Decision Models for Operation and Maintenance of Offshore Wind Farms Considering Uncertainties

by

Sathishkumar Nachimuthu

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Department of Mechanical Engineering
University of Alberta

Abstract

Wind energy is an important renewable resource to meet the continually increasing global energy demand. The high wind power potential in the sea has led to the development of wind farms in the sea, referred to as offshore wind farms (OWFs). OWFs are an array of wind turbines built in the sea to generate electricity from the abundant wind energy in the sea. In addition to high productivity, OWFs do not produce any noise pollution to human life and do not affect wildlife (especially birds). These advantages have made OWFs, a reliable renewable option to meet future energy demand through green energy.

On the downside, the cost of energy produced by OWFs is high when compared to the cost of energy from wind farms in the land. Almost one-third of the cost of energy produced by OWFs is due to operation and maintenance (O&M) activities and is twice expensive as the wind farms in the land. The high O&M cost of OWFs is mainly due to its operating environment. The marine environment affects the reliability of offshore wind turbines (OWTs), creates uncertainty in turbine component lifetimes, and thereby increases the number of maintenance activities, effort, and costs. Also, the uncertain weather conditions and sea-state conditions limit accessibility to OWF for maintenance activities and increase downtime and production losses.

The high O&M cost at OWFs creates a necessity to better analyze the situation in OWF maintenance and the associated uncertainties, identify maintenance problems, and come up with cost-effective solutions. This thesis aims to model the uncertainties in OWF

maintenance and their effects on O&M costs, and identify critical maintenance decision problems and propose solutions for the identified problems through decision models considering uncertainties.

Firstly, an O&M model for the next future trip to the OWF is proposed to study the seasonal effects of the uncertainties on the O&M costs of OWFs. The proposed O&M model is a function of stochastic time elements of maintenance. Using the proposed model, the seasonal variations of offshore O&M costs, considering uncertainties are obtained. The results show that the O&M costs are lower in summer and higher in winter. Secondly, a resource decision problem for corrective maintenance of OWT, considering uncertainty in turbine failure information is studied. The problem situation is described, and a decision model is proposed to find a cost-effective resource option to address the described problem. Also, the use of the proposed model is demonstrated through a case study. The results of the case study show that the proposed model is mainly dependent on the probability of occurrence of different failure classifications of OWT. Finally, a decision problem related to maintenance technicians for corrective maintenance of OWT is studied. The uncertainty in maintenance technicians for OWF maintenance is modeled, and a mathematical model is proposed to find the appropriate/optimal number of technicians to send for corrective maintenance of OWT. A simple case study demonstrates the use of the mathematical model and figures out the appropriate number of technicians to send for two corrective maintenance categories.

This thesis study would promote the state of the art of research on OWF maintenance. The knowledge generated from this thesis will help the offshore O&M team better plan maintenance activities and make cost-effective resource decisions to reduce the overall O&M costs and the cost of energy of OWFs.

Preface

This thesis study is an original research work by Sathishkumar Nachimuthu. Research work conducted for this thesis study has been published. The generated journal paper and conference paper are with Sathishkumar Nachimuthu as the first author, Dr. Ming J. Zuo as the corresponding author and Dr. Yi Ding as the co-author.

Chapter 3 is published as a conference paper (peer-reviewed). The conference paper is:"Nachimuthu S, Zuo M J, and Ding Y. Modelling factors affecting operation and maintenance costs of offshore wind farms. *Proceedings of the 2018 IISE Annual Conference*. K. Barker, D. Berry, C. Rainwater, eds. Orlando, Florida, USA, May 19-22, 2018. pp. 1920-1925". Sathishkumar Nachimuthu did the original research work. Dr. Ming J. Zuo provided comments and suggestions to improve the quality of the research work. Reviews and edits on paper manuscripts were provided by both Dr. Ming J. Zuo and Dr. Yi Ding to improve the paper.

Chapter 4 is published as a journal paper (peer-reviewed). The journal paper is: "Nachimuthu S, Zuo M J, and Ding Y. A Decision-making Model for Corrective Maintenance of Offshore Wind Turbines Considering Uncertainties. *Energies*. 12 (8), Article Number 1408, APR 2, 2019 (13 pages)". Sathishkumar Nachimuthu did the original research work. Dr. Ming J. Zuo provided comments and suggestions to improve the quality of the research work. Reviews and edits on paper manuscripts were provided by both Dr. Ming J. Zuo and Dr. Yi Ding to improve the paper.

This thesis is dedicated to my parents
V. Nachimuthu and N. Kousalyadevi

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CHAPTER 1

INTRODUCTION

1.1 Background

The global energy demand is increasing rapidly with the growth in human population and economic activities, as most of the day-to-day activities such as communication, transportation, healthcare, etc., are dependent on energy. The use of conventional energy sources (minerals, fossil fuels, etc.) results in greenhouse gas emissions and global warming. To meet the growing energy needs of the global population while minimizing the greenhouse gas emissions, effective utilization of all the renewable energy sources (wind, solar, biomass, geothermal, hydro, nuclear, etc.) is required.

Among the renewables, wind energy is one of the most important sources and has been continuously utilized since the 20th century for electricity generation [1, 2]. Though onshore wind energy (energy that is generated on land) has been utilized, the limited land area and the need to reduce noise pollution are forcing the wind energy sector to expand into offshore regions [3, 4]. The advantages of high productivity, having no visual impact or noise impact on human life, and not needing to control the impact on wildlife (especially birds) has paved the way for the continual development of Offshore Wind Farms (OWFs) from 20 MW to 18000 MW of global cumulative installed capacity between 2004 and 2018 [3-5].

The high cost of energy, which is the major disadvantage of OWFs, remains a hindrance to their future growth and expansion. About 25% - 30% of the cost of energy produced by OWFs is due to the Operation and Maintenance (O&M) activities, which is twice as expensive as onshore installations [6]. The remote location, harsh marine environment, and the lack of adapting access equipment make the O&M of OWFs complicated and expensive due to high repair costs, repair crew and spare parts transportation costs, and production losses [7]. Therefore, OWFs are very expensive assets, not only to design and build but also to operate and maintain. As the Offshore Wind Turbines (OWTs) are being installed in water depths up to 40 m and as far as 80 km from shore, the cost and complexity of O&M are continually increasing. The success of the offshore wind technology and its future growth mainly depends on how the stakeholders work towards reducing the O&M costs.

1.2 Wind Turbines

Wind energy is a special form of kinetic energy in the air. It varies with the geographical locations, time of day, season, and height above the earth's surface, weather, and local landforms. The available energy in the wind can be converted into electrical energy using wind turbines. Wind turbines are power generating machines that are driven by the kinetic energy of the wind. Most of the modern large wind turbines have three blades, and the wind turns these blades (kinetic energy into mechanical energy), which in turn spins a generator to generate electricity (mechanical energy into electrical energy).

The classification of wind turbines may be based on the rotating axis of the turbines. With this classification, there are two types of turbines, namely horizontal axis wind turbines (rotating axis of the turbine is parallel to the ground) and vertical axis wind turbines (rotating axis of the turbine is perpendicular to the ground) [2, 8]. Horizontal axis and vertical axis wind turbine configurations are given in Figure 1.1.

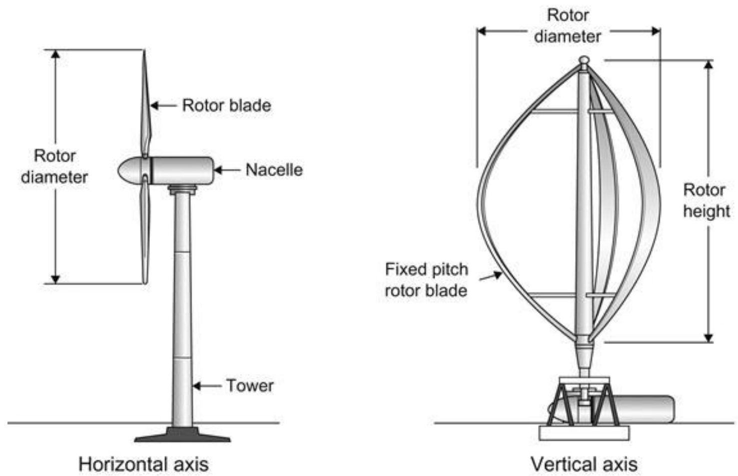

Figure 1.1: Horizontal and vertical axis wind turbine configurations [8]

Horizontal axis wind turbines dominate the wind industry and may be further classified into two categories based on drive train configurations, i.e., gearbox-operated turbines and direct drive turbines [9]. In gearbox-operated wind turbines, the blades spin a shaft that is connected through a gearbox to the generator. The gearbox is a mechanical device that converts the turning speed of the blades into the significantly higher speed required by the generator to generate electricity from wind energy. Gearbox-operated wind turbines dominate the wind industry, and a typical horizontal axis wind turbine with a gearbox is given in Figure 1.2. Gearbox-operated wind turbines generally require more maintenance as the failure of any part of the gearbox may lead to a turbine halt. Direct drive wind turbines use direct drive generators with no gearbox requirements. The direct drive turbines have better performance and reliability over gearbox-operated wind turbines [8]. A typical horizontal axis wind turbine with a direct drive is shown in Figure 1.3.

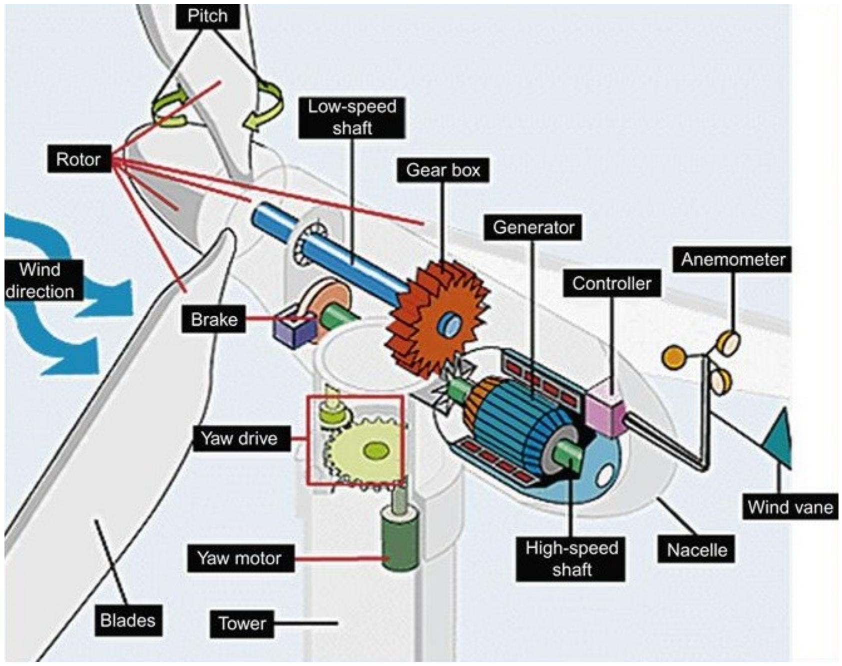

Figure 1.2: Horizontal axis gearbox-operated wind turbine [8]

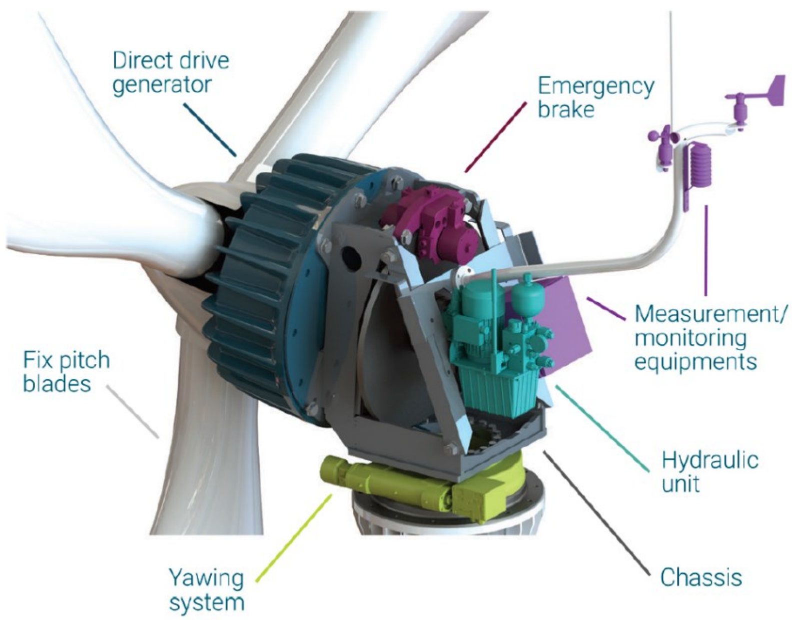

Figure 1.3: Horizontal axis direct drive wind turbine [8]

Wind turbines need to be installed in locations where there is enough wind available to generate electricity. The wind is the result of the movement of air due to atmospheric pressure gradients, and it flows from regions of high pressure to the regions of low pressure. The generation and movement of the wind are also affected by uneven solar heating, Coriolis force (the force that is generated due to earth's self-rotation), and local geography [2]. Wind resource at a site is evaluated using a comprehensive index called "wind power density." Wind power density is defined as "the available wind power in airflow through a perpendicular cross-sectional unit area in a unit time period" [2]. The available power in the wind is proportional to the cubic power of the mean wind speed, air density, and blade swept area. In order to obtain a high wind power, higher wind speed, higher air density and longer length of blades are required. Once a site is selected based on wind resource availability, arrays of wind turbines are constructed and installed to generate electricity and are called "wind farms."

Wind farms installed in the land to generate power from wind energy are referred to as "onshore wind farms." The world's first-ever wind farm was established in land in 1980 with a total capacity of 0.6 MW and is shown in Figure 1.4.

Figure 1.4: World's first-ever wind farm at Crotched Mountain, N.H., USA [10]

In recent years, the growth of the wind industry has been phenomenal, and the global wind power capacity stood at a huge 597 GW in 2019.With this total installed capacity, wind energy still currently contributes only 5% of the world electricity generation. The wind industry is continually looking to expand the wind power capacity by developing more wind farms. However, limited land area "onshore," environmental impacts, noise pollution, and the remote areas far away from the electricity demand center have motivated the wind industry to develop wind farms in the sea. Wind farms installed in the sea to generate power from wind energy are referred to as “offshore wind farms.”

1.3 Offshore Wind Farms

The amount of wind energy available in the sea is much greater than that is available in the land. As many of the world’s largest cities that demand a lot of electricity are located near the sea and/or oceans, OWFs adjacent to these cities could potentially meet the energy demand with locally generated renewable power. According to the Global Wind Energy Council, the energy available from European offshore wind energy sites could provide seven times the current energy demand and so most of the OWFs are in European waters [8]. For example, the London Array wind farm located 20 km off the coast from North Foreland, Kent coast, UK with a total capacity of 630 MW supplies its power to London, the capital city of England and the largest city of the United Kingdom [11]. London Array wind farm is shown in Figure 1.5.

Figure 1.5: London Array Wind Farm [11]

The technology for offshore wind turbines is similar to that of onshore wind turbines [8]. Offshore wind turbines are horizontal axis wind turbines with three-bladed rotors, drive trains, and towers like onshore wind turbines but have different foundations. Major offshore wind turbine foundations are monopiles, tripods, space frames, and floating turbine foundations [8]. The type of foundation to be used is dependent on the offshore location, water depth, and seabed geology. In shallow waters, up to a depth of 30 m, monopiles (a single pile driven into the seabed onto which the turbine tower is bolted) are used. In transitional waters with a depth range of 30 m to 60 m, tripods or multiple piles are used. Deep waters with a depth of more than 60 m require floating structures [8]. Different types of offshore turbine foundations are shown in Figure 1.6.

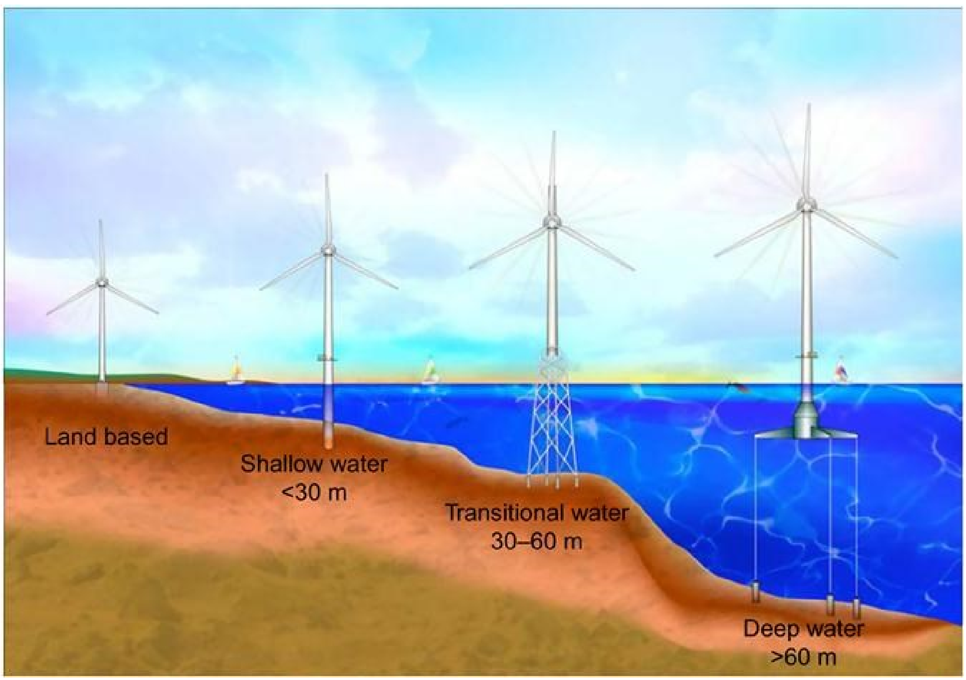

Figure 1.6: Offshore turbine foundations [8]

Offshore wind turbines must be installed and operated in the marine environment. Marine technologies used to prevent seawater damage to offshore oil and gas installations have been adapted for use by the wind turbine industry. In addition, special access vessels/ships, helicopters, and trained technicians are utilized to overcome the complexity involved in construction, installation, and O&M of wind turbines in the sea.

The offshore operating environment has both advantages and disadvantages. The wind regime at sea is better than land and results in the more reliable wind with higher wind speed and less turbulence. Higher average wind speeds in the sea result in increased power potential and efficiency. Another advantage is that there is no noise pollution and environmental impacts. On the downside, the offshore turbines experience excessive force/load due to heavy winds and high waves in the sea. The marine environment affects the reliability of offshore wind turbines, creates uncertainty in turbine component lifetimes, and thereby increases the number of maintenance activities, effort, and costs.

