*, pp. 331-336, 2009. doi: 10.1109/ICAL.2009.5262904.
- [49] B. Kamagalu, J.S. Kumar, and G.S. Virk, "Design of multi-terrain climbing robot for petrochemical applications," *Adaptive Mobile Robotics - Proceedings of the 15th International Conference on Climbing and Walking Robots and the Support Technologies for Mobile Machines, CLAWAR 2012*, pp. 639-646, 2012. doi: 10.1142/97898144159580082.
- [50] H. Kim, T. Kang, and H. Choi, "Walking and Climbing Robot for Locomotion in 3D Environment," *Proceedings of the 21st International Symposium on Automation and Robotics in Construction*, 2017. doi: 10.22260/isarc2004/0045.
- [51] M. Jeon, B. Kim, S. Park, and D. Hong, "Maintenance robot for wind power blade cleaning," *29th International Symposium of Automation and Robotics in Construction, ISARC 2012*, 2012.
- [52] D.G. Lee, S. Oh, and H.I. Son, "Maintenance Robot for 5-MW Offshore Wind Turbines and its Control," *IEEE/ASME Transactions on Mechatronics*, vol. 21, no. 5, pp. 2272-2283, 2016. doi: 10.1109/TMECH.2016.2574711.
- [53] T.P. Sattar, H.L. Rodriguez, and B. Bridge, "Climbing ring robot for inspection of offshore wind turbines," *Industrial Robot*, vol. 36, no. 4, pp. 326-330, 2009. doi: 10.1108/01439910910957075.
- [54] A. Sahbel, A. Abbas, and T. Sattar, "System Design and Implementation of Wall Climbing Robot for Wind Turbine Blade Inspection," *Proceedings of 2019 International Conference on Innovative Trends in Computer Engineering, ITCE 2019*, pp. 242-247, Feb. 2019. doi: 10.1109/ITCE.2019.8646326.
- [55] H.-M. Chung, S. Maharjan, Y. Zhang, F. Eliassen, and K. Strunz, "Placement and Routing Optimization for Automated Inspection with UAVs: A Study in Offshore Wind Farm," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 5, 2021.
- [56] H. Shakhathreh, A.H. Sawalmeh, A. Al-Fuqaha, Z. Dou, E. Almaita, I. Khalil, N.S. Othman, A. Khreishah, and M. Guizani, "Unmanned Aerial Vehicles (UAVs): A Survey on Civil Applications and Key Research Challenges," *IEEE Access*, vol. 7, pp. 48572-48634, 2019. doi: 10.1109/ACCESS.2019.2909530.

- [57] P.B. Quater, F. Grimaccia, S. Leva, M. Mussetta, and M. Aghaei, "Light Unmanned Aerial Vehicles (UAVs) for cooperative inspection of PV plants," *IEEE Journal of Photovoltaics*, vol. 4, no. 4, pp. 1107-1113, 2014. doi: 10.1109/JPHOTOV.2014.2323714.
- [58] J.R.T. Neto, A. Boukerche, R.S. Yokoyama, D.L. Guidoni, R.I. Meneguette, J. Ueyama, and L.A. Villas, "Performance evaluation of unmanned aerial vehicles in automatic power meter readings," *Ad Hoc Networks*, vol. 60, pp. 11-25, May 2017. doi: 10.1016/j.adhoc.2017.03.003.
- [59] S. Montambault, J. Beaudry, K. Toussaint, and N. Pouliot, "On the application of VTOL UAVs to the inspection of power utility assets," *2010 1st International Conference on Applied Robotics for the Power Industry, CARPI 2010*, IEEE, 2010. doi: 10.1109/CARPI.2010.5624443.
- [60] R.V. Meshcheryakov, P.M. Trefilov, A.V. Chekhov, S.A.K. Diane, K.D. Rusakov, E.A. Lesiv, M.A. Kolodochka, K.O. Shchukin, A.K. Novoselskiy, and E. Goncharova, "An application of swarm of quadcopters for searching operations," *IFAC-PapersOnLine*, vol. 52, no. 25, pp. 14-18, 2019. doi: 10.1016/j.ifacol.2019.12.438.
- [61] K. Máthé and L. Buşoniu, "Vision and control for UAVs: A survey of general methods and of inexpensive platforms for infrastructure inspection," *Sensors (Switzerland)*, vol. 15, no. 7, pp. 14887-14916, 2015. doi: 10.3390/s150714887.