Whenever an offshore wind turbine fails, there is a need to initiate and execute maintenance to repair or replace the failed turbine. If the turbine failure is unexpected, then the required resources to perform maintenance may not be available. Depending on the type of failure, it may take a considerable time to get the access vessels, technicians, and spare parts to address the failed turbine. Once all the resources are in place and ready for maintenance execution, there is a chance that the maintenance could be delayed due to adverse wind and wave conditions in the sea. Such conditions are referred to as the "harsh marine environment," and their occurrence is uncertain. The harsh marine environment limits the accessibility to the OWF, affects maintenance execution, and increases the downtime. Therefore, the successful execution of any maintenance activity with minimal downtime at OWF is entirely dependent on the decisions taken by the O&M team on maintenance planning and execution.

Maintenance planning and execution at OWFs involves three types of decisions, namely strategic, tactical, and operational. Strategic decisions are decisions that influence the O&M over the life cycle of the wind turbine/farm (e.g., where should the maintenance base be located?).All decisions that influence O&M for more than five years are considered as strategic decisions in this thesis. Tactical decisions are decisions that influence O&M for a period of at least one and at most five years (e.g., Should the helicopter be purchased or chartered?). Operational decisions are decisions that influence O&M for a short period, i.e., days, weeks, and months (e.g., Which turbine should be visited tomorrow?). All decisions that influence the O&M for less than a year are referred to as short-term decisions in this thesis. The marine environment affects all three types of maintenance decisions and makes maintenance decision-making a challenging task for the O&M team. These challenges must be addressed through research and development so that we can fully utilize the advantages of OWFs.

1.4 Motivation and Research Objectives

Numerous research studies have been carried out in OWF maintenance, and many models were developed to assist the offshore O&M team in maintenance decision-making [12]. Though there are many models in the literature to assist maintenance decision-making at OWFs, the cost of O&M remains high. The high O&M cost at OWFs creates a necessity to better analyze and model the situation in OWFs, motivates to identify maintenance decision problems, and come up with better solutions through decision models.

This thesis aims to focus on maintenance decision problems at OWFs, propose decision models considering uncertainties to assist the OWF stakeholders in decision-making and to demonstrate the use of the decision models through simple case studies.

The objectives of this research are:

(i) To model the uncertainties in OWF maintenance and to study the seasonal variations of O&M costs considering uncertainties.

(ii) To identify critical maintenance decision problems and propose decision models for maintenance decision-making at OWFs considering uncertainties.

1.5 Organization of Thesis

The thesis is organized as follows. Chapter 2providesthe fundamentals of O&M and a comprehensive literature review of recent studies of O&M on OWFs. The uncertainties encountered by the OWFs and the existing decision models for offshore wind farm maintenance are summarized in Chapter 2.Chapter 3 presents the investigation on the effect of the uncertainties on the O&M costs of OWFs using time elements of maintenance execution for four different seasons, namely spring, summer, autumn, and winter. The stochastic time elements are modeled for the next maintenance trip scenario to figure out the seasonal variations of O&M costs at OWFs. Chapter 4 presents a decision model for a future corrective maintenance trip to an offshore wind turbine. The situation of random turbine failure with uncertainty in turbine failure information is investigated, and a mathematical model is proposed to assist resource decision-making. Also, a case study is done to demonstrate the use of the proposed model. Chapter 5 presents a short-term maintenance-staffing model for OWFs, considering various uncertainties. Chapter 6, the final chapter, presents the summary and conclusions of this thesis and suggests possible areas for future research.

CHAPTER 2

LITERATURE REVIEW

This chapter aims to introduce the fundamental concepts useful for the theme of this research. Types of uncertainties and the types of decision models reported in the literature will be summarized. Finally, the specific research topics of this study will be outlined.

2.1 Terms and Definitions

As mentioned in Section 1.4, our study object is an offshore wind farm. The wind farm consists of multiple wind turbines. In this section, the technical terms facilitating our study of offshore wind farms are introduced.

Components are functionally independent elements and are building blocks in the design of machines and software [13]. For example, gearbox, blades, and generator are some of the components of a gearbox-operated horizontal axis wind turbine shown in Figure 1.2. The many wind turbines may be regarded as components of the offshore wind farm shown in Figure 1.5.

A **system** is a collection of items (subsystems, components, software, human operators, etc.) whose proper, coordinated operation leads to its proper functioning [13]. For example, a wind turbine may be a system of many electrical and mechanical components. A wind farm may be a system consisting of many wind turbines as subsystems.

Failure is an event or state in which a component (or system) cannot perform one or more of its required functions within the specified time duration under specified conditions. A failure often requires equipment to be shut down and repaired or replaced [15]. For example, the function of a gearbox is to convert the turning speed of the blades into a relatively higher speed required by the generator to produce electricity. A sudden fracture or bending of a gear tooth in a gearbox prevents the gearbox from performing its function and is considered as a gearbox failure.

The **reliability** of an asset or item (e.g., component, complex system, computer program, human being, etc.) is defined as the probability of performing its purpose adequately for the period intended under the encountered operating and environmental conditions [14].For example, the reliability of a wind turbine for 1,000 hours of operation is 99.8%. This means that there is a 99.8% probability that the wind turbine will operate for 1000 operational hours without a failure.

The non-repairable system is a system that is discarded after a failure. An example of a non-repairable system is light bulbs. The reliability of a non-repairable component (or system) is characterized by Mean Time to Failure (MTTF). In the lifetime of a non-repairable device, the device fails once, and MTTF represents the average time until this failure occurs.

The repairable system is a system that, when a failure occurs, can be restored into operational condition after a certain action of repair (addition of a new part, exchange of parts, removal of a damaged part, changes or adjustment to settings, software update, etc.), other than replacement of the entire system. Examples of repairable systems are wind turbines, car engines, electrical generators, and computers. The reliability of repairable component (or system) is characterized by Mean Time Between Failures (MTBF). MTBF is calculated by dividing the total operating time of the system by the number of failures experienced by the system during the operating period.

A **series system** is a configuration of all components of a system such that the failure of any one component leads to the failure of the system [13]. For example, the major components of a wind turbine, including the blades, pitch control system, brake system, gearbox, yaw system, generator, and controller, are connected in a series configuration, as shown in Figure 1.2. Failure of any one of these components leads to the failure of the wind turbine. For a series system, reliability increases if the number of components in the system decreases.

A **parallel system** is a configuration of having all the components of a system linked to each other such that failure of all the components leads to the failure of the system [13]. For example, in a four-cylinder engine, which is a parallel system, the engine fails only if all four cylinders fail to run. For a parallel system, reliability decreases if the number of components decreases.

Maintainability is the probability that a given maintenance action for an item under given conditions of use can be carried out within a stated time interval, and this is when the maintenance is performed under stated conditions and using stated procedures and resources [14]. Maintainability is a function of equipment design and usually is measured by Mean Time to Repair (MTTR). MTTR is the average time needed to restore the component (or system) to its full operational condition upon failure. It is calculated by dividing the total repair time of the asset by the number of failures over a given operating period. For any component (or system), the lower the MTTR, the easier the maintenance.

Availability is the ability of an item to be in a state to perform a required function under given conditions at a given instant of time or over a given time interval if the required external resources are provided [14]. In simple terms, availability may be stated as the probability that an asset will be in operating condition when needed. The time during which a component (or system) is either fully operational or ready to perform its intended function is called as uptime. The time during which a component (or system) is inoperable or cannot perform its intended function is called as downtime. For example, a wind turbine with an availability of 95% indicates that the turbine is in operating condition for 9.5 hours out of

10 hours. The turbine has an average downtime of 0.5 hour and an average uptime of 9.5 hours.

Maintenance is the combination of all technical and associated administrative actions, including supervision actions intended to retain an item or to restore it to a state in which it can perform its required function [14]. Maintenance of a wind turbine includes but is not limited to inspection at regular intervals, proper cleaning and lubrication, and replacement of a component after a specified number of hours of operation.

Proactive maintenance is the maintenance carried out at predetermined intervals or depending on prescribed criteria intended to reduce the probability of failure or the degradation of the functioning of an item [14]. Proactive maintenance action on a wind turbine is to inspect the turbine periodically to make sure that it is functioning properly and to take necessary actions (e.g., cleaning, lubrication, etc.) if needed.

Corrective maintenance is the maintenance carried out after failure and intended to put an item into a state in which it can perform a required function [14]. For example, the replacement of a failed gearbox of a wind turbine using a new identical gearbox is a corrective maintenance action.

Lifecycle is defined as the consecutive and interlinked stages of a product system, from the raw material acquisition or generation from natural resources to final disposal [15]. The typical stages involved in a lifecycle of a wind farm include Planning and Design, Acquisition, Construction and Installation, Commissioning, Operation and Maintenance, and Decommissioning.

Accessibility is a qualitative or quantitative measure of the ease of gaining access to a component (e.g., offshore wind turbine) for maintenance [14].

2.2 Fundamentals of Operation and Maintenance of Offshore Wind Farms

In this section, a brief overview of maintenance strategies, maintenance optimization techniques, and the needed resources in the Operation and Maintenance (O&M) of Offshore Wind Farms (OWFs) are provided.

2.2.1 Maintenance Strategies for Offshore Wind Farms

The two maintenance strategies that are generally used for the maintenance of OWFs are proactive maintenance and corrective maintenance.

2.2.1.1 Proactive Maintenance

As described earlier in Section 2.1, **proactive maintenance** aims to reduce the probability of occurrence of unexpected failures and to bring a degrading component either to an "as good as new" state or to a state where the degradation is lowered by a certain amount. Proactive maintenance strategy involves systematic inspection, detection, and correction of minor faults either before they occur or before they develop into major faults [13, 16]. The proactive maintenance strategy may be divided into two types, namely, preventive maintenance and predictive maintenance.

Preventive Maintenance is a kind of maintenance that is conducted after a specific period of the component (or system) utilization [17, 18]. It is a planned/scheduled maintenance that is performed based on the age or time of operation of the component (or system) with the help of statistical reliability analysis (the estimated probability that the component will fail in a specified period). Preventive maintenance activities include inspection, lubrication, parts replacement, cleaning, and adjustment [17, 18].

Predictive maintenance, also known as **condition-based maintenance,** is the kind of maintenance that is initiated as a response for a deteriorating component (or system) condition based on the indicators that measure the physical condition of the component (or system) [17, 19]. The commonly used indicators to measure the condition of the component (or system) are temperature, vibration, noise, lubrication, and corrosion [20]. When such an indicator reaches a specified system deterioration level, the maintenance work is initiated to prevent system failure.

2.2.1.2 Corrective Maintenance

As described earlier in Section 2.1, **corrective maintenance** is a strategy, which involves maintenance actions that are performed to restore a failed component. The corrective maintenance actions could be broadly classified as "repair" and "replacement." The process of bringing a failed component (or system) back to the operating state to perform its intended function is generally known as repair. For a wind turbine, the repair is further classified as minor repair and major repair. Repair actions for failures caused by minor faults, typically involving sensor or instrumentation failure, are considered as minor repairs. Repair actions for failures that require more extensive maintenance work are considered as major repairs. For example, repair actions to resolve the failure of major mechanical components such as gearbox and shaft are major repairs. The process of replacing a failed component (or system) with a new identical component (or system) is known as a replacement.

2.2.2 Maintenance Optimization

An OWF O&M team may select all or a combination of a few or any one of the maintenance strategies based on their requirements. Regardless of the chosen maintenance strategy, the amount of maintenance to be executed plays an important role in determining the success of the O&M. Insufficient maintenance decreases the component (or system) reliability, and excessive maintenance increases the cost of maintenance. Therefore, it is very important to figure out the best balance between the cost of maintenance and system reliability, and this is achieved through maintenance optimization [21-23]. Maintenance optimization is defined as “a method aimed at determining the most effective and efficient maintenance plan (i.e., inspection time and frequency, work preparation, required maintenance resources) so that the best possible balance between direct maintenance costs (e.g., manpower cost, logistics, and transportation costs) and indirect maintenance costs (e.g., loss of power production and assets) is achieved” [7]. Two techniques that are widely used for maintenance optimization are reliability centered maintenance and risk-based maintenance [16].

Reliability Centered Maintenance (RCM) is a technique used to optimize the practices of the maintenance strategy in order to prevent the reliability level of the system from dropping below a certain specified value [13, 24]. In simple terms, the RCM technique establishes the appropriate maintenance plan for the component (or system) to minimize the probability of failures at the lowest cost. For wind turbines, RCM is generally applied to critical components and subsystems whose failures could result in catastrophic system failures or high loss of power production.

Risk-Based Maintenance (RBM) aims at reducing the overall risk of failure of the operating facilities by minimizing the overall maintenance effort, scope of the maintenance work, and cost of the maintenance program in a structured and justifiable way [16]. The risk of a component/system failure is evaluated (or quantified) as the probability of failure and the consequence of a failure of the system/component under consideration. In RBM, the inspection and maintenance schedule is optimized based on quantified risks caused by the failure of components (or systems). For wind turbines, the high-risk components (e.g., rotor blades, gearbox, and generator) are inspected and maintained with greater frequency. In contrast, low-risk components (e.g., brake) the inspection and maintenance frequency are minimized to reduce the total scope of work and cost of maintenance program.The optimality criteria for maintenance optimization at OWFs are O&M cost, production loss, power output, availability, and reliability. In general, we aim to minimize the O&M costs and production losses and to maximize power output, availability, and reliability.

2.2.3 Resources Required for Offshore Wind Farm Maintenance

Regardless of the maintenance strategy, various resources are required to perform maintenance activities at OWFs. The resources required to perform the maintenance activities include spare parts, maintenance technicians, vessels, and helicopters [25].

The spare parts are maintained in the onshore maintenance facility for replacement purposes. Maintenance technicians are classified into three major types: turbine technicians (onshore and offshore), foundation technicians, and electrical technicians [25]. Turbine technicians are responsible for the maintenance of the turbines. Foundation technicians work on the maintenance of the turbine foundation, whereas the electrical technicians work on substations and cables. Vessels (also known as access vessels) are ships that are specifically designed and manufactured for marine transportation. The access vessels are used for the transportation of maintenance technicians and spare parts from the onshore maintenance facility to the offshore wind turbine to perform maintenance. Helicopters are also used to access the offshore wind turbine for maintenance. The typical layout of an OWF with all its associated O&M elements (including vessels and helicopters) is shown in figure 2.1.

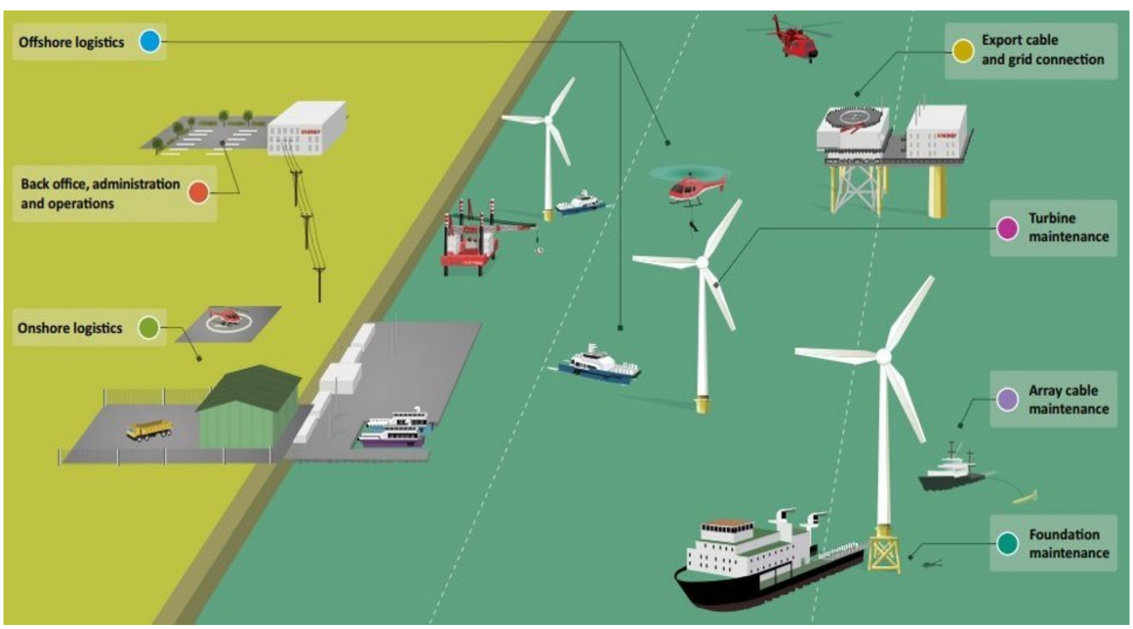

Figure 2.1: Layout of an OWF with the O&M elements [26]

2.3 Uncertainties in Offshore Wind Farm Maintenance

As stated in Section 1.3, OWF maintenance is exposed to uncertainties, and these uncertainties may be categorized into two types, namely, natural uncertainties and epistemic uncertainties.

2.3.1 Natural Uncertainties

The marine environment of OWFs is characterized by wind speed and wave height. Wind speed and wave height differ greatly throughout a year, and these variations occur naturally [6]. The wind speed and wave height highly influence the accessibility to an OWF. Gaining access to an offshore wind turbine for maintenance is difficult or impossible in harsh weather conditions due to wave heights and wind speeds exceeding the operational limit of the vessels and helicopters. During certain months, the wave height may remain above the operational limit of vessels and helicopters for the whole month. During this period, there is no accessibility to OWF for maintenance. Therefore, the uncertainty in wind speed and wave height delays maintenance and increases downtime and O&M costs [6].

The reported works [27-35] investigated wind speed and wave height conditions at OWFs. Douard et al. [27] modeled the meteorological and marine scenarios at OWFs using the Hidden Markov model. The marine parameters considered by Douard et al. [27] in the model are wind speed and wave height and are assumed as independent parameters. They utilize the historical data of wind speed and wave height in the model to develop future meteorological scenarios and to compute waiting times for each failure instance of the OWF elements. Scheu et al. [28] used the significant wave height parameter to model weather conditions at OWFs, as it is the most important limiting factor for maintenance execution at OWFs in terms of both magnitude and persistence. Scheu et al. [28] obtained the time series of significant wave height (every 6 hours) using the Markov process based on the historical wave height data for a given site. Scheu et al. [28] utilized the wind-wave correlation data to generate corresponding wind speeds.

Feuchtwang and Infield [29] developed a probabilistic model to calculate the expected delay caused by the wind and wave conditions for maintenance execution at OWFs. Feuchtwang and Infield [29] developed an event tree for offshore O&M to calculate expected delays directly from probabilities assigned to the branches of the event tree. Feuchtwang and Infield [29] considered access limits of vessels (also known as limiting operational conditions), required access times for maintenance work execution, and site wind and wave data as inputs to their “statistical model of access” which gives the expected delay as output.

Dowell et al. [30] analyzed the wind and wave data collected from an OWF in the North Sea and computed waiting times for maintenance execution at OWFs. Dowell et al. [30] developed empirical waiting time distributions for major maintenance (maintenance that requires a jack-up vessel) and minor maintenance (maintenance that requires a Crew Transfer Vessel) activities at OWFs. The waiting times developed by Dowell et al. [30] will be used in this thesis. Dinwoodie et al. [31] presented a wave height prediction model based on historical data for improved maintenance scheduling at OWFs. Dinwoodie et al. [31] collected wave data from the FINO 1 offshore research platform located 45km off the German coast. Dinwoodie et al. [31] used both auto-regression (AR) and artificial neural networks (ANNs) to predict the wave height.

Wilson and McMillan [32, 33] investigated the relationship between weather and wind turbine failures in [32] and then developed a wind speed dependent failure rate model in [33]. Wilson and McMillan [32] developed wind distributions corresponding to each sub-assembly failure in a wind turbine. Wilson and McMillan [32] used non-parametric distributions to fit the wind data recorded on the day when a failure has occurred to a sub-assembly in the wind turbine. Wilson and McMillan [33] used Bayes Theorem to calculate the wind speed dependent failure rates. Richter et al. [34] used the wind speed data from FINO 3 research platform, which is placed in the North Sea, about 80 km away from the German island Sylt, and modeled wind speed. The wind speed data from FINO 3 was fitted to a Weibull distribution using maximum likelihood estimation.

The model developed in [35] considered uncertainties in the weather forecast, repair time, and Operational Range Limitations (ORL) of vessels and investigated the effects of uncertainties on O&M costs. The model in [35] expressed the O&M cost as a function of these uncertainties, estimated the total maintenance expenses for the turbine lifetime of 20 years, and compared the variations in maintenance expenses with and without considering uncertainties. The uncertainty model developed in [35] for weather considers only the delay in accessing the target wind farm and does not consider the delay when performing the repair/maintenance at the target turbine. Also, the weather uncertainty model in [35] does not consider seasonal weather uncertainty changes. Reiterating the first objective of this thesis stated in Section 1.4, that is, to model the uncertainties on OWF maintenance, the seasonal variations of O&M costs considering both delay in accessing the turbine and delay at the turbine will be studied in this thesis.

2.3.2 Epistemic Uncertainties

The uncertainties that arise due to limited data and knowledge of the system, process, or mechanism are referred to as epistemic uncertainties. In OWFs, the expected lifetime of the offshore turbine and its components is considered as the epistemic uncertainty. The details on the uncertainty in turbine/component lifetimes and its quantification are given in the following paragraphs.

As stated earlier in Section 1.3, offshore wind turbines are installed and operated in the marine environment. Offshore turbines experience excessively more load than onshore turbines, and so the expected life of offshore turbines is different from that of onshore turbines. The challenge to offshore wind maintenance teams is that the expected lifetime of the offshore turbine components could not be evaluated accurately because of data inaccuracy, data incompleteness, and the unavailability of data from OWFs. Data limitations from OWFs make lifetimes of offshore turbines and its components an epistemic uncertainty.

Uncertainty in component lifetimes affects the number of corrective maintenance activities and, eventually, the availability and power output of the wind turbine/farm. Scheu et al. [36] analyzed the effect of uncertainty in component reliability estimations on OWF availability and figured out that the change in distributions of failure patterns might affect the wind farm availability up to 20%. Therefore, the uncertainty in components lifetime must be quantified to achieve the desired level of wind farm availability. The reported works [16, 37, 38, 39, and 40] addressed the quantification of uncertainty in components lifetime. The reported works [37] addressed data accuracy problem, [38] addressed data incompleteness issue, and [16, 39, and 40] addressed data unavailability issues for offshore turbine failure data. The details on the reported works [16, 37, 38, 39, and 40] are given in the following paragraphs.

Sainz et al. [37] identified that the real measurements obtained from OWFs may contain wrong data and proposed an automatic filtering technique to eliminate the wrong data from the overall data set. Sainz et al. [31] proposed a robust statistical technique by combining the least median of squares (LMedS) and a random search to filter the poor-quality RAM data in wind farms. Sainz et al. [37] compared the proposed technique with least mean squares, a classical technique for data elimination. The comparison showed that the proposed technique is more robust, eliminates various filtering steps, and reduce the time and costs required for the process.

Guo et al. [38] proposed a three-parameter Weibull failure rate function to quantify the failure rates of wind turbines with incomplete field failure data. Also, a comparative analysis of the proposed model with the traditional Weibull failure rate function was performed using the German and Danish wind farm data, and the effectiveness of the proposed three-parameter Weibull failure rate function is proved.

Karyotakis [16], in his doctoral thesis, proposed a model to quantify the offshore turbine failure rates using the available onshore failure data. To consider the effect of weather and sea-state conditions on the reliability of the offshore wind turbine, Karyotakis [16] included the "environmental stress factor" in the model. Utilization of offshore wind turbines is higher compared to equivalent onshore wind turbines due to the higher winds offshore, and to consider this utilization effect on the reliability of offshore turbines, Karyotakis [16] included “power rating stress factor” in the model. With appropriate values for both the factors and onshore turbine failure data, the failure rates for offshore wind turbines can be calculated using the model proposed by Karyotakis [16].

Carroll et al. [39] collected and analyzed the failure data of 350 offshore turbines throughout Europe and proposed failure rates for offshore wind turbine and its sub-assemblies. Carroll et al. [39] developed failure rates by year of operation, cost category, and failure modes for the components/sub-assemblies that are the highest contributor to the overall failure rate. Also, information on repair times, average repair costs, and the average number of technicians required for repair are also provided by Carroll et al. [39]. The failure rates and repair time, repair costs reported in [39] will be used in this thesis.

Zhang et al. [40] performed a dynamic fault tree analysis on floating offshore wind turbines, discussed the sequentially dependent failures and redundant failures and, evaluated the overall turbine reliability. Zhang et al. [40] used the failure data of wind turbines and towers on land to estimate the failure rate of floating offshore wind turbines. Zhang et al. [40] employed the failure data of offshore structures and devices to evaluate the failure rate of floating offshore wind turbines’ floating foundation system.

2.4 Reported Decision Models for Offshore Wind Farm Maintenance

In this section, the decision models [42-73] for OWF maintenance in the literature are summarized.

2.4.1 Long-term Decision Models

As stated in Section 1.3, decisions that influence O&M for more than five years are referred to as strategic decisions in this thesis. Models that address strategic O&M decisions are referred to as long-term decision models in this thesis. The long-term decision models [42-60] addressed the strategic decisions related to wind farm design for reliability, location and capacity of maintenance accommodations, selection of wind farm maintenance strategy, spare parts inventory management, and outsourcing of repair services [41].

The design of an OWF, that is, the layout and the location of installations of wind turbines, has a great influence on the later O&M decisions as these factors determine the distance of wind turbines from the onshore maintenance facility and also the distance between the turbines. When wind turbines go far into the sea, O&M becomes expensive and difficult because of the harsh environment of the sea. Therefore, the design of wind farms must take into account not only the reliability and power production issues but also O&M implementation issues. Afanasyeva et al. [42] presented a Net Present Value model for the optimization of wind farm design, considering uncertainty in different input parameters. The model [42] considered the O&M costs in the optimization of wind farm design. Samorani [43] studied the effect of the design of the wind farm layout on energy production and maintenance costs. Chen and MacDonald [44] proposed a system-level cost of energy (COE) optimization model incorporating the maintenance, replacement, and overhaul costs to determine the optimal placement of wind turbines. In our study in this thesis, we focus on an offshore wind farm with given distances and locations.

For a given offshore wind farm, whenever maintenance is initiated upon a random turbine failure, the repair activity of the failed turbine component may be performed either on-site or on the onshore maintenance facility. The location and the capacity of the on-site and off-site maintenance accommodations play a major role in determining the O&M costs. The decision on location and capacity of maintenance accommodations are considered as strategic decisions as these decisions will influence the O&M costs throughout the lifecycle of the windfarms. The factors that could be considered when dealing with this decision problem include but not limited to [41],

(i) Distance between the turbine platform and the maintenance accommodations.
(ii) Travel time between the OWF and the maintenance accommodations.
(iii) Installation and operating costs of each maintenance accommodation.
(iv) Wind farm reliability, which determines the expected demand for repair.

De Regt [45] optimized the location of offshore maintenance accommodations by treating the location problem as a "Weber" problem. Besnard et al. [46] proposed a mathematical model to determine the optimal location of maintenance accommodations, the number of technicians, choice of transfer vessels, and the possibility of using a helicopter in OWFs. Again, in this thesis work, we assume that such accommodations are already in place for our O&M problems to be addressed.

For an existing OWF, the selection of an optimal maintenance strategy from the available maintenance strategies is a strategic decision [41] if the time duration considered is more than five years. Andrawus et al. [47] identified and assessed the condition-based maintenance activities over the logistics life cycle of wind turbines, i.e., 18 years, to maximize the return on investment. Utne [48] proposed an efficient maintenance execution framework for the offshore wind turbines located in deep-sea for the turbine lifetime of 20 years. Ramírez and Sørensen [49] presented an optimal risk-based inspection (RBI) planning for offshore wind turbines for the turbine lifetime of 20 years. Sarker et al. [50] considered corrective maintenance as an opportunity to perform preventive repair and replacements, proposed an opportunistic preventive maintenance optimization model for the turbine lifetime based on the age of turbine components. Kerres et al. [51] evaluated the economic worthiness of different maintenance strategies on the critical components of a Vestas V44-600 kW wind turbine for the turbine lifetime of 20 years and concluded that the corrective maintenance strategy is the most cost-efficient maintenance strategy for the gearbox and generator of V44 turbine. May et al. [52] studied the economic worthiness of condition monitoring systems for offshore wind turbines by simulating the O&M operations incorporating condition monitoring systems for 20 years and concluded that usage of multiple condition monitoring systems on the same sub-system has a great potential for O&M cost savings.

If the O&M team at an OWF runs out of spares during a random turbine component failure, there will be a substantial increase in downtime and production losses, and the availability of the wind farm is affected. Therefore, it is very important to maintain a good number of spares to achieve the desired availability. The area of maintenance that figures out the best balance between the numbers of turbine component spares kept in stock, and the cost of handling and storage of all the spares to achieve maximum availability is known as the "spare parts inventory management" [41]. With the knowledge of the reliability of turbine components and the accessibility to the wind farm, the spare parts inventory optimization is performed.

Nnadili [53] investigated the logistics planning and inventory management of floating offshore wind turbine components for the turbine lifetime of 20 years. Lindqvist and Lundin [54] studied the spare parts inventory management of wind farms to determine the optimal stock levels, and the reorder size for critical components for the turbine lifetime of 20 years. Jin et al. [55] developed a mixed-integer non-linear optimization model to determine the optimal maintenance strategy and spare parts inventory policy for OWFs over the turbine lifetime of 20 years. Tracht et al. [56] proposed a spare parts planning model for OWFs considering the availability of vessels and the variations in meteorological conditions for the lifespan of wind turbines. In this thesis, we assume that the optimal level of spare parts is maintained for maintenance execution, and all the spare parts are always available.

After the turbine manufacturer service contract period (which is generally in the range of 2-5 years), the wind farm owner is responsible for the O&M activities [57]. To reduce the O&M costs and to obtain high-quality services, the OWF stakeholders decide to outsource the maintenance activities to external service providers [58] for the remaining lifetime of the turbines, and this is a strategic decision. The two types of outsourcing contracts are [41],

(i) The wind farm owner pays a lump sum to the external service provider/contractor to take care of the O&M activities for a fixed period.
(ii) The wind farm owner pays a fixed amount to the contractor for each failure.

Poore and Walford [59] studied the maintenance outsourcing for OWFs for the turbine lifetime of 20 years and concluded that it is an efficient policy to reduce the O&M costs, especially during the early years of operation of turbines. Jin et al. [60] proposed a mathematical model to minimize the O&M costs of wind turbines under a performance-based service contract, that is, the wind farm owner defines an availability goal and signs a contract with the service provider. Jin et al. [60] performed a comparative study on outsourcing O&M for gearbox for ten years and twenty years and concluded that a twenty-year contract has better cost savings in comparison to a ten-year contract. In this thesis, we assume that cost-effective O&M contracts are already in place for OWF maintenance.

2.4.2 Medium-term Decision Models

As stated in Section 1.3, tactical decisions influence O&M for a period of at least one and at most five years. Models that address tactical O&M decisions are referred to as medium-term decision models in this thesis. The medium-term decision models [61-65] addressed tactical decisions related to maintenance support organizations, such as the location of warehouses and vessel fleet size and mix.

Gallo et al. [61] proposed a maintenance model to investigate the impacts of the location of warehouses on the profitability of OWFs for two years. Van de Pieterman et al. [62] determined the optimum number of access vessels for an OWF consisting of 130 wind turbines in the Netherlands using a simulation tool that best projects O&M aspects for 1 to 5 years. Halvorsen-Weare et al. [63] proposed an optimization model to determine the annual vessel fleet size for the maintenance of OWFs. Li et al. [64] proposed a decision support tool to determine the annual requirements of vessel and maintenance technicians for the optimal maintenance planning at OWFs. The decision support tool in [64] incorporated two optimization models: a deterministic model for known accurate failure rates and a stochastic model for uncertain failure rates. Dalgic et al. [65] investigated the optimal jack-up vessel chartering strategy using a time-domain Monte Carlo approach considering the charter period, vessel characteristics, climate parameters, and failure characteristics of turbine components. Dalgic et al. [65] also established annual charter rates for the jack-up vessel. In this thesis work, we assume that an optimal number of technicians and vessel fleet size and the mix is maintained at OWFs for maintenance.

All the assumptions stated in Section 2.4.1 and 2.4.2 ensure that this thesis work will focus on an OWF with cost-effective maintenance accommodations, O&M contracts, spare parts inventory, and maintenance support organization (warehouses, maintenance technicians, and fleet size and mix of vessels). The strategic and tactical maintenance decisions have already been made for the OWF to be analyzed in this thesis. So, this thesis work will focus on short-term maintenance decisions.

2.4.3 Short-term Decision Models

As stated in Section 1.3, decisions that influence O&M for less than a year are short-term decisions. Models that address short-term decisions are referred to as short-term decision models in this thesis. The short-term decision models [66-73] addressed decisions related to scheduling of maintenance tasks and resources and routing of maintenance vessels. [41].

Scheduling of maintenance activities for an OWF is generally done for a period of 3 days – 7 days and is a challenging task as it is dependent on multiple factors such as the availability of vessels and maintenance technicians, availability of spare parts, weather, and sea-state conditions [41]. Zhang et al. [66] proposed a maintenance-scheduling model for preventive maintenance at OWFs to minimize the overall downtime and production losses. The scheduling optimization model by Zhang et al. [66] considered both wake effects and wind effects on maintenance. Zhang et al. [66] used a genetic algorithm to solve the optimization model. Zhang et al. [66] studied the maintenance schedule optimization problem for a utility-scale OWF with 25 turbines and concluded that their proposed approach results in a significant reduction in downtime energy losses.

Besnard et al. [67] developed an opportunistic short-term maintenance model for opportunistic preventive maintenance during corrective maintenance execution, considering production and weather forecasts. The model is developed for two different time horizons (a day and a week) and for wind farms that follow flexible maintenance schedules. The model proposed by Besnard et al. [67] gives a set of preventive and corrective maintenance activities to be performed on the current day and maintenance plan forecast for the following days. Besnard et al. [67] studied the model for five 3MW wind turbines for a period of 60 days. The results of the work showed that 43% of the total preventive maintenance cost could be saved if this opportunistic maintenance with flexible everyday schedule optimization is adopted at the OWFs. Besnard et al. [68] also presented a stochastic optimization model for performing service maintenance activities during corrective maintenance execution, considering the probabilistic variations in production forecasts and weather forecasts. Besnard et al. [68] used data from Lillgrund, an offshore wind farm located in the southwest of Sweden, to study the model. The results show that the approach could save 32% of the transportation and production losses.

Ravindranath [69] developed a short-term decision-making model for scheduling maintenance tasks and resources (vessels and maintenance technicians) at the OWFs, considering constraints in weather, energy prices, vessel characteristics, and maintenance technician's skills. The time horizon considered in this model is a day, and it helps the

OWF maintenance managers and planners to make better maintenance tasks and resource scheduling decisions each day. The model in [69] developed a maintenance schedule for four days and studied two different scenarios of maintenance execution at OWF on a given day. The first scenario had twelve maintenance technicians available for maintenance execution, with seven to eight technicians, work on average per day, whereas the second scenario had seven technicians available. Both the scenarios performed the corrective maintenance activities within the given 4-day period.

Once the maintenance activities are scheduled, the vessels then travel to the desired turbine for maintenance. During the travel to the turbine, a collision between the vessels and the offshore structures such as turbines and grid infrastructure may result in structural damages to both vessels and wind turbines. Dai et al. [70] proposed a risk assessment framework for offshore collisions, investigated the risk magnitude of such collisions between maintenance vessels and wind turbines, and concluded that the collisions even at low speed might cause serious structural damages. Therefore, along with scheduling, better routing of vessels must also be considered to avoid the offshore collision. In the case of multiple random turbine failures, the optimal routing and scheduling could reduce the downtime largely.

Stalhane et al. [71] proposed an arc-flow model and a path-flow model to find the optimal routing and scheduling of maintenance activities for a given fleet of vessels at OWFs. Irawan et al. [72] proposed a mixed-integer linear programming model for the routing and scheduling of maintenance activities at OWFs considering multiple vessels, multiple periods, multiple bases, and multiple wind farms. The model [72] also figures out the number of technicians required for each vessel. Raknes et al. [73] proposed a mathematical model for optimal maintenance scheduling and routing of vessels considering the multiple work shifts and the option of staying offshore.

It is observed that the works [67 and 68] on maintenance task scheduling assumed that the information about turbine failure is always available and known for corrective maintenance of offshore turbines. With this assumption, the kind of needed repair is known, the resource decisions are certain, and the maintenance team easily picks the desired resources for maintenance. The short-term models [67 and 68] then focused on their objectives, such as opportunistic preventive maintenance to minimize the total maintenance costs. Though today's turbines are usually equipped with condition monitoring (CM) systems, there may arise scenarios that such condition monitoring systems are unable to indicate the exact failure classification upon failure. That is, no information on the kind of needed repair/failure classification and spare parts requirements are obtained from the CM systems. Such scenarios arise when natural events, including but not limited to storms, icing, and waves, occur, and these natural events account for 60% of offshore turbine failures [16]. The occurrence of these natural events is unpredictable and leads to failure of both turbine components and the CM systems, respectively. When turbine failure information becomes unavailable, resource decision-making turns out to be uncertain, and the short-term models [67 and 68] are inapplicable to address this maintenance problem situation. The resource decision-making problem for a corrective maintenance trip to OWF, considering uncertainty in turbine failure information, will be studied in this thesis.