- [62] A.S.M. Shihavuddin, X. Chen, V. Fedorov, A.N. Christensen, N.A.B. Riis, K. Branner, A.B. Dahl, and R.R. Paulsen, "Wind turbine surface damage detection by deep learning aided drone inspection analysis," *Energies*, vol. 12, no. 4, pp. 1-14, 2019. doi: 10.3390/en12040676.
- [63] L. Wang and Z. Zhang, "Automatic Detection of Wind Turbine Blade Surface Cracks Based on UAV-Taken Images," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 9, pp. 7293-7309, 2017. doi: 10.1109/TIE.2017.2682037.
- [64] A. Khadka, B. Fick, A. Afshar, M. Tavakoli, and J. Baqersad, "Non-contact vibration monitoring of rotating wind turbines using a semi-autonomous UAV," *Mechanical Systems and Signal Processing*, vol. 138, 106446, 2020. doi: 10.1016/j.ymssp.2019.106446.
- [65] F. Zhang, G. Marani, R.N. Smith, and H.T. Choi, "Future trends in marine robotics," *IEEE Robotics and Automation Magazine*, vol. 22, no. 1, 2015. doi: 10.1109/MRA.2014.2385561.
- [66] S. Chutia, N.M. Kakoty, and D. Deka, "A review of underwater robotics, navigation, sensing techniques and applications," *ACM International Conference Proceeding Series*, vol. Part F1320, 2017. doi: 10.1145/3132446.3134872.
- [67] GL Garrad Hassan, "A guide to UK offshore wind operations and maintenance," *Scottish Enterprise and The Crown Estate*, 2013.

- [68] R. Capocci, G. Dooly, and D. Toal, "Offshore renewable energy systems: Solutions for reduction in operational costs," *12th International Conference on Ecological Vehicles and Renewable Energies, EVER 2017*, 2017. doi: 10.1109/EVER.2017.7935940.
- [69] Y. Cao, B. Li, Q. Li, A.A. Stokes, D.M. Ingram, and A. Kiprakis, "A nonlinear model predictive controller for remotely operated underwater vehicles with disturbance rejection," *IEEE Access*, vol. 8, pp. 158622-158634, 2020. doi: 10.1109/ACCESS.2020.3020530.
- [70] I.R. Hudson, D. Jones, and B.D. Wigham, "A review of the uses of work-class ROVs for the benefits of science: Lessons learned from the SERPENT project," *International Journal of the Society for Underwater Technology*, vol. 26, no. 3, pp. 83-88, 2005. doi: 10.3723/175605405784426637.
- [71] A. Molero, R. Dunia, J. Cappelletto, and G. Fernandez, "Model predictive control of remotely operated underwater vehicles," *Proceedings of the IEEE Conference on Decision and Control*, pp. 2058-2063, 2011. doi: 10.1109/CDC.2011.6161447.
- [72] N. Sakagami, K. Hirayama, R. Taba, S. Kobashigawa, S. Arashiro, F. Takemura, and S. Takahashi, "Development and field experiments of a human-portable towed ROV for high-speed and wide area data acquisition," *Artificial Life and Robotics*, vol. 26, no. 1, 2021. doi: 10.1007/s10015-020-00616-4.
- [73] Y. Zhang and L. Wang, "Real-Time Disturbances Estimating and Compensating of Nonlinear Dynamic Model for Underwater Vehicles," *Mathematical Problems in Engineering*, vol. 2018, 2018.
- [74] J. Guerrero, J. Torres, V. Creuze, and A. Chemori, "Adaptive disturbance observer for trajectory tracking control of underwater vehicles," *Ocean Engineering*, vol. 200, p. 107080, 2020.
- [75] K. L. Walker et al., "Experimental Validation of Unsteady Wave Induced Loads on a Stationary Remotely Operated Vehicle," in *Proceedings - IEEE International Conference on Robotics and Automation*, vol. 2021-May, pp. 2242-2248, 2021.
- [76] Y. Gu, J. C. Goez, M. Guajardo, and S. W. Wallace, "Autonomous vessels: state of the art and potential opportunities in logistics," *International Transactions in Operational Research*, vol. 28, no. 4, pp. 1706-1739, 2021.
- [77] B. S. Anderson, "Cost reduction in E&P, IMR, and survey operations using unmanned surface vehicles," in *Proceedings of the Annual Offshore Technology Conference*, vol. 6, pp. 4417-4426, 2018.