Though the model [69] pointed out the importance of assigning an optimal number of maintenance technicians for corrective maintenance, the model did not study the impact of insufficient maintenance technicians on energy loss/production loss. In this thesis, we will investigate the possibilities of having insufficient maintenance technicians at the turbine for corrective maintenance and the decision problem of assigning an appropriate number of maintenance technicians for corrective maintenance.

2.5 Summary

In this chapter, the fundamentals of OWF O&M relevant to the theme of this research have been described. The types of uncertainties in OWF maintenance are reviewed, and the existing literature is summarized. Seasonal variations of O&M costs at OWFs will be studied using the stochastic time element of maintenance execution in chapter 3 of this thesis.

The need to reduce high O&M costs at OWFs has motivated the research community to identify maintenance decision problems at OWFs and provide solutions through decision models. The decision models for OWF maintenance in the literature have been reviewed and summarized. Though the long-term and mid-term decision models presented in sections 2.2.1 and 2.2.2 have issues to address, the scope of this thesis is limited to short-term decisions, i.e., maintenance decisions that influence O&M for less than one year. As stated in section 2.4.3, there are situations (e.g., corrective maintenance of an offshore wind turbine) during which the turbine failure information becomes unavailable at OWFs, and the decision on resource combination becomes uncertain. A decision model to find a cost-effective resource combination for a corrective maintenance trip to an offshore wind turbine, considering uncertainty in turbine failure information, will be proposed in chapter 4.

Whenever turbine failure information becomes unavailable, resource decision making turns out to be uncertain. The possibilities of having insufficient maintenance technicians at the turbine for corrective maintenance will be investigated, and a model to assign the appropriate number of maintenance technicians for corrective maintenance will be proposed in chapter 5 of this thesis. Finally, some concluding remarks and possible future work will be given in chapter 6.

CHAPTER 3

MODELING OF UNCERTAINTY IN OFFSHORE OPERATION AND MAINTENANCE

In this chapter, the concept of capturing the uncertainties in O&M of OWFs using the time elements of maintenance execution is introduced, and the uncertainties are modeled as stochastic time elements for the next future trip. Also, the O&M cost model for the next future trip is proposed, and the seasonal variations of the O&M costs at the OWFs are studied using the proposed model. A version of this chapter has been published as a conference paper in [74]. The symbols used in this chapter are specific to and applicable only to this chapter. The $ values in this chapter are US dollars unless otherwise specified.

3.1 Problem Description

As stated in section 1.3 of chapter 1, the increased O&M cost for offshore wind farms is mainly caused by uncertainty factors including but are not limited to weather, sea-state conditions, and component lifetimes. The weather and sea-state conditions limit accessibility to OWF and increase downtime and production losses. Uncertainty in component lifetime affects the number of corrective maintenance activities and thereby increases maintenance effort and costs.

Very few studies in the literature have represented the O&M cost as a function of different uncertainties. Three such studies have been carried out for OWFs. The model developed in [35] considered the uncertainties in wind speed, wave height, repair time, and Operational Range Limitations (ORL) of vessels and investigated the effects of uncertainties on O&M costs. The model in [35] expressed the O&M cost as a function of these uncertainties, estimated the total maintenance expenses for the turbine lifetime of 20 years, and compared the variations in maintenance expenses with and without considering uncertainties. The weather forecast uncertainty model in [35] represents the uncertainty in wind speed and significant wave height and uses an error term to describe the difference between the forecasted value and the actual value. The error terms for both wind speed and significant wave height take a mean value of zero and a standard deviation of $0.005 \cdot t$, where t denotes time in hours. The farther the forecast is, the larger the uncertainty in the forecast. This means, for a forecast of 24 hours the standard deviation is 0.12 and for a forecast of 48 hours the standard deviation is 0.24. The repair time uncertainty is modeled as an error term to describe the difference between actual repair time and expected repair time. The error term for the repair time uncertainty is assumed lognormal distributed and has a mean greater than or equal to one. The uncertainty in ORL of vessels represents access uncertainty. There is a possibility that the wave conditions exceed the deterministic threshold value of the operational range of vessels when the vessel is in the sea. This uncertainty is modeled using an error term to describe the difference between the actual value at the site and the deterministic threshold value of having access by the vessel. The error term is assumed normally distributed with a mean of one and the standard deviation of σ, due to lack of data and knowledge on ORL of vessels. The uncertainty model developed in [35] for wind speed and wave height considers only the delay in accessing the target wind farm and does not consider the delay when performing the repair/maintenance at the target turbine. In addition, the weather uncertainty model in [35] does not consider seasonal weather uncertainty changes. The main aim of this chapter is to investigate the effect of uncertainties in OWF maintenance execution using stochastic time factors for the next future trip. The objectives are to propose a model that represents the O&M cost as a function of various uncertainties for the next future trip and to study the seasonal variations of O&M costs considering uncertainties.

The failure cost categories are classified into three types, namely minor repair, major repair, and replacement. According to [39], any failure with a total repair material cost up to €1000 is considered as a minor repair, between €1000 and €10,000 is considered as a major repair and over €10,000 is considered as a replacement. This type of categorization based on material cost ensures that the repair costs are independent of the distance from shore. The failure rate of minor repair is taken to be 6.81/turbine/year, of a major repair is 1.17/turbine/year, and of replacement is 0.29/turbine/year [39]. Irrespective of the type of the wind farm, the number of turbines and the distance from the shore, the probability that the immediate next future trip to the OWF will result in a minor repair is 0.82, a major repair is 0.14, and a replacement is 0.04 [39]. Since the failure cost categories have different probabilities of occurrence and different repair characteristics (repair cost and repair time), all three categories are included in our analysis to find the maintenance cost for the next future trip. In our study, both major repair and replacement are considered as major maintenance, and minor repair is considered as minor maintenance.

3.2 Stochastic Time Variables

The components of wind turbines may experience unforeseen failures during their operation (uncertainty in the component lifetime). Now, the maintenance team does not know whether it is minor or major maintenance. However, the maintenance team is ought to attend the failed component and needs to travel to the target wind farm to fix the problem. Natural variations of weather and sea-state conditions highly influence the accessibility (using vessels) to OWF. For example, vessels can access the wind farm only if wave heights are less than $2\ \mathrm{m}$ [16]. During certain months wave heights are more than $2\ \mathrm{m}$ and accessibility to OWF is almost impossible. This uncertainty in weather and sea-state conditions delays the execution of maintenance activity and thereby increases downtime and O&M costs. After arriving at the target turbine, the crew carries out the required maintenance on the turbine component, and this completes a maintenance execution activity. From the interpretation of the complete maintenance execution activity, we believe that three time variables are involved in maintenance execution, namely waiting time, repair time, and travel time.

The hypothesis here is to employ the time variables involved in a maintenance execution to capture the uncertainties for OWF maintenance by treating them as stochastic factors. The amount of time a maintenance operation is delayed due to constraints on sea state and wind speed is termed as waiting time [30]. The time it takes to travel back and forth, the wind farm is the travel time. Repair time is defined as the amount of time the maintenance technicians spend in carrying out the repair [39]. All three stochastic time factors are treated as independent of each other. The waiting time model developed in [30] is selected in our study as it captures all the delays due to weather and sea-state uncertainties. The travel time is treated as a random variable and is modeled using probability theory. To consider the uncertainty in repair time, the model developed in [75] is selected in our study. This study is concerned only with time variables involved in executing the maintenance and does not consider time variables such as logistic time for spare parts and lead-time for maintenance vessels that are involved in preparing and planning maintenance and hence the sum of waiting time, repair time and travel time is considered as "Failure Restore Time" (FRT) [30].

The model in [35] expresses O&M cost for the turbine lifetime of 20 years as a function of various uncertainties, namely weather forecast uncertainty, repair time uncertainty, and ORL of vessels. The model proposed in this chapter expresses the O&M cost for the next future trip as a function of stochastic time factors (waiting time, travel time, and repair time). Our proposed model using stochastic time factors will calculate the total maintenance expenses for the next future trip. The proposed model serves as an improvement of the existing model reported in [35], as it considers the delay when performing a repair at the turbine and is capable of studying the seasonal O&M cost variations. The reported model from [35] is given in equation (3.1), and our proposed model is given in equation (3.2).

$$O\ \&\ M\ cost\ \ for\ turbine\ lifetime\ of\ 20\ years = f\ (weather\ \ forecast,\ repair\ time, ORL\ of\ vessels) \tag{3.1}$$

$$O\ \&\ M\ cost\ \ for\ the\ next\ \ future\ trip = f\ (waiting\ time, repair\ time, travel\ time) \tag{3.2}$$

In the following sub-sections, we analyzeeach of the three stochastic time variables.

3.2.1 Waiting Time

The waiting time represents the total delay in maintenance execution due to weather and sea-state conditions. The waiting time includes two time elements: delay time before travel can start and delay time while the maintenance crew is at the target wind turbine.

Crew Transfer Vessels (CTVs) are used in our model, and they are capable of carrying the needed equipment for any of the three types of possible maintenances. When there is a need to travel to the OWF to perform maintenance, there might be a delay in the start due to sea-state conditions. CTVs have an operational range limit based on wave heights up to $1.5\ \mathrm{m}$ [76]. If the wave height exceeds $1.5\ \mathrm{m}$, the maintenance crew has to wait onshore until the sea-state conditions come under the operational limit of the CTV. This delay before the travel can start is the first element of the waiting time. The waiting time before travel can start is the time the maintenance crew has to wait onshore until weather and sea-state conditions become accessible to complete the entire maintenance execution activity, which includes the travel to the turbine and the repair activity at the turbine. The waiting time with respect to the maximum wave limit of CTV corresponding to $1.5\ \mathrm{m}$ wave limit can be used in modeling the waiting before travel can start. Since our analysis is focused on the next future trip, at this point of time, the crew does not know which type of maintenance that they are going to perform. Therefore, the waiting time before travel can start is the same for all three maintenance categories, and it is denoted by $WT_{before\ travel\ starts}$. During the entire travel, the wind speed and wave height will be within the operational range of the vessels, and travel will not be interrupted, i.e., no delay during the travel.

Once the crew has arrived at the target turbine, there may be a waiting time due to uncertainty in weather and according to the type of maintenance executed. This second element of waiting time is denoted by $WT_{at\ the\ turbine}$. This second element of the waiting time includes all the delays due to the sudden change of weather conditions when the crew is already at the turbine. Once this waiting time is over, one of the three maintenance types (minor repair, major repair and, replacement) will be executed. Cranes that are carried on all CTVs are needed only for major repair and replacement, and they are not needed for minor repairs. Thus, the waiting time at the target turbine is zero for a minor repair. The waiting times for major repair and replacement are affected by both wind speed and wave height [30]. Cranes are designed for use up to a certain maximum in-service wind speed at offshore. If the wind speed exceeds the in-service speed of cranes, the crew has to wait until the wind speed decreases to the operational limit of the cranes to execute maintenance. The model developed in [30] for waiting time at the turbine is selected for this study as it used both hourly mean wind speeds and hourly mean significant wave height data from the FINO1 research platform in the North Sea. FINO1 is one of the German research platforms in the North and Baltic Seas for investigation of environmental conditions that might be conducive to the exploitation of wind power offshore. It is situated in the North Sea about 40km north of Borkum and was brought into service in 2003. The FINO1 research platform is instrumented with a large suite of meteorological and oceanographic instruments where comprehensive measurements and analyses are undertaken for the determination of ambient conditions (meteorology, hydrology, oceanography, etc.) [77]. It is assumed that the maximum in-service wind speed for the cranes used for maintenance is $10\ \mathrm{m/s}$.

The total waiting time, including waiting time before travel and waiting time at the turbine for the next future trip, is given in equation (3.3).

$$WT_{next\ future\ trip} = WT_{before\ travel\ starts} + WT_{at\ the\ turbine} \tag{3.3}$$

$$WT_{at\ the\ turbine} = \alpha \times WT_{minor} + \beta \times WT_{major} + \gamma \times WT_{replacement} \tag{3.4}$$

where α denotes the probability that the needed repair is minor, β is the probability that the needed repair is major, γ is the probability that the needed repair is a replacement, $\alpha + \beta + \gamma = 1$, and WT represents waiting time. The parameters α, β and γ can be estimated from past repair records. From the data analyzed in [39], α = 0.82, β = 0.14, and γ = 0.04. We will use these numbers in our illustrating calculations later in this chapter.

The results from [30] provide CDF of waiting times ($WT_{before\ travel\ starts} + WT_{at\ the\ turbine}$) for minor repair, major repair, and replacement for a whole year and all the four seasons, namely spring, summer, autumn, and winter. The mean values of Gamma distributed waiting times from [30] for minor repair, major repair, and replacement for the whole year and for different seasons are given in Table 3.1. The numbers for major repair and replacement are the same in their study.

Table 3.1: Expected Values of Gamma distributed waiting times [30]

Year/Season	**Minor repair** WT_{minor}	**Major repair** WT_{major}	**Replacement** $WT_{replacement}$
Whole year	186.55	1247.00	1247.00
Spring	52.25	212.48	212.48
Summer	34.80	68.00	68.00
Autumn	49.47	170.46	170.46
Winter	102.50	356.91	356.91

3.2.2 Repair Time

The repair time is treated as a stochastic variable because there may be a difference between the expected repair time and actual repair time on site [35]. The repair time model presented in [75] is selected for our study. Repair time is assumed lognormal distributed with a mean value of 160.08 hours for a minor repair, 423.36 hours for a major repair, and 2788.56

hours for a replacement [39, 75]. The repair time for the next future trip is given in equation (3.5).

$$RT_{next\ future\ trip} = \alpha \times RT_{minor} + \beta \times RT_{major} + \gamma \times RT_{replacement} \tag{3.5}$$

where α denotes the probability that the needed repair is minor, β is the probability that the needed repair is major, γ is the probability that the needed repair is a replacement, $\alpha + \beta + \gamma = 1$, and RT denotes repair time.

3.2.3 Travel Time

The travel time to the OWF is varying because it depends on the experience and risk willingness of the vessel skipper or helicopter pilot, and hence it is a random variable. None of the studies in the literature has considered travel time as a stochastic variable in modeling O&M costs for OWFs. The travel time is an important stochastic time variable involved in maintenance execution because the travel time not only affects the downtime but also affects the number of hours the maintenance technicians spend on the vessel during the travel to the wind farm. This uncertainty in travel time affects the wages paid for the maintenance technicians and total O&M costs. This is the reason to consider travel time in our O&M model. To avoid the use of a helicopter in our study and to get same travel time for various types of repairs, it is assumed that the same type of CTV from the same manufacturer is used to access the OWF. A wind farm with a distance of 150 km from shore and a CTV with a speed of 20 knots is used in [78] to calculate the travel time. The calculated travel time of 8.1 hours for a round trip is considered as the mean travel time and is assumed lognormal distributed [78]. The travel time for the next future trip is denoted as $TT_{next\ future\ trip}$. The travel time might get affected due to varying wave heights and wind speeds. Wind speed directly influences the wave height. The wave height variations in the sea affect the travel speed, which in turn affects the travel time. To simplify our analysis and exclude the hydrodynamics of the sea, the travel time is assumed to be independent of the wave height and wind speed in this chapter. This dependence will be considered in future work.

3.2.4 O&M Cost Model

Our proposed model expresses O&M cost for the next future trip as a function of three stochastic time variables involved in maintenance execution as given below,

$$O\ \&\ Mcost\ \ for\ the\ next\ \ future\ trip = a \times WT_{next\ future\ trip} + b \times RT_{next\ future\ trip} + c \times TT_{next\ future\ trip} \quad (3.6)$$

where $WT_{next\ future\ trip}$ is the waiting time, $RT_{next\ future\ trip}$ is the repair time, $TT_{next\ future\ trip}$ is the travel time, a is the cost per hour of waiting time, b is the cost per hour of repair time, and c is the cost per hour of travel time. The cost per hour of the respective time variables affects the cost of maintenance technicians and the cost of the vessel, provided both maintenance technicians and vessel rentals for maintenance are paid on an hourly basis. To simplify our analysis, the set-up time, which is also uncertain, is not considered in this study. Set-up time is the total time it takes to get spare parts in place, lower crane legs to establish a stable platform, assemble crew, transfer technicians, and reach the target turbine component before starting the actual repair work.

3.3 Seasonal Variations of O&M Cost

To study the seasonal variations of O&M cost considering uncertainties for the next future trip, the values of the stochastic time factors in the models given in Section 2 are needed. The degree of uncertainty is denoted by the coefficient of variation (CV) of a random variable. CV is the ratio of the standard deviation to the expected value of the random variable expressed in percentage. The larger the coefficient of variation, the larger the uncertainty in the random variable. The time values are calculated for the same mean and 10% CV and 90% CV. To simplify our analysis, *a*, *b,* and *c* in equation (3.6) are assumed to be the same and all equal to \$199, which is the sum of the per hour maintenance labor cost (\$125) and per hour vessel cost (\$74) as given in Table 3.2. We have used the values of α = 0.82, β = 0.14, and γ = 0.04, as stated before. The mean values of waiting times for various types of repairs are given in Table 3.1. The mean values of the repair times are taken to be 160.08 hours for a minor repair, 423.36 hours for a major repair, 2788.56 hours for a replacement. The mean value of travel time is taken to be 8.1 hours. Other data given in Table 3.2 are not used in this study. The repair times and the travel times are assumed to be the same for each of the four seasons considered.

Using the data described above, we have calculated the total O&M cost for each of the four seasons when the coefficient of variation is equal to 10% and 90%. The calculated O&M costs are given in Table 3.3 and plotted in Figure 3.1. From the results in Table 3.3 and Figure 3.1, we can see that the O&M cost is very high during the winter season and the lowest during the summer season. In addition, the autumn season is better than the spring season by a considerable amount of savings in O&M costs. Therefore, the summer and autumn season are the better picks to plan and execute inspections and preventive maintenance activities at OWFs, to reduce both the O&M costs and the cost of energy.