- [78] A. Porter and S. Phillips, "Determining the Infrastructure Needs to Support Offshore Floating Wind and Marine Hydrokinetic Facilities on the Pacific West Coast and Hawaii," 2016.
- [79] L. Kretschmann, H. C. Burmeister, and C. Jahn, "Analyzing the economic benefit of unmanned autonomous ships: An exploratory cost-comparison between an

- autonomous and a conventional bulk carrier," *Research in Transportation Business and Management*, vol. 25, pp. 76-86, 2017.
- [80] H. Ferreira et al., "Autonomous bathymetry for risk assessment with ROAZ robotic surface vehicle," in *OCEANS '09 IEEE Bremen: Balancing Technology with Future Needs*, pp. 1-6, 2009.
- [81] Lloyds Register, "Design Code for Unmanned Marine Systems - Additional Design Procedure," 2017.
- [82] M. Schiaretti, L. Chen, and R. R. Negenborn, "Survey on autonomous surface vessels: Part I - A new detailed definition of autonomy levels," in *Lecture Notes in Computer Science*, vol. 10572 LNCS, pp. 219-233, 2017.
- [83] H. Ghaderi, "Wider implications of autonomous vessels for the maritime industry: Mapping the unprecedented challenges," in *Advances in Transport Policy and Planning*, vol. 5, pp. 263-289, Elsevier Inc., 2020.
- [84] S. G. Pierce et al., "Quantitative inspection of wind turbine blades using UAV deployed photogrammetry," in *9th European Workshop on Structural Health Monitoring, EWSHM 2018*, pp. 1-12, 2018.
- [85] D. Xu, C. Wen, and J. Liu, "Wind turbine blade surface inspection based on deep learning and UAV-taken images," *Journal of Renewable and Sustainable Energy*, vol. 11, no. 5, 2019.
- [86] J. H. Liu and K. Padrigalan, "Design and development of a climbing robot for wind turbine maintenance," *Applied Sciences*, vol. 11, no. 5, pp. 1-15, 2021.
- [87] Ö. Netland, I. B. Sperstad, M. Hofmann, and A. Skavhaug, "Cost-benefit evaluation of remote inspection of offshore wind farms by simulating the operation and maintenance phase," *Energy Procedia*, vol. 53, pp. 239-247, 2014.
- [88] L. X. Coggins and A. Ghadouani, "High-Resolution Bathymetry Mapping of Water Bodies: Development and Implementation," *Frontiers in Earth Science*, vol. 7, pp. 1-11, 2019.
- [89] D. F. Campos, A. Matos, and A. M. Pinto, "Multi-domain inspection of offshore wind farms using an autonomous surface vehicle," *SN Applied Sciences*, vol. 3, no. 4, pp. 1-19, 2021.
- [90] J. Albiez et al., "Repeated close-distance visual inspections with an AUV," in *OCEANS 2016 MTS/IEEE Monterey, OCE 2016*, 2016.
- [91] G. R. Cho et al., "Evaluation of Underwater Cable Burying ROV through Sea Trial at East Sea," *IFAC-PapersOnLine*, vol. 53, no. 2, pp. 9658-9663, 2020.
- [92] D. L. McLean, M. D. Taylor, A. Giraldo Ospina, and J. C. Partridge, "An assessment of fish and marine growth associated with an oil and gas platform jacket using an augmented remotely operated vehicle," *Continental Shelf Research*, vol. 179, pp. 66-84, 2019.

- [93] A. Restivo and M. Brune, "Removing marine growth using an ROV with cavitation technology," in *Proceedings of the Annual Offshore Technology Conference*, vol. 1, pp. 271-293, 2016.
- [94] L. G. García-Valdovinos et al., "Modelling, Design and Robust Control of a Remotely Operated Underwater Vehicle," *International Journal of Advanced Robotic Systems*, vol. 11, no. 1, pp. 1-16, 2014.
- [95] G. Collins, A. Clausse, and D. Twining, "Enabling technologies for autonomous offshore inspections by heterogeneous unmanned teams," in *OCEANS 2017 - Aberdeen*, pp. 1-5, 2017.
- [96] A. Gray and E. Schwartz, "Anglerfish: an ASV controlled ROV," in *29th Florida Conference on Recent Advances in Robotics (FCRAR)*, pp. 105-110, 2016.
- [97] S. Aracri et al., "Soft Robots for Ocean Exploration and Offshore Operations: A Perspective," *Soft Robotics*, 2021.
- [98] S. I. Rich, R. J. Wood, and C. Majidi, "Untethered soft robotics," *Nature Electronics*, vol. 1, no. 2, pp. 102-112, 2018.
- [99] K. I. Jang et al., "Soft network composite materials with deterministic and bio-inspired designs," *Nature Communications*, vol. 6, pp. 1-11, 2015.
- [100] Z. Ren, W. Hu, X. Dong, and M. Sitti, "Multi-functional soft-bodied jellyfish-like swimming," *Nature Communications*, vol. 10, no. 1, 2019.
- [101] M. Chellapurath et al., "Analysis of Station Keeping Performance of an Underwater Legged Robot," *IEEE/ASME Transactions on Mechatronics*, pp. 1-12, 2021.
- [102] C. Zhao, P. Thies, J. Lars, and J. Cowles, "ROV launch and recovery from an unmanned autonomous surface vessel – Hydrodynamic modelling and system integration," *Ocean Engineering*, vol. 232, p. 109019, 2021.
- [103] G. Conte et al., "Experimental testing of a cooperative ASV-ROV multi-agent system," *IFAC-PapersOnLine*, vol. 49, no. 23, pp. 347-354, 2016.
- [104] W. Myeong and H. Myung, "Development of a Wall-Climbing Drone Capable of Vertical Soft Landing Using a Tilt-Rotor Mechanism," *IEEE Access*, vol. 7, pp. 4868-4879, 2019.
- [105] M. T. Pope et al., "A Multimodal Robot for Perching and Climbing on Vertical Outdoor Surfaces," *IEEE Transactions on Robotics*, vol. 33, no. 1, pp. 38-48, 2017.
- [106] K. Hang et al., "Perching and resting-A paradigm for UAV maneuvering with modularized landing gears," *Science Robotics*, vol. 4, no. 28, pp. 1-11, 2019.
- [107] S. Wu et al., "UAV-Borne Coherent Doppler Lidar for Marine Atmospheric Boundary Layer Operations," in *The 28th International Laser Radar Conference (ILRC 28)*, vol. 176, 2018.

- [108] B. M. Batalden, P. Leikanger, and P. Wide, "Towards autonomous maritime operations: An introduction to safe maritime activities," in 2017 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA), pp. 1-6, 2017.
- [109] "Atlantis Project, Project Atlantis – The Atlantic Testing Platform for Maritime Robotics." [Online]. Available: atlantis-h2020.eu. [Accessed: June 5, 2022].
- [110] M. Fisher et al., "An overview of verification and validation challenges for inspection," *Robotics*, vol. 10, no. 2, pp. 1-29, 2021.
- [111] T. M. Welte et al., "Operation and Maintenance Modelling," John Wiley and Sons, pp. 269-303, 2018.
- [112] F. Judge et al., "A lifecycle financial analysis model for offshore wind farms," *Renewable and Sustainable Energy Reviews*, vol. 103, pp. 370-383, 2019.
- [113] T. R. Ryan and R. Valerdi, "Costing for an autonomous future: A discussion on estimation for unmanned autonomous systems," in *Procedia Computer Science*, vol. 44, pp. 547-557, 2015.
- [114] S. Ho and L. Y. Liu, "Valuation and Strategies for Investments on Automation and Robotics," in *Proceedings of the 17th ISARC*, pp. 1-6, 2000.
- [115] M. Boscoianu, C. Cioaca, V. Vladareanu, and C. E. Boscoianu, "An Active Support Instrument for Innovation in Deep Uncertainty-The Strategic Management Ingredients in Robotics and Mechatronics," *Procedia Computer Science*, vol. 65, pp. 210-217, 2015.
- [116] A. G. Rumson, "The application of fully unmanned robotic systems for inspection of subsea pipelines," *Ocean Engineering*, vol. 235, p. 109214, 2021.
- [117] "Rope Robotics." [Online]. Available: roperobotics.com. [Accessed: Nov. 21, 2021].
- [118] M. Bilgili and H. Alphan, "Global growth in offshore wind turbine technology," *Clean Technologies and Environmental Policy*, vol. 24, no. 7, pp. 2215-2227, 2022.
- [119] O. Khalid et al., "Applications of robotics in floating offshore wind farm operations and maintenance: Literature review and trends," *Wind Energy*, vol. 25, no. 11, pp. 1880-1899, 2022.