Table 3.2: Inputs to calculate O&M costs [30, 39, 78, and 79]

O&M cost model inputs	Minor repair	Major repair	Replacement
Average number of technicians	2.61	3.44	9.14
Maintenance technician cost/hour	$ 125	$ 125	$ 125
Repair cost	$ 186	$ 2296	$ 54347
Vessel cost/hour	$ 74	$ 74	$ 74
Fixed vessel trip cost	$ 118.50	$ 118.50	$ 118.50

Table 3.3: OWF O&M costs for the next trip from this study

Season	10% Coefficient of Variation	90% Coefficient of Variation
Spring	$82,763	$142,954
Summer	$74,033	$127,876
Autumn	$80,638	$139,284
Winter	$97,402	$168,241

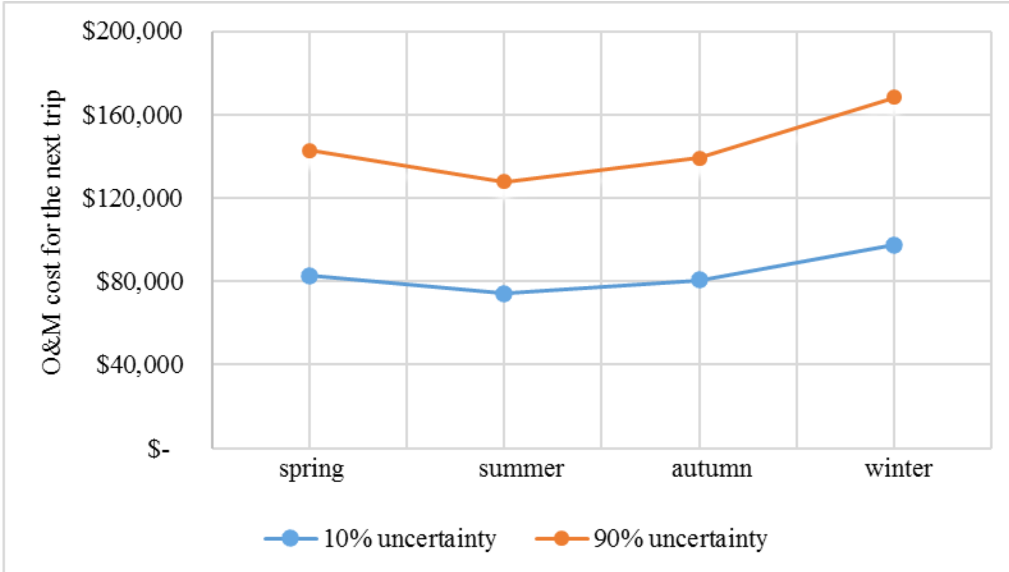

Figure 3.1: OWF O&M Costs for different seasons

3.4 Summary

This chapter expresses the uncertainties in OWF maintenance execution through stochastic time variables for the next future trip and demonstrates the effects of the uncertainty factors on total O&M costs for different seasons. The model developed in this chapter would help to assess the seasonal O&M cost for a specific OWF location and would aid in planning both inspection and preventive maintenance activities to minimize the O&M cost. This conceptual approach of time variable analysis for capturing the effect of uncertainties could also consider the uncertainty in the logistic time of spare parts and uncertainty in the lead-time of vessels. Possible future work includes lead-time and logistic time in the O&M model, the number of maintenance technicians to assign to a trip, and other types of cost in Table 3.2.

In this chapter, we have got a better understanding of the seasonal variations of O&M costs at OWFs. As stated in section 1.4 of chapter 1, our next objective is to identify and solve short-term maintenance decision problems at OWFs. In the next chapter, i.e., chapter 4, a decision model for corrective maintenance at OWFs, considering uncertainty in turbine failure information, will be presented.

CHAPTER 4

DECISION MODEL FOR CORRECTIVE MAINTENANCE OF OFFSHORE WIND TURBINE

Through the literature review in Section 2.3.1 and Section 2.3.2 of chapter 2, a better understanding and knowledge of uncertainties in OWF maintenance is obtained. In chapter 3, the uncertainties in OWF maintenance are modeled using stochastic time elements of maintenance execution, and the seasonal variations of O&M costs of OWFs are studied for the next future trip. With a better understanding of the effect of uncertainties on offshore O&M costs as documented in Chapter 3, our next objective is to identify critical maintenance decision problems at OWFs and propose decision models to aid decision-making at OWFs.

In this chapter, the different types of resource combination to address an offshore wind turbine failure is discussed and a short-term resource decision-making model is proposed for the next corrective maintenance trip for offshore wind turbines, considering the uncertainty in turbine failure information. Also, a case study is presented to demonstrate the use of the proposed model. A version of this chapter has been published as a journal paper in [81]. The symbols used in this chapter are specific to and applicable only to this chapter. The $ values in this chapter are US dollars unless otherwise specified.

4.1 Problem Description

As stated in Section 1.3, the accessibility limitations of vessels and helicopters imposed by the weather and sea-state conditions combined with the unavailability of failure data make maintenance decision-making at OWFs, a complex and challenging task for the O&M team. The high O&M costs at OWFs creates a necessity to identify maintenance decision problems (either long term or short term) that have a significant effect on the life cycle O&M costs and to provide solutions to one decision problem at a time through simple maintenance models. The corrective maintenance and its associated resource decisions (both short-term and long-term) contribute more than 60% to the life cycle O&M costs and are the highest cost driver of OWF O&M [80]. The high cost associated with the corrective maintenance resource decisions was the motivation to identify short-term resource decision problems for corrective maintenance of the OWFs.

Few models [67, 69] in the literature have addressed the short-term maintenance problems at OWFs. As described in Section 2.4.3, both the short-term models [67, 69] reported in the literature assumed that the information about turbine failure is always available and known for offshore turbine maintenance. With this assumption, the kind of needed repair is known, the resource decisions are certain, and the maintenance team easily picks the desired resources for maintenance. The short-term models [67, 69] then focused on different objectives such as opportunistic preventive maintenance [67] and resource-scheduling [69] to minimize the total maintenance costs. When the turbine failure information becomes unavailable, the resource decision-making turns out to be uncertain, and the short-term models [67, 69] are inapplicable to address this maintenance problem situation. In the following paragraphs, we describe the problem to be dealt with in this chapter in detail.

Each component failure of a wind turbine has different maintenance/repair severities, i.e., the effort needed from the maintenance technicians, the cost associated with the maintenance work, and the time needed to perform the repair vary for each component failure. It is reported in [82] that the grouping of turbine component failures with similar maintenance severity is done to develop failure classifications, and the reported methodology will be followed in our study. The offshore turbine component failures may be classified into a finite set of failure classifications, and each failure classification has a maintenance rank and a probability of occurrence. The "maintenance rank" of a failure classification is defined as "the natural number assigned to each failure classification based on the severity of maintenance involved in solving component failures, with 1 assigned to the failure classification of lowest maintenance severity and N assigned to the failure classification of highest maintenance severity." As each failure classification is assigned a maintenance rank, the total number of ranks is the same as the total number of failure classifications. The "probability of occurrence of a failure classification" is defined as "the sum of all the individual failure probabilities of turbine components under a specific failure classification."

Irrespective of the type of maintenance, certain resources are required to perform the intended maintenance task. Resources needed to complete a maintenance activity are an access vessel, maintenance technicians, and spare parts. The right combination of maintenance technicians, access vessels, and spare parts to address the offshore turbine failure is termed as "resource combination." In the case of an offshore wind turbine, different resource combinations are required to solve component failures under different failure classifications. For example, to solve the failure of a gearbox under a given failure classification, more number of maintenance technicians, expensive vessel and spare gearbox parts (assembled or individual spare parts) are required, whereas to solve the failure of a brake shoe falls under another failure classification, and less number of maintenance technicians, inexpensive vessels and brake shoe spare parts are required. Hence, two failure classifications could potentially result in two resource combinations. The failure of both the brake shoe and gearbox could also be addressed using one resource combination.

This provides us an intuitive understanding that there may exist two types of resource combinations to address the offshore turbine failure. We assume that the first type is resource combinations that are dedicated to addressing component failures under only one specific failure classification and are referred to as “A-type Resource Combinations” or simply “A-type RC’s” throughout the chapter. A-type RC is defined as “the combination of maintenance technicians, spare parts and vessels which can identify and solve component failures under single failure classification.” A-type RC’s cannot solve the failures that occurred in turbine components under other failure classifications. We assume that the second type is the resource combinations that are capable of solving turbine component failures under multiple failure classifications within a specified maintenance rank and are referred to as “B-type Resource Combinations” or simply “B-type RC’s” throughout the chapter. The B-type RC for the n^{th} ranked failure classification is defined as “the combination of maintenance technicians, spare parts and vessels which can solve component failures under the rank “1 to n” failure classifications.” From the definition, it is understood that if a B-type RC is sent to address the n^{th} ranked failure classification, it cannot solve component failures under rank “n+1 to N” failure classifications.

Though today’s turbines are usually equipped with condition monitoring (CM) systems, we consider the scenario that such condition monitoring systems are unable to indicate the exact failure classification upon a turbine failure. That is, no information on the kind of needed repair/failure classification and spare parts requirements are obtained from the CM systems. Such scenarios arise when natural events, including but not limited to storms, icing, and waves, occur, and these natural events account for 60% of the offshore turbine failures [83]. The occurrence of these natural events is unpredictable and leads to the failure of both the turbine components and the CM systems, respectively. The human-influenced events are generally reliability related issues of the CM systems. It is reported in [84] that the reliability of the CM system is not 100%, and the CM systems sometimes fail to produce an alarm when the turbine component requires immediate attention for maintenance. The event of the CM systems not producing an alarm leads to component failure and apparently turbine failure. During this CM system unreliability event, the information failed turbine component is not obtained from the CM systems. Hence, these random natural and human-influenced events (of failure) leads to a situation where the O&M team will have no direct information from the CM systems to make resource related maintenance decisions. In this chapter, we focus on this scenario of corrective maintenance where the information on the failed turbine component and its failure classification is not known.

A wind farm may have many turbines in operation, which may fail anytime in the future. If any wind turbine at an offshore wind farm failed suddenly and no information on the failed turbine component and its failure classification could be obtained from the CM systems, the O&M team do not know the exact resource combination to address the failed turbine. In this situation, the O&M team is unsure about which type of vessel to use, how many maintenance technicians to send, whether to take spare parts or not and which spare parts to take. This creates uncertainty in making decision on the resource combination for maintenance execution. The hypothesized problem situation is "a corrective maintenance trip to an offshore wind turbine with unknown turbine failure information." The aim of our study is "to find a cost-effective resource combination for the hypothesized problem situation." In this problem, the failure classification is not known at the time of maintenance initiation, and all the resource combinations that are available in the onshore port turn out to be decision choices for the O&M team. The resource combination to be selected by the O&M team might solve the unknown failure in one trip or might not solve the unknown failure in one trip and necessitate an additional trip to solve the identified failure known from the first trip. Therefore, the O&M team is put into a situation to select only one resource combination among all the available resource combinations considering the two possible results of their decision. In order to make a decision, the cost associated with each decision choice must be evaluated, taking into account the probability of occurrences of different failure classifications. Then, the resource combination with the least cost could be selected as a cost-effective resource combination to address the unknown turbine failure. The objectives are to propose a simple and useful mathematical model to aid decision-making and to demonstrate the use of the proposed model through a case study. The proposed model will assist multiple OWF stakeholders in making critical resource decisions for a corrective maintenance trip. The proposed model addresses the maintenance problem situation for which the information on turbine failure is not available and so it cannot be compared with the short-term models [67, 69] in the literature.

4.2 Mathematical Model

In this section, the mathematical model for the described problem is proposed. If the offshore wind turbine has a finite number of failure classifications and each classification has a probability of occurrence, then:

$$\sum_{i=1}^{N} P_i = 1 \tag{4.1}$$

where P_i denotes the probability of occurrence of the i^{th} failure classification. The probabilities of occurrences of all the failure classifications are assumed known.

To address the component failures under respective failure classifications of offshore wind turbine, two different types of resource combinations are described earlier in Section 4.1. In our model, both types of resource combinations are considered as decision choices. Therefore, the selection of one resource combination among the available resource combinations (both A-type and B-type) is the only decision for the described problem. The decision is represented as a finite set of binary variables in our model:

$$S_{ij} = \begin{cases} 1, \text{ use type } j \text{ RC for failure classification } i \\ 0, \text{ don't use type } j \text{ RC for failure classification } i \end{cases} \tag{4.2}$$

$$\sum_{i=1}^{N} \sum_{j=1}^{2} S_{ij} = 1 \tag{4.3}$$

where S_{ij} denotes the type j RC for the i^{th} ranked failure classification. The above constraint ensures that only one S_{ij} is selected among the available N number of S_{ij}'s, to solve the unknown failure. All the type j RC's that are dedicated to addressing their respective i^{th} ranked failure classifications are assumed known.

The uncertainty in turbine failure information brings in two possible situations, namely trip success and trip failure. The "trip success" is defined as the situation where the unknown turbine failure is solved in a single maintenance trip using either an A-type RC or a B-type RC. The "trip failure" is defined as the situation where the unknown turbine failure cannot be solved in a single maintenance trip and necessitates an additional trip to solve the identified known failure using an appropriate A-type RC. Both the probability of trip success and trip failure depends on the decision and the probability of occurrences of the failure classifications. The trip success and failure situations, along with their probabilities, are considered in the model.

When an A-type RC, which is dedicated to the i^{th} failure classification, is sent to address the unknown failure, the trip is successful when the failure classification is i and the trip is a failure when the failure classification is not i. For A-type RC, the probability of the maintenance trip to be a success is P_i, and the probability of the maintenance trip to be a failure is $1–P_i$. If the failure classification is not i, we are able to identify that the failure is k, and a single next trip with an A-type RC for k will solve the failure. When a B-type RC that is dedicated to the n^{th} failure classification is sent to address the unknown failure, the trip is successful when the failure classification is *1,2,3,..., n,* and, the trip is a failure when the failure classification is k ($k>n$). For B-type RC, the probability of the maintenance trip to be a success is $P_1 + P_2 + P_3 + ... + P_n$, and the probability of the maintenance trip to be a failure is $P_{n+1} + P_{n+2} + P_{n+3} + ... + P_N$. A single next trip with an A-type RC for k will solve the failure.

The objective is to find the expected total maintenance cost of the decision, to figure out the cost- effective decision and solve the unknown turbine failure. The total maintenance cost in our model includes the maintenance technicians cost, access vessel cost, special maintenance vessel cost (jack-up, crane, etc.), spare parts cost and, production losses due to downtime. The maintenance technicians and vessels are in use from the point of time they get ready to execute maintenance to the point of time they get back to shore after the maintenance activity. In addition, the turbine is unavailable until the maintenance crew gets the turbine back to operation. Therefore, the mathematical model formulation involves various deterministic time elements of maintenance, namely lead-time, logistic time, waiting time, travel time, failure identification time, and repair time.

The time to get the vessel ready for maintenance is the lead-time and, the time to get the spare parts is the logistics time. It is assumed that all the resources (the vessels, the technicians, and the spare parts) are always available in the onshore port for maintenance execution. This assumption eliminates the lead-time of vessels and the logistic time of spare parts in our model. The total delay in maintenance execution due to weather and sea-state conditions is the waiting time and is the sum of "the delay before travel starts" and "the delay at the turbine" [30]. It is dependent on the weather and does not depend on the decision. Hence, the waiting time is a constant in our model. The time to identify the failure occurred at the turbine and figure out the component that requires maintenance is the failure identification time. The failure identification time does not depend on the decision and is a constant in our model. The time taken to travel back and forth the turbine using vessels is called the "travel time" and is the sum of the "travel time to the turbine" and "travel time from the turbine." The travel time is dependent on the decision, as the vessel speed may differ for different resource combinations. To calculate the travel time, the average distance of the turbines from the shore is considered in our model. The wind speed and wave height variations in the sea may affect the travel speed, which in turn affects the travel time. To simplify our analysis and exclude the hydrodynamics of the sea, the travel time is assumed to be independent of the wave height and wind speed in this chapter.

The time it takes to perform the actual maintenance work is the repair time. In the case of trip success, the repair activity is completed successfully, and the turbine failure is solved in one trip. In our model, the trip success situation includes repair time. In the case of trip failure, the component failure is only identified and is not repaired on the first trip. The certain amount of time spent to identify the failure in the first trip (waiting time, failure identification time, and travel time) along with the fixed cost for an additional trip to solve the known failure using an A-type RC is considered for trip failure. The fixed cost/purchase cost of spare parts is not considered in our model; instead, the cargo handling costs of spare parts are considered as the spare parts cost in our model. The spare parts cost is the total tonnage of spare parts in a resource combination times the cargo handling cost per tonnage. To simplify our analysis, the weight of the spare parts is considered the only cargo weight in our model. Other weights, such as the weight of the maintenance tools, technicians are not considered. The mathematical model for the described problem is given in Equation (4.4) as:

$$Z = \sum_{i=1}^{N}\sum_{j=1}^{2} S_{ij} \times g_{ij} \times D + \sum_{i=1}^{N}\sum_{j=1}^{2} S_{ij} \times H_{ij} + \sum_{i=1}^{N}\sum_{j=1}^{2} S_{ij} \times t_{ij} \times C_{ij} + \sum_{i=1}^{N}\sum_{j=1}^{2} S_{ij} \times \alpha_{ij} \times r_{ij} \times C_{ij} + \sum_{i=1}^{N}\sum_{j=1}^{2} S_{ij} \times \beta_{ij} \times A \tag{4.4}$$

$$C_{ij} = V_{ij} + (n_{ij} \times M) + R \tag{4.5}$$

$$\alpha_{ij} = P_i \quad \text{for j=1} \tag{4.6}$$

$$\alpha_{ij} = \sum_{k=1}^{i} P_k \quad \text{for j=2} \tag{4.7}$$

$$\beta_{ij} = 1 - P_i \quad \text{for j=1} \tag{4.8}$$

$$\beta_{ij} = \sum_{k=i+1}^{N} P_k \quad \text{for j=2} \tag{4.9}$$

Z	Expected total maintenance cost for S_{ij}
g_{ij}	Weight of spares for S_{ij} in tons
D	Cost per tonnage of spares
H_{ij}	Cost of special vessel for S_{ij}
t_{ij}	Travel time for S_{ij}in hours
C_{ij}	Cost of vessel, maintenance technicians, and revenue loss per hour for S_{ij}
V_{ij}	Vessel cost per hour for S_{ij}
n_{ij}	Number of maintenance technicians for S_{ij}
M	Maintenance technician cost per hour

R	Revenue loss per hour
r_{ij}	Repair time for S_{ij} in hours
α_{ij}	Probability of trip success for S_{ij}
B_{ij}	Probability of trip failure for S_{ij}
P_i	Probability that the failure is of classification i
A	Fixed additional trip cost of sending an A-type RC to solve known failure, which includes vessel cost, technicians cost, spare parts cost, and revenue loss due to downtime

The above mathematical model describes the expected total maintenance cost of sending S_{ij} to address the unknown failure. The first two terms in the model are the sum of the spare parts cost and fixed special vessel cost of S_{ij}. The third term in the model is the total cost, including vessel cost, technicians cost, and revenue loss incurred because of the travel to and from the turbine using S_{ij}. The fourth term in the model is the trip success using S_{ij}. The trip success considers the total cost, including the vessel cost, technicians cost ad revenue loss incurred because of the repair activity at the turbine using S_{ij} and the probability that the turbine failure could be solved by S_{ij}. The fifth term in the model is the trip failure using S_{ij}. The trip failure considers the total cost, including the vessel cost, technician cost, and revenue loss, to solve the known failure using an appropriate A-type RC and the probability that the turbine failure could not be solved by S_{ij}. The waiting time and failure identification time are constants in our proposed model, and both the time elements do not affect the decision and the results. Therefore, the waiting time and failure identification time are not included in the model. In the equations (4.6), (4.7), (4.8) and (4.9), $j = 1$ represents the A-type RC and $j = 2$ represents the B-type RC.

With appropriate inputs, the proposed model is capable of calculating the expected cost of each decision choice. Utilizing the enumeration method, the expected total cost of all the resource combinations is evaluated and, the resource combination with the minimum expected cost is selected as the cost-effective option to address the unknown turbine failure. The mathematical model formulated above includes both types of resource combinations described earlier in Section 4.1, as decision choices, and this allows the decision makers to consider all the available resource combinations for decision-making. In addition, the simplicity of the model ensures that it takes less time and less technical effort to solve the model. Hence, all the OWF stakeholders could use the model anytime. Given the failure classifications, their probabilities, and resource combinations (decision choices) and, using the proposed model, the O&M team at any OWF would be able to figure out the cost-effective resource combination to address the unknown turbine failure.

4.3 Case Study

The objective of the case study is to demonstrate the use of the proposed model for offshore wind turbine maintenance. To simplify our analysis, a wind farm model with identical turbines is selected for our case study.

4.3.1 Wind Farm Models

The OWEZ wind farm model reported in [82] is selected for the study. The OWEZ wind farm has 36 identical VESTAS 3 MW wind turbines with a total capacity of 108 MW. The wind farm is in the North Sea at 10 km - 18 km distance from the harbor, and the turbines are installed to a maximum depth of 20 m. Four failure classifications for corrective maintenance reported in [82] for a 3 MW wind turbine is applicable for the selected OWEZ wind farm model and is given in Table 4.1.

In accordance with the vessel characteristics reported in [39] and the weight of spares under each failure classification reported in [82], the A-type RC's and B-type RC's for corrective maintenance is given in Table 4.2. From Table 4.2, it could be observed that S_{11} and S_{12} have identical resource elements, which means both A-type and B-type RC's are identical for imperfect maintenance in this study.

Table 4.1: Failure classifications for a 3 MW offshore wind turbine [82]

Maintenance rank	Failure Classification	Definition
1	Imperfect maintenance	An imperfect maintenance operation where there is no requirement for spare parts.
2	Minimal replacement	A minimal replacement of small sized sub-components with a maximum weight of 1 tonne.
3	Perfect replacement I	A perfect replacement of medium weight sub-components with a maximum weight of 50 tonnes.
4	Perfect replacement II	A perfect replacement of medium or large sized sub-components, with weight 50 tonnes to 100 tonnes.

The probabilities of different failure classifications reported in [82] are applied to the OWEZ wind farm model. The reported probabilities are considered as the base case model in the study. It can be observed that the majority of the corrective maintenance for the base case model is imperfect maintenance. Thus, the base case model is interpreted as OWF in which the turbines are relatively new, and their operating age is less than five years, that is, the turbines are operating in its first 5-year service period.

As the base case model is interpreted as OWF with turbines that have operational years less than five years old, three other models are established for OWFs with increasing age of turbines with appropriate assumptions to demonstrate the powerfulness of the proposed model for different OWFs. The model 1 represents the OWF in which the turbines in operation are five to ten years old. For the wind farm model 1, it is assumed that the majority of corrective maintenance corresponds to a minimal replacement, and it has the highest probability of occurrence. The probability of other failure classifications is then descended in the order of imperfect maintenance, perfect replacement I, and perfect replacement II. The model 2 represents the OWF in which the turbines in operation are ten to twenty years old. For the wind farm model 2, it is assumed that the majority of corrective maintenance corresponds to perfect replacement I, and it has the highest probability of occurrence. The probability of other failure classifications is then descended in the order of perfect replacement II, minimal replacement, and imperfect maintenance.

Table 4.2: Decision Choices [39, 82]

Resource Combination	**Resource Elements**
S_{11}	No Spare part + Access Vessel (Crew Transfer Vessel -small) + 2 maintenance technicians
S_{21}	Required Spare part + Access Vessel (Crew Transfer Vessel -small) + 3 maintenance technicians. (Use of permanent internal crane for replacement).
S_{31}	Required Spare part + Crane Vessel + Access Vessel (Crew Transfer Vessel small) + 6 maintenance technicians.
S_{41}	Required Spare part + Access Vessel (Crew Transfer Vessel -small) + Access Vessel (Jack- Up Vessel) + 6 maintenance technicians.
S_{12}	No Spare part + Access Vessel (Crew Transfer Vessel - small) + 2 maintenance technicians
S_{22}	All Class B Spare parts + Access Vessel (Crew Transfer Vessel-Large) + 3 maintenance technicians (Use of permanent internal crane for replacement).
S_{32}	All Class B and C Spare parts + build-up crane with a vessel + Access Vessel (SUVs) + 6 maintenance technicians.
S_{42}	All Class B, C and D spare parts + Access Vessel (SUVs) + Access Vessel (Jack- Up barge) + 6 maintenance technicians

The model 3 represents the OWF in which the turbines are either more than twenty years old or affected by storms or other natural disasters. For the wind farm model 3, it is assumed that the majority of corrective maintenance corresponds to perfect replacement II and it has the highest probability of occurrence. The probability of other failure classifications is then descended in the order of perfect replacement I, minimal replacement, and imperfect maintenance. The reported probabilities for the base case are changed for different failure classifications to represent the wind farm models 1, 2, and 3. The probabilities of failure classifications of the base case model and the three different wind farm models are given in Table 4.3. The probability numbers in Table 4.3 are absolute values and are not in percentages.

Table 4.3: Probabilities of failure classifications for different OWF models [82]

Failure Classification	**Probability**			
	Base Case Model	**Wind Farm Model 1**	**Wind Farm Model 2**	**Wind Farm Model 3**
Imperfect maintenance	0.9952	0.0023	0.0010	0.0010
Minimal replacement	0.0023	0.9952	0.0015	0.0015
Perfect replacement I	0.0010	0.0015	0.9952	0.0023
Perfect replacement II	0.0015	0.0010	0.0023	0.9952

4.3.2 Time and Cost Inputs

The values of time elements are essential inputs to find the expected total maintenance cost. Travel time is calculated using a 14 km average distance of the wind turbines from the shore and average speed of different access vessels. The repair time for rank 1 failure classification is assumed to be 4 hours in our study. It is reported in [30] that it will take 48 hours to switch out the component in question and replace a working unit for major maintenance. This time reported in [30] is the repair time for rank 2, 3, and 4 failure classifications in our study. The cost per tonnage of spares is a standard metric to find the cargo handling costs [85], and we will use the same metric in our case study. The reported work in [82], which defined the failure classifications, did not provide any weight data for individual spare parts. Based on the turbine components listed under each failure classification reported in [82], the maximum cargo weight of spare parts for a failure classification is considered as the cargo weight of a resource combination. The fixed cost for corrective maintenance trip from [39] is the additional trip cost in this case study. All the time and cost inputs required to find the expected total maintenance cost are given in Tables 4.4 and 4.5.

Table 4.4: Inputs to calculate expected total maintenance cost [30, 39, 78 and 82]

Resource Combination	**Travel Speed (km/hr)**	**Travel Time (hours)**	**Repair Time (hours)**	**Access Vessel Cost/hour**	**Crane/Jack up Vessel cost**	**Weight of Spare Parts (tonnes)**
S_{11}	37.04	0.76	4	\$62.50	N/A	0
S_{21}	37.04	0.76	48	\$62.50	N/A	1
S_{31}	37.04	0.76	48	\$62.50	\$105,259	50
S_{41}	37.04	0.76	48	\$62.50	\$119,294	100
S_{12}	37.04	0.76	4	\$62.50	N/A	0
S_{22}	46.30	0.60	48	\$93.75	N/A	11
S_{32}	18.52	1.50	48	\$93.75	\$105,259	600
S_{42}	18.52	1.50	48	\$93.75	\$119,294	600

Table 4.5: Inputs to calculate expected total maintenance cost [79, 85 and 86]

Parameter	**Values**
Maintenance Technician cost/hour	70
Cost/tonnage of spares	\$29.72
Revenue Loss/hour	\$18,684
Fixed cost for corrective maintenance trip for offshore wind turbine	\$500,000

4.3.3 Results

The expected total maintenance cost of each decision choice for a specific wind farm model is represented as a 4×2 matrix (there are eight decision choices in this study):

$$Z_n = \begin{bmatrix} z_{11} & z_{12} \\ z_{21} & z_{22} \\ z_{31} & z_{32} \\ z_{41} & z_{42} \end{bmatrix}$$

Where Z_n is the cost matrix of the wind farm model *n*. The elements z_{ij}*'s* of the matrix Z_n represent the expected total maintenance cost values (in $'s) of sending respective S_{ij}*'s* for a specific wind farm model *n*. That is, the element z_{11} represents the expected total maintenance cost of sending S_{11}, the element z_{21} represents the expected total maintenance cost of sending S_{21}, and so on. It is earlier stated in Section 4.3.1 that both A-type and B-type RC's have identical resource elements for imperfect maintenance, which indicates, the elements z_{11} and z_{12} of the matrix will have identical values. The minimum of the z_{ij}*'s* in the matrix Z_n is selected as the optimal solution, and the corresponding resource combination is identified to be the cost-effective resource combination.

Using the model in Section 4.2, the model inputs in Section 4.3.1 and 4.3.2, and using the explicit enumeration method, the expected total maintenance cost is calculated for all the available resource combinations (decision choices) for the different wind farm models of Table 4.3 and the results are shown in matrix form.

The cost matrix for the base case model (Z_0) is:

$$Z_0 = \begin{bmatrix} 91951 & 91951 \\ 515401 & 922110 \\ 621730 & 1072754 \\ 637456 & 1087414 \end{bmatrix}$$

The cost matrix for the wind farm model 1 (Z_1) is:

$$Z_1 = \begin{bmatrix} 513354 & 513354 \\ 922366 & 922110 \\ 621935 & 1072960 \\ 637250 & 1087414 \end{bmatrix}$$

The cost matrix for the wind farm model 2 (Z_2) is,

$$Z_2 = \begin{bmatrix} 513931 & 513931 \\ 515045 & 512740 \\ 1039273 & 1072388 \\ 637821 & 1087414 \end{bmatrix}$$

The cost matrix for the wind farm model 3 (Z_3) is:

$$Z_3 = \begin{bmatrix} 513931 & 513931 \\ 515045 & 512740 \\ 622300 & 653925 \\ 1054794 & 1087414 \end{bmatrix}$$

The minimum value of the cost matrix Z_n for the wind farm model *n* represents the optimal solution; that is, the corresponding resource combination is identified to be the cost-effective resource combination.

To prove the effectiveness of the proposed model, it is appropriate to compare the results of the proposed model with the traditional practice of solving the described problem. When no information on the failed turbine is obtained from the CM systems, generally, the offshore O&M team sends technicians to inspect the failed turbine in a small Crew Transfer Vessel, identify the failure classification and then send the required resource combination to solve the turbine failure. To compare the results of the proposed model with the general practice, the cost of the general practice is assumed as the sum of the inspection activity cost using S_{11} and the fixed cost of corrective maintenance trip for an offshore wind turbine.

All the inputs presented in Section 4.3.1 and 4.3.2 are used to calculate this cost of traditional practice and is found to be $514,353. The estimated cost of traditional practice is used to compare the results of the proposed model and to find the cost savings if any.

The cost-effective resource combination for each wind farm model considered in this study with the total expected maintenance cost and the cost savings in comparison with the traditional practice are given in Table 4.6.

Table 4.6: Cost-effective resource combination for different wind farm models given in Table 4.3

Wind farm model	**Cost-effective resource combination**	**Expected total maintenance cost (in $'s)**	**Cost savings (in comparison with traditional practice)**
Base case	S_{11}	91591	82.12%
Model 1	S_{11}	513354	0.19%
Model 2	S_{22}	512740	0.31%
Model 3	S_{22}	512740	0.31%

The optimal resource combination can be directly selected from Table 4.6. From the results, it could be observed that S_{11} (which is the same as S_{12} in this study) is the cost-effective option to address the corrective maintenance for turbines that are in operation for less than ten years (base case model and wind farm model 1). In addition, S_{22} is the cost-effective option to address the corrective maintenance for turbines that are in operation for more than ten years (wind farm model 2 and 3). Comparing the results of the proposed model with the traditional practice, the proposed model produces very high cost savings of 82.12% for the base case model and considerable cost savings for the other three different wind farm models. It has to be noted that the proposed model is for one corrective maintenance trip and when there are multiple corrective maintenance problem instances with no information from CM systems, the cost savings will be more for the wind farm models 1, 2, and 3.

The results that are generated from the model are not only dependent on the probability of failure classifications (given in Table 4.3) but also on the cost estimates (given in Table 4.4 and Table 4.5). The value of the "fixed cost for corrective maintenance trip for an offshore wind turbine" in Table 4.5 is assumed to be the same for all types of corrective maintenance because of insufficient data, and this affects both the estimated cost of the general practice and also the results generated from the models. This assumption on the fixed cost for corrective maintenance is a key reason that the base case has a huge amount of savings in comparison with the other three wind farm models. More accurate fixed costs for different types of corrective maintenance will result in better estimates for the general practice and, more accurate results for the wind farm models 1, 2, and 3. Accurate cost data in maintenance decision-making and sensitivity analysis of the proposed model to the cost estimates (in Table 4.4 and Table 4.5) will be studied in our future work.

The case study provides a better understanding of the use of the proposed model to address a corrective maintenance situation when there is no information on the turbine failure type. Three different wind farm models are considered in addition to the base case, and the powerfulness of the model for different OWFs is demonstrated. The case study also gives us an understanding that when the number of failure classifications for an OWT/OWF increase, then the complexity in finding the cost-effective resource combination also increases.

4.4 Summary

In this chapter 4, a short-term resource decision problem for corrective maintenance at offshore wind turbine is identified and described. A simple mathematical model is proposed to solve the decision problem. The model is proposed in such a way that the expected cost of the decision is mainly dependent on the probabilities of occurrences of failure classifications. The maintenance team at all offshore wind farm will have their own failure classifications, resource combinations, and access to accurate failure data and, this model will assist the maintenance team in making resource decisions to address the corrective maintenance problem stated in this chapter.

As described in Section 2.2.3 and Section 4.1, the three elements, namely vessel, spare parts, and maintenance technicians, constitute a resource combination. As stated in Section 2.4.3, the effect of insufficient maintenance technicians on production loss of offshore wind turbines/farms has not been studied by the model reported in [69]. In the next chapter, i.e., chapter 5, we will investigate the possibilities of having insufficient maintenance technicians at the turbine for corrective maintenance and propose a model to assign appropriate number of maintenance technicians for corrective maintenance of offshore turbines.

CHAPTER 5

MAINTENANCE STAFFING MODEL FOR CORRECTIVE MAINTENANCE OF OFFSHORE WIND TURBINE

As mentioned in Chapter 4, maintenance staffing problem for corrective maintenance of offshore wind turbine is the principal focus of this chapter. In this chapter, the possibilities of having insufficient maintenance technicians at the offshore wind turbine for needed maintenance is studied. Also, a simple mathematical model is proposed to figure out the appropriate number of technicians for a corrective maintenance trip to an offshore wind turbine. The symbols used in this chapter are specific to and applicable only to this chapter. The $ values in this chapter are US dollars unless otherwise specified.

5.1 Problem description

As stated in section 2.2.3 of chapter 2, the resources that are required to perform maintenance at offshore wind farms (OWFs) are spare parts, maintenance technicians, and vessels. If anyone of the resources is not available, then the maintenance cannot be initiated at OWFs. Two important assumptions related to the availability of maintenance resources that are earlier stated in section 2.4.1 and section 2.4.2 of chapter 2 must be recollected.
They are,

(i) An optimal level of spare parts is maintained for maintenance execution, and all the spare parts are always available.

(ii) An optimal number of technicians and vessel fleet size and the mix is maintained at OWFs for maintenance.

The above-stated assumptions ensure that all the resources are available for all maintenance activities at OWFs. Therefore, in this study, whenever an offshore wind turbine experiences an unforeseen failure, corrective maintenance could be initiated as all the resources are always available. The reported work in [87] studied the influence of multiple working shifts (day shifts and night shifts) on the O&M costs of OWFs. The work in [87] reported that multiple working shifts (day shifts and night shifts) bring considerable advantage over a single working shift (day shift) in minimizing the overall O&M costs at OWFs. From work reported in [87], it is intuitively understood that OWFs established/capable of establishing facilities and resources to execute maintenance at both day shifts and night shifts. In this study, we assume that the OWF has all the facilities to execute maintenance in multiple working shifts, that is, corrective maintenance is executed in both day shits and night shifts [87]. Also, we assume that the O&M has a mixed fleet of technicians and vessels for day shifts, night shifts, and rotating shifts (day and night shifts) [87, 88]. It is reported in [76, 78] that all corrective maintenance activities at OWFs could be executed using Crew Transfer Vessels (CTVs). Therefore, this study assumes that all corrective maintenance activities are executed using CTVs.

In the scenario of corrective maintenance execution, the offshore O&M team will have information on the type/category of corrective maintenance (minor or major) required at the turbine. Based on the type/category of maintenance required, the appropriate vessel is selected for maintenance execution. Once the weather and sea-state conditions become accessible for maintenance, the required number of spare parts are moved from onshore maintenance facility/onshore inventory and placed in the vessel selected for maintenance execution. Then, the required technicians board the vessel (with spare parts) and travel to the turbine using the vessel to perform the needed maintenance.