- [120] F. Wen, J. Pray, K. McSweeney, and H. Gu, "Emerging Inspection Technologies – Enabling Remote Surveys/Inspections," in *Day 1 Mon, May 06, 2019, 2019*.
- [121] B. E. Schäfer, D. Picchi, T. Engelhardt, and D. Abel, "Multicopter unmanned aerial vehicle for automated inspection of wind turbines," in *24th Mediterranean Conference on Control and Automation, MED 2016*, pp. 244-249, 2016.
- [122] D. L. McLean et al., "Enhancing the Scientific Value of Industry Remotely Operated Vehicles (ROVs) in Our Oceans," *Frontiers in Marine Science*, vol. 7, 2020.

- [123] F. Rémoit et al., "Deployment and maintenance of wave energy converters at the Lysekil Research Site: A comparative study on the use of divers and remotely-operated vehicles," *Journal of Marine Science and Engineering*, vol. 6, no. 2, pp. 1-21, 2018.
- [124] M. J. Kaiser, "The role of factor and activity-based models in offshore operating cost estimation," *Journal of Petroleum Science and Engineering*, vol. 174, pp. 1062-1092, 2019.
- [125] A. G. Gonzalez-Rodriguez, "Review of offshore wind farm cost components," *Energy for Sustainable Development*, vol. 37, pp. 10-19, 2017.
- [126] A. Ioannou, A. Angus, and F. Brennan, "A lifecycle techno-economic model of offshore wind energy for different entry and exit instances," *Applied Energy*, vol. 221, pp. 406-424, 2018.
- [127] M. J. Kaiser and B. F. Snyder, "Modeling offshore wind installation vessel day-rates in the United States," *Maritime Economics and Logistics*, vol. 14, no. 2, pp. 220-248, 2012.
- [128] "Wind farm costs," *Guide to a Floating Offshore Wind Farm*. [Online]. Available: <https://guidetofloatingoffshorewind.com/>. [Accessed: Apr. 2, 2023].
- [129] R. Hammond and A. Cooperman, "Windfarm Operations and Maintenance cost-Benefit Analysis Tool (WOMBAT)," *National Renewable Energy Lab. (NREL)*, 2022.
- [130] A. Martinez and G. Iglesias, "Site selection of floating offshore wind through the levelised cost of energy: A case study in Ireland," *Energy Conversion and Management*, vol. 266, p. 115802, 2022.
- [131] H. Hersbach et al., "The ERA5 global reanalysis," *Quarterly Journal of the Royal Meteorological Society*, vol. 146, no. 730, pp. 1999-2049, 2020.
- [132] E. Gaertner et al., "Definition of the IEA 15-Megawatt Offshore Reference Wind Turbine," *International Energy Agency, NREL/TP-75698*, 2020.
- [133] M. Asgarpour and J. Dalsgaard Sorensen, "OM modeling of offshore wind farms — State of the art and future developments," in *2016 Annual Reliability and Maintainability Symposium (RAMS)*, pp. 1-6, 2016.
- [134] J. Carroll, A. McDonald, and D. McMillan, "Failure rate, repair time and unscheduled OM cost analysis of offshore wind turbines," *Wind Energy*, pp. 1-20, 2013.
- [135] A. Robertson et al., "Definition of the Semisubmersible Floating System for Phase II of OC4," 2014.
- [136] I. Dinwoodie and D. McMillan, "Testing the Robustness of Optimal Vessel Fleet Selection for Operation and Maintenance of Offshore Wind Farms," *Ocean Engineering*, vol. 145, pp. 334-343, 2017.

- [137] Lerch, M., De-Prada-Gil, M., Molins, C., Benveniste, G. (2018). Sensitivity analysis on the levelized cost of energy for floating offshore wind farms. *Sustainable Energy Technologies and Assessments*, 30, 77-90.
- [138] Maienza, C., Avossa, A.M., Ricciardelli, E., Coiro, D., Troise, G., Georgakis, C.T. (2020). A life cycle cost model for floating offshore wind farms. *Applied Energy*, 266, 114716.
- [139] Garcia-Teruel, A., Rinaldi, G., Thies, P.R., Johanning, L., Jeffrey, H. (2022). Life cycle assessment of floating offshore wind farms: An evaluation of operation and maintenance. *Applied Energy*, 307, 118067.
- [140] Martínez-Ruiz, Y., Manotas-Duque, D.F., Ramírez-Malule, H. (2020). Evaluation of investment projects in photovoltaic solar energy using the DNPV methodology. *International Journal of Energy Economics and Policy*, 11(1), 180-185.
- [141] Siddiqui, A.S., Marnay, C., Wiser, R.H. (2007). Real options valuation of US federal renewable energy research, development, demonstration, and deployment. *Energy Policy*, 35(1), 265-279.
- [142] Locatelli, G., Invernizzi, D.C., Mancini, M. (2016). Investment and risk appraisal in energy storage systems: A real options approach. *Energy*, 104, 114-131.
- [143] Hagspiel, V., Hannevik, J., Lavrutich, M., Naustdal, M., Struksnæs, H. (2018). Real options under technological uncertainty: a case study of investment in a post-smolt facility in norway. *Marine Policy*, 88, 158-166.
- [144] Jiang, Z., Jovan, F., Moradi, P., Richardson, T., Bernardini, S., Watson, S., Weightman, A., Hine, D. (2022). A multirobot system for autonomous deployment and recovery of a blade crawler for operations and maintenance of offshore wind turbine blades. *Journal of Field Robotics*, 40(1), 73-93.
- [145] Trojanowska, M., Kort, P.M. (2010). The worst case for real options. *Journal of Optimization Theory and Applications*, 146(3), 709-734.
- [146] Papatzimos, A.K., Dawood, T., Thies, P. (2018). Cost-effective risk-based inspection planning for offshore wind farms. *Insight - Non-Destructive Testing and Condition Monitoring*, 60(6), 299-305.
- [147] Yang, A., Meng, X., He, H., Wang, L., Gao, J. (2022). Towards Optimized ARMGs' Low-Carbon Transition Investment Decision Based on Real Options. *Energies*, 15(14), 5153.
- [148] Khalid, O., Hao, G., MacDonald, H., Cooperman, A., Devoy McAuliffe, E., Desmond, C. (2023). Cost-benefit assessment framework for robotics-driven inspection of floating offshore wind farms. *Wind Energy*, 27(2), 152-164.
- [149] Olayiwola, O., Elsdén, M., Dhimish, M. (2024). Robotics, Artificial Intelligence, and Drones in Solar Photovoltaic Energy Applications—Safe Autonomy Perspective. *Safety*, 10(1), 32.

- [150] Gaertner, E., Rinker, J., Sethuraman, L., Zahle, E., Anderson, B., Barter, G.E., Abbas, N.J., Meng, F., Bortolotti, P., Skrzypinski, W., et al. (2020). IEA wind TCP task 37: definition of the IEA 15-megawatt offshore reference wind turbine. National Renewable Energy Lab.(NREL), Golden, CO (United States).
- [151] Liu, Y., Hajj, M., & Bao, Y. (2022). Review of robot-based damage assessment for offshore wind turbines. *Renewable and Sustainable Energy Reviews*, 158, 112187.
- [152] Xu, D., Wen, C., & Liu, J. (2019). Wind turbine blade surface inspection based on deep learning and UAV-taken images. *Journal of Renewable and Sustainable Energy*, 11(5).
- [153] Reddy, A., Indragandhi, V., Ravi, L., & Subramaniaswamy, V. (2019). Detection of Cracks and damage in wind turbine blades using artificial intelligence-based image analytics. *Measurement*, 147, 106823.
- [154] Wang, W., Xue, Y., He, C., & Zhao, Y. (2022). Review of the Typical Damage and Damage-Detection Methods of Large Wind Turbine Blades. *Energies*, 15(15), 5672.
- [155] Du, Y., Zhou, S., Jing, X., Peng, Y., Wu, H., & Kwok, N. (2020). Damage detection techniques for wind turbine blades: A review. *Mechanical Systems and Signal Processing*, 141, 106445.
- [156] Kaewniam, P., Cao, M., Alkayem, N.F., Li, D., & Manoach, E. (2022). Recent advances in damage detection of wind turbine blades: A state-of-the-art review. *Renewable and Sustainable Energy Reviews*, 167, 112723.
- [157] Regan, T., Beale, C., & Inalpolat, M. (2017). Wind turbine blade damage detection using supervised machine learning algorithms. *Journal of Vibration and Acoustics*, 139(6).
- [158] Yang, X., Zhang, Y., Lv, W., & Wang, D. (2021). Image recognition of wind turbine blade damage based on a deep learning model with transfer learning and an ensemble learning classifier. *Renewable Energy*, 163, 386-397.