Some of the maintenance technicians reaching the turbine may not be able to perform the needed maintenance activity due to “seasickness”[89]. **Seasickness** is the reaction of the human body's inner ear balance system to the unfamiliar motion of the ship. This unfamiliar motion is mainly caused by wind and wave conditions in the sea. OWFs located far away from the shore/coast (with a distance of at least 150 km from the coast/shore) are exposed to adverse wind and wave conditions, and there are high chances that the maintenance technicians who travel to these OWFs may get seasickness [78, 89]. The maintenance activities at OWFs ought to be precise and error-free. When the technicians sent to address the offshore turbine failure become seasick, they are not 100% fit to perform the required precise maintenance. Therefore, seasickness may result in a shortage of maintenance technicians for needed maintenance. This shortage of maintenance technicians at the turbine due to seasickness is the uncertainty in maintenance technicians for corrective maintenance of offshore wind turbines.

The shortage of maintenance technicians at the turbine increases downtime and availability. The cost associated with downtime is significantly large when compared to the cost of maintenance technicians and vessels [79, 86]. The offshore O&M team must aim to complete the corrective maintenance activity as quickly as possible by sending an optimal/appropriate number of technicians to the offshore turbine in a vessel with the required spare parts.

Very few works [39, 69] in the literature has investigated the maintenance technicians' factor in OWF maintenance. The reported work in [39] analyzed a total of 350 offshore wind turbines between 5-10 OWFs throughout Europe. With a data set of 1768 turbine years of operational data, the reported work in [39] analyzed the offshore turbine failures and categorized the failures into three types, namely minor repair, major repair, and replacement. The analysis in [39] established failure rates, failure costs, average repair time, and the average number of technicians required for all three failure categories. The reported work in [39] considered maintenance technicians as a deterministic factor in the modeling of offshore O&M costs.

As stated earlier in Section 2.4.3, the reported work in [69] developed a short-term decision-making model for scheduling maintenance tasks and resources (vessels and technicians) at the OWFs, considering constraints in weather, energy prices, vessel characteristics, and maintenance technician's skills. The time horizon considered in that model is a day, and it helps the OWF maintenance managers and planners to make better maintenance tasks and resource scheduling decisions each day. The model in [69] also developed a maintenance schedule for four days and studied two different scenarios of maintenance execution at OWF on each given day. The first scenario had twelve technicians available for maintenance execution, with seven to eight technicians, work on average per day, whereas the second scenario had seven technicians available. Both the scenarios performed the corrective maintenance activities within the given 4-day period. The reported work in [69] assumed the maintenance technicians as a deterministic factor and pointed out the importance of assigning an optimal number of technicians for corrective maintenance.

Both the reported works [39, 69], assumed maintenance technicians to be a deterministic factor and did not study the uncertainty in the number of technicians for corrective maintenance. Therefore, any valuable information on the uncertainty in maintenance technicians will help the offshore O&M to better plan and execute corrective maintenance activities, and this was the motivation to study the uncertainty in maintenance technicians in this chapter.

When a certain number of technicians are sent to the offshore turbine for corrective maintenance, the uncertainty in technicians brings in two possible situations, namely trip success and trip failure. The trip success is defined as the situation where enough number of technicians are available for maintenance at the turbine. Trip failure is defined as a situation where there are not enough technicians available for maintenance at the turbine. In the trip success situation, the maintenance crew completes the required maintenance and return to the shore.

In the trip failure situation, the maintenance team at the turbine may need additional technicians to execute the maintenance. Though there is a possibility that the maintenance team could wait at the turbine and ask for additional technicians from the onshore port, this study focuses on the situation that the maintenance team at the turbine returns immediately to the shore to get a completely different group of technicians for the required maintenance. Therefore, the technicians on the first trip are not involved in the second trip. Once different group of technicians are onboard, the maintenance crew travels again to the offshore turbine irrespective of the time of the day (day or night) and completes the maintenance on the second trip.

The objectives of this chapter are to model the uncertainty in maintenance technicians for OWF maintenance and to propose a simple mathematical model to assign an appropriate number of technicians for the described corrective maintenance situation of the offshore wind turbine. The failure cost categories, namely minor repair and major repair [39], which is described earlier in section 3.1 of chapter 3 will be used later in this chapter for illustrating the use of the proposed model. The reported values from [39] on the number of technicians required for minor repair is 2.61 and for major repair is 3.44. We will use these values in our illustrating calculations later in this chapter.

5.2 Uncertainty in maintenance technicians

The offshore O&M team sends a certain number of technicians to the offshore turbine for corrective maintenance execution. In a marine environment, both ships and maintenance technicians are exposed to a multitude of motions because of weather and sea-state conditions. Ship motions limit maintenance technicians' ability to perform maintenance tasks and result in seasickness (also known as motion sickness), which symptoms include but are not limited to mental fatigue, physical fatigue, headache, sleepy, dizziness, anxiety and nausea [90]. As precision maintenance is required for the offshore wind turbine, in this study, we assume that the maintenance technicians who get seasick during travel to the offshore turbine and lose body balance are not allowed to perform any maintenance at the offshore turbine. Therefore, the number of technicians available for maintenance at the turbine is the difference between the number of technicians sent to the turbine and the number of technicians who get seasickness. The number of technicians sent to the turbine is a certain factor, but the number of technicians who get seasick during travel is uncertain.

At OWFs, there would be multiple corrective maintenance trips to the multiple offshore turbines of the farm, and the number of technicians who get seasickness may vary with each corrective maintenance trip, and these variations are random. As a result, the ratio of the number of technicians who get seasickness to the number of technicians sent to the turbine is also random. Therefore, the ratio of technicians who get seasickness to the technicians sent to the turbine is the random variable that represents the uncertainty in maintenance technicians due to seasickness in this study. When this ratio is expressed in percentages or absolute decimal values, the random variable can take any value in the interval [0%, 100%] or an equivalent [0, 1]. The random variable cannot take values more than 100% because the number of technicians who can get seasickness cannot be greater than the number of technicians sent to the turbine. As the outcomes of the random variable are percentages ranging from 0% to 100% and can take absolute values only in the interval [0, 1], the random variable is assumed to follow a beta distribution with two positive shape parameters α and β. If a random variable x follows beta distribution, the probability density function (pdf) of the beta distribution, for $0 \leq x \leq 1$ and shape parameters $\alpha > 0$ and $\beta > 0$, is given as [91],

$$f(x) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1} \tag{5.1}$$

The Gamma function is given as [91],

$$\Gamma(z) = \int_0^\infty e^{-t} t^{z-1} dt \qquad z \neq -1, -2, -3, \ldots \tag{5.2}$$

The mean (μ) and variance (σ^2) of the beta distribution is given as,

$$\mu = \frac{\alpha}{\alpha + \beta} \tag{5.3}$$

$$\sigma^2 = \frac{\alpha\beta}{(\alpha + \beta + 1)(\alpha + \beta)^2} \tag{5.4}$$

The pdf plots of beta distribution with different shape parameters are shown in Figure 5.1, Figure 5.2, Figure 5.3, and Figure 5.4.

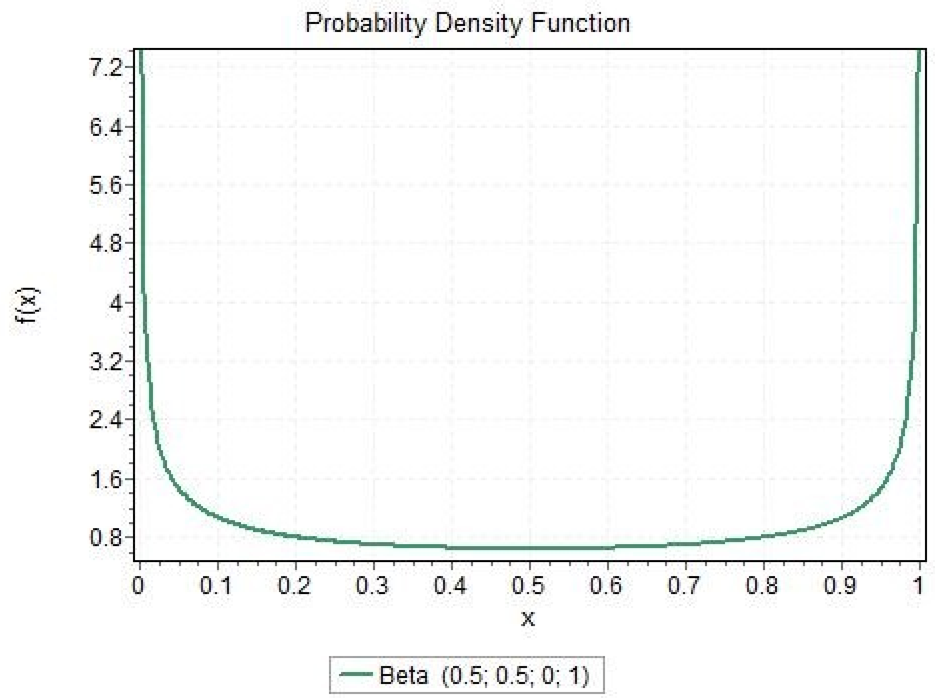

Figure 5.1: Pdf of beta distribution for 0≤x≤1 and shape parameters α=0.5 and β=0.5

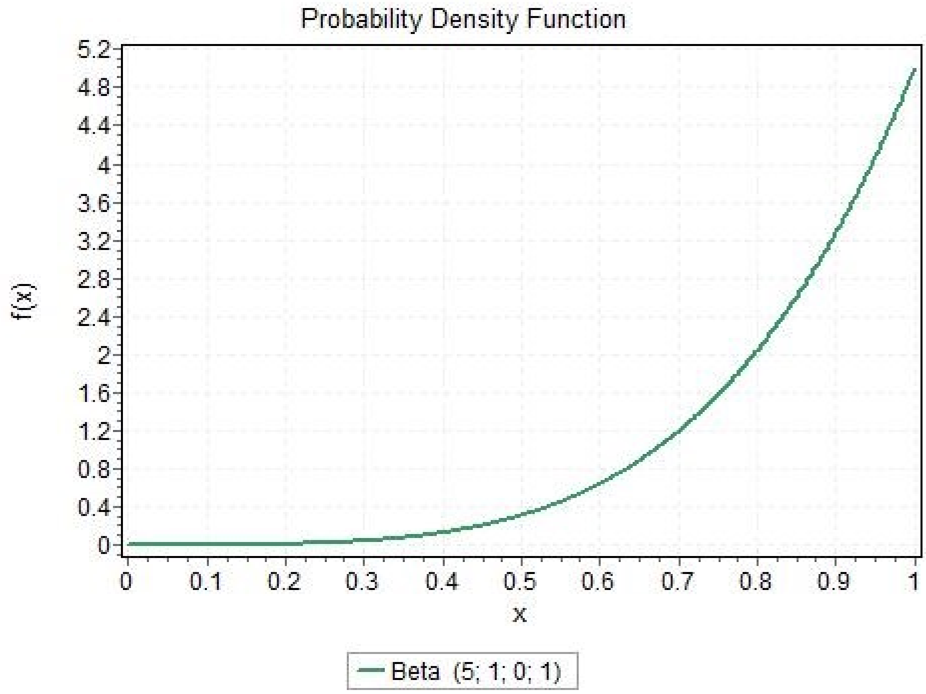

Figure 5.2: Pdf of beta distribution for 0≤x≤1 and shape parameters α=5 and β=1

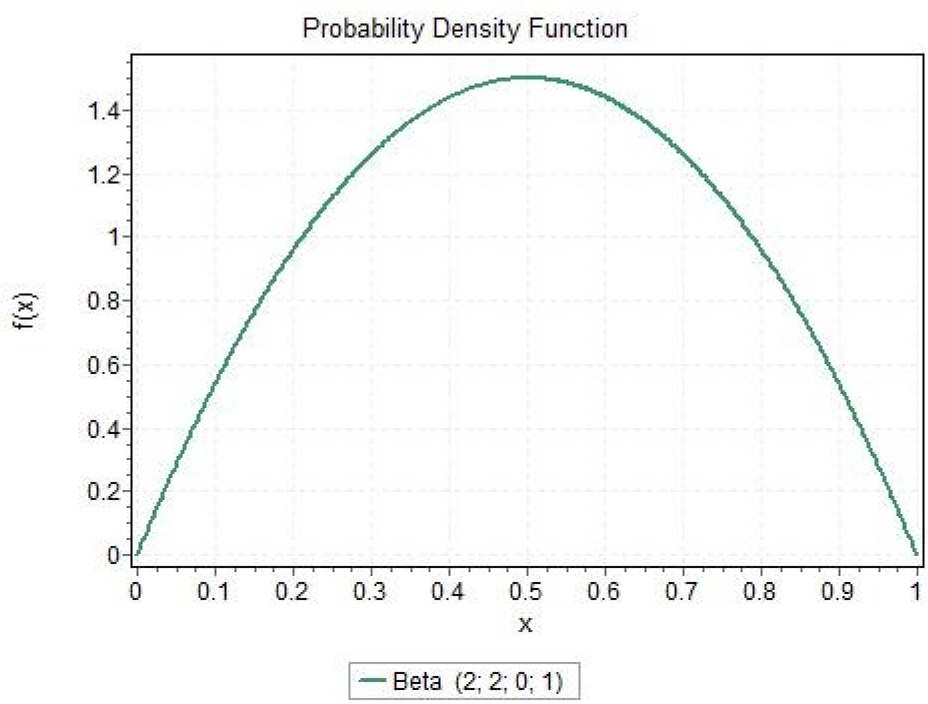

Figure 5.3: Pdf of beta distribution for 0≤x≤1 and shape parameters α=2 and β=2

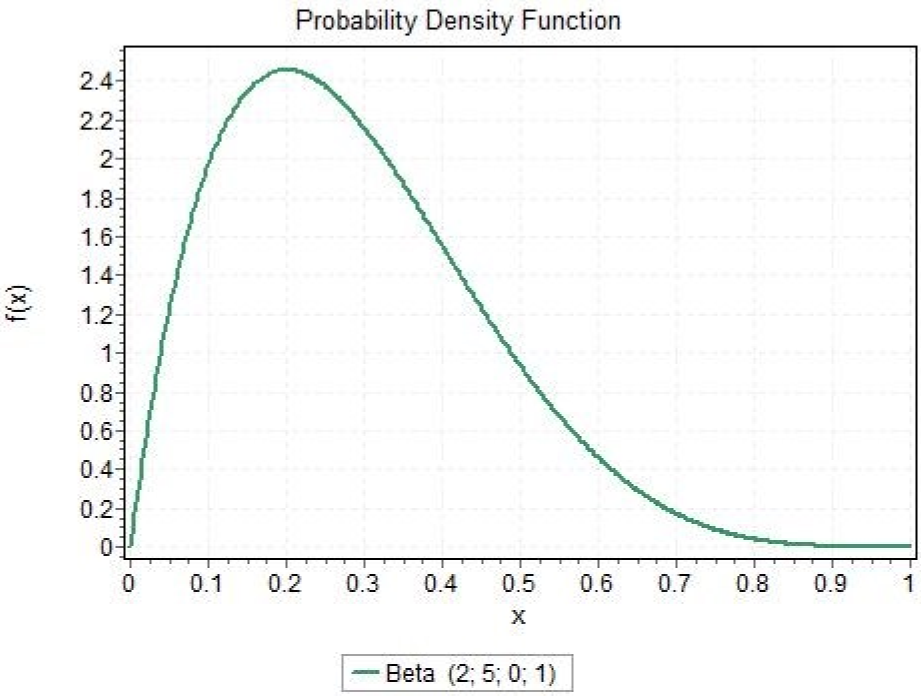

Figure 5.4: Pdf of beta distribution for $0 \leq x \leq 1$ and shape parameters $\alpha=2$ and $\beta=5$

5.3 Mathematical model

If an offshore wind turbine has a finite number of corrective maintenance categories, then each category requires a predetermined number of technicians to send to the turbine to execute the needed maintenance. Upon a turbine failure, the O&M team knows the type/category of corrective maintenance required at the failed turbine, and they ought to send at least the predetermined number of technicians required for that specific corrective maintenance category. As corrective maintenance activities are executed using CTVs [92], the maximum limit of maintenance technicians a CTV can carry is the maximum technicians that the offshore O&M team could be sent at the most for a corrective maintenance trip. Therefore, the decision variable (z), that is, the number of technicians to send to the turbine for corrective maintenance, is represented as a finite set of positive integers and is given in equation 5.5.

$$z = [L, L+1, L+2, \dots, U] \tag{5.5}$$

The lower limit of the set (L) is the predetermined number of technicians for a given corrective maintenance category, and the upper limit of the set(U) is the maximum limit of technicians a CTV can carry. The selection of the number of technicians to send to the turbine(z)among the available choices in equation 5.5 is the only decision in our model.

If z technicians are sent to the turbine for corrective maintenance, then the ratio of the number of technicians who get seasickness to the number of technicians sent to the turbine is given as,

$$\frac{y}{z} = p \tag{5.6}$$

where z is the number of technicians sent to the turbine, y is the number of technicians who get seasickness, and p is the beta distributed random variable.

The ratio of the minimum number of technicians required at the turbine for maintenance execution to the number of technicians sent to the turbine is given as,

$$\frac{L}{z} = q \tag{5.7}$$

where L is the predetermined number of technicians required at the turbine for corrective maintenance execution, and z is the number of technicians sent to the turbine.

The probability of having enough technicians at the turbine for corrective maintenance, that is, the probability of trip success is given as,

$$\gamma = P[(p \leq (1 - q))] \tag{5.8}$$

where γ is the probability of trip success, and p is the beta distributed random variable.

The probability of not having enough technicians at the turbine for corrective maintenance, that is, the probability of trip failure is given as,

$$1 - \gamma = P[(p > (1 - q))] \qquad (5.9)$$

Both the probability of trip success and trip failure depend on the decision, the number of technicians who get seasickness, and the minimum number of technicians required at the turbine for maintenance execution. The trip success and failure situations, along with their probabilities, are considered in the model.

The objective is to minimize the expected total maintenance cost of the decision, to figure out the cost-effective decision on the number of technicians to send on a trip for successful corrective maintenance execution. The total maintenance cost in our model includes the technicians' cost, access vessel cost, and production losses due to downtime. The technicians and vessels are in use from the point of time they get ready to board the vessel to the point of time they get back to shore after the maintenance activity. In addition, the turbine is unavailable until the maintenance crew gets the turbine back to operation. Therefore, the mathematical model formulation involves various deterministic time elements of maintenance, namely lead-time, logistic time, waiting time, travel time, and repair time.

The time to get the vessel ready for maintenance is the lead-time and, the time to get the spare parts is the logistics time. As mentioned earlier in section 5.1, all the resources (the vessels, the technicians, and the spare parts) are always available in the onshore port for maintenance execution and so the lead-time of vessels and the logistic time of spare parts are eliminated in our model. The total delay in maintenance execution due to weather and sea-state conditions is the waiting time and is the sum of “the delay before travel starts” and “the delay at the turbine” [30]. It is dependent on the weather and does not depend on the decision on the number of technicians to send. Hence, the waiting time is a constant in our model.