- [159] Jang, Y., Kim, H., Kim, H., & Kang, K. (2021). Identification of debonding damage at spar cap-shear web joints by artificial neural network using natural frequency relevant key features of composite wind turbine blades. *Applied Sciences*, 11(12), 5327.
- [160] Sanati, H., Wood, D., & Sun, Q. (2018). Condition Monitoring of Wind Turbine Blades Using Active and Passive Thermography. *Applied Sciences*, 8(10), 2004.
- [161] Chen, X., Shihavuddin, A.S.M., Madsen, S.H., Thomsen, K., Rasmussen, S., & Branner, K. (2020). AQUADA: Automated quantification of damages in composite wind turbine blades for LCOE reduction. *Wind Energy*, 24(6), 535-548.
- [162] Chen, X., Sheiati, S., & Shihavuddin, A.S.M. (2023). AQUADA PLUS: Automated damage inspection of cyclic-loaded large-scale composite structures using thermal imagery and computer vision. *Composite Structures*, 318, 117085.

- [163] Spencer, M., Sheiati, S., & Chen, X. (2023). AQUADA GUI: A graphical user interface for automated quantification of damages in composite structures under fatigue loading using computer vision and thermography. *SoftwareX*, 22, 101392.
- [164] Bhalaji Kharthik, K.S., Onyema, E.M., Mallik, S., Siva Prasad, B.V.V., Qin, H., Selvi, C., & Sikha, O.K. (2024). Transfer learned deep feature based crack detection using support vector machine: a comparative study. *Scientific Reports*, 14(1), 14517.
- [165] Henderson, K., Salado, A. (2020). Value and benefits of model-based systems engineering (MBSE): Evidence from the literature. *Systems Engineering*, 24(1), 51-66.
- [166] Honore-Livermore, E., Dallolio, A., Birkeland, R., Langer, D.D., Haskins, C., Johansen, T.A. (2021). MBSE modeling of a SoS with a small satellite and autonomous surface vessels for persistent coastal monitoring. In 2021 16th International Conference of System of Systems Engineering (SoSE). IEEE.
- [167] Ren, Z., Verma, A.S., Li, Y., Teuwen, J.J.E., Jiang, Z. (2021). Offshore wind turbine operations and maintenance: A state-of-the-art review. *Renewable and Sustainable Energy Reviews*, 144, 110886.
- [168] Yang, H., Lin, C.Y. (2022). Promising Strategies for the Reduction of Pollutant Emissions from Working Vessels in Offshore Wind Farms: The Example of Taiwan. *Journal of Marine Science and Engineering*, 10(5), 621.
- [169] Zhang, Y., Roeder, J., Jacobs, G., Berroth, J., Hoepfner, G. (2022). Virtual Testing Workflows Based on the Function-Oriented System Architecture in SysML: A Case Study in Wind Turbine Systems. *Wind*, 2(3), 599-616.
- [170] Alstad, J.P. (2019). Development of COSYSMO 3.0: An extended, unified cost estimating model for systems engineering. *Procedia Computer Science*, 153, 55-62.
- [171] Shafiee, M., Zhou, Z., Mei, L., Dinmohammadi, F., Karama, J., Flynn, D. (2021). Unmanned Aerial Drones for Inspection of Offshore Wind Turbines: A Mission-Critical Failure Analysis. *Robotics*, 10(1), 26.
- [172] BladeRobots [Online]. Available: <https://bladerobots.com/>. [Accessed: Apr. 9, 2025].
- [173] Robotics and automation advance the offshore wind industry [Online]. Available: <https://www.hydro-international.com/content/article/robotics-and-automation-advance-the-offshore-wind-industry>. [Accessed: Apr. 9, 2025].
- [174] Marine robotics for offshore wind – nice to have or a necessity? [Online]. Available: <https://www.rivieramm.com/expert-views/expert-views/marine-robotics-for-offshore-wind-ndash-nice-to-have-or-a-necessity> [Accessed: Apr. 10, 2025].
- [175] M. Abadi, *et al.*, TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems, 2015. Software available from <https://www.tensorflow.org/>.

- [176] F. Chollet *et al.*,
Keras, 2015.
Available at: <https://keras.io>.

APPENDIX

The scripts developed in Chapter 5 are uploaded to the GitHub which can be accessed through the following link: https://github.com/iOmerKhalid/Phd_UCC_Thesis.