The time taken to travel back and forth the turbine using vessels is called the "travel time" and is the sum of the "travel time to the turbine" and "travel time from the turbine." The travel time depends on the vessel speed and does not depend on the decision on the number of technicians to send, and so is a constant in our model. As the travel cost depends on the number of technicians sent to the turbine, the cost associated with travel is included in the model. The time it takes to perform the actual maintenance work is the repair time. In the case of trip success, there will be enough technicians at the turbine, and the maintenance will be executed. In our model, the trip success situation includes repair time. In the case of trip failure, there will not be enough technicians at the turbine, and so additional technicians are needed to execute the maintenance. As described in section 5.1, in the trip failure situation, the maintenance crew at the turbine return to the shore. Then, a completely different group of technicians execute the maintenance on the second trip. Therefore, the certain amount of time spent on the first trip and additional wait time (the time spent at the shore to get a different group of technicians onboard) before the start of the second trip along with the cost of the second trip is considered for trip failure. The mathematical model for the described problem is given as,

$$Z = [T \cdot ((z \cdot a) + b + c)] + [\gamma \cdot (R \cdot ((z \cdot a) + b + c))] + [(1 - \gamma) \cdot (Z + W \cdot c)] \tag{5.10}$$

Z	Expected total maintenance cost
z	number of technicians sent for corrective maintenance
T	Travel time
a	technicians' cost per hour
b	vessel cost per hour
c	revenue loss per hour
γ	Probability of trip success
R	Repair time
$1-\gamma$	Probability of trip failure
W	Wait time (the time spent at the shore to get a different group of technicians onboard) before the start of the second trip

The above mathematical model describes the expected total maintenance cost of sending z number of technicians for the corrective maintenance of the offshore turbine. The first square bracket term in the model is the cost associated with travel to the turbine and travel from the turbine irrespective of trip success or trip failure using z. The travel cost includes the technicians' cost, vessel cost, and revenue loss. The second square bracket term in the model is the trip success cost using z. The trip success cost includes the technicians' cost, vessel cost, and revenue loss incurred because of corrective maintenance execution using z, and the probability that the maintenance will be successfully executed using z. The third square bracket term in the model is the trip failure cost using z. The trip failure considers the cost incurred because of the wait time at the shore to get a different group of technicians onboard, the total cost including the vessel cost, technicians cost, and revenue loss to complete the corrective maintenance using a different group of technicians in the second trip, and, the probability that the maintenance will not be successfully executed using z. The model in equation 5.10 is simplified as,

$$Z = \frac{[T \cdot ((z \cdot a) + b + c)] + [\gamma \cdot (R \cdot ((z \cdot a) + b + c))] + [(1-\gamma) \cdot W \cdot c]}{\gamma} \tag{5.11}$$

$$Z = \frac{(z \cdot a + b + c) \cdot (T + \gamma R) + (1-\gamma) \cdot W \cdot c}{\gamma} \tag{5.12}$$

With appropriate inputs, the proposed model in equation 5.12 can calculate the expected cost of each decision choice. Utilizing the enumeration method, the expected total cost for each value of z is calculated, and the z with minimum expected total maintenance cost is selected as the cost-effective option to send for corrective maintenance. Given, the shape parameters of the beta distributed random variable p (which represents uncertainty in technicians), the minimum number of technicians required for corrective maintenance, the maximum limit of CTV, and the decision choices of the number of technicians to send for corrective maintenance, and, using the proposed model, the O&M team at OWF would be able to figure out the optimal number of technicians to send for any category of corrective maintenance of offshore wind turbine.

5.4 Case study

To demonstrate the use of the proposed model, we select a corrective maintenance category of offshore wind turbines earlier stated in section 5.1, that is, major repair, and two scenarios of the offshore marine environment, namely low motion and high motion scenarios [90]. The low motion scenario is a marine environment with a moderate breeze and smaller waves, and the high motion scenario is a marine environment with a strong breeze and larger waves [90, 93, and 94]. The marine characteristics for the low motion and high motion scenarios are given in Table 5.1.

Table 5.1: Characteristics for low motion and high motion scenarios [90, 93, 94, 95]

Marine Parameter	**Low Motion Scenario**	**High Motion Scenario**
Mean Wind Speed	11-16 knots	22-27 knots
Beaufort Wind Scale	4	6
Sea State	3-4	5
Significant Wave Height	0.5 m - 1 m	1.5 m – 2 m
Maximum Probable Wave Height	1.5	4

The significant wave height in Table 5.1 is a visual estimate of the average wave height in the sea. It is a standardized statistic to denote the characteristic height of the random waves in a sea state [96].In the time-domain analysis, the significant wave height is defined as the average height of the highest one-third of all waves [97]. For example, for a significant wave height of 10 m, 1 wave height in 100 wave heights will be larger than 15.1 m, and 1 wave height in 1000 wave heights will be larger than 18.6 m. It is understood that when experiencing a significant wave height of 2 m, waves close to double this height can be expected to occur [96]. From Table 5.1, it is observed that the maximum probable wave height is 4 m for a high motion scenario. Therefore, a CTV with an operational limit of 2 m significant wave height can execute the major repair for both low motion and high motion scenarios [92].

It is reported in [39] that for offshore wind turbines, the average number of technicians required for major repair is 3.44, and so at the least four technicians are sent to the offshore turbine for a major repair. We will use this number to represent the pre-determined number of technicians (L) for a major repair. The maximum limit of technicians that the CTV can carry (U) is twelve [78]. The finite set of values, also the decision choices for the offshore O&M team for major repair is,

$$z_{major\ repair} = [4,5,6,7,8,9,10,11,12] \tag{5.13}$$

It is reported in [90] that, irrespective of the distance from shore, on average, 20% of technicians get seasickness during travel and lose body balance at the turbine for the sea state of 3-4. The values reported in [90] for sea state 3-4 corresponds to the low motion scenario of Table 5.1. Therefore, the beta distributed random variable that represents uncertainty in seasickness is assigned a mean of 0.20 and a standard deviation of 0.05 for low motion scenario. The pdf of the beta distributed random variable with shape parameters (α=12.60 and β=50.40) for a low motion scenario is given in Figure 5.5.

It is also reported in [90] that, irrespective of the distance from shore, on average, 46.2% of technicians get seasickness during travel and lose body balance at the turbine for the sea state 5. The values reported in [90] for sea state 5 corresponds to the high motion scenario of Table 5.1. Therefore, the beta distributed random variable that represents uncertainty in seasickness is assigned a mean of 0.46 and a standard deviation of 0.10 for high motion scenario. The pdf of the beta distributed random variable with shape parameters (α=11.02 and β=12.83) for a high motion scenario is given in Figure 5.6.

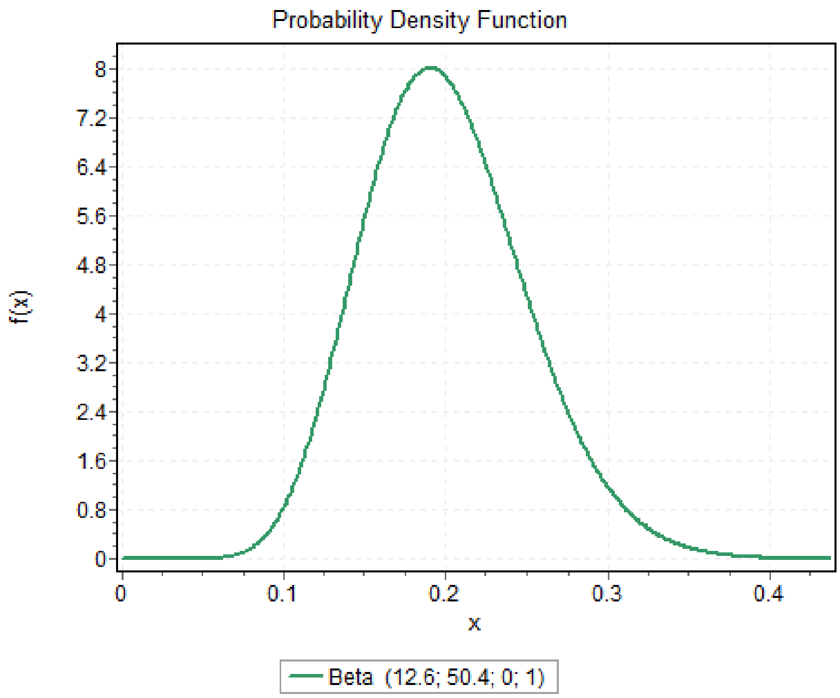

Figure 5.5: Pdf of beta distribution with shape parametersα=12.60 and β=50.40 for low motion scenario

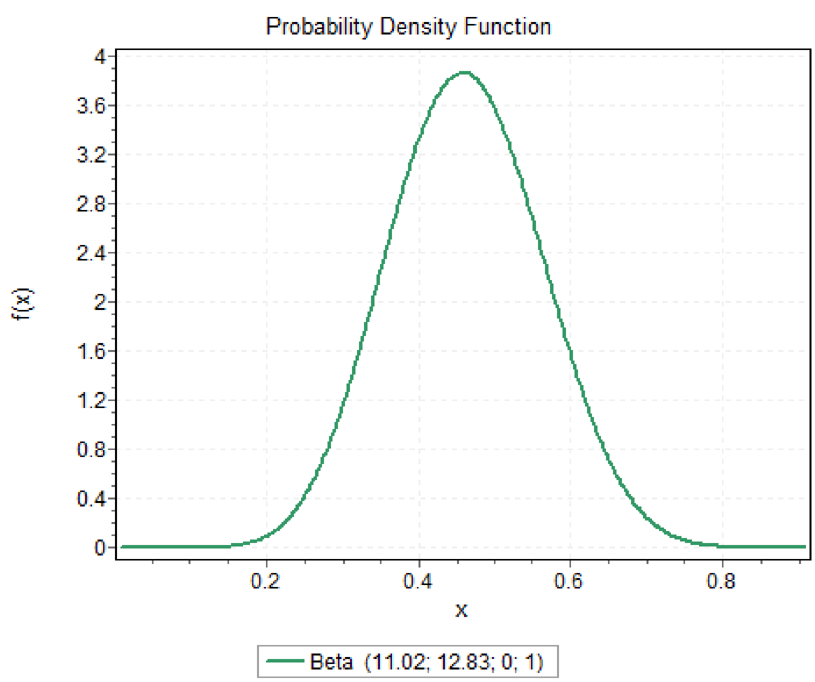

Figure 5.6: Pdf of beta distribution with shape parametersα=11.02 and β=12.83 for high motion scenario

The CTV travel at a speed of 23 knots in low motion scenario and 15 knots in high motion scenario [92]. For 150 km turbine from shore [78], we get the round-trip travel time (T) for low motion scenario as 7.04 hours and high motion scenario as 10.8 hours. The repair time for major repair is the same for low motion and high motion scenarios and is 423.36 hours [30, 39]. All other required inputs to calculate the expected maintenance cost (Z) is given in Table 5.2.

Table 5.2: Input parameters to calculate the expected O&M cost [78, 79, 85, 86]

Parameter	**Value**
Cost of technicians/hour (a)	\$125
Cost of vessel/hour (b)	\$74
Revenue loss/hour (c)	\$18,684
Additional wait time to get a different maintenance crew onboard for the second trip (W)	2 hours

Using equations 5.8 and 5.9, the probability of trip success and probability of trip failure for each decision choice of equation 5.13 is calculated for the low motion scenario and high motion scenario. Using equation 5.12 and using the enumeration method, the expected total maintenance cost is calculated for each decision choice (in equation 5.13) for low motion scenario and high motion scenario, and the results are given in Table 5.3.

From the above table, it could be seen that the minimum expected total maintenance cost is achieved by selecting six technicians for the low motion scenario and nine technicians for the high motion scenario. Therefore, for major repair of the offshore wind turbine, the optimal number of technicians to send for the low motion scenario is six, and the high motion scenario is nine.

Table 5.3: Expected total maintenance cost of major repair in low and high motion scenarios

Decision choice (z)	**Expected total maintenance cost of major repair**			
	Low motion scenario		**High motion scenario**	
	Probability of Trip Success (γ)	Expected total maintenance cost (Z)	Probability of Trip Success (γ)	Expected total maintenance cost (Z)
4	0	N/A	0	N/A
5	0.5252	$8,499,591	0.0023	$116,426,511
6	0.9918	**$8,397,696**	0.1008	$10,681,743
7	0.9999	$8,450,052	0.3762	$8,937,494
8	1	$8,503,843	0.6471	$8,714,911
9	1	$8,557,643	0.8202	**$8,687,668**
10	1	$8,611,443	0.9122	$8,711,060
11	1	$8,665,243	0.9575	$8,752,244
12	1	$8,719,043	0.9793	$8,800,635

5.5 Summary

In this chapter, the effect of seasickness on OWF maintenance technicians is described. The uncertainty in maintenance technicians due to seasickness is modeled. Then, a mathematical model is proposed to find the optimal number of technicians to send for corrective maintenance of an offshore wind turbine. Also, the use of the proposed model is illustrated using a simple case study with two different offshore marine environment scenarios. The model proposed in this chapter would assist the offshore O&M team in making cost-effective decisions on the number of technicians to send for corrective maintenance of offshore turbine considering uncertainty in seasickness, and help reduce the overall O&M costs and the cost of energy at OWFs. Future work involves the investigation of different CTV configurations and their influence on the maintenance technician's seasickness.

CHAPTER 6

SUMMARY AND FUTURE WORK

The main contributions of this thesis are summarized in section 6.1. Suggestions for future research are provided in section 6.2.

6.1 Summary

OWF is among important renewable energy sources to meet the global energy demand through clean energy. As OWFs are installed and operated in the sea, they are continually exposed to the marine environment and associated uncertainties throughout their lifecycle. The uncertainties encountered by OWFs result in high costs of O&M and energy. This study aimed to model the uncertainties in OWF maintenance and their effects on OWF O&M cost and, to propose decision models considering uncertainties to assist the O&M team in making optimal/cost-effective maintenance decisions.

OWFs are exposed to uncertainties that include but are not limited to weather conditions, sea-state conditions, and component lifetimes. In chapter 3, an O&M cost model was proposed for the next maintenance trip using stochastics time elements to study the seasonal effects of uncertainties on offshore O&M costs. The seasonal variations of O&M costs at OWFs considering uncertainties were obtained in chapter 3, and the results showed that O&M costs were the lowest in summer and highest in winter. The model developed in chapter 3 would help to assess the seasonal O&M cost for a specific OWF location and plan both inspection and preventive maintenance activities to minimize the O&M cost.

The cost associated with the corrective maintenance of OWFs is very high because of their high downtime costs. The decisions related to corrective maintenance must be cost-effective to minimize the overall O&M costs. At OWFs, the turbine failure information could be unavailable for corrective maintenance, and so resource decision-making becomes a challenging task. In chapter 4, the resource combinations to address the offshore wind turbine failure classifications were described. A decision model was proposed for resource decision-making of corrective maintenance, considering uncertainty in turbine failure information. The case study presented in chapter 4 demonstrated the use of the proposed decision model. The results showed that the model was mainly dependent on the probability of occurrence of offshore turbine failure classifications. The O&M team at all OWFs have their own failure classifications, resource combinations, and access to accurate failure data. With this information, the model proposed in chapter 4 assist the offshore O&M teams in making cost-effective resource decisions for corrective maintenance, considering uncertainty in turbine failure information.

OWFs' high downtime cost requires that appropriate resources (spare parts, vessel, maintenance technicians) are always sent for corrective maintenance of offshore wind turbines. The offshore O&M team determines the resources required for different categories of corrective maintenance. As a result, a predetermined number of technicians are sent in a vessel with spare parts to address a specific corrective maintenance category. Because of the marine environment, there could be situations where few of the maintenance technicians arrive at the turbine but are not able to perform the required maintenance due to seasickness. In chapter 5, the possibilities of having insufficient maintenance technicians at the turbine for corrective maintenance of offshore wind turbine was studied. The uncertainty in maintenance technicians for OWF maintenance was modeled. A mathematical model was proposed to aid decision-making on the number of maintenance technicians to send for corrective maintenance of offshore wind turbines. The case study presented in chapter 5 demonstrated the use of the proposed decision model. The O&M team at OWFs has information on the number of technicians required for different corrective maintenance categories and the historical data on the number of technicians who get seasickness during travel to the turbine. With this information, the proposed model assists the offshore O&M teams in deciding the appropriate/optimal number of maintenance technicians to send to the turbine for corrective maintenance.

Overall, with the generated knowledge, this state-of-the-art study advances research on OWF maintenance and associated decisions considering uncertainties. An improved understanding of the seasonal effects of uncertainties on offshore O&M costs helps the offshore O&M teams better plan the maintenance activities. The proposed models on corrective maintenance resource decisions help offshore O&M teams to make appropriate/optimal resource decisions and, thus, minimize the overall O&M costs at OWFs.

6.2 Future Work

Although the O&M model for the next maintenance trip in chapter 3 and decision models of chapters 4 and 5 proposed in this thesis has addressed the shortcomings of the relevant reported work on OWF maintenance, there are a few challenges that are suggested for further consideration.

In this study, the vessels and spare parts are assumed to be always available in the onshore maintenance facility for the maintenance of OWFs. As a result, the O&M model for the next maintenance trip in chapter 3 treated the lead time of the vessels and logistic time of spare parts to be zero. If the vessels and spare parts are not available, the O&M cost model must include the lead time and logistic time. As the O&M cost model aims to study seasonal variations, it would be interesting to study if there are any seasonal variations in the lead time of vessels and logistic time of spare parts for OWF maintenance.

In the resource decision model proposed in chapter 4 for corrective maintenance of offshore wind turbines, the time elements of maintenance are lead time, logistic time, waiting time, travel time, and repair time. The time elements are treated deterministic in the proposed model. The future work is to consider the time elements of maintenance as stochastic time variables and propose a resource decision model for corrective maintenance of offshore wind turbines.

In the model proposed in chapter 5 for making appropriate decisions on the number of maintenance personnel to send for corrective maintenance, it is assumed that all the corrective maintenance categories are executed using crew transfer vessels (CTV). It will be interesting to study the use of the helicopter for corrective maintenance at OWFs, its associated costs, travel time, and the allocation of maintenance personnel in a mixed fleet of CTV and helicopter for corrective maintenance.

Overall, it is expected that through this thesis and the suggested research, the O&M team of OWFs can benefit from cost-effective maintenance planning and maintenance decision-making. The improved maintenance planning and cost-effective decision-making will reduce the operation and maintenance costs and the cost of energy of OWFs.

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